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Bachelor thesis Economics of Markets and Organizations

The effect of technology experience on one's attitude towards the implementation of Artificial Intelligence in medicine with opportunities for productivity increases

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Abstract

Artificial Intelligence is starting to get a very prominent role in markets and organizations. The Dutch health care system is an example of one of these markets. Due to the rapid development of AI, the opportunities regarding productivity increases keep expanding. To explore these opportunities, a literature review is conducted in which potential productivity increases after the AI's implementation are analyzed. One opportunity of the use of AI in medicine is that AI sometimes could take over general tasks of doctors, resulting in doctors having more time to perform intensive treatments. Moreover, AI in some cases is able to execute treatments more accurately and efficiently perform than doctors are able to. Subsequently, placebo effects could result in a treatment performed by AI being more effective than if the treatment is executed by a doctor. If a patient has more trust in an AI-controlled treatment, the treatment could be more productive through this mechanism. Nonetheless, in order for AI to be implemented in medicine, the acceptance of people for this idea is important. Therefore in this paper, the effect of having experience with technology on one's attitude towards the increasing implementation of AI in medicine are tested. Three datasets on attitudes towards AI in medicine, technology experiences and other characteristics are used to create linear regression analyses and other models to form tables and figures which showed a statistically significant effect of technology experience on one's attitude towards the use of AI in medicine. Individuals with more technology experience, on average, are more likely to have a more positive attitude towards the use of AI in medicine. In addition, technology experience has less of an effect when one is older and men are more likely to have a more positive attitude towards the use of AI in medicine than women. By exploring its civil and economic relevance, the thesis could contribute to academic knowledge whilst addressing a modern and relevant societal issue.

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1. Introduction

Since the internet revolution in 1990, the world has drastically changed. One of the most recent technology revolutions is the rise of Artificial Intelligence (AI). AI is growing rapidly in popularity and a lot of people have some form of experience with it. The rising importance of AI in many aspects of human endeavor is expected to cause some fundamental changes in organizations and markets soon (Reis et al., 2020). Due to the rapid development of AI, such as the rise of natural language processing systems like ChatGPT, the possibilities of what one or a party could achieve by using this technology keep expanding. Because of its never stopping progression, there is a gap in the literature regarding the role of AI on organizational productivity.

AI gets increasingly more integrated in everyday life, understanding its role within organizational processes, could be of interest for individuals or parties associated with organizations. It is evident that with the increasing incorporation of AI, issues such as performance, trustworthiness, privacy and explainability could arise (Dinh et al., 2018). These complexities could affect individuals' acceptance towards AI which is relevant for the pace of the integration of AI. Hence why exploration of the perception of the demanding side of the market is of interest, establishing what characteristics have a relation with one's attitude towards AI.

The form of organization used in this research will be the Dutch health care sector. This sector is an extreme form of an organization due to the stakes that come with it. Therefore, examining the people's attitudes on the increasing implementation of AI in medicine could set the stage for most markets in general. In Europe, many countries are experiencing labor shortages in the health care sector (De Vries, et al 2023). In addition, globally, the demand for health care workers is predicted to increase by 40 million before 2030 (Parzonka, et al 2023). By increasing the integration of AI, doctors could have the opportunity to split the workload and AI is maybe even able to be more efficient as opposed to a doctor in some fields. Increasing the implementation of AI in the health care sector could be part of the solution for this problem in the form of a productivity increase per health care worker. Patient compliance is a big issue in health care, which indicates that the patient has a lot of control over what treatment they will take (Murphy & Coster 1997). Hence why examining the perception of demanding side, and in particular patients, is of importance. Furthermore, to explore what characteristics might have an effect on one's attitude towards AI could be of importance to policy makers and doctors, making the opportunity to influence this attitude possible.

The research question is:

Does having more experience with technology result in a more positive attitude towards the implementation of artificial intelligence in medicine, resulting in productivity increases?

The paper is structured as follows:

The discussion about the research question is divided into two parts. First, a literature review is conducted where the opportunities of the use of AI in the health care sector in the form of productivity increases are explored. I expect that an increased integration of AI in health care is correlated with a productivity increase in that sector. This correlation is based on the idea that AI might be able to take over some of the doctors' workload, that AI might be more efficient in some treatments and that through placebo effects an AI-controlled treatment could be more effective if the patient prefers said treatment. Relevant literature is reviewed to analyze the possibilities of these mechanisms individually and combined. The aim of the literature review is to examine through what mechanisms AI could contribute to increase productivity in the health care sector.

After exploration of the opportunities in productivity increases, an extensive data analysis regarding individuals' attitudes towards the use of AI in medicine and what characteristics are correlated with said attitude, is examined. The main relationship analyzed is how technology experience affects one's attitude towards AI in medicine. I expect this relationship to be positive, where more technology experience is correlated with a more positive attitude towards AI in medicine. I expect if an individual has more experience with technology, they have more knowledge of how technology works and they therefore could be more aware of the abilities of AI. For this data analysis, the Longitudinal studies for the Social Sciences (Liss) will be used with OLS regressions and ordered probit models. Subsequently, the combination of the results from the data analysis and the relevant literature are compared with and contrasted to similar papers whilst describing the limitations of this paper. Lastly, the conclusions will be drawn from the combination of the findings from the literature review and from the data analysis and potential future research suggestions are commented on.

2. Literature

2.1 General attitude towards AI

In a global study conducted by Neudert, et al 2020, survey data was used from a sample of over 150,000 respondents from 142 countries regarding peoples' perceptions of the risk of using AI in decision making in general. They found that the acceptance of the use of AI differed prominently between regions, with North Americans and Western Europeans being more likely to see the development of AI as harmful and respondents from South and East Asia are more likely to view the development as beneficial. They concluded that especially in Western regions, skepticism regarding the use of AI is high, indicating that people are more risk averse. This makes any misstep in the development AI dire, suggesting that in many countries public agencies will struggle to convince citizens that AI is beneficial (Neudert, et al 2020). Schepman & Rodway 2023 analyzed the General Attitudes towards Artificial Intelligence Scale (GAAIS), which is an instrument to measure the general attitudes towards AI, separated between positive and negative attitudes. The study is based on data from a sample of 304 participants from the UK. They found that the GAAIS is significantly associated with different fields of trust, highlighting corporate distrust. For a higher integration of AI, firms need to safely and ethically implement the technology. Higher levels of corporate distrust are associated with a more negative attitude towards the positive and negative aspects of AI (Schepman & Rodway 2023). This adds to the idea of Neudert that any misstep in the development of AI could negatively influence trust, which is correlated with a more negative attitude towards AI. Based on this, the overall trust in the health care sector could be of importance for peoples' attitude towards implementing AI in medicine. However, there is little recent research regarding the trust of people in health care, making it difficult to conclude the relationship between trust in health care and the attitude towards the use of AI in medicine.

Determining how the general attitudes towards AI changed over time can be relevant to set the stage for future expectations. Fast & Horvitz analyzed news articles from the New York Times over 30 years with certain key words that indicate positive and negative attitudes, aiming to find the trends of the attitude towards AI over time. It is important to note that these findings are based on news articles and therefore may not be a reliable representation of the peoples' perception. To determine external validity, Fast & Horvitz replicated the study with the online forum Reddit for fewer years, suggesting that Reddit could generalize the public at large. For this analysis they found a similar trend in attitudes over the years. They found that the discussion regarding AI has been increasing since 2009 and has consistently been more positive than negative. Moreover, an increase is concluded in the hope for a beneficial impact of the use of AI in health care. This sets the stage for exploration of the opportunities that arise with the increasing integration of AI in health care. However, specific issues such as the fear of losing control over AI have been increasing in recent years (Fast & Horvitz 2017).

2.2 The role of Artificial Intelligence in medicine

There will be a discussion regarding an increase in AI-controlled treatments in medicine. Let us start by addressing the necessity for AI being more integrated in medicine. Many countries are faced with labor shortages in the health care sector in Europe (De Vries, et al 2023). This could result in hospital staff working overtime to keep up with treatments. Moreover, the global demand for health care staff is expected to increase by 40 million before 2030, resulting in an increasing labor demand according to the World Health Organization (Parzonka, et al 2023). De Vries, et al 2023, attempted to examine the effectiveness of recruitment and retention strategies, but there is scarce evidence regarding that these strategies are effective to tackle these labor shortages. The study suggested that bundles of these strategies are more effective (De Vries, et al 2023). These bundled strategies, however, could be time consuming and might therefore be an inefficient way to challenge labor shortages. Increasing the implementation of AI in medicine due to a more positive attitude towards it could be part of the solution to tackle these labor shortages.

The implementation of AI is growing rapidly in the public health care sector and is set to leave a big mark (Malik, et al 2019). In the field of pathology, in which the cause and development of a disease is of interest, AI has made major improvements. Studies even demonstrated how AI could make pathological interpretations more efficient, accurate and useful as opposed to the traditional approach (Rajpurkar, et al 2022). These studies examined how AI can make a more accurate survival prediction for a range of cancer types compared to the conventional approach. For radiology, where images are used to diagnose diseases, Baum et al found that the use of AI-enhanced devices improved image quality and hence improved accuracy. The treatment group had full access to these AI-enhanced devices and the control group had limited access to the devices. Before the intervention, both the treatment and control group had similar scores in image quality and scan time (Baum, et al 2023). Hamet & Tremblay summarized a sum of these studies and concluded that the incorporation of AI in medicine is predicted to accomplish more efficient and effective health care delivery. Nonetheless, maintaining human touch in health care is deemed as highly important due to ensure responsible AI integration (Hamet & Tremblay 2017).

To further explore this human touch in the increasing implementation of AI in medicine, we will discuss the opportunities in AI-human collaboration instead of AI versus human competition. An increase in AI usage in medicine reduces manual labor and therefore increases the amount of time a doctor has for primary care, which translates to an overall productivity and output increase (Malik, et al 2019). Manual labor is defined as tasks, where person-focused care is not necessary whereas primary care is defined as first-contact person-focused care. If a doctor knows the patients' preferences, he can discriminate in his way of treating patients and therefore give computer-controlled (AI-controlled) treatments to patients with a positive attitude towards the implementation of AI in medicine. This results in a doctor having more time for primary care or other tasks, which increases the output and productivity per doctor.

2.3 Placebo effects

Now that the perspective from the health care providers' side is discussed, let us explore the opportunities of the increased integration of AI from the patient's perspective. Kaptchuk & Miller did research on placebo effects in medicine. A placebo effect in the health sector is described as an improvement in symptoms that are attributable to therapeutic interactions or rituals. This implies that placebo effects are the belief in the effectiveness of the treatment (Eccles 2002). A study was conducted on placebo effects where experiments demonstrated how placebo effects could positively affect one's symptoms (Kaptchuk & Miller 2015). It is made evident that placebos can provide relief and hardly ever provide cure. One of the examples used is a study regarding the side effects of asthma patients, where one group of patients were given medicine for asthma, and the other group of patients were given a 'fake' medicine. Both groups experienced similar decreases in suffering from the side effects of asthma. The study concluded that placebo cannot cure one's asthma but can dramatically reduce one's suffering of the side effects (Kaptchuk & Miller 2015). This implies that placebo effects could play a role in the productivity increase followed by an increase in integration of AI in medicine. As stated above, placebo effects are the belief in the effectiveness of the treatment, which also translates to a trust in a treatment. If a patient has a more positive attitude towards a computer-controlled treatment as opposed to a regular doctor performed treatment, the treatment could be more effective due to placebo effects, which is considered to be a productivity increase. To examine the preference in a computer-controlled treatment, a survey was conducted in Minnesota in 2020 regarding the attitudes and acceptance of AI in medicine. The study sent out two different surveys where one of the surveys had context about how AI works, and the other survey did not. The group that received the survey with context had significantly more trust in the AI's cancer diagnosis than in the doctor's diagnosis and over 40% of the other group preferred the AI's diagnosis as well (Stai, et al 2020). Despite these interesting results, there were only 264 respondents and due to the survey being conducted in the United States, the study's internal and external validity can be questioned. However, based on the results, the study suggests that there already is some form of preference for AI applications in medical practice. If one prefers AI to perform a treatment over a doctor, the computer-controlled treatment could be more effective. This could set the stage for a productivity increase through the mechanism of placebo effects.

3. Data section

After exploration of the opportunities for productivity increases, the second part of the research objective is to examine whether having more experience with technology results in a more positive attitude towards the implementation of AI into medicine. The three datasets used for the data analyses were retrieved from the Liss panel, which collects their data through online surveys. The Liss panel, founded in 2007 and managed by a non-profit organization with over 5,000 households, is ideally suited for studies where a realistic representation of the Dutch population is of importance. Respondents are picked from a sample received from the Central Bureau of Statistics of the Netherlands, aiming to realize this realistic representation.

The primary dataset utilized to explore the research objective is named “Artificial Intelligence in Medicine”, which shows the results of a survey regarding individuals’ attitudes towards the use of AI in medicine. The secondary dataset is called “Technostress”, and it was merged with the primary dataset to add the relevant independent variable to the research. This independent variable is the fraction of time spent at work with a screened device and is used as a proxy for one’s experience with technology. This survey was conducted in early 2020, which was several months prior to the survey regarding AI in medicine, making a control for survey bias between the two surveys possible. The tertiary dataset is the provided background variables dataset, updated by the Liss panel monthly. The tertiary dataset was conducted in January of 2020. Below, the primary dataset will be discussed first, followed by the secondary and the tertiary dataset.

The primary dataset consists of a survey held in April 2020 with over 2000 respondents regarding their attitudes towards the implementation of AI into medicine. Each respondent answered a total of 58 questions regarding the implementation of AI into medicine, consisting of 19 general questions regarding the topic, 33 questions about specific fields of the implementation and 6 questions about daily life. The dependent variable extracted from this dataset is one’s attitude towards the statement: “I find computers to perform medical tasks a bad idea”, where the dataset was built so that the respondents were divided into four groups. The statements reviewed by the respondents either differed in phrasing and/ or answer options depending on the group, whereas the aim of every respective question remained the same. A brief discussion on the differences between the groups is described below.

What group was the respondent assigned to:	Observations	Percentage
Group 1	566	23.18
Group 2	586	24.00
Group 3	641	26.25
Group 4	649	26.58

For group 1, the respondents reviewed statements where they got to answer with five possible answers; strongly disagree, disagree, neither agree nor disagree, agree and strongly agree, with their respective numbering being; 1, 2, 3, 4 and 5. For group 2, the respondents reviewed the same statements as group 1 with five possible answers, but only the endpoints were labeled. Therefore, the 5 possible answers were; strongly disagree, *blank*, *blank*, *blank*, strongly agree, with their corresponding numbers; 1, 2, 3, 4 and 5.

For groups 3 and 4, the same statements were reviewed, but instead of an agree-disagree answer scale, the respondents had a construct specific answer scale. The statement was, however, not finished and the answer of the respondent would complete the statement. An example is that the statement would be: "I find computers to perform medical tasks ...", with the answer options, very safe, safe, neither safe or unsafe, unsafe and very unsafe. For group 3, similarly to group 1, the respondents had a construct-specific answer scale, with five labeled answers, where the answers depended on their respective statement. For group 4, similarly to group 2, the respondents had a construct-specific answer scale, with two labeled answers (endpoints) and three blank answers, where the answers depended on their respective statement.

In the data analysis, these four groups will be merged into one, resulting in avoiding a loss in observations whilst performing the data analysis. In table A1 below, the summary statistics can be found for the dependent variable between the groups. By analyzing the means and standard deviations between the groups for the dependent variable in the table, one could conclude that these values seem similar.

Furthermore, the distributions of the responses to the dependent variable's question for all four groups are shown in figure A1. For most groups, there is a similar trend visible with a strong rise between the first and second answer and a steady decline for the remaining three. Despite group 2 not strictly following this trend, a grand bias increase because of this seems unlikely.

In addition to the examination of the fitness to merge between groups, it is relevant to analyze the summary statistics after merging of the datasets as well, due to the loss of respondents after merging of the three datasets. In table A2, the summary statistics of the dependent variable are presented after the merging of the three datasets. In the table, the observations, mean and standard deviation of the different groups still seem to be similar. The distributions are shown in figure A2, where the trend of the density of the different answers between the groups seems alike with a strong rise from the first to the second answer followed by a steady decline. Hence, merging the groups based on the means, standard deviations and distributions is not expected to result in a great bias increase for the analysis. Moreover, a merger between the groups would result in a sample size four times the size of the sample if only one of the groups is considered in the analysis, which is preferred even when the probability of a slight bias increase, due to the merger, is considered.

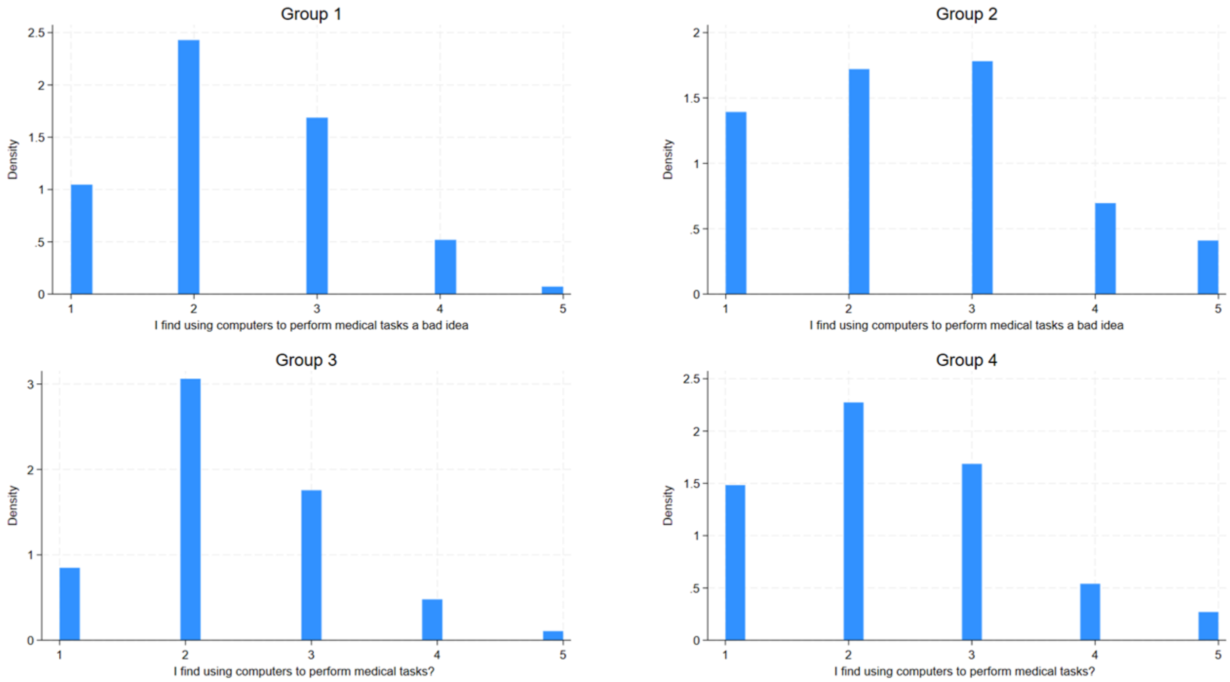
Table A1

This table shows the summary statistics of the dependent variable prior to merging

(1)	Observations	Mean	Std. Dev.	Min	Max
Group 1	566	2.328	0.917	1	5
Group 2	586	2.502	1.165	1	5
Group 3	641	2.349	0.869	1	5
Group 4	649	2.334	1.063	1	5

Note. The table presents the summary statistics regarding the dependent variable: Attitude towards the idea of computers performing medical tasks prior to merging with the secondary and tertiary dataset.

Figure A1: *Histograms showing the distributions of the density of answers for the dependent variable prior to merging*



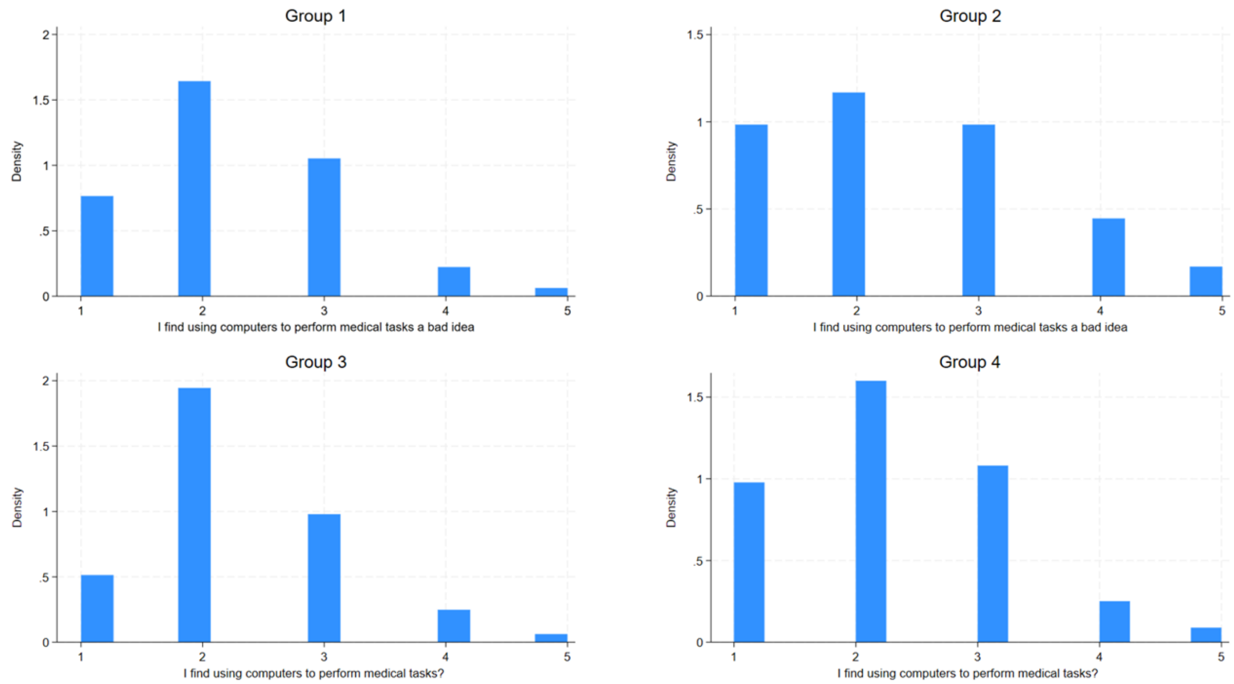
Note. The figure shows distributions for the dependent variable for the four groups of respondents before merging with the secondary and tertiary dataset.

Table A2: *This table shows the summary statistics of the dependent variable after merging with the secondary and tertiary dataset.*

(1)	Observations	Mean	Std. Dev.	Min	Max
Group 1	235	2.247	0.905	1	5
Group 2	244	2.373	1.128	1	5
Group 3	241	2.307	0.850	1	5
Group 4	270	2.219	0.960	1	5

Note. The table presents the summary statistics regarding the dependent variable: Attitude towards the idea of computers performing medical tasks after merging with the secondary and tertiary dataset.

Figure A2: *Histograms showing the distributions of the density of answers for the dependent variable after merging*



Note. The table presents the summary statistics regarding the dependent variable: Attitude towards the idea of computers performing medical tasks after merging with the secondary and tertiary dataset.

The secondary dataset used in this study is named “Technostress” from the Liss panel data archive, covering the months January and February in 2020. This dataset is taken into the analysis, because it includes the relevant independent variable. The independent variable is the fraction of time at work spent with a screened device “Screentime at work”, which will be used as a proxy for technology experience. This independent variable is a categorical variable with 4 possible answers. These possible answers were; 0-25 %, 26-50 %, 51-75 %, over 75%. By merging the primary dataset with the secondary dataset regarding technology use, only 990 respondents remain, due to exclusively perfect merging on individuals between the datasets being relevant.

For the data analysis, the inclusion of control variables is necessary. Almost every respondent in the Liss panel must complete a background questions survey, making this dataset suitable for control variables. The control variables “Age”, “Female” and “Education” will be added by a final merger with the tertiary dataset named “Background variables”, covering the month January in

2020. The control variable "Age" is measured as a continuous variable, "Female" as a binary with male having the value 0 and female having the value 1 and "education" measures the highest level of education achieved. The education variable had a range of 1 to 7, with a higher value indicating a higher level of education achieved. Due to level 1 only having two observations, level 1 and level 2 were merged together, resulting in a reliable reference for the dummy variables and the range being 1 to 6. These control variables were added, because they are relevant for the studied relationship. Individual's attitude towards the use of AI in medicine could be correlated to their age and gender, because these variables could have a relation with a lot of individuals' opinions. Furthermore, one's education seems to be a good control due to someone's education having the chance to shape their way of thinking. This could result in education having an effect on one's attitude towards the use of AI in health care. Moreover, one's education level could have an effect on how much one uses technology in work. As a result of almost every respondent in the Liss archive completing the "Background variables" survey, no observations were lost after merging with the tertiary dataset. The final observation count is 990.

The summary statistics for the relevant independent variable, the control variables after the merging of the three datasets are presented in table A3.

To examine the fitness of the dependent and independent variable for the data analysis, a similar dependent and independent variable will be used for a proxy fitness analysis. The similar dependent variable is retrieved from the primary dataset and serves as a substitute for "The attitude towards the use of AI in medicine". This dependent variable covers the responses to the statement "I find computers to perform medical tasks alarming", where a lower value indicates a more positive attitude. This variable is denoted as "Similar Attitude. AI". The similar independent variable is retrieved from the secondary dataset, which serves as a substitute the respondents' corresponding experience with technology. This independent variable covers the dependency on ICT information on work and is called "ICT-use at work", where a higher value indicates more dependency. In the proxy fitness analysis, the summary statistics and an OLS regression will be utilized for the "similar" dependent and independent variable, aiming to find results which have close correspondence to the actual analysis. The summary statistics for this proxy analysis' dependent and independent variable are also shown in the bottom two rows in table A3. The dependent variable and the similar dependent variable have the same value range, making the comparison between means relevant. These two means seem to be alike.

The OLS regression results and the ordered probit model results for the regular and the proxy analysis will be discussed in the results section. For simplicity, the answers of the "similar" independent variable were adjusted to reversed scaling, resulting in the answer scale being in the same direction as the actual independent variable used for the analysis.

Table A3: *This table shows the summary statistics of dependent variable and independent variables.*

Variables	Observations	Mean	Std. Dev.	Min	Max
Attitude. AI	990	2.285	0.967	1	5
Screentime at work	990	2.549	1.220	1	4
Age	990	47.255	12.224	19	96
Female	990	0.504	0.500	0	1
Education	990	4.237	1.345	1	6
Similar Attitude. AI	990	2.341	0.941	1	5
ICT-use at work	990	3.878	1.104	1	5

Note. The table presents the summary statistics for the main analyses and for the proxy fitness analysis. The bottom two rows present the similar dependent and independent variable for the proxy fitness analysis.

In Figure A3, the distribution of the density of the independent variable, the fraction of time spent at work with a screened device, is presented. The correlations between all the variables are shown in table A4 with a range from –1 to 1, where –1 indicates a perfect negative linear relationship and 1 indicates a perfect positive linear relationship.

In the results section, data will be analyzed to measure the fitness of the proxies. Before this data analysis, a brief literature review is held to enrich the proxy fitness analysis. In a study about AI in general it is stated that Artificial Intelligence is the ability of machines to replicate human intelligence (Du-Harpur, et al 2020). For the dependent variable, "I find computers to perform medical tasks a bad idea", in the primary dataset, it would be safe to assume that the term computer is interchangeable for AI due to it performing a task normally a doctor would. In a paper Helpman & Rangel, specifically stated in an example that technology experience is the amount of time people spend at work with technology, which is in identical correspondence with the independent variable "amount of time spent at work with a screened device" (Helpman & Rangel 1991). They make the distinction between experience and schooling, where experience is exclusively acquired through the job.

Figure A3: *Histograms showing the distributions of the density of answers for the relevant independent variable*

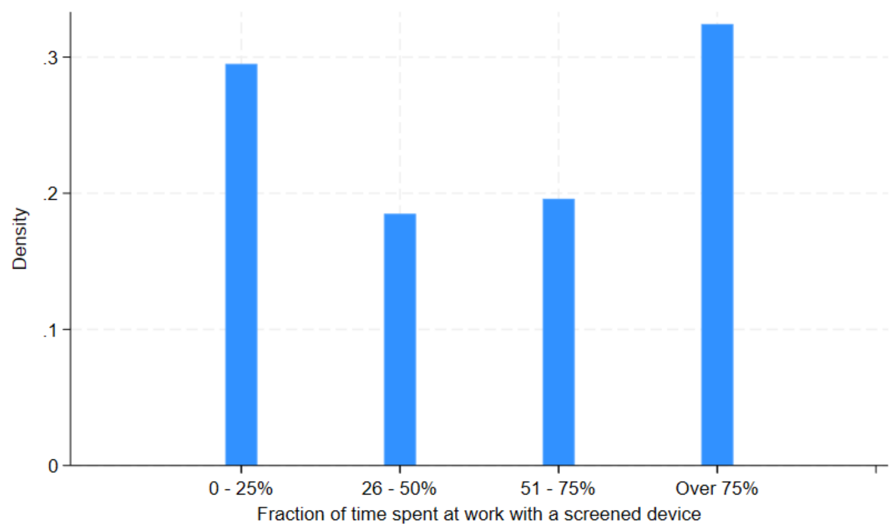


Table A4: *This table presents the correlation between every variable.*

	Attitude. AI	Tech. exp	Age	Female	Education
Attitude. AI	1				
Screentime at work	-0.129	1			
Age	0.029	-0.138	1		
Female	0.163	0.008	-0.062	1	
Education	-0.181	0.282	-0.226	0.0083	1

Note. The table presents correlation coefficients between all the variables for the actual analysis.

4. Methodology

The objective of the data research is to examine how computer use in the past could predict one's attitude towards the implementation of AI into medicine. To perform a data analysis regarding this objective, Stata/SE 17.0 is used to create models for the analyses and to create descriptive summary statistics.

For the analysis, an OLS regression, a multilinear OLS regression and an ordered probit model are utilized. The OLS regressions are simple to interpret and hence a quick way to examine a relationship between variables. The downsides for the OLS models in this analysis are that it violates the assumption that the dependent variable is continuous and normally distributed, potentially resulting in a lack in reliability due to the categorical natured dependent variable. For this categorical dependent variable, an ordered probit model could be preferred. The ordered probit model is not as straight forward to interpret as the OLS regression models. However, ordered probit models are designed for ordinal dependent variables, making the model fitting for the "Attitude towards AI" variable. Moreover, the thresholds parameters give deeper insights into the distribution of the outcomes for the different categories. For both models, causal claims cannot be made and only the relationships between variables can be interpreted.

Multiple sensitivity analyses were performed to validate the results of the models used. For both the multilinear regression model and the ordered probit model, checking for outliers is important. The datasets did not contain any outliers and Liss panel is usually punctuated about their data, hence dropping outliers was not necessary. All the results for the two models were retrieved with robustness checks, where the command accounted for heteroskedacity by using robust standard errors. Both models also included several control variables, including an interaction term.

The standard function for this multilinear regression including the interaction term is the following:

$$Y_i = c + \alpha \text{ screentime}_i + \beta x_i + \beta i_i + \epsilon$$

Where,
Y_i = Attitude towards the use of AI in medicine

c = constant

x = age, female and education, where the education levels from the lowest to the highest value are; primary school, vmbo, havo/vwo, mbo, hbo and wo.

i = interaction term between age * screentime

ϵ = error term

To check for multicollinearity in the OLS multilinear regression model, the variance inflation indicator or VIF for short was used. For simplicity, the VIF is calculated from the model with all the control variables except for the interaction term. If we would analyze the VIF with the interaction term, the check for multicollinearity would not be reliable since the interaction term consists of multicollinearity. Despite the absence of a rule of thumb for a certain threshold where the VIF becomes problematic, the value of 10 is adopted by many (O'Brien 2007). Based on the values in table A5, the mean VIF is well below this value and therefore not considered to require fixing.

Table A5: *VIF test (interaction term not included)*

Variable	VIF
Screentime at work	1.11
Age	1.07
Female	1.01
Educ	
2	4.52
3	3.88
4	7.56
5	8.09
6	6.04
Mean VIF	4.16

Note. The table presents the variance inflation indicators for column (2) of the regression model with the control variables. Therefore, the table does not present the regression results of the interaction term (age * screentime at work).

5. Results

To examine the relationship between an individual's attitude towards the use of AI in medicine based on their experience with technology, OLS regressions and an ordered probit with the same variables are used. The OLS regressions estimate the causal effect of the fraction of time spent at work with a screened device on one’s attitude towards the use of AI in medicine. In table A6, the regression results are presented. In column 1, the simple linear regression is presented where the coefficient of “Screentime at work” is -0.103, which is negative and statistically significant. This indicates that an individual who allocates one extra unit to fraction of time at work spent with a screened device, on average has 0.103 more allocated to the probability of being in a more positive attitude category as opposed to someone who does not allocate one extra unit to screentime at work at the 1% significance level.

Next to the relevant independent variable, some control variables were added to the regression as well. These are presented in the second column. After the addition of the control variables, the coefficient of “Screentime at work” has become less negative, but remains significant at the 5% significance level. It seems that if an individual is female, on average they have a less positive attitude towards the use of AI in medicine at a 1% significance level. Age does not have a statistically significant relationship with the dependent variable and this coefficient is also very small. The results of the table suggest that higher educated individuals on average have a more positive attitude towards the use of AI in medicine at different significant levels depending on the education levels.

In the third column, the last control variable is age * screentime, which is the interaction term. The coefficients and statistical significance between the second and the third column do not differ drastically. The coefficient of “Screentime at work” does have a big change, but this change of the effect is now dependent on the interaction term as well. The interaction term, age * screentime indicates how the effect of having a greater fraction of time with a screened device at work differs between ages. For each additional unit increase of time spent at work with a screened device, older individuals tend to have a less positive attitude towards AI compared to younger individuals. For example, a 30-year-old male with 0-25% screentime has a predicted attitude of 2.959 whereas a 50-year-old male with the same screentime has a predicted attitude of 2.841, but when the 30-year-old has a screentime of 51-75%, his attitude towards AI is predicted to be 2.710 and the 50-year-old with the same screentime has a predicted attitude of 2.738 ceteris paribus. This shows that the positive effect of an increase in fraction of time at work spent with a screened device is more pronounced for younger individuals. The interaction term is statistically significant at 10%.

Table A6: *This table presents the OLS regressions on one's attitude towards the use of Artificial Intelligence in medicine of the individuals technology experience*

	(1)	(2)	(3)
Screentime at work	-0.103***	-0.064**	-0.234**
	(0.026)	(0.026)	(0.100)
Age		-0.001	-0.010
		(0.003)	(0.006)
Female		0.319***	0.319***
		(0.060)	(0.059)
Education			
2		-0.397*	-0.401*
		(0.217)	(0.219)
3		-0.677***	-0.706***
		(0.211)	(0.213)
4		-0.519**	-0.538***
		(0.203)	(0.205)
5		-0.688***	-0.704***
		(0.201)	(0.202)
6		-0.861***	-0.864***
		(0.204)	(0.207)
Screentime at work * age			0.004*
			(0.002)
Constant	2.546***	2.926***	3.370***
	(0.076)	(0.252)	(0.360)
Observations	990	990	990
R^2	0.017	0.075	0.078

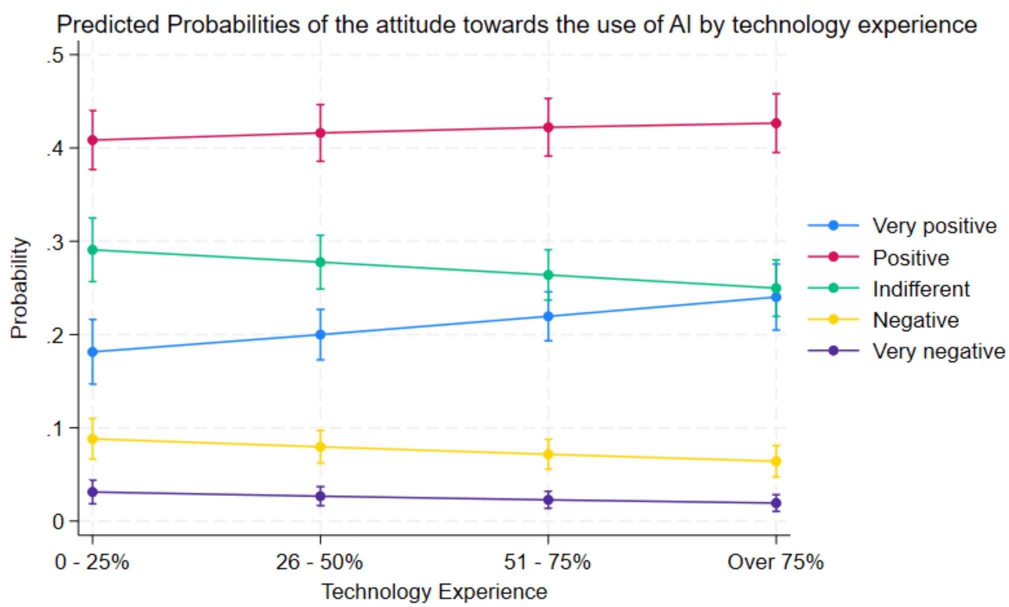
Note. The table presents a regression in column (1) where the dependent variable is one's attitude towards the use of AI in medicine and the independent variable is the fraction of working time spent with a screened device. In column (2), the dependent and the relevant independent variable remains the same, but the control variables; "Age", "Gender" and "Education" are added. In column (3), in addition to the added control variables in column (2), an interaction term between age and technology experience is added. Furthermore, * indicates $p < 0.1$, ** indicates $p < 0.05$ and *** indicates $p < 0.01$.

Despite the simple interpretation of the multilinear regression model, the model could lack reliability due to the dependent variable being categorical. As a result, a more fitting model in the form of an ordered probit model will also be included in the data analysis. Unlike the multilinear regression model, one can exclusively interpret the signs and the significance of the coefficients in the ordered probit model to examine the direction of the relationships. The "screentime at work" variable has a statistically significant negative sign, which indicates a negative relationship between the dependent and this independent variable. Further calculations are needed to examine the predicted effect of an additional unit of a variable. This examination will be shown below.

An interpretation for this ordered probit model is as follows. For simplicity, the second column without the interaction term will be interpreted. If one has a unit higher in technology experience, on average they have a 0.026 higher probability for outcome 1, 0.001 higher probability for outcome 2, 0.018 lower probability for outcome 3, 0.005 lower probability for outcome 4 and 0.002 lower probability respectively outcome 5.

These interpretations of the second column are graphically displayed in figure A4. The figure shows that a rise in technology experience is correlated to a rise in a "Very positive" and "Positive" attitude and a decline in an "Indifferent", "Negative" and "Very negative" attitude.

Figure A4: *The figure graphically presents the interpretation of the ordered probit model*



Note. The figure graphically presents the interpretation of the results of the second column (2) of table A7.

Table A7: *This table presents the ordered probit model on one's attitude towards the use of Artificial Intelligence in medicine*

	(1)	(2)	(3)
Screentime at work	-0.109***	-0.070**	-0.260**
	(0.029)	(0.030)	(0.114)
Age		-0.000	-0.010
		(0.003)	(0.007)
Female		0.379***	0.379***
		(0.069)	(0.069)
Education			
2		-0.438*	-0.442*
		(0.223)	(0.225)
3		-0.719***	-0.750***
		(0.220)	(0.222)
4		-0.561***	-0.581***
		(0.209)	(0.210)
5		-0.749***	-0.767***
		(0.207)	(0.208)
6		-0.945***	-0.948***
		(0.214)	(0.216)
Screentime at work * Age			0.004*
			(0.002)
Cut1	-1.081	-1.506	-2.000
	(0.091)	(0.274)	(0.400)
Cut2	-0.053	-0.329	-0.820
	(0.085)	(0.271)	(0.396)
Cut3	1.005	0.657	0.169
	(0.090)	(0.272)	(0.396)
Cut4	1.699	1.369	0.882
	(0.110)	(0.275)	(0.399)
Observations	990	990	990
Pseudo R^2	0.006	0.028	0.030

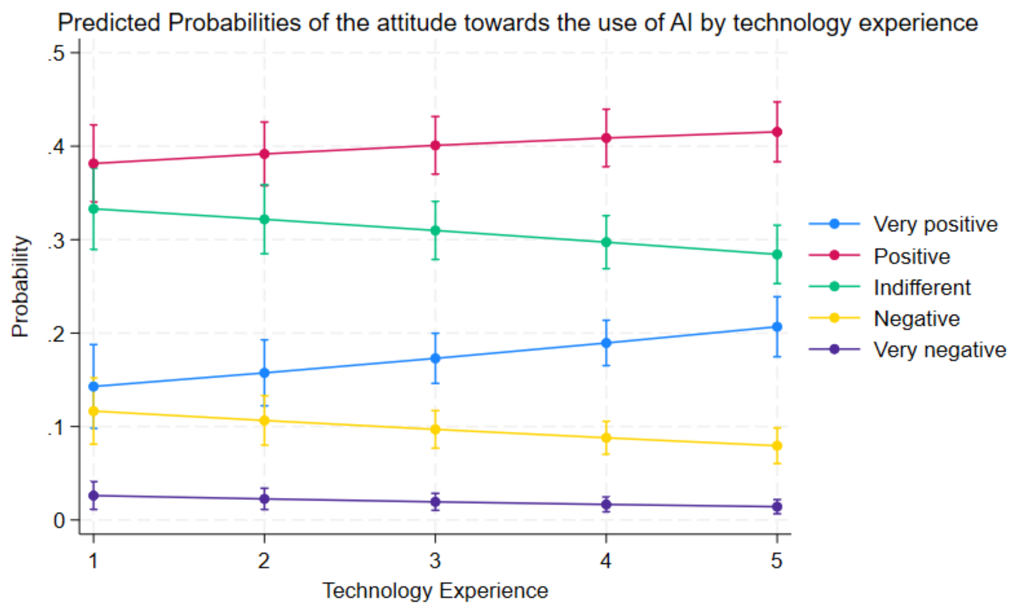
Note. The table presents an ordered probit model in column (1) where the dependent variable is one's attitude towards the use of AI in medicine and the independent variables are what fraction of working time spent with a screened device, one's gender and one's age. In column (2), the dependent and the relevant independent variable remains the same, but the control variables; "Age", "Gender" and "Education" are added. In column (3), in addition to the added control variables in column (2), an interaction term between age and technology experience is added. The cut points are used to calculate the probabilities for the 5 different outcomes of the dependent variable with a lower dependent variable indicating a more positive attitude towards the use of AI in medicine. Furthermore, * indicates p < 0.1, ** indicates p < 0.05 and *** indicates p < 0.01.

For the proxy fitness analysis, an OLS regression model is presented with the previously discussed "similar" dependent and independent variable in table B1 in the appendix. Table B1 presents the results similarly to table A6, which presents the results of the actual analysis. The results are similar in the ordering of added control variables and the interaction term, resulting in column 1 in table B1 being able to be compared to column 1 in table A6. The interaction term is the only control variable that differs from the actual analysis due to a different relevant independent variable for technology experience. In the first column of the two tables, the coefficients seem to be very similar with the standard errors and significance being alike as well. In column 2, where the control variables except for the interaction term are added, the coefficient of the relevant independent variable follows a similar trend with a magnitude decrease. The categorical variable "education" does not seem to differ in the effect, but it does differ in statistical significance. For the proxy fitness analysis, the lower education levels are not significant whereas these are in the actual analysis. As stated above, the interaction term differs between table A6 and table B1, making a comparison challenging. There is a grand difference between the coefficients for the relevant independent variable in table A6 and table B1, but one must be careful making conclusions due to the difference in the interaction term.

Similar to the actual analysis, an ordered probit model is used for the proxy fitness analysis as well and can be analyzed in table B2 in the appendix. As disclosed above, the ordered probit model's interpretation is not as straight forward as the OLS regression model. However, a comparison between table A7 and table B2 is still possible. The coefficients, standard errors, statistical significance and the cuts are similar for the first column, For the second column, the coefficients with their statistical significance of the relevant independent variables seem alike, but the cuts differ vastly. This is more evident for the third column with the added interaction term. It is important to note that the 'similar' independent variable for technology experience has 5 values whereas the actual independent variable only has 4 values. For simplicity, in figure A5 the interpretations of the ordered probit model will be graphically presented to be compared with figure A4. This will be done in the same way as before where only the interpretations for column 2 are shown.

The interpretations of the two models seem to be very similar with almost every outcome on the attitude towards AI in medicine following the same trend with a rise in “Very positive” and “Positive”, a steady decline for “Indifferent” and “Negative” and a slight decline for “Very Negative”, when technology experience increases.

Figure A5: *The figure graphically presents the interpretation of the ordered probit model for the proxy fitness analysis*



Note. The figure graphically presents the interpretation of the results of the second column (2) of table B2.

6. Discussions

Now that a relationship between technology experience and one's attitude towards the use of AI is concluded, interpretations, comparisons and contrasts are stated. Based on the data analysis, an individual who spends a greater fraction of time with a screened device at work, on average has a more positive attitude towards AI. Similarly to technology experience, education has a positive effect on one's attitude, suggesting that more knowledge in general or about technology is correlated with a more positive attitude. This suggests that further experience with computers could be correlated with a more positive attitude towards the use of AI in medicine. Policymakers could act on this information to influence the overall acceptance towards AI.

Furthermore, a comparison between similar papers is conducted. The primary dataset used for the data analysis is also used in other papers regarding people's attitudes towards the use of AI in medicine. Ongena et al researched women's preferences on an AI controlled mammography diagnosis in which they concluded that over 75% of women in the survey do not trust a fully controlled AI diagnosis (Ongena, et al 2021). This is surprising since studies have shown that AI is very suitable for mammography screening and could even outperforms radiologists (McKinney, et al 2020). Since Ongena et al studies the AI versus human competition and my data analysis, the attitude towards AI and not the competition, the results are difficult to compare. Another paper using the same primary LISS dataset explored the attitude of AI in medicine and examined these attitudes for different fields. Similarly to the Ongena et al paper, the results in the paper suggested that the overall attitude towards AI in medicine is less positive than the media portrays (Yakar, et al 2022). One of the relationships found in that paper was that people with a higher level of education or with more trust in technology efficiency on average would have a more positive attitude towards the use of AI in medicine. This finding in some measure in line with the results from my data analysis and relates to the positive relationship between technology experience and the acceptance towards the use of AI in medicine.

Limitations of the data analysis are that the proxy used for technology experience might not be a perfect fit. The proxy "Screentime at work" exclusively covers the amount of time a screen was used at work, but not all technology makes use of a screen. Moreover, the data used for the analysis, is retrieved from a survey conducted in the Netherlands which could be an issue for external validity. Subsequently, this could also have caused problems to relate the results from the data analysis with the relevant literature, since not all papers were conducted from data from the Netherlands. A more globally spread survey to use for the data analysis, could be part of the solution to this. Finally, the final observation count for the data analysis after the merging of the datasets was just below a 1000 respondents, which is not a very large number and might disturb the internal validity.

7. Conclusions

Based on the results of the data analysis, technology experience has a statistically significant relationship with a more positive attitude towards the use of AI in health care with relevant literature concluding a similar relationship. This relationship, however, is small and it seems like other factors as gender and in some cases education may have a bigger effect. Moreover, the interpretation of the interaction term suggests that the effect of technology experience on one's attitude is dependent on one's age where the effect of technology experience on one's attitude towards the use of AI in medicine on average gets less positive as the individual gets older. To conclude the data analysis, the OLS regressions and ordered probit models show similar results and similar trends after the inclusion of control variables. This suggests that it could be safe to conclude a positive relationship between technology experience and one's attitude towards the use of AI in medicine. Even the proxy fitness analysis presented similar results to the actual analysis with some minor differences and literature supported the use of the proxies.

Due to the labor shortages and an increase in expected labor demand, there are opportunities in more AI-controlled treatments to tackle these shortages. An increase in integration of AI in medicine could result in a productivity increase per worker due to doctors being able to focus more on primary care (Malik, et al 2019). Additionally, computer-controlled treatments could even be more effective with AI being, in some cases, more accurate and efficient as opposed to a regular doctor (Hamet & Tremblay 2017). Based on the data analysis, we know that there is a relation between the experience with technology, education level and one's attitude towards AI. Policymakers could focus on familiarizing more individuals with technology to try to improve the overall acceptance towards AI in medicine. Since the integration of AI seems to be already in progress, improving on the involvement of people could have a positive effect on the acceptance. This could result in productivity increases described by the mechanisms above. Moreover, if a patient has a very positive attitude towards AI, the computer-controlled treatment, in some cases, could even be more effective than a doctor performed treatment, due to placebo effects. If a doctor is aware of these preferences of the patient, they could discriminate in the treatments, where they could supply (partially) computer-controlled treatments to patients with a more positive attitude towards it thus assisting in the opportunities of productivity increases. Moreover, doctors could play a role in familiarizing the people as well by showing people how AI could improve treatments or by showing how the technology works. These mechanisms could contribute to the opportunities of the increasing integration of AI in medicine for productivity increases per worker. As a result of the productivity increases per worker, the integration of AI in health care could be part of the solution to tackle labor shortages.

The survey used in the data analysis is not as recent as the papers discussed which may have caused issues. Artificial intelligence is ever growing which results in a continuous gap in people's acceptance towards the use of AI. The survey used in this data analysis is from 2020 and some might argue that a lot has changed since then. This survey was also held in the Netherlands, which could be an issue for external validity. For future research, a more recent survey regarding people's attitude towards the use of AI in medicine in combination with relevant characteristics such as technology experience could be used to examine if the arrival of natural language processing systems like ChatGPT influenced individuals' attitudes. ChatGPT is something a lot of people are familiar with and the chatbot became popular after 2020. Therefore, future research based on updated surveys with added characteristics that are relevant to technology in general are interesting to study. As stated in the discussions, a more globally spread sample might improve on external validity and the proxy used for technology experience in the form of fraction of time at work with a screened device might not be the best proxy. Thus, in the future, a more fitting proxy for technology experience might result in less biased estimates.

8. Appendix

8.1 Tables

Table B1: *This table presents the OLS multilinear regression for the proxy fitness analysis on one's attitude towards the use of Artificial Intelligence in medicine of the individuals technology experience.*

	(1)	(2)	(3)
ICT-use at work	-0.092***	-0.054*	-0.061
	(0.028)	(0.028)	(0.109)
Age		0.000	-0.000
		(0.003)	(0.009)
Female		0.242***	0.242***
		(0.059)	(0.059)
Education			
2		-0.203	-0.204
		(0.202)	(0.198)
3		-0.244	-0.246
		(0.206)	(0.206)
4		-0.202	-0.203
		(0.192)	(0.191)
5		-0.368*	-0.369*
		(0.191)	(0.191)
6		-0.524***	-0.524***
		(0.197)	(0.197)
Age * ICT-use at work			0.000
			(0.002)
Constant	2.697***	2.723***	2.752***
	(0.111)	(0.247)	(0.475)
Observations	990	990	990
R^2	0.012	0.045	0.045

Note. The table presents a regression where in column (1) the dependent variable used is; "I find computers to perform medical tasks alarming" and the relevant independent: "The dependency on ICT information during work". In column (2), the dependent and the relevant independent variable remains the same, but the control variables; "Age", "Gender" and "Education" are added. In column (3), in addition to the added control variables in column (2), an interaction term between age and technology experience is added. Furthermore, * indicates $p < 0.1$, ** indicates $p < 0.05$ and *** indicates $p < 0.01$.

Table B2: *This table presents the ordered probit model for the proxy fitness analysis on one's attitude towards the use of Artificial Intelligence in medicine of the individuals technology experience.*

	(1)	(2)	(3)
ICT-use at work	-0.109***	-0.064**	-0.070
	(0.029)	(0.032)	(0.121)
Age		-0.000	-0.000
		(0.003)	(0.009)
Female		0.287***	0.287***
		(0.069)	(0.069)
Education			
2		-0.233	-0.234
		(0.218)	(0.216)
3		-0.263	-0.265
		(0.222)	(0.222)
4		-0.227	-0.228
		(0.207)	(0.206)
5		-0.420**	-0.421**
		(0.206)	(0.206)
6		-0.597***	-0.598***
		(0.215)	(0.214)
Age * ICT-use at work			0.000
			(0.002)
Cut1	-1.081	-1.340	-1.364
	(0.091)	(0.278)	(0.530)
Cut2	-0.053	-0.187	-0.212
	(0.085)	(0.276)	(0.528)
Cut3	1.005	0.841	0.817
	(0.090)	(0.278)	(0.527)
Cut4	1.699	1.731	1.706
	(0.110)	(0.295)	(0.528)

Observations	990	990	990
Pseudo R^2	0.005	0.018	0.018

Note. The table presents an ordered probit model where in column (1) the dependent variable used is; “I find computers to perform medical tasks alarming” and the relevant independent: “The dependency on ICT information during work”. In column (2), the dependent and the relevant independent variable remains the same, but the control variables; “Age”, “Gender” and “Education” are added. In column (3), in addition to the added control variables in column (2), an interaction term between age and technology experience is added. The cut points are used to calculate the probabilities for the 5 different outcomes of the dependent variable with a lower dependent variable indicating a more positive attitude towards the use of AI in medicine. Furthermore, * indicates $p < 0.1$, ** indicates $p < 0.05$ and *** indicates $p < 0.01$.

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