The Impact of Artificial Intelligence on Self-efficacy and Autonomy

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Abstract

Title: The Impact of Artificial Intelligence on Self-efficacy and Autonomy

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Artificial intelligence has become more prominent in our daily life, raising important questions in regard of its psychological impact. As individuals delegate more mundane tasks to AI systems, concerns emerge regarding whether overreliance on these tools may influence two main components of self-regulation: self-efficacy and autonomy.

Self-efficacy is one's belief in their capability to manage tasks and challenges, meanwhile autonomy reflects self-governed regulation and alignment with one's values. Despite their importance, very little work has been done to study how everyday AI impacts these psychological constructs.

This study investigated how the frequency of AI use predicts differences in individuals perceived self-efficacy and autonomy. Self-efficacy was measured using the New General Self-Efficacy Scale, and autonomy was assessed through the Index of Autonomous Functioning. Linear regression analyses and one-way ANOVA comparing low, medium, and high AI-use groups were conducted to evaluate these relationships.

Across all analysis done, the results showed no significant association between AI use and either self-efficacy or autonomy. Regression coefficients were small and non-significant and AI-use groups did not differ meaningfully in their levels of these psychological constructs. Finally, the implications of these results are discussed, along with some limitations and ideas for future studies.

Keywords: Artificial Intelligence, Self-efficacy, Autonomy, Survey, Human–AI Interaction

Sumário

Título: O impacto da inteligência artificial na autoeficácia e autonomia.

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A inteligência artificial tornou-se mais presente no nosso dia-a-dia, levantando questões importantes relativamente ao seu impacto psicológico. À medida que as pessoas delegam tarefas mais quotidianas a sistemas de IA, surgem preocupações sobre se uma dependência excessiva destas ferramentas pode influenciar dois componentes essenciais da autorregulação: a autoeficácia e a autonomia.

A autoeficácia corresponde à crença do indivíduo na sua capacidade para gerir tarefas, enquanto a autonomia reflete uma autorregulação autodeterminada e alinhada com os seus valores. Apesar da sua relevância, existe ainda pouca investigação dedicada a compreender de que forma o uso quotidiano de IA afeta estes constructos psicológicos.

O presente estudo investigou como a frequência de utilização de IA prevê diferenças na autoeficácia e autonomia que os indivíduos possuem. A autoeficácia foi medida através da New General Self-Efficacy Scale, e a autonomia foi avaliada utilizando o Index of Autonomous Functioning. Foram realizadas análises de regressão linear e ANOVA comparando três diferentes grupos para avaliar estas relações.

Em todas as análises realizadas, os resultados não revelaram qualquer associação significativa entre o uso de IA e a self-efficacy ou autonomia. Os coeficientes de regressão foram pequenos e não significativos, e os grupos de utilização de IA não diferiram de forma relevante nestes constructos psicológicos. Por fim, discutem-se as implicações destes resultados, bem como algumas limitações e direções para futuros estudos.

Palavras-chave: Inteligência Artificial, Autoeficácia, Autonomia, Inquérito, Interação Humano–IA

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With this thesis, I gave one of my biggest steps in my leaning journey, it has been the result of many years of commitment to university and school. It has never been easy, and it surely would not be possible without those that have always been on my side and supported me.

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To my parents, I owe everything that I have. Their unconditional love, trust, encouragement have always been my rock that I can rely on. They always believed in me even when sometimes I didn't believe in myself.

I am equally thankful for my friends and extended family who accompanied me through this long journey, whether it would be late-night conversations, shared frustrations, or simple words of motivation, it has made this process much more pleasurable and far more meaningful.

Lastly, I would like to dedicate this thesis to all the Portuguese who have given their lives to make this country a better one; their sacrifices have shaped the opportunities we enjoy today and will continue to inspire future generations. In a more personal note, I also wish to dedicate this work to Pedro Manata Silva, who is unfortunately no longer with us, but whose life has always been dedicated to making this country a better place and whose sacrifice shall never be forgotten. I would also like to add my sincere support to his widow Vanessa and his two sons, Diogo and Fábio.

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Glossary

AI	Artificial Intelligence
NGSE	New General Self-Efficacy Scale
IAF	Index of Autonomous Functioning
GCOS	General Causality Orientations Scale
SDT	Self-Determination Theory
ANOVA	Analysis of Variance
e.g.	*exempli gratia*, for example
i.e.	*id est*, this is
M	Sample Mean
N	Total number of responses
P	p-value
R^2	Multiple correlation squared, measure of strength of association
SD	Standard Deviation
SE	Standard Error
SS	Sum of Squares
F	F-statistic
β	Beta Coefficient

1. Introduction

"If people believe they have no power to produce results, they will not attempt to make things happen" -Bandura in Self-Efficacy - The Exercise of Control (Bandura, 1997)

Bandura's quote makes present the central role of self-efficacy in human motivation and action. Individuals who believe in their capabilities approach challenges with greater persistence, adaptability and confidence (Bandura, 1997). Alongside self-efficacy, autonomy also plays a central role in our behaviour, autonomy can be described as the experience of acting with a sense of volition and self-endorsement (Ryan & Deci, 2000a).

McKinsey, the famous consulting company that has a worldwide presence, did a survey that stated that 78% of surveyed organizations used AI on at least one business function and that percentage is increasing year by year (McKinsey & Company,2025b). The same company also states that 92% of companies are planning to invest more in gen AI for the next years (McKinsey & Company,2025a). This has shown that AI has a worldwide presence and its influence is growing with more investment being planned to be given to its adoption.

As AI tools become embedded in daily activities, from the most mundane (like writing assistance) to more high stakes (such as medical decision-making support), concerns have emerged about their potential impact on these psychological constructs. In Shneiderman, (2022) it is argued that reliance on algorithmic systems may reduce personal agency or foster overdependence, whereas in Logg et al (2019) it is suggested that AI might enhance competence by providing guidance, feedback, or cognitive support. Although there are many theories about AI's influence in our psychological constructs, there is limited empirical evidence, particularly regarding how everyday AI use.

The topic that will be discussed in this paper is whether the use of AI will influence the various processes of decision making in the long run. This was chosen between a range of topics that encompass decision making.

The goal of the research is to find whether there is a correlation between different variables that are part of the decision-making progress and the extensive use of AI. We will measure various characteristics to see whether there is a correlation between different processes of thinking and the use of AI.

The primary research question is whether the use of AI can influence human decision-making, especially in the dimensions of Self-Efficacy and Agency?" which will be defined by answering a questionnaire on Qualtrics that is related to the variables we will study. Those questions will be the following:

1.” How does extensive AI use influence the autonomy of a person?”

2. “Does extensive AI usage affect individuals’ general self-efficacy compared to non-heavy users?”

Thus, the research questions will be the following:

RQ1. “To what extent does extensive use of artificial intelligence influence individual autonomy?”

RQ2. “How does extensive artificial intelligence use affect perceived general self-efficacy in individuals compared to non-heavy users?”

1.1. Managerial & academic relevance

Whether it is for managers or for researchers, it is a highly important work that will have impact whether there is a correlation or not for the result section.

Researchers will use it for more experimental research that will see whether there is a causation between the variables and more practical uses of the correlation of the study.

Managers can use this work to optimize the collaboration between human and AI, have a better risk management strategy and a better strategic planning and/or enhance the training and/or the employee development with customized training programs designed for a specific AI use.

After the current introductory chapter, Chapter 2 presents a comprehensive literature review that lays the theoretical foundation for this study. The chapter begins with an introduction to Artificial Intelligence and its rapid growth in our new everyday life, followed by a discussion of the risks and limitations associated with AI systems, including algorithmic errors and human overreliance. This has been complemented by a detailed analysis of the autonomy construct, based on the Self-Determination theory and the General Causality Orientations Scale, as well as an in-depth review of Self-Efficacy and its processes. The chapter concludes with distinctions between coping self-efficacy and task self-efficacy thus concluding the conceptual basis for the study.

Chapter 3 describes the methodology of the study It explains the correlational survey-based research design, the procedures used for participant recruitment, and the structure of the online questionnaire. This chapter also adds the measurement instruments, including the Index of Autonomous Functioning (IAF) for autonomy and the New General Self-Efficacy Scale (NGSE) for self-efficacy, as well as the items to measure AI Use. Later, the statistical approach is introduced, detailing the use of simple linear regression and one-way ANOVA as the primary analytical techniques.

In Chapter 4, it is presented the empirical results, beginning with the descriptive statistics for all the study variables, followed by the hypothesis testing. This includes the regressions that were mentioned beforehand as well as the ANOVA models.

Finally, Chapter 5 discusses the study's results, interpreting the results considering existing theory and previous research. This chapter also addresses the limitations that are present in this study as well as proposing directions for future research, concluding with broader implications of the findings for the field of human–AI interaction.

2. Literature review

2.1. Introduction to the Artificial Intelligence

Early definitions of AI, according to Holmes et al (2004) define it as "a field of science and engineering concerned with the computational understanding of what is commonly called intelligent behaviour, and with the creation of artefacts that exhibit such behaviour". This highlights the key characteristic of Artificial Intelligence, that is the intelligent human behaviour. In medicine, it already has a place, by showing that it can analyse complex data, improve diagnostics accuracy, and support decision-making.

There are also problems about how AI and algorithms related to its shape the life of a person that has been constantly exposed to it, in a recent study (Athanasoula, Salpa, Apergi, and Vlachos, 2025) that reviewed 28 studies published between 2015 and 2025, has found that the type of content consumed in social media apps, such as thinspiration and fitspiration material, was more consistently associated with disordered eating than the overall amount of time spent on social media. This highlights the effects that social media and technology in general have in the life of human beings.

Knowing this, the focus will change to AI and their errors, so that the thesis can be easier to understand.

2.1.1. Artificial Intelligence and its errors

Artificial intelligence is more than ever embedded in decision-making processes across sectors such as medicine, finance, justice, and transportation (Rahwan et al.,2019). As much as these systems promise efficiency and efficacy, recent research shows that processes driven by AI remain vulnerable to two sources of errors that are: algorithmic errors (Agudo et al.,2024) and human overreliance (Klingbeil et al., 2024). This remains a paradox, while humans delegate control to AI systems expecting precision, they become more prone to errors and diminish their autonomous judgement.

In research conducted by Chanda and Banerjee (2024), it offers a comprehensive analysis of AI failures by including the dual framework of omission and commission errors.

Omission errors happen when an AI system fails to do something that should have been done, an example given by the paper is that some scenarios needing decision-making by the AI got excluded. Error of commission happens when AI is doing something that should not have been done, the example that was fed to us by the paper is Irrelevant data columns got fed as inputs to the AI solution.

This study categorizes 28 factors underlying AI failure across the input, processing, and output stages. For example, omission errors happen in input design and have led to failures in autonomous vehicles as well as facial recognition technologies. On the other hand, commission errors manifest when systems act on flawed assumptions or amplify existing social biases through feedback loops.

Agudo et al. (2024) would conduct another study that further contributes to the literature. This research examined “human-in-the-loop” decision systems, that is a model of AI that requires human interaction. In this experiment, there were two judicial decision-making simulations where one group had the AI’s recommendation before judging and the other had after they made the decision. The experiment was based on judging people’s case in court and telling where they had a high, medium, low probability of guilt in the first experiment and in the second one they used a 0-100 scale. Also, in the first experiment, they only had 3 cases when in the second one they had 9, thus reinforcing the robustness. The participants that did not see AI’s recommendation before were more accurate in the incorrect trials than participants who had seen it first. Although it is undeniable that AI helped accuracy when it was correct, there was anchoring effect in incorrect decision made by AI, especially when it came first, even when there was a low automation bias, their accuracy still dropped after exposure to incorrect AI recommendations.

2.2. Description of variables

2.2.1. Autonomy

Ryan and Deci were the great drivers of the biggest studies in autonomy; in 1985 they would create one of the most influential papers in this area. They proposed that individuals differ in their general tendency to regulate behaviours through self-determined versus controlled processes, which they made clear on the General Causality Orientations Scale (GCOS).

The GCOS identifies 3 major components in motivational orientations which are: Autonomy, Control, and non-agentic orientation (can be defined as impersonal). These 3 factors influence and reflect how people perceive and understand the causes of their own behaviour. These three factors can be described as such:

- Autonomy orientation: Autonomy orientation is described on the paper as people that regulate their own behaviours with a sense of personal causation. When more a person is autonomy oriented, they tend to "seek out opportunities for self-determination and choice" and are guided by their values and interests.
- Control orientation: People with more control orientation tend to act primarily in response to external stimulus such as rewards, deadlines, and social approval.
- Impersonal orientation: If a person is more oriented to this factor, they would typically feel more unable to have weight on the outcomes and experience their behaviour as more guided by external factors than their own contribution.

In the paper it is highlighted how these three causality orientations will profoundly affect a person's well-being and performance, and it concludes by showing how a bigger autonomy orientation would support intrinsic motivation and persistence making a person less dependent, stressed and with more vitality. (Deci & Ryan, 1985)

In 2000, building on the ideas that were laid out by the past paper, Deci and Ryan would develop autonomy's importance in a person's well-being. Autonomy would be positioned as one of three basic psychological needs essential for motivation and well-being, with the other two being competence and relatedness. (Ryan & Deci,2000a & Ryan & Deci, 2000b)

Autonomy would function as psychological foundation for self-regulation and well-being. When people feel that their behaviour comes from self-endorsed values, they experience greater satisfaction and perform in a more efficient manner (Deci & Ryan,2000).

2.2.2 Self-Efficacy

The variable self-efficacy would be our target of our utmost attention due to its key role in our decision-making abilities, motivation and execution of the tasks that would be handed to us.

In this field, we have the giant contribution of Canadian psychology professor at Stanford University Albert Bandura, he is one of the most cited professors in the psychology field and one of its most influential. He has published many articles that have revolutionized this field. In Bandura's 1997 book Self-Efficacy- the exercise of control "Self-efficacy refers to one's beliefs in one's capability to organize and execute the courses of action required to achieve given results."

Bandura has taught us that we as people are a result of natural endowment, socio-cultural experiences, and fortuitous circumstances that alter the course of our development trajectories (Bandura, 1986) we see that self-efficacy is not a fixed ability or skill that we either have or don't have, rather it is more capability that would be influenced by multiple factors (Bandura, 1997).

In (Schwartz & Gottman, 1976) we can see that people often fail to perform to an optimal capacity even when they know what to do and even have the skills to be able to do it. Also, (Schunk, 1984) stated that students with low efficacy avoid challenging tasks, whereas those with high efficacy engage more often.

Building on this previous research is (Zimmerman, Bandura & Martinez-Pons ,1992), that demonstrated how these beliefs were being translated into an academic outcome through self-regulatory processes (setting higher personal goals as an example). The findings demonstrated that students that believed in their abilities were more probable of having better academic results. Two years after this research, in (Zimmerman & Bandura,1994), they would expand this framework by establishing a reciprocal causation between beliefs and outcomes. In this study, Students' successes enhanced their self-efficacy mechanisms and self-regulatory standards, forming a cyclical feedback loop that would reinforce their motivation and effort.

In professional sports there is the common phrase of that player has a lot of confidence when things are going well and when it's not going well, there is the phrase that he is low on confidence, in (Wood & Bandura, 1989) we see that skills can easily be overruled by doubt and people with high capacity fail to use their capabilities under these beliefs.

Bandura's theory of Self-Efficacy works on the assumption that there are 4 (four) psychological processes that produce the performance that we know, and they are:

- Cognitive processes- Cognitive processes include a person's self-appraisal of their capacities, their skills, resources, their goals, their capacity to generate options and their selection in a problem-solving scenario and sustaining the necessary attention and functioning for task completion. (Bandura, 1997)
- Motivational processes- Self-efficacy would change one's control of their emotions. There are 3 (three) forms of cognitive motivators that we know that are: causal attributions, outcome expectancies and cognized goals. (Bandura, 1997)
- Affective processes: (Ehrenberg, Cox, and Koopman, 1991) found that self-efficacy was negatively correlated with depression among adolescents, thus suggesting perceived inability to influence events that significantly affect one's life may give rise to feelings of futility and despondency (Bandura 1986). (Munroe-Chandler, Hall, and Fishburne 2008) would also add to these processes by showing how Motivational General-Mastery imagery (MG-M) would make the players feel more confident and capable. This can help to regulate emotional states such as anxiety or arousal before competition.
- Selection processes: The fourth process that Bandura identified is the selection process. As humans, we are creatures of choices and decisions, these choices such as career decisions, social networks, family setup, and even use of time would directly influence a person's functioning and decision making. As Bandura explained, "people's self-efficacy beliefs influence the types of activities and environments they choose to engage in". The more perceived self-efficacy, the more challenging the activities they select. In the opposite side, people with low perceived self-efficacy would avoid challenging settings thus restricting their experiences and, in the end, it hinders their personal development. (Bandura, 1997)

However, Self-efficacy is not a uniform construct, it will manifest differently depending on the context and/or nature of the challenge faced, thus researchers have distinguished between task self-efficacy and coping self-efficacy (Bandura,1997). The following section focuses on two distinct types of self-efficacy in order to provide a more comprehensive understanding of the construct at play.

2.2.2.1. Coping Self-Efficacy

Coping can be defined as either a behavioural or cognitive efforts to manage situations that are appraised as stressful (Lazarus & Folkman, 1988). On this study we have two key types of coping which are:

- Problem-focused coping- Involves either addressing or altering the source of the stress.
- Emotion-focused coping- Can be defined as responses that focus on managing emotional responses to stressful events.

The choice of what coping strategy an individual does is named Secondary appraisal. Secondary appraisal answers the question: what if anything can be done about it? (Lazarus, 1984). Secondary Appraisal would take into consideration some factors, for example, it would take into consideration the resources it has to counteract a stressful situation, the less stress they would experience (Lazarus 1984). Later research by Lazarus would show us that secondary appraisals is also rooted in their values, goals and beliefs which is their global meaning systems (Lazarus, 1991).

A high sense of Coping Self-Efficacy ability would effectively adopt strategies and courses of action that transform an environment from a hazardous one to a more benign (Benight & Bandura, 2004). This would also have the consequences of a better assessment of potential threats, better stress reactions and a faster recovery of one's well-being. Whereas a low sense of Coping Self-Efficacy would magnify threats and worry about threats that would rarely happen.

2.2.2.2. Task Self-Efficacy

The concept of Task Self-Efficacy derives from Bandura's theory of Self-Efficacy.

According to (Pajares, 1997), self-efficacy should be understood as a more context- and task-specific judgment rather than a more global sense of confidence. When self-efficacy assessments correspond closely to the task that is at hand, they predict better the success than more global measures of confidence and self-concept.

Since Self-Efficacy is not a fixed ability, it will vary across different situations and tasks while being influenced by five identifiable primary sources that are affected by a person's interpretations of former and current experiences. (Bandura, 1997)

According to Bandura and Gosselin & Maddux, self-efficacy beliefs are not static. There are five primary sources that would affect a person's interpretation of past and actual experiences. And they are:

- Mastery experiences- Mastery experiences are accomplishments that we did by good performances. Success is consistently the strongest predictor of future successes, especially after a person has suffered from setbacks and had a lot of effort in mastering it (Bandura 1997).
- Vicarious experiences- Social modelling, also known as vicarious experiences, is the act of observing similar, but most importantly, competent models. It boosts efficacy, particularly when a person's ability is ambiguous or it lacks direct experience (Bandura, 1986) and (Schunk & Zimmerman, 2007)
- Verbal persuasion- Verbal Persuasion is linked to feedback and encouragement. It would increase efficacy when paired with real opportunities to improve, on the opposite side, unfounded praise can backfire after failure (Fan & Williams, 2010) (Bandura, 1997)
- Physiological/emotional states- Physiological and emotional conditions that can be both actual and perceived and would directly affect self-efficacy through their influence on a person's emotional and cognitive processing. (Bandura, 1997)
- Imaginal Experiences- The 5th source is Imaginal experiences. It was an addition to the model that was proposed in (Tsang et al.,2012), Bandura alluded to the importance of imagery (Bandura, 1997) but didn't formalize it as a primary source. Imaginal experiences refer to a visualization or mental rehearsal of successful or unsuccessful results that is either deliberate or not. This visualization would improve self-efficacy. (Tsang et al.,2012)

3. Methodology

3.1. Research Design

The study was implemented using a correlational survey-based approach. This design was appropriate because the research aimed to examine the statistical associations between AI use and two psychological constructs (Self-efficacy and Autonomy). The correlation approach allowed the observation of variations and would support an efficient collection of data from participants.

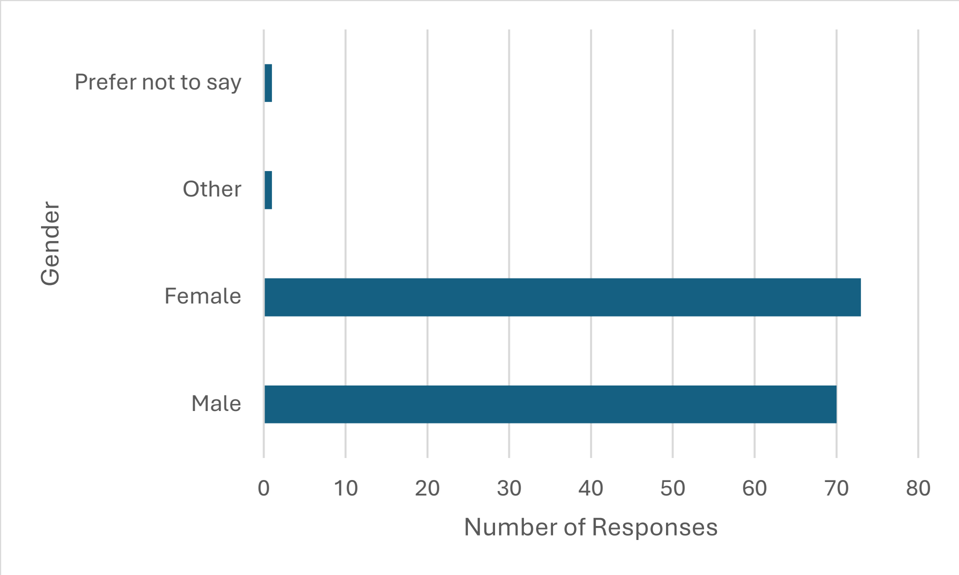
The survey was designed by using Qualtrics which is one of the most widely used survey designing tools, and was distributed through social media platforms (Instagram, LinkedIn and WhatsApp) to reach a more diverse audience.
The data collected through Qualtrics was analysed using R, a statistical programming language that is widely used for quantitative research as well as data analysis.

3.2. Procedure

The survey was distributed in English to increase the sample size as well as helping the results to have a more international scope.
After a brief introduction outlining the subject and intentions of the survey, participants would complete four main parts: the first one was a general information section where there where question about what gender, age, employment status and educational level. The second part focused on participants' use of AI tools. The third part assessed autonomy through the IAF (index of autonomous functioning) (Weinstein et al.,2012), which allowed to measure how the autonomy would differ when correlated with the usage of AI tools. The fourth part measured self-efficacy using the new general self-efficacy scale (Chen et al., 2001) which assessed participants' general belief in their capability to handle life's challenges effectively.
This survey was completely anonymous so that respondents would not be pressured providing an answer they are not sure about and might be wrong. The complete questionnaire can be seen in the appendix.

3.3. Participants

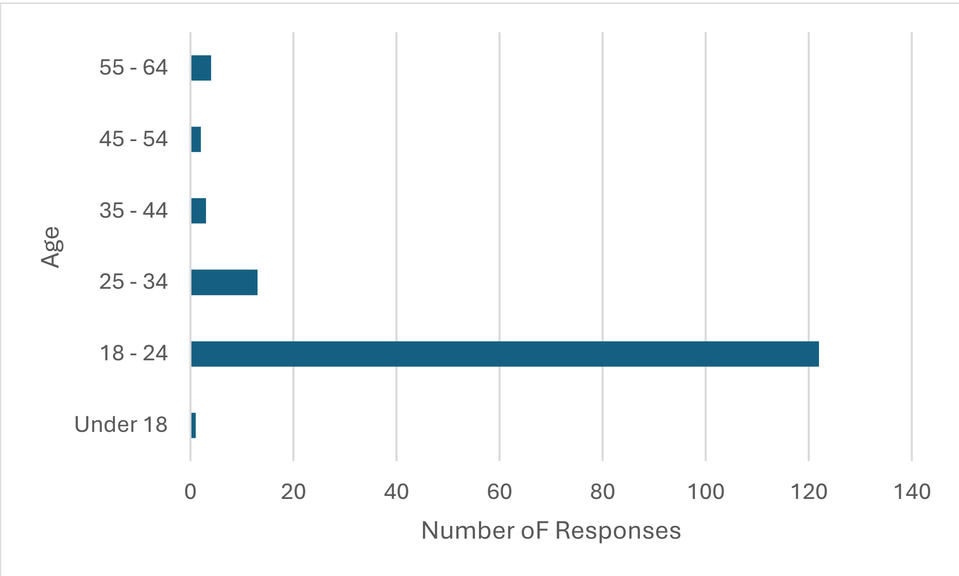
The survey distributed through social media and personal networks yielded received close to 192 answers, from these answers there would be excluded 47 for not being completed, and there would remain 145 complete answers.
Among these participants, 70 identified as male, 73 were female, 1 preferred not to say and 1 identified meaning that the sample was relatively balanced (48.27% were male and 50.34% were female). The gender distribution of the sample is illustrated in Figure 1.
Figure 1
Gender distribution



In terms of age, the sample was predominantly composed of young adults. The age group that was predominant in the study was 18-24 years old (84%) the remaining age groups were under 18, 25 to 34, 35 to 44, 45-54 and 55-64. The age distribution is presented in Figure 2.

Figure 2

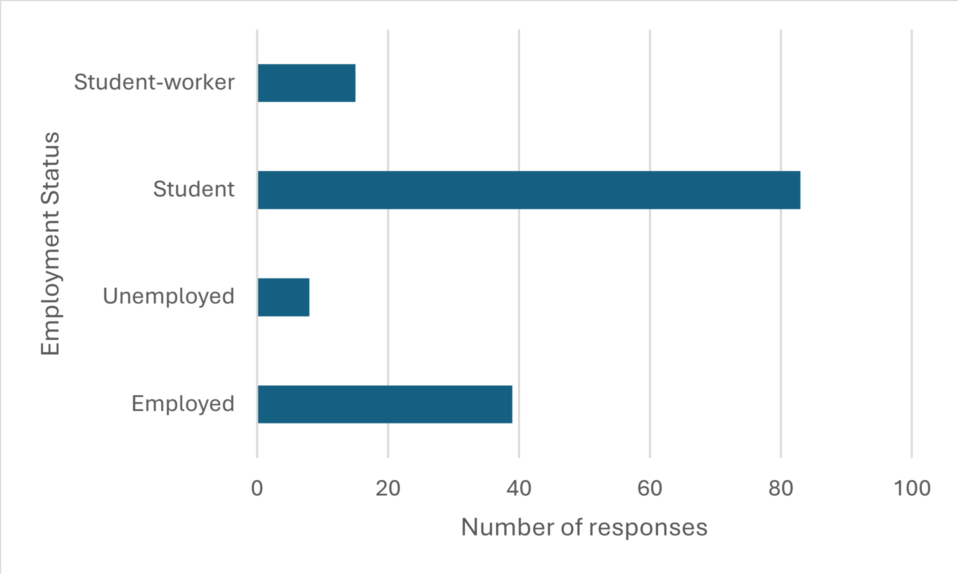
Age Distribution



Employment status varied across the sample, and the distribution was the following: Most respondents were students (57%), followed by employed (27%), student workers (10%), and unemployed participants (6%). This distribution is shown in Figure 3.

Figure 3

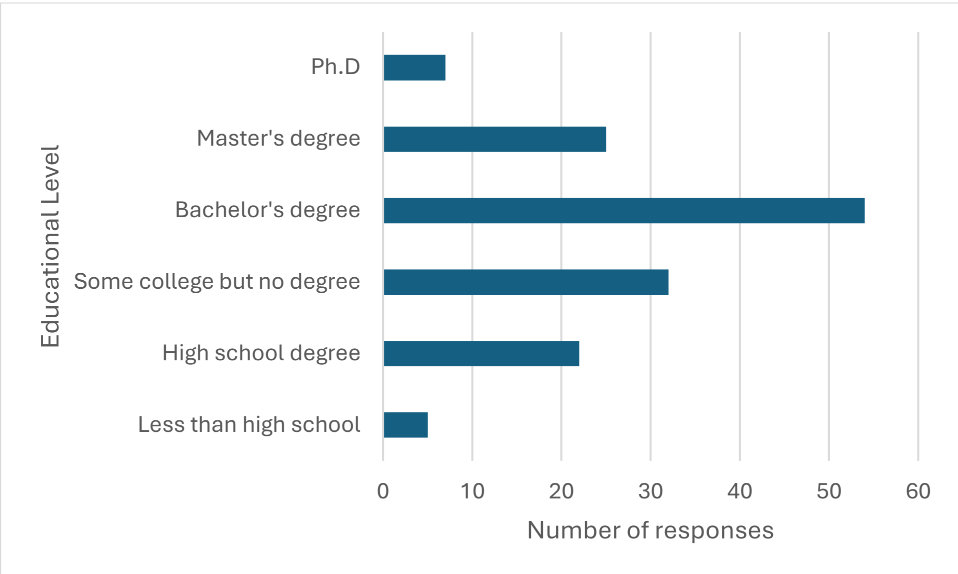
Distribution of Employment Status



Educational level also displayed variability within the sample, with 5 participants having less than high school diploma, 22 having a high school degree, 32 people having some college but still no degree, 54 having a bachelor's degree, 25 having a master's degree and 7 having a Ph.D. The distribution of the educational levels is presented in Figure 4.

Figure 4

Distribution of Educational Level



Overall, the sample is a good starting point, since there are different people with different backgrounds thus having some diversity.

3.4. Measurement Variables

3.4.1. Dependent variables

There are 2 dependent variables on this study, we are providing a special focus to them due to their importance and they are:

- Autonomy: Autonomy was the first dependent variable. It was measured using a version of IAF (index of autonomous functioning) a validated instrument to measure Autonomy across its three dimensions: Interest-taking, Susceptibility to Control and Self-Congruence or Authorship. Each of the dimensions was measured through separate subscales. The questionnaire included reverse-coded items for the Susceptibility to Control subscale (items 3,7,8,12 and 15). The Authorship subscale contained items 2,5,9,11,16. Interest-taking had items 4,6,10,13,14. All items were provided with a 5-point Likert scale ranging from Not at all true to Completely true.
  The full version of the questionnaire will be available in the appendix.
- Self-Efficacy: Self-efficacy was the second dependent variable. It was measured by using the New General Self-Efficacy (NGSE) (Chen et al., 2001). The scale consists of eight items that assess individuals' general belief in their capability to perform effectively across a wide variety of challenging situations. Participants responded with a 5-point Likert scale ranging from Strongly disagree to Strongly agree. The NGSE was chosen among other scales due to its high reliability, one-dimensionality and the fact that this measure is well-suited for assessing broad capability beliefs in everyday contexts and has been validated extensively across different populations and cultures.

3.4.2. Explanatory variables

The explanatory variable in this study was AI use. It was measured through a section of the questionnaire composed of five items dedicated to it. It can be separated on 2 fronts, the usage of AI and whether the user bought any type of AI subscription model. Four items measured general AI use through a 5-point Likert scale, other was measured through a binary option about whether the user pays for ChatGPT premium. For the ANOVA sequences, it would later divide the users into Low (up until de 33rd percentile), Medium (from the 33rd to the 66th percentile) and High use (from the 66th to the 100th percentile).

3.5. Regression

$Y=\beta 0+\beta 1(\text{AI Use}) +\varepsilon$

A simple linear regression examined whether AI Use predicted the two main dependent variables that were previously mentioned (Self-Efficacy and Autonomy). This approach would allow for the assessment of direction, magnitude and the statistical significance or not of the association between the AI use and each of the dependent variables. The outputs of this simple regression would give us:

- Unstandardized coefficients (β)
- Standard errors (*SE*)
- F-statistic
- R^2 and *Adjusted* R^2
- p-values
- Residual standard error

3.6. ANOVA

A one-way ANOVA was conducted for each of the dependent variables. As previously mentioned, AI Use variable was divided into three categories: Low. Medium and High. This categorical grouping allowed an evaluation of whether mean levels of self-efficacy and autonomy would differ across different intensities of AI engagement.

The ANOVA tested the null hypothesis by comparing the mean of the dependent variable across each of the three AI use groups.

H0: $\mu Low = \mu Medium = \mu High$

The analysis would provide:

- Between-group and within-group sum of squares
- Mean squares
- F-statistic
- p-values

4. Results

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for this study. The table reports the number of observations (N), mean, standard deviation (SD) as well as the minimum and the maximum score in the sample.

Overall, participants reported a high level of AI use (M = 12.97, S = 2.59), indicating that engagement with AI tools was high among participants of the questionnaire.

Autonomy, represented as the IAF total score, reflected a moderate level of autonomy in the sample. The maximum score one can reach on this scale is 45. Among all the measured variables, autonomy was the one that had the most variability, indicating substantial individual differences in how respondents regulate their behaviour in self-determined ways. Scores ranged from low levels of autonomy (0) to the maximum score of 45.

As described in the Methods section, the IAF total was calculated using the following formula: IAF total= Authorship + Interest Taking - Susceptibility to Control (reverse-coded).

Self-efficacy levels were high among responders, with observed values ranging from 18 to 40 and an average of 31.72. This indicates that, on average, participants reported strong beliefs in their capability to manage tasks and demands. This distribution shows moderate variability, suggesting differences in perceived competence across respondents.

Interest Taking, the dimension that is associated with curiosity and volatile behaviour also experienced substantial variability, suggesting that participants differed considerably in their tendency to engage and reflect on their internal experiences and motivations.

Susceptibility to control, which reflects the tendency to act based on external forces, showed a moderate to high mean level. Because this scale is reverse scored when in comparation to actual autonomy, high values indicated that the respondents experienced a grand degree of vulnerability to external influences.

In addition to these central statistics, the table shows that although participants engaged with AI frequently, a high variation between the low end of the spectrum (3) and the highest end (15) was still present, thus allowing for a meaningful differentiation between low, moderate and high level users of AI in the subsequent analysis, more specifically in the ANOVA cases.

Table 1

Descriptive Statistics

Variable	N	Mean	SD	Min	Max
AI Use	145	12.97	2.59	3	15
Autonomy (Authorship)	145	19.37	2.96	12	25
IAF Total	145	22.63	8.32	0	45
Interest Taking	145	18.59	4.42	6	25
Self-Efficacy	145	31.72	5.28	18	40
Susceptibility to Control	145	14.70	3.63	7	25

The correlation matrix presented in Figure 5 displays the Pearson correlations between all key variables in the study: AI Use, Self-Efficacy, the Index of Autonomous Functioning (IAF Total), and its three subdimensions (Authorship, Interest Taking, and Susceptibility to Control).

Overall, the correlations between AI Use and the psychological variables were very small, ranging from –.05 to .13. AI Use showed weak and meaningless associations with Self-Efficacy (*r = .09*), IAF total (r =.03) Authorship (*r = .13*), Interest Taking *(r = –.05*), and Susceptibility *(r = .04)*.

In contrast, the IAF Subscales demonstrated strong internal correlations, as expected from a coherent scale. Authorship correlated highly with IAF Total *(r = .70)* and moderately with Interest Taking *(r = .43)* and Susceptibility *(r = .30)*. Interest Taking displayed the strongest association with IAF Total *(r = .85)*, thus indicating that this dimension aligns substantially with overall autonomy. Susceptibility to Control was also positively correlated with IAF Total *(r = .69),* suggesting consistent positive relationships between the scale's structure).

Self-Efficacy showed moderate correlations with some of autonomy-related variables, including IAF Total *(r = .32)*, Authorship *(r = .60),* and Interest Taking *(r = .26),* thus indicating that individuals with a higher autonomy also tend to report greater perceived ability.

Figure 5

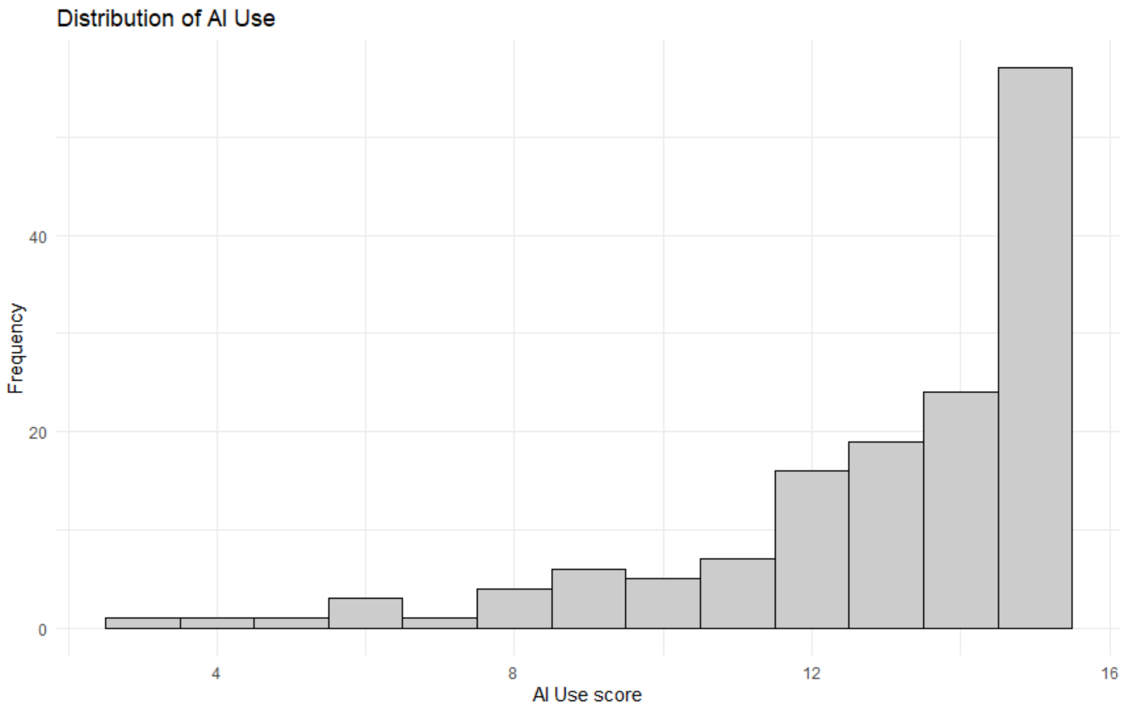
Spearman Correlation Coefficients across all variables

Figure 6 presents the distribution of AI Use scores across participants. The histogram presented shows a right-skewed distribution, thus indicating that most respondents reported relatively high levels of AI use with most scores clustering near the upper end of the scale (14–16 points). At the other end of the scale, we observed that it was reported much less frequently with almost no responses between 0 and 8 points.

The distribution demonstrated that AI use was not evenly spread within the sample; it was instead heavily concentrated among frequent users. This pattern suggests that the sample consists primarily of individuals who already engage substantially with AI tools in their daily lives. This skewness has several methodological implications, as it can reduce variability and limit the detection of associations between AI use and psychological variables.

Figure 6

Distribution of AI use



4.2. Hypothesis Testing

4.2.1 Answering RQ1

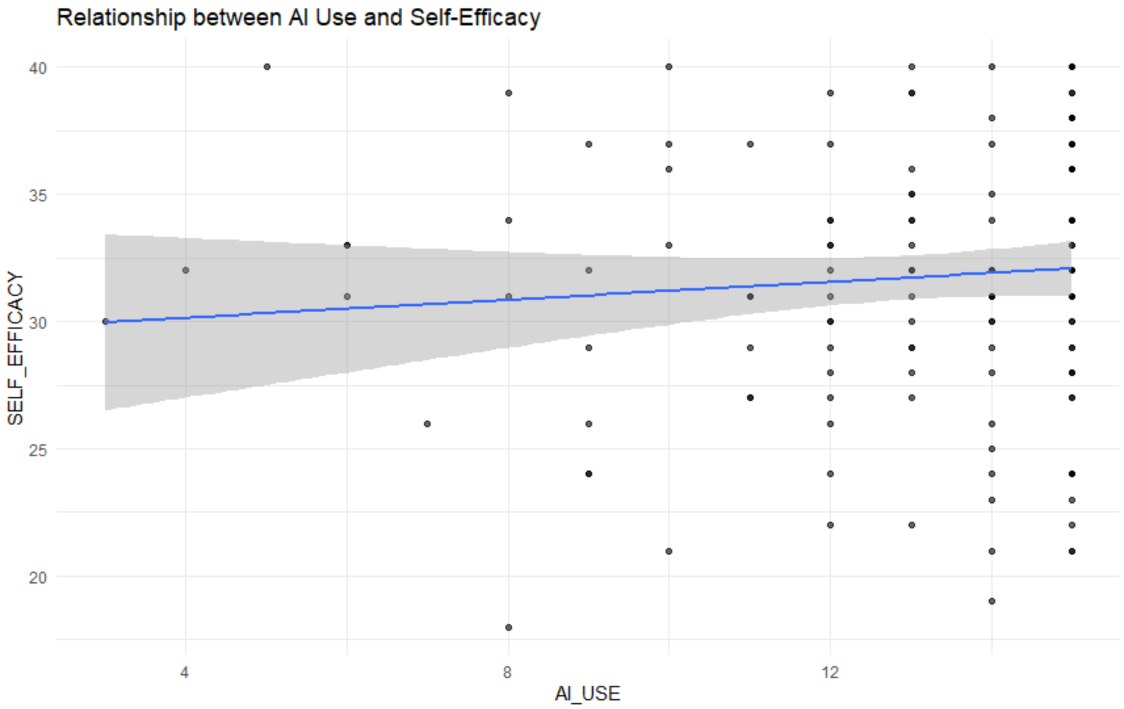
Figure 7 demonstrates the association between AI Use and Self-Efficacy using a scatterplot with an overlaid linear regression line. Each point is an individual participant's scores on both variables. As shown, the data points are spread widely across the vertical axis, indicating substantial variability in self-efficacy levels regardless of AI use frequency.

The regression line displays a slight positive slope, suggesting a minimal tendency for self-efficacy to increase as AI use rises.

The scatter of data points indicates substantial variability in self-efficacy across all AI use. This dispersion visually reinforces the regression results, which found no statistically significant association between the two variables

Figure 7

Relationship between AI use and Self-Efficacy



As described previously, a simple linear regression tested whether AI use predicts self-efficacy. The regression output is presented in Table 2.

The model was not statistically significant, $F\ (1,\ 143) = 1.068$, $p = .303$, as well as explaining little variance in self-efficacy ($R^2 = .007$) with an identical adjusted value. AI use was not a significant predictor of self-efficacy (*Adjusted* $R^2 = 0.0005$) indicating that it had no explanatory value in the model. The regression coefficient for AI use was small and statistically non-significant, $\beta = 0.176,\ SE = 0.170,\ p = .303$. Although the coefficient indicates a positive relationship, it was nonsignificant and showed an elevated standard error. These statistics were in evidence in the scatterplot above.

The only significant term in the model was the constant. To conclude, the results indicate that higher levels of AI use were not associated with meaningful differences in self-efficacy.

Table 2

Linear Regression of AI use predicting Self-Efficacy

Regression: AI Use Predicting Self-Efficacy

	Dependent variable:
	SELF_EFFICACY
AI_USE	0.176
	(0.170)
Constant	29.445***
	(2.248)
Observations	145
R^2	0.007
Adjusted R^2	0.0005
Residual Std. Error	5.283 (df = 143)
F Statistic	1.068 (df = 1; 143)
Note:	*p<0.1; **p<0.05; ***p<0.01

As previously described, a One-way Anova examined whether Self-Efficacy differed across three different levels of AI use (low, medium and high). As shown in table 4, the effect of AI use on self-efficacy was not statistically significant $F\ (2,\ 142) = 1.10$, $p = .337$. The between-group sum of squares was small (*SS=61.14*) when compared to the residual sum of squares (*SS = 3,959.82*), indicating that only a small portion of total variance could be attributed to differences between AI groups.

The mean square for each AI use group *(MS=30.57)* was slightly higher than the residual mean square *(MS=27.89*), meaning that the variability between groups can be compared to random variability between groups.

Taken together, the ANOVA results would indicate that participants' self-efficacy levels would not differ in meaning way across different user groups of AI.

Table 3

One-way ANOVA for Self-Efficacy Across AI Use Groups

Term	Df	Sum of Squares	Mean Square	F	p-value
AI_USE_group	2	61.14	30.57	1.1	0.337
Residuals	142	3,959.82	27.89		

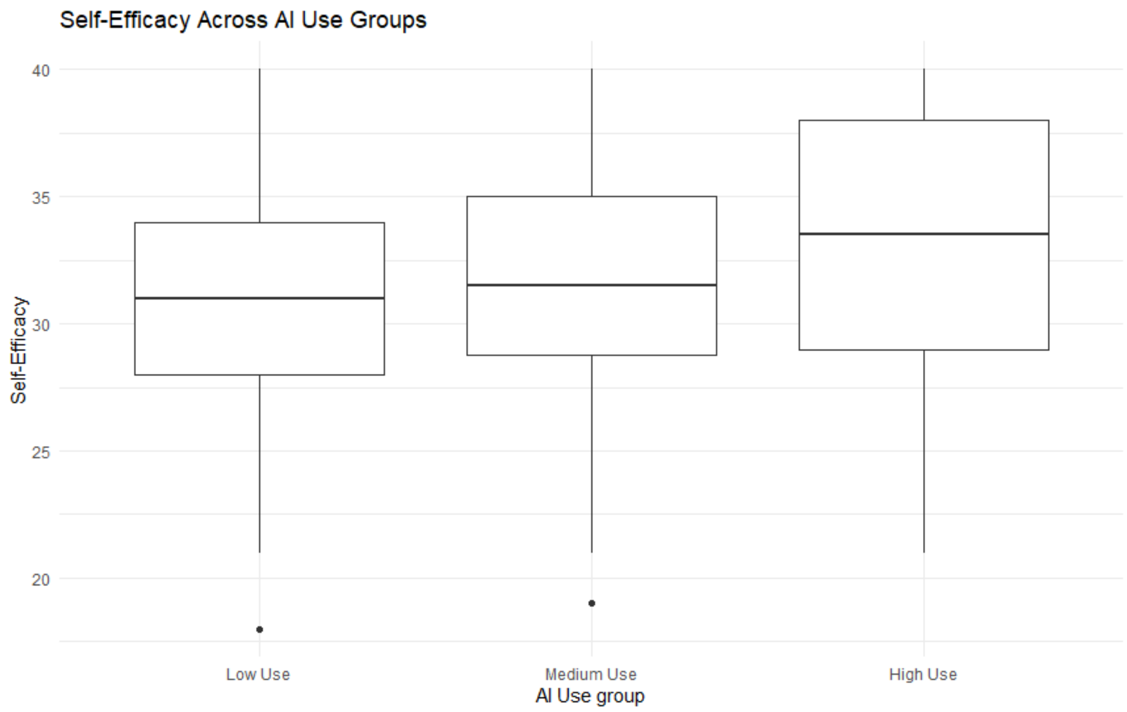
Figure 8 presents boxplots comparing self-efficacy scores across three levels of AI use: Low, Medium, and High. Across all presented groups, the distribution of Self-Efficacy shows little variation across all groups, with overlapping interquartile ranges and comparable medians. The median self-efficacy score shows only a small increase from Low use to High Use groups, but since this difference is minimal it does not show a strong or systematic pattern.

All groups display moderate variability, reflected in the height of the boxes and the length of the whiskers. Each category also does contain a small number of outliers at the lower end of the scale, indicating that isolated participants in every AI-use group reported substantially lower self-efficacy when compared to the majority of responses.

Overall, the boxplots visually reinforce the ANOVA results, showing no meaningful differences in self-efficacy across varying levels of AI use.

Figure 8

Boxplot of Self-Efficacy across different AI use groups



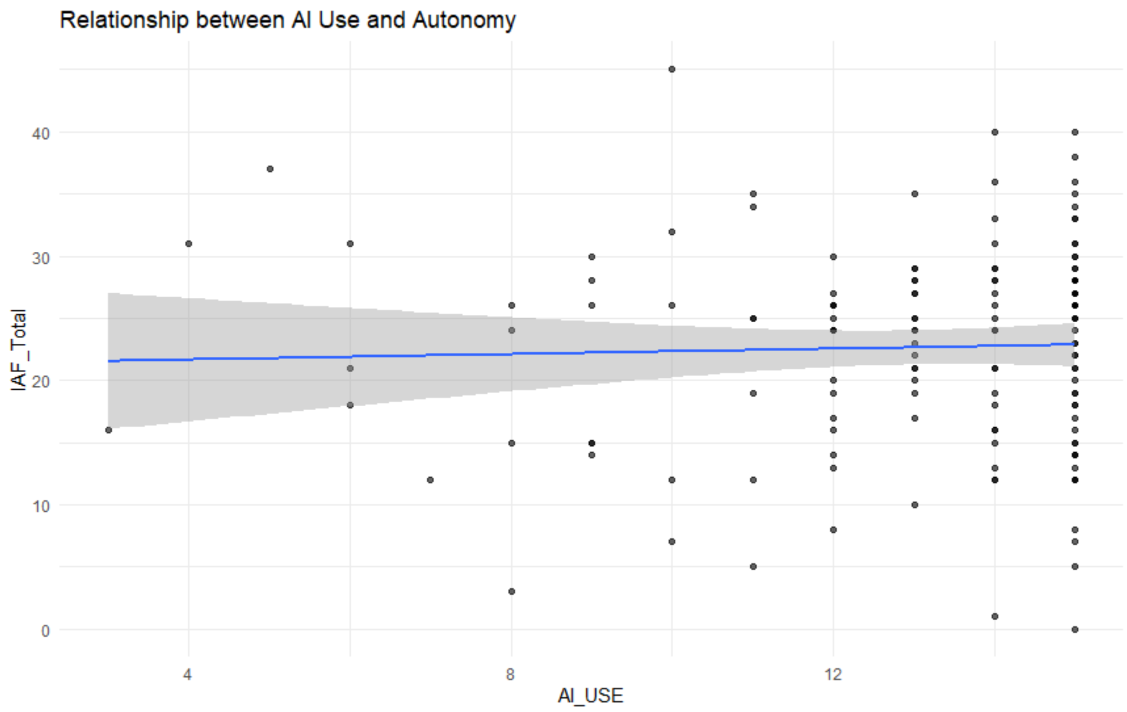
4.2.2 Answering RQ2

Figure 9 illustrates the relationship between AI use and autonomy, measured by the Index of Autonomous Functioning (IAF Total). Each point is an individual participant's scores on both variables. The fitted regression line shows a very slight positive slope, suggesting a minimal upward trend as AI increases however, the relationship between these variables is extremely weak and it reflects the high degree of uncertainty in the estimate.

The scatter of data points indicates substantial variability in autonomy across all AI use. Participants from all ranges of AI use display a broad range of autonomy scores, from very low to the maximum, with no clear clustering or pattern. This dispersion visually reinforces the regression results, which found no statistically significant association between the two variables.

Figure 9

Relationship between AI use and Autonomy



As with the previous variable, a simple linear regression would be conducted for this variable. This model was not statistically significant, *F (1,143) = .165, p=.685* and cannot explain any variance in autonomy with R^2 being 0.001 and adjusted R^2=-0.006 suggesting that the predictor had little to none explanatory value.

The regression coefficient for AI would also be small and non-significant, *β = .109, SE = .269, p = .685*. This coefficient indicates that there is a minimal and unreliable positive association, meaning that any increase in AI would not be associated with a meaningful change in autonomy. The significant standard error and non-significant p-value would make sure that the estimated effect is indistinguishable from null. These results were already in evidence in the scatterplot above and it has put in evidence that there is no statistical evidence between AI use and autonomy.

Concluding, the regression results demonstrate that AI use does not, in any way, predict autonomy.

Table 4

Linear Regression of AI use predicting Autonomy

Regression: AI Use Predicting Autonomy

	Dependent variable:
	IAF_Total
AI_USE	0.109
	(0.269)
Constant	21.221***
	(3.553)
Observations	145
R^2	0.001
Adjusted R^2	-0.006
Residual Std. Error	8.347 (df = 143)
F Statistic	0.165 (df = 1; 143)
Note:	*p<0.1; **p<0.05; ***p<0.01

A one-way ANOVA was conducted to examine if this test could prove any type or relationship between the variables at play. The analysis would be done in the same manner as the one done with the other variable. As shown in table 7, the effect of AI was not statistically significant, $F(2, 142) = 0.79$, $p = .457$. The between-group sum of squares *(SS=109.51)* was small when in relation to the residual sum of square *(SS=9,866.11)*, thus indicating that differences in autonomy across the AI use groups accounted for only a small and negligible portion of total variance.

The mean square for the AI use groups *(MS=54.76)* was smaller than the residual mean square *(MS=69.48),* concluding that the variability in autonomy scores between the groups would be minimal and was overshadowed by the variability within these groups.

Concluding, the regression did not find that there was a difference between the Autonomy and AI use levels.

Table 5

One-way ANOVA for Autonomy Across AI Use Groups

Term	Df	Sum of Squares	Mean Square	F	p-value
AI_USE_group	2	109.51	54.76	0.79	0.457
Residuals	142	9,866.11	69.48		

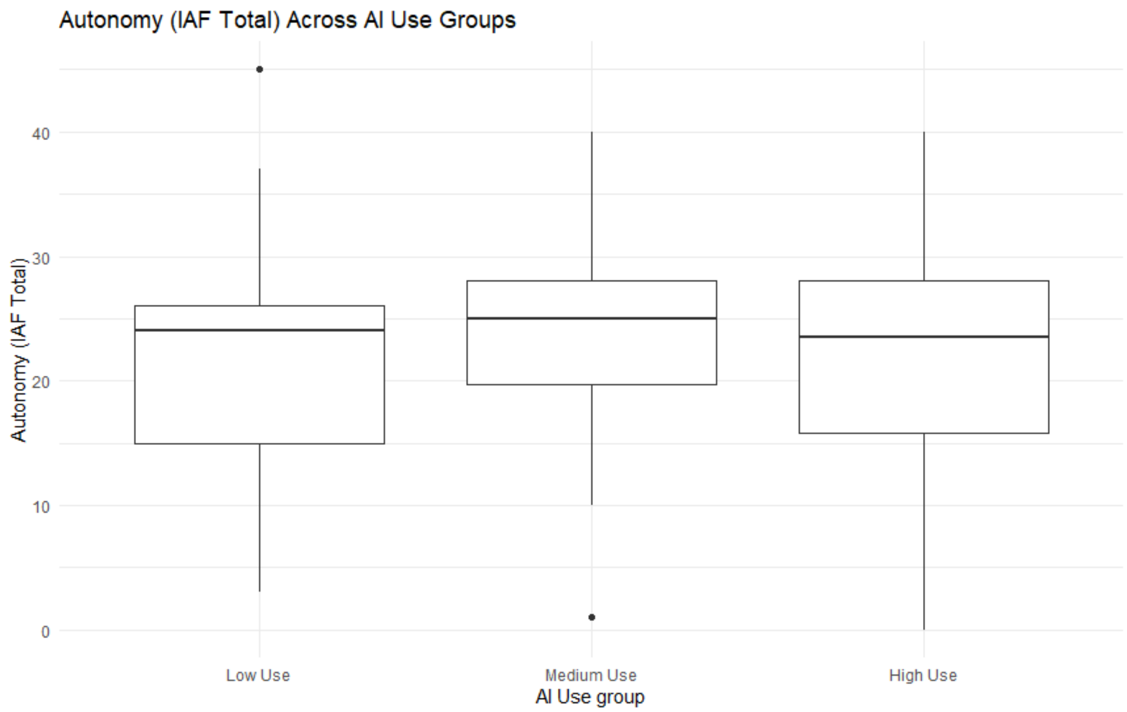
Figure 10 displays boxplots comparing autonomy levels (IAF Total scores) across the three AI-use groups: Low, Medium, and High. Across all presented groups, the distribution of Autonomy shows little variation across all groups, with overlapping interquartile ranges and comparable medians.

The median Autonomy score differ slightly from Low use to High Use groups, but since this difference is minimal it does not show a strong or systematic pattern linking AI use to autonomy. Each group presents considerable variability, with relatively wide boxes and whiskers extending across a broad range of autonomy scores. Outliers are present in all categories, including a very low autonomy score in the Medium Use group and extremely high scores in both the Low and High Use groups.

Overall, the boxplots visually reinforce the ANOVA results, showing no meaningful differences in autonomy across varying levels of AI use.

Figure 10

Boxplot of Self-Efficacy across different AI use groups



5. Discussion

5.1 Summary of Results

The theme and purpose of this study is to exam whether the use of AI influences two important and fundamental psychological constructs that are self-efficacy and autonomy. Drawing on Bandura's works and Self-Determination Theory (Ryan & Deci, 1985; 2000), the study would explore whether different levels of AI engagement would be associated with differences with behavioural changes in an individual's perceived capacity (which is self-efficacy) and their autonomy.

The findings from both the linear regressions and the one-way ANOVA tests and analysis were consistent around all outcomes. AI use did not correlate with self-efficacy, nor were there statistical differences between the low, medium and high AI use groups. The regression showed a minimal and non-significant coefficient; the ANOVA did not reveal any differences between groups as well. This would suggest that, in this sample, the frequency of AI engagement would not be related to a decrease or increase participants' beliefs in their ability to execute their tasks.

In a similar way, the results for autonomy demonstrated an insignificant association between AI use and the IAF total score. The linear regression model wouldn't explain none of the variance in their autonomy levels, and the ANOVA would confirm that across AI groups. This would indicate that AI tools did not appear to influence participants' sense of autonomy.

Concluding, the results would show consistently that AI use, when measured in everyday, general use contexts, would not significantly impact participants' self-efficacy or autonomy.

5.2 Implications

5.2.1 Theoretical applications

The absence of any significant association between AI use and the variables autonomy and self-efficacy can carry significant theoretical implications. In Bandura (1997) we could see that self-efficacy can emerge from mastery of tasks or experiences, social modelling and feedback. If AI was acting as a replacement for thinking because people were relying so much on it, there could be a decrease on self-efficacy because of it. If they would use it frequently, it could also mean that there could be a replacement to practice of certain tasks or exercise, replacing the mastery experiences that Bandura advocates for. However, the results did not report the lower self-efficacy theory, remaining basically the same, regardless of AI use. This could be because of past success that AI brings when using it much. One factor for the improvement of Self-Efficacy are the past successes, if you had any success on a task beforehand, you would feel more capable of doing it after, this could mean that even if AI is hurting self-efficacy in the dimensions referred before, it would be offset by the increase in it by the successes that AI brings in its package.

Moving on to Self-determination and most importantly Self-Determination Theory (Ryan & Deci,2000), autonomy can be fostered/increased when individuals feel that the actions that they do originate from their own values and/or interests. There are concerns that are being raised about how AI can reduce autonomy by prompting users toward choices that are part of an algorithm, thus going to a more deterministic path, or it could also be doing tasks on their behalf. The findings that we've encountered have gone in a opposite direction than the narrative, indicating that general AI usage does not appear to reduce the autonomy, the study reveals that participants did not report feeling less autonomous or more regulated by external factors as their AI use increased.

Taken together, the findings are consistent with recent literature indicating that the psychological effects of technology and automation depend heavily on contextual factors. In Parasuraman & Manzey (2010) we observed automation-related complacency and attention shifts and how they typically emerge in high-demand or high-stakes environments, whereas the study examined a general, almost routine use of AI. Furthermore, young users do not form a uniform group regarding their technology, in Bennett & Maton (2010), it was observed that the variability that was observed among these users likely would dilute potential associations between AI use and psychological constructs such as self-efficacy or autonomy, likely contributing to the non-significant results observed.

These results would imply that psychological constructs and dimensions such as autonomy and self-efficacy may be more resilient to technological influence that what we assumed beforehand. Alternatively, AI use at the level that we were assessing here could not be sufficiently immersive or commanding to impact these constructs. These factors favour that a more moderate or routine use of AI tools may integrate naturally into the mundane life without any dramatic shift in autonomy and self-efficacy.

5.2.2 Practical and Societal Implications

These findings can provide valuable insight for educators, employers, policymakers, and technology designers. As AI tools become a bigger part of our life, being it on a more academic, professional, and personal level, there is widespread concern that overreliance on it would diminish the competence of humans and/or reduce the individual's capability to think on its own.

This study found no evidence for that kind of negative psychological effects, users who frequently engaged with AI tools did not report lower self-efficacy or autonomy. This would suggest that AI, for the general population, may function as a complementary tool rather than a replacement for our endeavours.

For organizations that are implementing AI systems, these findings give assurance that the adopting of AI does not erode or diminish workers' confidence or their intrinsic motivation. In a more educational setting, such as schools and universities, concerns that students who use AI feel less capable or autonomous was not supported by the data. The psychological impact of AI should focus how it is integrated (support learning, enhance decision-making, or automate routine tasks) rather than the amount of use.

The research also highlights the need for a responsible AI design, where systems support user autonomy rather than constraining it. The autonomy on AI may still be fomented by the stigma that it has around it and the many errors that it makes, making it still not a 100 percent foolproof method, thus not reducing the human input part and therefore not reducing autonomy.

5.3 Limitations

Despite the contributions to this study, it has several limitations that need to be acknowledge when reading/ analysing it.

The first limitation is that the data was based on self-report measures, which may be subject to biases such as social desirability, recall errors, or subjective interpretations of the participant's AI use (Fisher ,1993). In particular, the self-report measures of AI use may not reflect the complexity of a person's engagement and depth of the use of AI. They could also overestimate self-efficacy or autonomy to appear more capable than they are. Future studies can incorporate a feature such as digital usage logs for better proof.

Secondly, the study assessed general AI use, instead of specific types of AI usage. In Logg et al (2019) it was shown that the people's use of algorithmic advice would vary depending on the domain, task type and context meaning that different tools may have different impact in our psychological dimensions. For instance, generative AI writing assistants when compared to decisions-support systems, predictive recommendation engines and creative tools may influence autonomy and self-efficacy in different ways. A more fine-tuned questionnaire may help in understanding each type's contribution to these psychological dimensions.

Third, the sample size, although adequate for the analysis conducted, may limit the detection of effects. It can be possible that more subtle relationships between AI use and psychological constructs exist but were not detected due to these limitations (Cohen,1992). A bigger sample size may provide a better understanding of this subject.

Fourth, the cross-sectional design presents an additional limitation. Measuring all variables at a single point in time prevents conclusions about causality (Maxwell & Cole, 2007). It remains unclear whether AI use influences autonomy and self-efficacy or whether individuals with certain psychological profiles simply use AI more or less, more longitudinal or experimental designs would be needed to clarify these causal pathways.

Another question that has arrived in the making of this study is the common method bias. Since all the variables were collecting using the same measurement method (questionnaire) and at the same time, this can inflate, supress or even distort associations between the constructs (Podsakoff et al., 2003). Multi-method approaches such as behavioural tasks, interviews or observer ratings would mitigate this issue.

The nature of this sample also restricts generalizability. Since the sample lacks demographic and cultural diversity, the results may not extend to broader populations. Autonomy and self-efficacy are known to have variation across different cultural contexts and sociocultural environments (Markus & Kitayama, 2010).

Finally, the study assessed psychological outcomes in everyday, low-stakes I use contexts. Meanwhile, the psychological impact of AI may differ between high-stakes domains such as academic performance, professional decision making and creative productions or low-stakes domains (Shneiderman, 2022).

5.4 Future research

Although the present study helps to contribute to the understanding of how everyday AI use relates to a person's autonomy and self-efficacy, several opportunities remain open for future research and studies. These opportunities are essential to overcome the limitations defined by this thesis but also to deepen the psychological study of human-AI interaction.

First, future research should prioritize the integration of objective measures of AI use, that can be done with access to digital usage logs, app-level tracking, or system-generated interaction data. This would provide more accurate insights into how frequently and for what purposes do people engage with AI tools. Combining objective metrics with self-report scales would help in reducing biases and allow researchers to distinguish between perceived and real AI reliance.

Second, research should explore specific types of AI tools instead of general usage. As Logg et al. (2019) proved, people react differently to algorithms depending on its task and context. Therefore, separating generative AI, decision -support systems, recommendation algorithms, translation tools, and creative AI would help to reveal if there is any link between usage and distinct psychological effects. Future questionnaires should be adapted to capture these invisible nuances and enabling researchers to uncover whether certain AI modalities have stronger implications for autonomy and self-efficacy.

Third, future investigations need to benefit from larger and more diverse samples. Increasing sample size would improve statistical power and help detect smaller and more subtle effects that may be unnoticed in the present study. Including participants from different cultural, educational and economic backgrounds would also help researchers to examine sociocultural variations in the relationship between AI use and psychological constructs.

Fourth, longitudinal and experimental research designs should be employed to examine causal relationships. Longitudinal studies can track changes in autonomy or self-efficacy as individuals adopt or increase AI use over time. More experimental designs such as assigning participants to complete tasks with or without AI would enable researchers to isolate immediate psychological impacts of AI's assistance as well as addressing the causality concerns.

Finally, future research should expand beyond the small world of everyday, low-stakes AI environments to examine high-stakes contexts. As mentioned before with Shneiderman (2022), the psychological impact of AI differs depending on its use. Studying how AI shapes psychological constructs in an academic, organisational, medical, or financial setting may uncover effects that were not observable in general populations.

5.5 Conclusion

AI is being analysed more due to its implications in everyday life. This shift has implications in how we see our quotidian life and how the world progresses over time. This study came to see how that is shown across two different psychological constructs (self-efficacy and autonomy). Although there wasn't a significant correlation between AI use and the two constructs, I hope that this negation opens more doors than it closes by showing that AI has a bigger potential than what most of us assume. I would also hope that this study serves as an inspiration for further research to more of AI's impacts, because this field still has more to offer than this study.

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- 7. Appendix

Introduction

Welcome and thank you for considering participating in this experiment on the influence of AI. I, Miguel Gomes am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of the professor Vinicius Faria Ribeiro. The study consists of answering to a couple of questions. And it will take about 5 minutes to complete. Your participation will contribute to research on AI. <Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that it will not be possible to link your responses to your identity. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals, always in an aggregated form, never about any individual responseWe ask you to take the study in one go, without interruptions. There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for circa 5 minutes.   You may change your mind and drop out at any point of the study during its completion.   If you have any questions about this study, please s-mjmgomes@ucp.pt. By continuing you agree to participate.

General Information

Q2.1 Gender

- ○ Male
- ○ Female
- ○ Non-Binary
- ○ Prefer not to say

Q2.2 What is your Age

- ◯ Under 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ 55 - 64
- ◯ 65 - 74
- ◯ 75 - 84
- ◯ 85 or older

Q2.3 What is your employment Status

- ◯ Employed
- ◯ Unemployed
- ◯ Retired
- ◯ Student
- ◯ Student-worker
- ◯ Other

Q2.4 What is your educational level

- Less than high school
- High school degree
- Some college but no degree
- Bachelor's degree
- Master's degree
- Ph.D.

Usage of AI

Q3.1 Tell us if you agree/disagree with the following statements

Q3.2 I often use AI tools such as ChatGPT, Copilot, Gemini or other AI tools in your daily life

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q3.3 I use AI tools for different types of tasks (e.g., writing, studying, planning, coding).

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q3.4 I would feel confident doing complex tasks without AI support.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q3.5 I rarely use AI tools.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q3.6 I pay for any type of premium AI (ex: ChatGPT Premium)

- No
- Yes

Autonomy part

Q4.1 Below is a collection of statements about your general experiences. Please indicate how true each statement is of your experiences on the whole. Remember that there are no right or wrong answers. Please answer according to what really reflects your experience rather than what you think your experience should be.

Q4.2 My decisions represent my most important values and feelings.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.3 I do things in order to avoid feeling badly about myself.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.4 I often reflect on why I react the way I do.

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.5 I strongly identify with the things that I do

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.6 I am deeply curious when I react with fear or anxiety to events in my life.

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.7 I do a lot of things to avoid feeling ashamed.

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.8 I try to manipulate myself into doing certain things.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.9 My actions are congruent with who I really am.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.10 I am interested in understanding the reasons for my actions

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.11 My whole self stands behind the important decisions I make.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.12 I believe certain things so that others will like me.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.13 I am interested in why I act the way I do.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Q4.14 I like to investigate my feelings.

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.15 I often pressure myself.

- Not at all true
- A bit true
- Somewhat true
- Mostly true
- Completely true

Q4.16 My decisions are steadily informed by things I want or care about.

- ◯ Not at all true
- ◯ A bit true
- ◯ Somewhat true
- ◯ Mostly true
- ◯ Completely true

Self-efficacy part

Q5.1 I will be able to achieve most of the goals that I have set for myself.

- ◯ Strongly disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Strongly agree

Q5.2 When facing difficult tasks, I am certain that I will accomplish them.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.3 In general, I think that I can obtain outcomes that are important to me.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.4 I believe I can succeed at most any endeavor to which I set my mind.

- ◯ Strongly disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Strongly agree

Q5.5 I will be able to successfully overcome many challenges

- ◯ Strongly disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Strongly agree

Q5.6 I am confident that I can perform effectively on many different tasks.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.7 Compared to other people; I can do most tasks very well.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

Q5.8 When I am confronted with a problem, I can usually find several solutions.

- ○ Strongly disagree
- ○ Somewhat disagree
- ○ Neither agree nor disagree
- ○ Somewhat agree
- ○ Strongly agree