The influence of Artificial Intelligence and organizational levels on meaning at work.

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Dissertation submitted in partial fulfilment of requirements for the MSc in Management with specialization in Strategy, Entrepreneurship & Impact, at the Universidade Católica Portuguesa, 04-01-2023.

Abstract

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As AI can change essential tasks, it can affect occupational boundaries and consequential team and organizational structures, thereby changing work's social relations, structures and meaning (Craig et al., 2019). Experiencing meaning at work has many positive effects in both work and life in general, and it is therefore, essential to optimize as much as possible. This research aims to find out whether AI does influence meaning at work, how it influences meaning at work and if this influence of AI differs over organizational levels. The results of this research indicate that AI negatively influences meaning at work significantly. Although AI negatively influences all components (positive meaning, meaning-making and greater good motivations) of meaning at work, the influence differentiates over those components, where positive meaning is influenced the most and greater good motivations the least. Other than that, it is found that AI's influence differs over organizational levels, where the strategic (higher) organizational level was significantly affected more than operational (lower) level. These findings imply that AI influences certain aspects of work more than others. Theoretical and managerial implications are discussed.

Keywords: Artificial Intelligence, Meaning, Meaning at Work, Organizational levels, Positive Meaning, Meaning-Making, Greater Good Motivations

Sumário

Título: A influência da inteligência artificial e níveis organizacionais no significado do trabalho.

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Como a inteligência artificial (IA) pode alterar tarefas essenciais, ela pode afetar os limites ocupacionais e consequentes equipas e estruturas organizacionais, alterando assim as relações sociais, estruturas e o significado do trabalho (Craig et al., 2019). Experienciar significado no trabalho tem muitos efeitos positivos tanto no trabalho quanto na vida em geral, sendo essencial optimizar o máximo possível. Esta investigação tem como objetivo descobrir se a IA influencia o significado no trabalho, como ela influencia o significado no trabalho e se essa influência é diferente em diferente níveis organizacionais. Os resultados desta investigação indicam que a IA influencia negativamente o significado no trabalho de forma significativa. Embora a IA influencie negativamente todos os componentes (significado positivo, criação de significado e motivação para o bem maior) do significado no trabalho, a sua influência é diferente para diferentes componentes, sendo o significado positivo mais influenciado e a motivação para o bem maior menos influenciada. Para além disso, verifica-se que a influência da IA difere nos níveis organizacionais, onde os níveis organizacionais mais altos foram mais afetados do que os mais baixos. Assim, a IA influencia certos aspectos do trabalho mais do que outros. Implicações teóricas e de gestão são discutidas.

Palavras-chave: Inteligência Artificial, Significado, Significado no Trabalho, Níveis Organizacionais, Significado Positivo, Criação de Significado, Motivações para o Bem Maior

Acknowledgement

This dissertation (provisionally) marks the end of my academic path and a large chapter of my life. I want to take this opportunity to show my appreciation for all the help I have received. Without all the help and support, I would not have been able to learn and enjoy it as much as I did.

Special thanks to:

Professor Filipa de Almeida - Who provided me with excellent assistance and suggestions to bring this thesis to a higher level. I am very grateful for your constant dedication, willingness to help and kindness.

My parents and stepparents - Who have encouraged me to make my own choices and supported me unconditionally in every step of my journey. Thank you for always being there for me when I needed you to be.

My friends - Who filled my academic career with a lot of laughter and joy.

Introduction

"Artificial Intelligence will make jobs kind of pointless,"

- Elon Musk (2019), CEO of Tesla (Clifford, 2016)

The role of Artificial Intelligence (AI) has become greater and greater; it is disrupting all kinds of industries and thereby is simultaneously threatening and creating opportunities for the future workplace (Xu et al., 2018).

Over the years, more tasks can be accomplished using AI; AI can not only do work that humans do not prefer, but it can also do it more accurate and faster than humans' physical and cognitive capacities (Misselhorn, 2018). While in 2014, less than 10 percent of the companies worked with AI and machine learning in their core business, in 2019, already 80 percent did (Ghosh et al., 2019). Moreover, Kelly (2012) stated in 2012 that before the end of this century, it is likely that 70 percent of today's occupations will be replaced by automation, and it is only a matter of time before that becomes reality.

It could be argued that humans have certain advantages that AI does not yet duplicate; humans are likely to outperform AI in evaluating subjective, qualitative matters using experience, insight, and holistic vision. Therefore, it could be that humans can perform better due to their intuitive capabilities (Jaharri, 2018), because many professions require learning from, analyzing, communicating about and, most of all, understanding human emotions (Harari, 2018). On the other hand, AI is also improving in these fields. Researchers have concluded that human intuition, which leads to human intuitive capabilities, is actually based on pattern recognition (Bishop, 2007). Although human emotion might be hard to understand for AI, the patterns behind those emotions are, in fact, explainable by its pattern data. In this sense, with the pace at which AI develops itself in the field of recognizing patterns and decision-making, it could be that AI can even outperform humans in tasks that require 'intuition' (Harari, 2018). The extent to which AI could outperform humans is hard to predict. Some, like Elon Musk, state it is only a matter of time until robots take over all our jobs, and we would need a universal basic income (Clifford, 2016). While others are still convinced AI will only be fully able to take over some of the jobs. Irrespectively of the extent to which AI is used in the workplace, it seems evident that AI is here to stay, it is becoming increasingly important not only for companies but also for employees.

As AI can replicate and improve aspects of human work, there are many questions about what consequences this will have for employees and what part humans will play in this new world (Leetaru, 2016). The influence of AI will be visible in all aspects of employees' work; it could change some aspects of their job or their whole job (Makarius et al., 2020). For instance, if all medical information and expertise is uploaded to a data bank, which is programmed into an 'artificial doctor machine', it could undoubtedly outperform any real doctor in its medical knowledge. A different example is self-driving vehicles, which have multiple cameras, and in that way, keep an eye on traffic in various directions and never reduce focus. With those features, they are likely to cause fewer accidents than human drivers (Harari, 2018). How does it feel for human beings to compete with that?

By changing aspects of work, the environment, tasks, contact, and perception of higher goals in the life of human beings could be affected (Lips-Wiersma & Morris, 2009). For instance, if one perceives that their work contributes to a greater good, and AI changes this perception, it could have consequences on their view of meaning in work and life (Steger & Dik, 2009). As for the doctor in the previous example, if their goal was to cure their patients to the best of their ability, to contribute to the world, and AI could do this in many cases in a much better or quicker way, it could affect how that doctor views his/her contribution. On top of that, as AI can substitute employees in an increasing number of tasks, their view on personal meaning, significance, and purpose in work is possibly changing as well (Steger et al., 2012).

As organizations have different organizational structures that all have their own tasks and responsibilities, AI likely has a distinct influence on the levels of those structures. The effects of AI on tasks and responsibilities also lead to changes for the employees. And, as explained prior, those changes in the work environment and tasks may lead to a different view of meaning at work (Wisskirchen et al., 2017). This thesis strives to understand how the meaning at work, of employees over different organizational levels, is affected by AI.

Problem statement

AI is becoming more prominent in the workplace, and its abilities greatly influence people's jobs. The effects of AI are likely to impact how employees feel about their careers and contribution. This thesis aims to research the influence of these consequences on work's

meaning, as well as the differences in the effect of AI over different organizational levels. Specifically, this thesis raises the following research questions:

Q1: How does AI influence employees' meaning at work?

Q2: How does the influence of AI on meaning at work differ over different organizational levels?

Relevance

As the workplace is changing because of AI, and it impacts or will impact the majority of jobs, it is valuable to understand this impact, and particularly how it affects meaning at work. Feeling more meaning at work can lead to greater meaning in life, satisfaction in life, career, and fewer depression symptoms (Steger, 2016). Therefore, it is important that employees view their job as meaningful. For AI not to interfere with one's view of meaning at work in a negative way, the first step is finding out what exactly AI's impact is on employees' view of meaning at work.

This thesis could interest multiple target audiences, but it primarily targets managers and employees. Managers can use this research's insights to be aware of what changes AI might cause to meaning at work of employees and to minimize the factors that negatively influence meaning at work by managing the implementation of AI. Other than that, this research can provide awareness for employees on what AI means for their meaning at work, thus also allowing them to make better informed choices regarding their occupations. In addition, this research will contribute to the theory of AI in the workplace and to the theory of meaning at work.

Structure

This short introduction is followed up by a literature review, which consists of the following topics: AI, meaning at work, and organizational levels. Subsequently, in the methodology chapter, the experimental approach is explained in detail. This includes information about the research strategy and design, giving an overview of the participants, the procedure, and an overview of all the variables. After that, the result section follows. In this section, information about data cleaning, scale reliability, and the analysis of the results of the experiment can be found. Then, the discussion consists of the research findings and main conclusions, academic

and managerial relevance, the limitations, and future research suggestions. Finally, the conclusion shortly summarizes the main take-aways of this research.

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Literature review

Artificial Intelligence

First, it is essential to understand exactly what AI is and what its abilities are to see its effect in the workplace. AI is the science and engineering of making intelligent machines, in particular intelligent computer programs. AI outlines the processes of machines that would demand human intelligence. The concept 'artificial intelligence' hence means 'investigating intelligent problem-solving behaviour and creating intelligent computer systems' (Wisskirchen et al., 2017, p.10). It is used as a computational part to accomplish goals, varying in different kinds of intelligence (McCarthy, 2007). AI can be divided into two types; 'weak artificial intelligence' and 'strong artificial intelligence'. 'Weak artificial intelligence' is used when a computer simulates intelligence by investigating cognitive processes. Whereas 'strong artificial intelligence' is used when computer processes are intellectual self-learning processes, the computer is able to 'comprehend' and optimize its behavior by being programmed in the right way (Wisskirchen et al., 2017). AI also encompasses sub-fields of machine learning and deep learning; these disciplines are comprised of AI algorithms which aim to create expert systems which make predictions or classifications based on data (IBM Cloud Education, 2020). Both machine learning and deep learning are sub-fields of AI, whereas deep learning is also a sub-field of machine learning. The difference between the two sub-fields is in how each algorithm learns. Deep learning is comprised of neural networks, and it automates much of the feature extraction piece of the process, eliminating the required manual human intervention and enabling the use of larger data sets. Machine learning does not automate that process and thus is more dependent on human intervention to learn. Machine learning algorithms learn by the hierarchy of features determined by humans where deep learning algorithms are able to work with a raw data set, which has no determined hierarchy beforehand (IBM Cloud Education, 2020). With this intelligence, many tasks priorly performed by humans can be automated (Halal et al., 2016). The tasks that will be executed by (the use of) this intelligent software will, at this time, mainly depend on the differentiation between routine and non-routine work, not on the physicality or cognition of the work (Jaimovich & Siu, 2020).

AI's perception

AI can be viewed as a threat or an opportunity, but most likely both simultaneously. Introducing AI in the workplace requires sensemaking for employees, affecting how employees think about themselves and their work experience. This can generate both work-related identity threat and work-related identity enhancement, with subsequent effects on well-being, behaviour, and

attitudes (Selenko et al., 2022). AI may negatively impact employees' identification with their jobs, this is because the implementation of AI expects to change professions and workplaces in general fundamentally. Due to technological improvements, AI is becoming more capable by the day, and therefore more and more humans are being outperformed in their manual and conceptual work by autonomous units. Humans are not only outperformed by these units in the pace and accuracy of their work but also by the costs, which is often lower using AI. This added value of AI, with respect to humans, puts a significant number of jobs at risk of being replaced (Frey et al., 2013). Besides influencing what humans work on content-related, AI also affects the way in which humans work, as human workers need to accommodate to work side by side with AI.

As mentioned, a possible outcome of automation, highlighted by the study by Halal et al. (2016), is that accelerating automation will provoke a crisis because of the millions of jobs that autonomous computers will replace. This shift would happen gradually, as we see that nowadays, repetitive, and monotonous jobs that AI could easily replace are already (getting) taken over by AI. However, as AI is improving and expanding its capabilities, it is a matter of time before more and more jobs will partly or totally be taken over by AI. The solution to people getting unemployed because of AI could be that people, who perform tasks in fields where AI is dominant, get trained to be able to perform tasks in other fields. The question is however whether the pace at which employees can be retrained and transitioned to new occupations is not slower than the pace of AI expanding its abilities. Let alone that not all humans might have the right capabilities to be retrained or transitioned (Harari, 2018). As such, AI will influence future jobs in many cases. These changes feed into employees' fears of being replaced by this technology (Bessen, 2018; Mirbabaie et al., 2022). Research by Mirbabaie et al. (2022) indicates that changes in loss of status position and the interaction with AI are predictors of an AI identity threat in the workplace.

AI's promise

On the other hand, AI could support identity functions and thereby bring employees closer to their ideal work selves; people can restructure, adapt, and expand their work identity (Endacott, 2021). Deranty and Corbin (2022) suggest that the arrival of AI on a more substantial level could make room for workers to focus more on creative or other rewarding parts of work. Autonomous computers can now complete repetitive and monotonous tasks, and humans can do less manual or labour-intensive work. This means that employees might have more free time

to develop skills in 'creative work' (Halal et al., 2016), creative work is central to the human experience and needs the use of capabilities, such as creativity and sensing emotions. These are core to the human experience and have been difficult to automate using AI technology so far, let alone on a bigger scale (Chui et al., 2015). Apart from shifting the focus of work content, it would also create the possibility of leaving behind the modern work ethic; workers would have more time to focus on tasks, as they have fewer tasks to do or work fewer hours (Weeks, 2011).

AI at the workplace

All these effects of AI might or might not result in a decrease in the total number of jobs (Bessen, 2018), but these consequences do impact how employees feel about their work (Brougham & Haar, 2018). This is because work contributes positively to one's self-worth (Cohn, 1978), meaning (Morse & Weiss, 1955), community (Katz & Kahn, 1978), healthy routines, and other aspects of well-being (Rosso et al., 2010). On top of that, people naturally desire to feel like they are contributing to the greater good; they want a purpose in their life (Rosso et al.,2010). Work is, in many cases, an excellent way to find this purpose and contribute to the greater good. If AI starts to replace human beings, this could also take away the purpose and contribution, and therefore they might have to look for a new source of self-worth and community (Wright & Schultz, 2018).

Meaning at work

So, what exactly is meaning at work? Meaning is the amount of perceived significance of an individual; it is a personal perspective. Because of this, something perceived as very significant and thereby meaningful for one individual may not be perceived that way by another (Rosso et al., 2010). Meaningful work can be defined as work that makes a positive contribution, in any way, and is personally enriching (Bailey et al., 2017). It helps to answer the question: "why am I here?". By asking this question, meaning becomes a subset of sensemaking in a broader existential question about the purpose of one's existence (Pratt & Ashford, 2003). Another definition of meaning is "the value of a work goal or purpose, judged to the individual's ideals or standards" (May et al., 2004, p. 14).

Logically having meaningful work and a calling positively correlates with a wide range of desirable well-being and work-related variables (Steger, 2016). Employees who perceive their work as meaningful report better psychological adjustment, which is a valuable quality to

organizations (Steger et al., 2012). Overall, people who perceive their work as meaningful have greater well-being than others (Arnold et al., 2007). Research by Steger and Dik (2009) explains that people who treat their careers as a calling have more significant meaning in life, life satisfaction, career decision-making efficacy, and fewer depression symptoms than others who do not approach their work that way. In this case, a calling is a belief that a career serves a greater good and offers meaningful and purposeful experiences. Meaningful work does not only affect one's career, but it also benefits one's life more broadly. Indeed, people with meaningful work enjoy better well-being in life (Steger, 2016).

A meaningful work experience can either be meaningfulness in work or at work (Bailey et al., 2017). While meaning in work focuses on the nature of work, meaning at work focuses on the context in which work is performed (Stein et al., 2019).
According to Lips-Wiersma and Morris (2009), meaningful work can be measured by the following factors: (1) developing and becoming oneself, which can be subdivided into personal growth, staying true to oneself and moral development; (2) serving others, which consists of making a difference and meeting the needs of humanity; (3) unity with others, which has three subthemes: shared values, belonging and working together; (4) expressing full potential, which can be expressed through creating, achieving and influencing.

Further, research by Lips-Wiersma and Wright (2012) gives four dimensions of meaningful work; these dimensions are developing the inner self, unity with others, service to others and expressing full potential. This research focuses on identifying stable meaning over time and on how research participants identified and actively took charge of meaning in their working life (Lips-Wiersma, 2002; Lips-Wiersma & Morris, 2009). The framework projects the tensions inherent to the search for meaning: "Tensions between the need to meet the needs of the self and the need to meet the needs of others; and the need for being (reflection) as well as the need for doing (action)." (Lips-Wiersma & Wright, 2012, p.660). These tensions are inherent to meaningful work because it was observed that a consistent lack of balance could cause meaninglessness and that participants struggle to get this balance right. However, the ongoing search for the balance between the needs of the self and the other tensions helped the participants rearticulate what meaning is to them.

According to Steger, Dik and Duffy (2012), meaning in work addresses three components: positive meaning, meaning-making, and greater good motivations. (1) Positive meaning, which is a subjective matter; it is a personal perspective on significance (Ross et al., 2010). Secondly, (2) meaning-making, as earlier described, meaningful work not only affects one in their job but also their life (Steger, 2016). Finally, (3) greater good motivations, one's need to contribute to the greater good, meaning that one's work is more meaningful when it positively impacts others (Steger & Dik, 2009).

These three components are assessed in a questionnaire that measures meaning at work, the Work As Meaning Inventory (WAMI). A low score on the WAMI reflects "an absence of work meaning, and may be predictive of poor work engagement, low commitment to one's organization and intentions to leave, low motivation, a perceived lack of support and adequate guidance from leadership or management." (Steger et al., 2012, p. 2). Also, people who score relatively low on the scales are likely to be absent more from work and experience a lower level of well-being and a higher level of psychological distress. In contrast, a high score predicts the opposite of these mentioned behavioural and mental implications.

These three models all state different components of meaning at work, but many factors overlap. Factors such as living up to one's full potential, contributing to others' well-being and contributing greater good are reflected in all models. For this research, the model of Steger, Dik and Duffy is chosen as a fundament because this model is based on a measurement tool to measure meaningful work, which is very fitting to what this research is aiming to do. The WAMI scores meaning at work using the three components, Positive Meaning, Meaning-Making through Work and Greater Good Motivations. According to literature AI is very likely to have an influence on meaning, this research assesses the influence of AI on meaning at work using this tool. Thus, it is hypothesized that:

H1: Artificial Intelligence negatively influences meaning at work for employees.

Predictors of meaning at work

Now that it is explained what meaning at work is and how it can be assessed, it is useful to know what predicts the perceived meaning at work. As it needs to become more apparent how the arrival of AI influences meaning at work, these predictors are very useful. Predictors of

meaningful work can be separated into three main categories: individual-level predictors, interpersonal predictors, and workplace characteristic predictors (Steger, 2016).

Individual-level predictors

The most frequently researched predictor category for meaningful work are individual-level variables, such as personality traits, and other workplace variables, such as job satisfaction. Research has found positive correlations between the degree of meaningful work one experiences and the extent to which people endorse their character strengths (Littman-Ovadia & Steger, 2010). Furthermore, research has also found that people who use their strengths in their work are more likely to view their work as meaningful (Harzer & Ruch, 2012; Littman-Ovadia & Steger, 2010).

Interpersonal predictors

Daily interactions with others within the organizational context have an essential position in the process of employees attaining more meaning at work (Wrzesniewski et al., 2003). This assertion has been supported by the research by Grant (2007) and Kahn (2007), who both found that close interpersonal relationships with co-workers positively impact the perception of meaningfulness in work. This is because a good co-worker relationship fosters a sense of belonging and a stronger sense of social identity (Rosso et al., 2010). Also, Lips-Wiersma and Morris (2009) found that good co-worker relationships are crucial for creating a bond and a sense of common purpose that contributes to meaningful work. Research by Colbert, Bono, and Purvanova (2016) showed that positive relationships at work are positively associated with meaningful work mainly because of the "giving to others" function, which is achieved by providing individuals with the opportunity to assist, mentor, support, or care for the other person. This has also been found in the qualitative research by Kennet and Lomas (2015), they found that people who mentor another person experience their work as more meaningful because of their mentorship. To summarize, the employees' experience of meaning at work can be optimized by interpersonal closeness and giving to others (Lysova et al., 2018).

Workplace characteristic predictors

An obvious workplace characteristic predictor of meaningful work is the performance of leaders in organizations. The leadership style and practice can have wide-ranging effects on employee performances and set the tone for how workplaces function. Leadership affects meaningful work because of the potential to improve the working experience for multiple

workers at a time. Also, leadership style has a big influence. Leaders with a more transformational leadership approach generally lead employees who find their work more meaningful (Judge & Piccolo, 2004). Passion, authenticity, energy, and vision-setting are emphatically present in transformative leadership. It shows that employees working for a transformational leader would connect those qualities with perceiving work as worthwhile and rich in purpose.

Another factor that makes employees experience their work as more meaningful is making employees feel supported. Having a good relationship with one's supervisor also positively correlates with meaningful work (Tummers & Knies, 2013). A good relationship in this context means that one feels supported, understood, cared for, and having a mutual trust relationship and control over one's job.

Lastly, an aspect that is important to meaningful work is organizations supporting higher ideals of employees. Volunteers are more likely to feel their job is meaningful, even if the voluntary work they do is entirely separate from their job (Rodell, 2013). This is because if a company communicates an appreciation of something of importance to employees and communicates that the organization is willing to support actions that benefit the greater good, this increases perceived meaningfulness at work (Steger, 2016).

The factors that predict meaning in work correspond in certain areas with the three components of the WAMI of Steger, Dik and Duffy (2012). It is likely that, if AI influences meaning at work, the influence of AI will not be equal in all aspects of work. For example, working alongside AI will probably not impact an employee's voluntary work experience but might influence leadership in many cases (Smith & Green, 2018). In research by Steger (2016), the theoretical and empirical predictors of meaningful work are organized into two models. The SPIRE model, which focuses on personal-level predictors and the CARMA model, which focuses on leadership and organizational-level predictors. The predictors of these models are linked to the components of WAMI by Steger, Dik and Duffy (2012).

Positive Meaning

Personalization. Aligning work with one's values, taking responsibility and adopting an ownership mentality for the employee's work and organization.

Respect. Leadership should be focused on respect and creating chances for beneficial interactions, which are essential to make positive, effective relationships in an organization.

Mattering. Leaders must express to employees how their contribution is essential to the success and health of the organization and its mission.

Autonomy. Giving employees enough authority and freedom to use their strengths, engage in mentoring, and other individualizations that enable personalization of work.

Meaning-Making

Integration. Integrating one's motivation and execution of their job with other elements of one's life.

Resonance. Knowing the organization's core values and mission and finding a way in which it resonates with an employee's personal mission and meaning through their everyday work.

Greater good motivations

Expansion. Seeking ways in which one's work can be grown to benefit some greater good. Employees need to expand concerns to embrace broader interests beyond themselves.

All components of the WAMI refer to meaningful work, but they are likely not be affected equally by AI. For instance, if AI is overtaking many tasks and responsibilities of an employee, it would be harder to personalize their job or add integration. However, that employee could still be looking for ways to benefit the greater good. These predictors are linked to the three components; therefore, it would make sense that if the predictors are not equally affected by AI, the components of meaningful work probably will not either. Consequently, it would make sense for the three components to be influenced differently by AI. There are some indications for suspecting that Greater Good motivations will be influenced more greatly by AI than the other two components of meaningful work. However, as research in this area is incipient, there is insufficient grounds to present a directional hypothesis, thus I hypothesize that:

H2: The influence of AI differentiates over the three components of Meaningful Work (Positive Meaning, Meaning-Making through Work, and Greater Good Motivations).

Organizational levels

As there is differentiation in tasks and responsibilities over organizational levels, the chance is significant that the influence of AI over these organizational levels is divergent. First, we must

specify how organizational levels can be categorized. In every company, a vertical hierarchy is present, meaning that multiple individuals or groups are under the supervision of one manager (Mihm et al., 2010). It is the most common way of coordinating specialized groups (Nadler et al., 1997). One way to categorize vertical hierarchy is by the research of Collins (2001); this is a hierarchy based on capabilities and traits. Level one is the: "highly capable individual"; these are regular employees who are talented, have good work habits, are knowledgeable, and are skilled. Level two consists of "contributing team members"; these employees are good at working together and are somewhat able to help their team reach their objectives. Level three is "the competent manager" who can effectively oversee people and resources and help the team to accomplish its goals. Level four is "the effective leader" who can lead the company to function at a high-performance level to accomplish ambitious and clear goals. Level five is "the executive" who can build sustainable greatness through a paradoxical combination of personal humility and professional will. AI will probably have a different influence on all these levels; level one likely has the most chance of being replaced by autonomous machines if they do repetitive work. In turn, levels 4 and 5 might also have to adapt because AI can take over 20% of their jobs (Chui et al., 2015).

An older model was constructed by Henry Mintzberg (1989), who states that an organization can consist of up to five core elements over three organizational levels in hierarchy. The way the elements interact determines the strategy of an organization. The model is displayed in Figure 1.

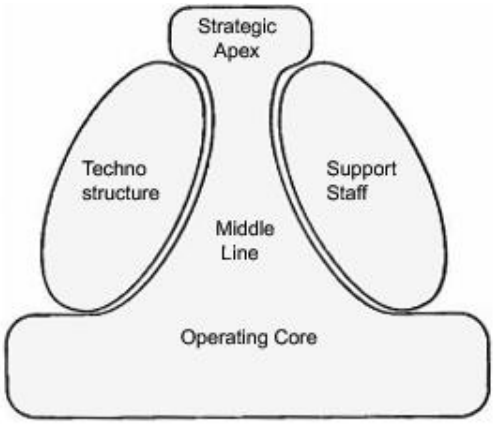


Figure 1
Note. Model by Mintzberg, 1989

In a simple structure, only the strategic apex, middle line and operating core are present, but as companies get more complex, the technostructure and support staff are added. A short

description of all elements; the strategic apex is a company's top management. They should provide the company with a vision, mission, and purpose. The middle line is the layer between the strategic apex and the operating core; they have to interact and follow up on orders of the strategic apex and supervise the operating core. The operating core consists of the workers that carry out the work, and this output can be linked to the goods and services that the organization produces and sells. The technostructure consists of analysts, planners and trainers who serve the organization by affecting the jobs of others by designing, training, and creating procedures. Support staff consists of supporting roles outside the operational workflow like accounting, IT and HR. This model sees the middle line, technostructure and support staff at the same hierarchical level.

Both models hierarchically display the organizational structure. Whereas capabilities and traits substantiate the model of Collins (2001), Mintzberg (1989) focuses more on the tasks and responsibilities of the different levels. Those different angles both are parts of what mark the different levels. Focusing on the research question, AI will primarily influence the tasks and responsibilities of employees. The model of Mintzberg focuses on tasks and responsibilities, and as this is what AI influences primarily, this model will be used.
Moreover, as AI takes over by automating routine and manual tasks, machines, computers, and robots replace employees typically in middle- and low-wage occupations, which often corresponds with low-skill jobs (Acemoglu & Restrepo, 2017). Low-skill jobs refer to blue-collar and white-collar workers who tend to specialize in routine and manual tasks that have been more prone to automation in the past 30 years (Autor & Dorn, 2013). In this sense, high-skill workers' work is protected better from automation because high-skill workers specialize in more complex tasks requiring human judgment, problem-solving, analytical skills, or various soft skills. In that way, high-skill jobs can be seen as more complex and, therefore, also harder to duplicate by AI technology. This is also seen in the research of Wisskirchen et al. (2017). The number of factory workers that are needed is constantly decreasing. Because manual workers are decreasingly needed, the need for highly qualified people is higher.

Keeping these facts in mind, it is plausible that low-skilled workers feel threatened more by the arrival of AI than high-skill workers, who have jobs that seem harder to duplicate, and thus experience more influence of AI on meaning at work. Assuming that work on higher organizational levels generally requires more high-skill workers and lower organizational levels generally require more low-skill workers, this would imply that people on lower

organizational levels experience more influence of AI than those on higher organizational levels. Thus, I hypothesize that:

H3: Operational levels will moderate the relationship between AI and meaning such that at lower (operational) organizational levels, AI will lead to lower meaning than at higher (strategic) organizational levels.

Methodology

Research strategy and design

This research aims to test the effect of AI at the workplace on employees' meaning at work, which is measured on multiple organizational levels. This research uses quantitative methods, which explain phenomena by collecting quantitative data and analyzing this data using statistical methods (Muijs, 2010). This research is based on an experimental study, which enables a researcher to observe and influence a specific phenomenon (Bailowas et al., 2021). This method fits well because it focuses on finding out the influence of AI on meaning at work over different organizational levels. In fact, it examines the cause-and-effect relationships between variables, AI, meaning at work, and organizational levels (Malhotra et al., 2017). There is some research on the effect of AI on meaning in work, but the differentiation on organizational levels has not yet been taken into consideration. For gathering data to test the hypothesis, a survey was composed with Qualtrics. A mixed methods design was used in which the main dependent variable is measured twice within subjects.

Participants

Participants for this study were recruited through various methods, one of them being the platform Profilic. Profilic is an online platform that enables researchers to conduct their surveys and thereby gather data. It connects the researcher and participant, which could consist of specific target groups. The researcher pays the participants that belong to the target group for answering all the questions in the survey. It is proven to be a fast and reliable way to recruit participants. The participants of Profilic were paid 7.66 British Pounds per hour and were filtered to include people who are either working full-time or part-time. Other participants were recruited using the LinkedIn network of the main researcher.

To study the difference between groups, a minimum of 64 respondents per group is required (Durlak, 2009). 283 complete answers were gathered, 11 of which were filled in by students, five by retirees, and one respondent by an unemployed person. Thus, there are 266 valid answers, because only working people were taken into consideration. Of these 266 participants, 45.1% are male, 53.1% are female, 0.4% are non-binary/third gender, and 0.8% prefer not to disclose. The mean age is 37.8 years (*SD* = 13,01), for more information see appendix A. The level of education is spread as follows; Less than high school: 0.8%, High school: 9.4%, Intermediate vocational education (MBO): 1.5%, Bachelor: 30.5%, Master: 53%, PhD 4.9%.

The organizational levels all have a minimum of 64 participants, strategic management 24.06%, tactical management 24.81% and operating Core 51.13%.

Procedure

After reading the informed consent form, this survey's participants started by answering general questions about their gender, age, and educational level. The general questions aim to get a clear picture of the respondents (Malhotra et al., 2017). Afterwards, participants were asked about their current work status and job sector. These two factors may both influence the perception of work. If someone is currently unemployed, someone might have a different view on work than if they are currently working. The current work situation might also affect the effect of AI on meaning in the workplace because, in this case, there is no current view on their work life, as they have no job. For this reason, only answers filled in by people who are currently working are considered as valid answers. Also, the job sector, might have an influence because the effects of AI are not similar over job sectors; therefore, the view on AI and its effect on their jobs may be affected.

Then, participants were asked about what organizational level they work in; this is either strategic management, tactical management, or operational core. Following are the questions of the Work as Meaning Inventory; participants are asked to answer those questions while keeping in mind their current job. The inventory consists of ten questions that assess the previously mentioned three components; positive meaning, meaning-making, and greater good (Steger et al., 2012). Afterwards, the participants are asked about the state of their technological awareness, this is asked because AI can only influence the meaning in the workplace for employees on any organizational level, there must be a minimal amount of awareness. This is simply because if the current and potential consequences of AI are not observed by one, this can also not cause an influence. This variable will also serve as a covariate.

At this point, the participant is introduced to a text about the independent variable, AI. This text is intended to give the participant a perspective on the current situation regarding AI. Thereafter, the participants are asked to answer the same ten questions of the Work as Meaning Inventory again, this time, they are asked to answer the questions imagining an AI agent works alongside them as their colleague in their current job, performing similar functions to theirs. Finally, is a question on whether the participant thinks AI is going to affect their job and job sector in the coming five and fifteen years. The survey can be found in Appendix B.

Independent variable

AI vs humans. The independent variable in this research is the perception of AI at the workplace (vs its absence in the control condition); this includes its current influence and prospects. In the first half of the survey, participants were asked to assess their view on meaning without providing them any information on how AI may disrupt the workplace (control condition). The experimental condition results of exposing the participants to a text about AI and its prospects for the future job market. In this way, the knowledge and view of participants are updated to the most likely situation. This text reads as follows:

'Artificial intelligence (AI) is a system or machine that mimics human intelligence to perform tasks. It can iteratively improve itself based on the information it collects. In a practical sense, this means that AI can already automate specific 'human' tasks, at the moment, this mainly concerns monotonous and repetitive tasks. However, AI is starting to surpass humans in more and more skills, even in understanding human emotions. It has been suggested that AI will be able to do more and more. Thus:

- AI may not only replace people's tasks, but it can also create new tasks for both people and AI to work on. As a result, people may have to retrain to perform the skills of the new position.
- Another option is to shift the job content of human workers more towards creative work (which is central to the human experience and needs the use of capabilities such as creativity and sensing emotions), as AI still needs to be developed more in this field.

An important question is how these developments in the AI field coexist with human needs. If AI can work alongside humans, as a colleague, how will humans feel at the workplace?'

This text aims to provide the participant with information about the current- and possible future effects of AI. It helps the participant understand what AI is and what it is (possibly) able of. Also, it challenges the participant to think about what the arrival of AI in the workplace would look like and mean for human workers by ending the text with a rhetorical question. All the information is based on research and the overall text is meant to have a neutral connotation. The goal of this information is for the participants to view their job from an angle that includes the presence of AI. With having the current- and possible future effects in mind, they might view their job in a differently, particularly in what concerns meaning.

Dependent variable

Meaningful work. Meaning in work will be measured using the Work as Meaning Inventory (WAMI) created by Steger, Dik and Duffy (2012). The participants answered the WAMI two times, the first time having in mind their current job and the second time after reading the scenario and imagining that they work alongside AI as their colleague. The position of colleague is chosen because this is a kind of collaboration that most people who work are familiar with. By choosing a collaboration position they are familiar with, it might be easier to imagine having this human worker replaced by AI. Also, having a good relationship with co-workers is an interpersonal predictor of meaning at work. The WAMI assesses three core components of meaningful work; (1) the degree to which people find their work to have significance and purpose, (2) the contribution their work makes to finding broader meaning in life and (3) the desire and means for one's work to make a positive contribution to the greater good. It incorporates the instruments; sense of calling, work orientations, organizational citizenship behaviours, withdrawal intentions, career commitment, organizational commitment, job satisfaction, intrinsic and extrinsic work motivation, satisfaction with life, depression, anxiety, hostility and meaning in life. All the questions of this inventory were presented with the Likert scale from 1 (Absolutely untrue) to 5 (Absolutely true).

Moderating variable

Organizational levels. The three levels of organizational structure by Henry Mintzberg (1989) are used to collect data on organizational levels. This model focuses on tasks and responsibilities, which are also the aspects of work that AI is most influential on. As previously stated, these three levels are the strategic apex, also described as top management, the middle line (which also consists of the technostructure and support staff) and the operating core. These levels give the most common display of how companies of different sizes are built up. Another reason for this choice is that this model is divided into three levels, which makes the feasibility of getting enough participants for each level more achievable. Respondents of the survey will have to choose in a question whether they belong to the strategic management (strategic top), tactical management (middle management) or the operating core (operations, operational processes).

Co-variables

Job sector

AI nowadays is best for repetitive and monotonous tasks (Halal et al., 2016), which means that AI is more fitting to one job sector than the other because of its different functions. Employees in different sectors might respond differently to AI in their work identity, as it also differs in the amount it affects in the workplace (Chuivet al.,2021). The participants are asked to state in which job sector they are currently working. It is a demographic question, where the participant is able to choose from various industry's or choose the option 'other' and fill in their industry when that industry is not included in the possibilities. The distribution of answers can be found in Appendix C.

Technological awareness

For Artificial intelligence to influence the meaning in the workplace for employees on any organizational level, there must be a minimal amount of awareness. This is simply because if the current and potential consequences of AI are not observed by one, this can also not cause an influence. Awareness of AI means the extent to which an employee views the likelihood of AI impacting their future workplace prospects (Brougham & Haar, 2018).

The research of Brougham and Haar (2018) shows that when employees are more aware of Smart Technology, Artificial Intelligence, Robotics, and Algorithms and their use in the workplace, they are more likely to have a lower organizational commitment and lower career satisfaction. They also conclude that awareness is positively related to turnover intentions, cynicism, and depression. The same outcome is concluded by Kong et al. (2021). They also found that awareness of AI positively correlates with job burnout. The fear of being replaced by AI leads to insecurity, resulting in tiredness and exhaustion. This fear also leads to a reduced commitment to the organization. To test this, participants are first asked if they feel they are currently aware of technological innovation, this could be answered in a 5-point Likert scale varying from 1 (Very unaware) to 5 (Very aware). The results of this question can be found in Appendix D.

Results

Data cleaning

First of all, only complete answers were accepted, because this is a within-subjects design, which aims to measure differences within a group. With incomplete data this would not be possible and thus these answers were deleted, this left 283 answers. Secondly, only people who work are taken into consideration. As explained before, the participants need to share their current view on the meaning in their job and if one has no job this is not possible. 17 participants indicated to not have a job at the time of answering the survey and were therefore excluded. In the end there are 266 valid answers.

Scale reliability

The scale to measure meaning at work is a scale developed by Steger, Dik and Duffy (2012), which is created based on literature and extensive research. To double check, I conducted reliability analysis to test for scales' Cronbach alpha. To run this test, I had to reverse the coding of question three of the WAMI this is because unlike all the other question, this question is phrased negatively. The WAMI scale presented an alpha of .915, which is considered an excellent coefficient (Gliem & Gliem, 2003). All the inter-item correlations are positive, which ensures that the reversed coding of question three is done correctly. The mean of the inter-item correlations is 0.523 (for more information, see Appendix E). The Positive Meaning component has presented an alpha of 0.849, which considered a good coefficient by Gliem and Gliem (2003) and the mean of the inter-item correlations is 0.589. The Meaning-Making through work component has an alpha of 0.793, which is considered an acceptable coefficient but could also be relatively low because it has only three items, therefore it is good to check the inter-item correlations mean, which is 0.564 for this component. The greater good motivations presented an alpha of 0.869, which is considered very good, and an inter-item correlation mean of 0.691.

Hypothesis testing

H1: Artificial Intelligence negatively influences meaning at work for employees.

To assess the influence of the AI scenario on meaning at work, the WAMI results from before the presentation of the scenario and the WAMI results from after the mentioned scenario are compared in a paired-samples t-test, also called the dependent t-test. This paired-samples t-test is a statistical method used to compare mean differences between two dependent groups, which means that all individuals are in both comparison groups. In this thesis, these groups consist of

all participants who score the WAMI before the AI scenario and after, but indeed remain the same group of participants. To ensure the outcome of the test is valid, five assumptions are tested.

1. The dependent variable, the WAMI, is measured on a continuous scale.
2. The independent variable, consist of two related groups, this means that the same subjects are present in both groups. The participants have all participated in both measures on the same dependent variable.
3. There are a couple of outliers for the WAMI scores before the scenario and two for the WAMI scores after the scenario. As these outliers are considered to be legitimate samples from the correct population, it is important to consider whether that data contains valuable information before potentially discarding them (Osborne & Overbay, 2004). Extreme scores, in this case, could indicate that a participant is extremely pleased or dissatisfied with their job, both of which should not be ruled out because it is a scenario that can reasonably be seen as possible. Therefore, it has been chosen not to delete them because there is no legitimate reason to believe that these scores are not valid.
4. The data of the WAMI pre and post of the scenario is approximately normally distributed for some tests. Looking at the tests of normality, Kolmogorov-Smirnov, and Shapiro-Wilk, the numbers on these tests do come back as significant (<.001) for both the WAMI before and after the scenario. We consider a variable is *not* normally distributed if the significance < 0.05, so in this case we do not believe that this variable follows a normal distribution. However, looking at the Q-Q Plots, the data does look approximately normally distributed for all group combinations (the Q-Q Plots can be found in Appendix G). Looking at the skewness and kurtosis, following the general guideline for skewness and kurtosis is that if the number is greater than +1 or lower than –1, they exceed the guidelines and are considered nonnormal (Hair et al., 2017, p. 61). In this case, the results of the WAMI scores before the AI scenario exceed those numbers (skewness = -1.203 and kurtosis = 1.929). While the skewness and kurtosis WAMI scores after the AI scenario do not exceed the guidelines (skewness = -0.731 and kurtosis = -0.008) and are therefore not considered nonnormal. Even though, it is relatively safe to go ahead with the mixed results of these tests for normality, because of having a sample that is considered large enough (Durlak, 2009), a non-parametric test has been performed. A Wilcoxon signed-rank is used, which does not assume normality in the data. The results of the Wilcoxon signed-rank test show that the mean

of the WAMI before the scenario is 36.47 (6.27) and 33.77 (7.95) after the scenario, with a significant difference of <.001. This corresponds with the results of the paired-samples t-test, more information can be found in Appendix H.

A within-subjects t-test indicated that the WAMI score was significantly higher in the pre-condition (M = 36.47, SD = 6.27) than in the post-condition (M = 33.77; MD = 2.70, SD = 7.95), $t(265) = 7.68$, $p < .001$. Thus, participants' meaning at work decreased after reading the AI scenario. More detailed information on the results of the WAMI can be found in Appendix F. Neither of the covariates has a significant effect (job sector: $t(14) = 1.38$, $p = 0.164$; technical awareness: $t(1) = 1.52$, $p = 0.291$).

H2: The influence of AI differentiates over the three components of Meaningful Work (Positive Meaning, Meaning-Making through Work, and Greater Good Motivations).

Two-way repeated measures ANOVA is used for this hypothesis. It tests the three components of the WAMI (Positive Meaning, Meaning-Making through Work, and Greater Good Motivations) before and after the AI scenario. The following five assumptions are tested.

1. The dependent variables, Positive Meaning, Meaning-Making through Work, and Greater Good Motivations, are measured at the continuous level.
2. The two within-subjects factors, consist of two related groups.
3. Looking at the boxplots of the components before and after the AI scenario, outliers have been detected in all the components scores before the scenario, and on the meaning-making component after the scenario. Outliers should only be removed when there is a good reason for doing so. The range of scores is relatively small and these outliers are not problematic and could be viewed as a representation of natural variations in the population. Therefore, there is no valid reason to believe it is necessary to delete these outliers.
4. The distribution of the dependent variable in each combination of the related groups is approximately normally distributed for some tests. Looking at the tests of normality, Kolmogorov-Smirnov and Shapiro-Wilk, all components have a significance of <0.001, which suggests the data is not normally distributed. Looking at the skewness and kurtosis, only the Positive Meaning pre scenario and Meaning-Making through work pre scenario are nonnormal according to the standards (Hair et al., 2017, p. 61), see “Table 1 – skewness and kurtosis H2”.

Table 1

Skewness and kurtosis H2

	Before scenario		After scenario	
Measure	Skewness	Kurtosis	Skewness	Kurtosis
Positive meaning	-1.21	1.87	-0.68	-0.27
Meaning-Making	-1.01	1.42	-0.74	-0.15
Greater Good	-0.72	-0.17	-0.43	-0.35

Looking at the Q-Q Plots, the data does look approximately normally distributed for all components. As the outliers detected have not been deleted, it makes sense that the normality tests are a little violated. Nonetheless, the results provided by this test can still be considered valid, as two-way repeated measures only require approximately normal data because it is quite robust to violations of normality. Nevertheless, a Wilcoxon signed-rank test can be found in Appendix H, to double check. The results of the Wilcoxon signed-rank test and paired samples t-test correspond, where all differences have a <.001 significance.

5. Sphericity, the assumption of sphericity is always satisfied when a repeated measures treatment variable has exactly two levels. In this research the measure is only repeated once, with only two levels, there is only one set of difference scores and only one variance; so, a scenario with unequal variances cannot occur.

All the means of the components of the WAMI decrease after reading the scenario, see "Figure 2 - Component scores before and after scenario". The means, standard deviations and mean differences can be found in "table 2 - Means, standard deviations, and mean differences of components of meaningful work".

Table 2

Means, standard deviations and mean differences of components of meaningful work

Measure	Before scenario	After scenario	*MD*
Positive meaning	15.58 (3.14)	13.94 (3.93)	-1.64 (-10.52%),
Meaning-Making	11.30 (2.55)	10.29 (2.94)	-1.00 (-8.89%)
Greater Good	11.11(2.89)	10.37 (2.80)	-0.74 (-6.66%)

Note. $p < .05$.

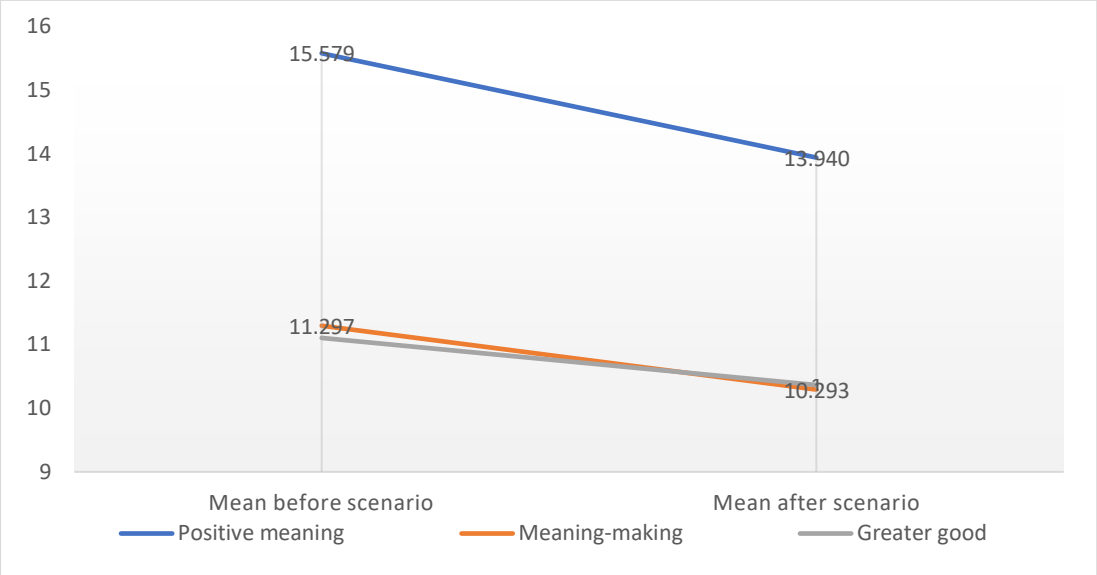


Figure 2

Component scores before and after scenario

A paired-samples t-test shows the results on significant differences between the different measures, see "Table 3 - Significance of differences components".

Table 3

Significance of differences

Measure	*df*	*t*	*p*
Positive meaning	265	8.71	< 0.001
Meaning-Making	265	7.19	< 0.001
Greater Good	265	5.44	< 0.001

Note. $p < .05$.

This indicates that there are significant differences between the means of the test before and after the AI scenario.

H3: Operational levels will moderate the relationship between AI and meaning such that at lower (operational) organizational levels AI will lead to lower meaning than at higher (strategic) organizational levels

To test this, a mixed methods ANOVA is chosen. The purpose of this method is to understand if there is an interaction between these two factors on the dependent variable by comparing the

mean differences. The dependent variable is the WAMI score, measured twice, once before the AI scenario and once after. This is measured over a between-subject variable, the organizational levels. To ensure the outcome of the test is valid, seven assumptions are tested.

1. The dependent variable is measured at the continuous level
2. The within-subjects factor consists of two categorical, "related groups". The same participants were present in both measurements of the WAMI.
3. The between-subjects factor consists of three categorical and independent groups. These are the groups divided by organizational level; strategic, tactical, and operational.
4. There are some outliers detected, but as explained in the assumptions of hypothesis 1 (assumption 3), there are no legitimate reasons to delete them as they could be viewed as a representation of natural variations in the population.
5. Again, we look at the Kolmogorov-Smirnov and Shapiro-Wilk tests to test normality. Only the strategic level data before the AI scenario is not considered nonnormal, see “Table 4 - Kolmogorov-Smirnov and Shapiro-Wilk tests H3”.

Table 4
Kolmogorov-Smirnov and Shapiro-Wilk tests H3

Measure	Kolmogorov-Smirnov		Shapiro-Wilk	
	Before	After	Before	After
Strategic	0.200	<.001	0.119	0.002
Tactical	0.023	<.001	0.021	0.004
Operational	<.001	<.001	<.001	<.001

Note. $p < .05$.

Looking at the skewness and kurtosis, none of the organizational levels are considered nonnormal according to the standards (Hair et al., 2017, p. 61), see “Table 5 – skewness and kurtosis H3”.

Table 5

Skewness and kurtosis H3

	Before scenario		After scenario	
Measure	Skewness	Kurtosis	Skewness	Kurtosis
Strategic	-0.10	-0.50	-0.80	0.09
Tactical	-0.53	0.83	-0.76	0.24
Operational	-0.98	-0.73	-0.50	-0.44

Note. $p < .05$.

Also, for this hypothesis, to double check, a Wilcoxon signed-rank test is performed. The results of the tests are identical; more details can be found in Appendix H.

6. There is a homogeneity of variances in both groups. Using a t-test, the outcome of the Levene statistic is not significant (0.328 and 0.329). Thus, we can reject the null hypothesis of equal population variances when the p-value is 0.05.
7. Sphericity, as in H2 the measure is only repeated once so the assumption of sphericity is satisfied because with one variance between measures, unequal variances cannot occur.

The means of the WAMI score decreased over all organizational levels after reading the scenario. The means, standard deviations and mean difference are shown in “Table 6 - Means and significant difference of organizational levels”.

Table 6

Means and significant difference of organizational levels

Measure	Before scenario	After scenario	MD	df	t	Sig.
Strategic	40.09 (3.59)	36.94 (6.08)	-3,16 (-7.87%)	63	4.55	<.001
Tactical	37.91(4.57)	34.49 (7.05)	-3.42 (-9.03%)	65	4.48	<.001
Operational	34.04 (6.95)	31.87 (8.64)	-2.17 (-6.38%)	133	4.48	<.001

Note. $p < .05$.

A paired- samples t-test indicates that there is a significant difference between the means of all organizational levels (tested separately) before and after the AI scenario (see “Table 6 -

Means and significant difference of organizational levels"). To see whether there are any statistically significant differences between the organizational levels a one-way analysis of variance (ANOVA) is used. Both the means before and after the scenario show to have a significant difference. Before the scenario: $t(2) = 26.907$, $p < 0.001$ and after the scenario: $t(2) = 9.810$, $p < 0.001$. Taking a closer look, I compare the levels individually with each other by looking at the results of the Tukey post hoc test (see "Table 7 - Mean differences over organizational levels").

Table 7

Mean differences over organizational levels

Measure	Scenario	MD	Sig.
Strategic - Tactical	Before	2.19	0.079
	After	2.45	0.167
Strategic - Operational	Before	6.06*	<0.001
	After	5.07*	<0.001
Tactical - Operational	Before	3.87*	<0.001
	After	2.62	0.063

*$p < .05$.

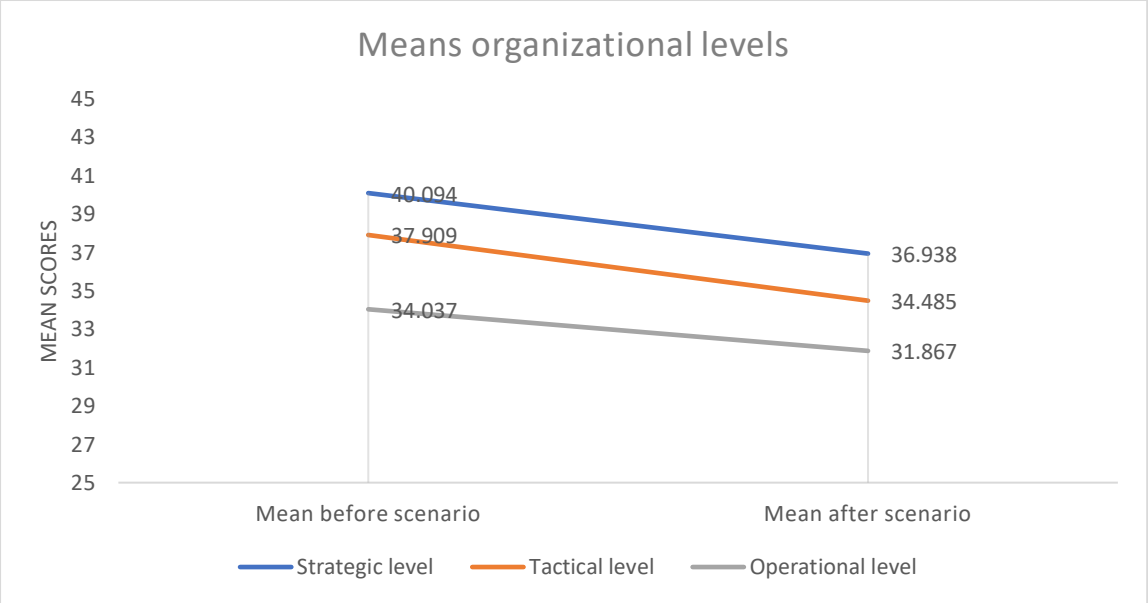


Figure 3

Scores WAMI organizational levels before and after scenario

Overall, all the means decreased between before and after the AI scenario, "see Figure 3 - Scores WAMI organizational levels before and after scenario". The results of the WAMI before the scenario show a statistically significant difference in the comparison means of the Strategic – Operational levels and Tactical – Operational levels. The results of the WAMI after the scenario only shows a significant difference for the Strategic and Operational levels comparison.

The combined results of the organizational levels and the components of meaning at work, can be found in table 8 - Means (and standard deviations) of the components over organizational levels.

Table 8

Means of the components over organizational levels

Measure	*Scenario*	*Strategic*	*Tactical*	*Operational*
Positive Meaning	Before	*17.59 (1.78)*	*16.15 (2.18)*	*14.33 (3.47)*
	After	*15.48 (3.36)*	*14.26 (3.53)*	13.03 (4.13)
Meaning-Making	Before	*12.45 (1.74)*	*11.92 (2.20)*	*10.44 (2.74)*
	After	*11.28 (2.30)*	10.73 (2.55)	9.60 (3.22)
Greater Good	Before	*12.30 (2.19)*	*11.02 (2.77)*	*10.57 (3.08)*
Motivations	After	11.13 (2.49)	10.35 (2.65)	9.98 (2.94)

Note. $p < .05$.

Remarkably, all the means over all organizational levels and different components decrease after the scenario. Moreover, all scores changed significantly. As "Table 9 - Mean differences of the components over organizational levels" shows, all the scores were significantly changed by the AI scenario.

Table 9

Mean differences of the components over organizational levels

Measure*	*Strategic*		*Tactical*		*Operational*	
	MD	*t(63)*	*MD*	*t(65)*	*MD*	*t(133)*
PM	*2.11 (3.26)*	5.17, $p < .001$	*1.89 (3.26)*	*4.55, p* < .001	*1.30 (2.80)*	*5.41, p* < .001
MM	*1.17 (2.00)*	*4.70, p* < .001	*1.20 (2.35)*	*4.13, p* < .001	*0.84 (2.37)*	*4.10, p* < .001
GG	*1.17 (2.21)*	*4.25, p* < .001	*0.67 (2.27)*	*2.39, p* = .020	*0.59 (2.19)*	*3.15 p* = .002

Note. $p < .05$.

* PM = Positive Meaning, MM = Meaning- Making, GG = Greater Good Motivations

Discussion

Research findings and main conclusions

There is no doubt that AI is changing many aspects of work. It impacts the majority of jobs, the way we work, and what we work on. Being aware of the impact that AI is making, and how it affects how we experience our work seems to be more valuable than ever, as AI is here to stay. This thesis researches the influence of these consequences on meaning at work. More specifically, it focuses on the differences in the effect of AI over different organizational levels, attempting to answer two research questions: How does AI influence employees' meaning at work? How does the influence of AI on meaning at work differ over different organizational levels? And three hypotheses:

H1: Artificial Intelligence negatively influences meaning at work for employees

H2: The influence of AI differentiates over the three components of Meaningful Work (Positive Meaning, Meaning-Making through Work, and Greater Good Motivations).

H3: Operational levels will moderate the relationship between AI and meaning such that at lower (operational) organizational levels AI will lead to lower meaning than at higher (strategic) organizational levels

The results of this research have supported H1, according to which AI was expected to negatively influence meaning at work. After reading the AI scenario, the mean of the second measurement was substantially lower than the first. There is a mean difference of -2.70, which is a decrease of 7.4%. This was in line with literature. The reasons for the effect of AI could vary.

People might fear of being replaced by AI as more and more tasks formerly performed by humans can now be automated by AI, this fear has many negative effects on employees and is therefore very likely to have an influence (Kong et al., 2021). Also, the participants were asked to imagine working alongside with AI as a colleague. When participants thought of as well working with AI as a colleague instead of only human co-workers, this was expected to have a negative effect. A good relationship with co-workers is an interpersonal predictor of meaningful work (Steger, 2016), and this relationship would be different with AI as a colleague.

Both the covariates were found not to have a significant interaction term. The covariate job sector was expected to have a significant interaction with the measurements on meaning, as one's job sector was expected to influence on the effect of AI. This is because AI influences job sectors in different ways and to different extents. Where one industry could be taken over completely, for example if autonomous vehicles are used more, taxi drivers could become unnecessary. Others, for instance the creative industry, might be less affected (Harari, 2018). Because of this reasoning, one's job sector was also expected to have an influence on meaning. It could still be very possible that job sectors influence the effect of AI. In this research the influence of job sectors on AI is measured over meaning at work. It could be that the covariate job sector has an impact on AI, but this impact is less substantial when it is measured over the impact of AI on meaning at work. To see the influence of job sectors on AI, it would be preferable to measure this effect directly.

Also, the covariate technical awareness was expected to have a significant interaction term, for the simple reasoning of needing a minimal amount of awareness for it to influence something. In performed research by Brougham and Haar (2018), technical awareness turned out to have negative effects in the workplace. In this research, that is not the case. Looking more closely into the research of Brougham and Haar (2018), they tested awareness by introducing the job insecurity measure by Armstrong-Stassen (2001), which asks whether you think your job could be replaced by technological innovations. Whereas this research asked directly whether the subject feels like they are aware of technological innovation. As these questions on technical awareness are asked in very different ways, it makes sense that the outcome is, therefore also different. However, similar questions to the measure of Armstrong-Stassen were asked to participants in this research. There are four questions on whether one thinks that AI will affect one's job or job sector within 5 or 15 years (see the results of these questions in Appendix I). For these questions, only the correlations of the WAMI after the scenario and the questions about the effect on the job sector and job within 5 years show a significant correlation. Also, the study of Brougham and Haar (2018) asked about Smart Technology, Artificial Intelligence, Robotics, and Algorithms in their questionnaire, while the survey of this research limits itself to AI, which might therefore have a different outcome.

The results also support H2, as they indicate differences between the two measurements of the three components of meaningful work. Relatively looking at the means of the first measurement of meaning at work, Positive Meaning scored the highest, followed by Meaning-Making and the last one is Greater Good Motivations, although the differences are not

significant. The measurement after the AI scenario shows a different order. The highest-scored component is still Positive Meaning, followed by Greater Good Motivations and then the Meaning-Making component. All three components have significantly decreased in means in the second measurements of meaning at work, in comparison with the first. More specifically, the Positive-Meaning component decreased the most by 10.52%, followed by Meaning-Making through Work, which decreased by 8.89%, and Greater Good, which decreased the least by 6.66%. This means that the influence of AI was the greatest on the degree to which people find their work to hold personal meaning, significance, or purpose. The influence of AI was smaller on the extent to which people experience their work as a source of broader meaning in life and was even smaller on the degree to which people see that their effort at work makes a positive contribution and benefits others or society. The differentiation between components is in line with the expectations substantiated by the literature review. As there are different predictors of meaning in work (Steger, 2016) (that correspond with the three components), it would make sense that the influence of AI will not be equal in all aspects of work. Looking at the literature, it is no surprise that the greatest impact of AI was on positive meaning. Positive meaning is a personal perspective on significance (Ross et al., 2010, Steger et al., 2012), which correlates with the predictors: personalization, respect, mattering and autonomy (Steger, 2016). These predictors positively contribute to how one views their job to have personal meaning, significance, or purpose. AI is proven to impact how employees feel about their work (Brougham & Haar, 2018). For instance, if half of the tasks one does can be automated by AI, this is likely to influence how one views the meaning or significance of their work, as their work could be done by AI. Therefore, it is logical for positive meaning to be affected a lot by AI, as AI influences their personal perspective on significance. Meaning-Making and Greater Good Motivations focus more on factors outside work by focusing on experiencing work as a source of broader meaning in life and contributing to the greater good. AI mainly shows to influence aspects within work. Therefore, it makes sense that these components are less affected than Positive Meaning, which focuses on aspects within work.

On the contrary, H3 was not supported. The data shows a reversed outcome than hypothesized. The strategic level shows to experience more impact of AI than those on the tactical and operational levels. The hypothesis was formulated to expect the operational level to experience more influence than the higher hierarchical levels. This was thought because primarily monotonous and repetitive tasks are already being automated and these tasks were expected to be present more at the operational level than at higher hierarchical levels in general. As shown

in the results, that is not the case. Even though, the strategic level scores their jobs higher on the WAMI on average, the mean decrease after reading the scenario about AI is substantially higher than the mean decrease of the operational level.

All the organizational levels show a decrease in the mean after having read the AI scenario. This was in line with the expectations that the effect of AI is likely to differ over organizational levels. As explained in the literature review, the tasks and responsibilities differ over the organizational levels (Mintzberg, 1989). It is likely that the effect of AI is not equal over different tasks and responsibilities. Overall, the detected trend is that people on a hierarchically higher organizational level perceive their work as more meaningful but appear to experience a more negative influence of AI in terms of meaning at work. The Positive Meaning component, which represents how people find their work to hold personal meaning, significance, or purpose, again decreased the most over all organizational levels. The reason for the strategic level to experience the most influence could be because their role in an organization is to oversee the market in which it operates, market trends and the company itself (Hill et al., 2014). It is their natural habit to put things in a bigger perspective as that is needed at that organizational level. By asking subjects from the strategic organizational level about their job and AI, they could have put this in a bigger perspective where they oversee the bigger effects on the job sector and market than just the job and its tasks. With that bigger perspective, it would make sense for them to experience more influence of AI, as the impact of AI will come across as more substantial than when only thinking about one's job.

Managerial & academic relevance

The findings of this research have both managerial and academic relevance. Both AI and meaning in work are topics that are widely studied. However, the combination of the topics needs more attention, as AI is taking a more prominent role in many aspects of work. The results of this research indicate that the presence of AI in the work field does influence one's meaning in work in a negative way. According to the research of Steger (2016), experiencing more meaningful work has many positive consequences in both work environment and private life, while a relatively low score on the WAMI can predict many negative effects that impact one's motivation, engagement, and commitment (Steger et al., 2012). In this sense, this research's outcome is very interesting from a managerial perspective. It suggests that it is particularly important to accommodate employees in a way they perceive a maximal amount of meaning in work with the arrival of-, working alongside with- AI. Future research should assess how to manage this in companies, as many companies are planning to- or are already

working with AI. Also, the strategic level's effect is more significant than the operational level. It would make sense to manage these levels in different ways. Managing the implementation and communication can significantly impact employees' perspectives on AI (Bauer et al., 2007). Managing people's expectations is essential because it will affect people's satisfaction working with these AI functions (Stone et al., 2016). As it has been explained before, different organizational levels have different tasks and responsibilities (Mintzberg, 1989), and we have found in this research that the influence of AI is not equal over organizational levels. The results of this research indicate that the strategic level experienced the most influence of AI, followed by the tactical level and lastly the operational level. Therefore, it is important that the implementation of AI within a company is managed in adjusted styles over organizational levels, in order to meet the different needs. So, in this case that would mean companies should be aware of the differences and manage the implementation of AI on the strategic level with extra care relatively to other levels.

This research also adds to academic relevance. It provides a base that can be built on with more extensive research. For instance, using the different components of the WAMI, a differentiation between factors that AI impacts can be made. It would be helpful to understand what aspects of AI are triggering the influence on meaning. Looking at the results of this research, all the means of the components of meaningful work significantly decreased, and therefore, it is hard to predict which aspects of AI are most influential. However, as mentioned, the positive meaning component decreased the most. Apparently, the scenario of AI caused the participants to change their personal perspectives on significance. This personal perspective differentiates for all employees but decreases the most on the strategic level. Nonetheless, giving extra attention to the predictors of meaning, e.g., mattering and personalizing, that correlate with positive meaning could possibly increase the positive meaning component. However, more research could be done on reducing the influence of AI on meaning and managing this, which again adds to the managerial relevance.

Limitations

A between-subject experiment, where one group was provided with the AI scenario before filling in the questionnaire, and the other group was not provided with any extra information, could have provided a more “independent” result. The within-subject design used in this thesis makes the subjects fill in the WAMI twice, where it is possible that when they fill the WAMI in for the second time, they feel the need to change their answers with respect to the first

WAMI. Whereas a between-subject design would prevent this from happening as the participants would only need to fill in the WAMI once. Even though a between-subject design might have had better control of genuine answering, a within-subject design was used. The reason for this choice was that the size of the sample of subjects would have needed to be doubled. For the within-subject design, three groups (organizational level groups) of 64 were needed, which leads to a bare minimum of 192 subjects (Durlak, 2009). With the between-subject design, at least 384 subjects were needed, as we needed three groups of 64 in both surveys. Because of time management and the difficulty of finding people, especially on the strategic level, the choice for the within-subject design was made.

Also, the effect of AI on meaning at work could have been scored more accurately, probably if the subjects worked alongside AI and experienced the consequences of that in their daily work. In this experiment, the scenario bases itself, particularly on the prospects of AI in the labor market, rather than actually experiencing the effects of AI firsthand. On the other hand, it could be argued that the view on work could also influence one's meaning in work, and it could therefore be seen as two separate research topics.

Future research

To reinforce the findings of this thesis, it would be interesting to see if the effect of AI vs. Humans, would also work the other way around. If the same design was used, but instead of a scenario focusing on the capabilities and prospects of AI, it would focus on the importance of the human aspect in work, a different outcome would be very likely. If the subjects would score the WAMI after that scenario about the importance of the human aspect higher than the WAMI they made previously without any extra information, it would reinforce the results of this research.

According to the results of this research, AI influences meaning at work, but it needs to become more apparent what aspects of work AI mainly influences that cause an impact on meaning. Furthermore, one step further, how to reduce these negative consequences. Once there is more information on this, learning how to work alongside AI is vital. Managing the implementation can change employees' perspectives on AI (Bauer et al., 2007). This force in work brings some challenges to the table; employees must understand the AI system and its decisions and know how to work with it; this is where management of AI becomes crucial. When people get frustrated using the promised functions, their trust and willingness to use them are significantly

reduced. (Stone et al., 2016). Future research could contribute to learning how to work with AI and manage this in a company. As this research has shown, there is a difference between the influence of AI on meaning at work over different organization levels. As these organizational levels experience different effects of having to work/ working with AI, they might need a different management approach.

Conclusion

It can be concluded that in this research experiment, AI had a significant influence on meaning at work. This influence of AI was not equal over all components of meaningful work, which implies that AI influences certain aspects of work more than others. Also, the influence of AI differentiated over organizational levels, where the hierarchically higher levels experienced relatively more influence of AI than the hierarchically lower level.

This research serves as a first step in investigating how AI will impact the future workplace. Much more research on how AI exactly influences meaning in work and how this is best managed in practice needs to be done. By doing so, we are a step closer to a futureproof and meaningful workplace.

Bibliography

Acemoglu, D., & Restrepo, P. (2017). *Robots and Jobs: Evidence from US Labor Markets*. https://doi.org/10.3386/w23285

Armstrong-Stassen, M. (2001). Reactions of older employees to organizational downsizing the role of gender, job level, and time. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 56(4), 234–243.

Arnold, K. A., Turner, N., Barling, J., Kelloway, E. K., & McKee, M. C. (2007). Transformational leadership and psychological well-being: The mediating role of meaningful work. *Journal of Occupational Health Psychology*, *12*(3), 193–203. https://doi.org/10.1037/1076-8998.12.3.193

Autor, D. H., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, *103*(5), 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Bailey, C., Madden, A., Alfes, K., Shantz, A., & Soane, E. (2017). The mismanaged soul: Existential labor and the erosion of meaningful work. *Human Resource Management Review*, *27*(3), 416–430. https://doi.org/10.1016/j.hrmr.2016.11.001

Bauer, T. N., Bodner, T., Erdogan, B., Truxillo, D. M., & Tucker, J. S. (2007). Newcomer adjustment during organizational socialization: A meta-analytic review of antecedents, outcomes, and methods. *Journal of Applied Psychology*, *92*(3), 707–721. https://doi.org/10.1037/0021-9010.92.3.707

Beans, C. (2018). Can robots make good teammates? *Proceedings of the National Academy of Sciences*, *115*(44), 11106–11108. https://doi.org/10.1073/pnas.1814453115

Benedikt Frey, C., Osborne, M. A., Dewey, D., Dorn, D., Flint, A., Goldin, C., Muellbauer, J., Mueller, V., Newman, P., Ó hÉigeartaigh, S., Sandberg, A., Shanahan, M., & Woolcock for their excellent suggestions, K. (2013). *THE FUTURE OF EMPLOYMENT: HOW SUSCEPTIBLE ARE JOBS TO COMPUTERISATION? **.

Berente, N., Gu, B., Recker, J., & Santanam, R. (2021). Managing Artificial Intelligence. *MIS Quaterly* .

Bessen, J. (2018). AI and Jobs: The role of demand . *National Bureau of Economic Research*.

Bhaskar Ghosh, H. J. W. A. B. and P. R. D. (2019). Taking a Systems Approach to Adopting AI. *Harvard Business Review*.

Białowąs, S., Reshetkova, A., & Szyszka, A. (2021). Experimental design. In *Experimental design and biometric research. Toward innovations* (pp. 9–35). Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu. https://doi.org/10.18559/978-83-8211-079-1/I1

Bishop, C. (2007). *Pattern Recognition and Machine Learning*. Springer.

Brougham, D., & Haar, J. (2018). Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

Chui, M., Hall, B., Singla, A., & Sukharevsky, A. (2021). The state of AI in 2021. *McKinsey*.

Chui M, Manyika J, & Miremadi M. (2015). Four fundamentals of workplace automation. *McKinsey Quarterly* .

Clifford. (2016). Elon Musk: Robots will take your jobs, government will have to pay your wage. *CNBC*.

Cohn, R. M. (1978). The Effect of Employment Status Change on Self-Attitudes. *Social Psychology*, *41*(2), 81. https://doi.org/10.2307/3033568

Colbert, A. E., Bono, J. E., & Purvanova, R. K. (2016). Flourishing via Workplace Relationships: Moving Beyond Instrumental Support. *Academy of Management Journal*, *59*(4), 1199–1223. https://doi.org/10.5465/amj.2014.0506

Collins, J. (2001). Level 5 Leadership. *Harvard Business Review*.
Craig, K., Thatcher, J. B., & Grover, V. (2019). The IT Identity Threat: A Conceptual Definition and Operational Measure. *Journal of Management Information Systems*, *36*(1), 259–288. https://doi.org/10.1080/07421222.2018.1550561
Deranty, J.-P., & Corbin, T. (2022). Artificial intelligence and work: a critical review of recent research from the social sciences. *AI & SOCIETY*. https://doi.org/10.1007/s00146-022-01496-x
Durlak, J. A. (2009). How to Select, Calculate, and Interpret Effect Sizes. *Journal of Pediatric Psychology*, *34*(9), 917–928. https://doi.org/10.1093/jpepsy/jsp004
Endacott, C. G. (2021). The Work of Identity Construction in the Age of Intelligent Machines. *Https://Escholarship.Org/Uc/Item/2kb6p061*.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
Gliem, J. A., & Gliem, R. R. (2003). Calculating, interpreting, and reporting Cronbach's alpha reliability coefficient for Likert-type scales. *Midwest Research-to-Practice Conference in Adult, Continuing, and Community Education*
Grant, A. M. (2007). Relational Job Design and the Motivation to Make a Prosocial Difference. *Academy of Management Review*, *32*(2), 393–417. https://doi.org/10.5465/amr.2007.24351328
Groom, V., & Nass, C. (2007). Can robots be teammates? *Interaction Studies. Social Behaviour and Communication in Biological and Artificial Systems*, *8*(3), 483–500. https://doi.org/10.1075/is.8.3.10gro
Gusher, T. (2020). *Living in an AI World Achievements and challenges in artificial intelligence across five industries*.
Hackman, J., & Oldman, G. (1976). Motivation through the Design of Work: Test of a Theory. *Organizational Behavior and Human Performance*.
Halal, W., Kolber, J., & Davies, O. (2016). Forecasts of AI and future jobs in 2030: Muddling through likely, with two alternative scenarios. *Journal of Futures Studies*, *21*(2), 83–96. https://doi.org/10.6531/JFS.2016.21(2).R83
Harari, Y. N. (2018). *21 Lessons for the 21st Century*.
Harzer, C., & Ruch, W. (2012). When the job is a calling: The role of applying one's signature strengths at work. *The Journal of Positive Psychology*, *7*(5), 362–371. https://doi.org/10.1080/17439760.2012.702784
Hill, C. W., Jones, G. R., & Schilling, M. A. (2014). Strategic management: theory: an integrated approach. Cengage Learning.
IBM Cloud education. (2020). *Artificial Intelligence (AI)*.
Jaimovich, N., & Siu, H. E. (2020). Job Polarization and Jobless Recoveries. *The Review of Economics and Statistics*, *102*(1), 129–147. https://doi.org/10.1162/rest_a_00875
Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
Judge, T. A., & Piccolo, R. F. (2004). Transformational and Transactional Leadership: A Meta-Analytic Test of Their Relative Validity. *Journal of Applied Psychology*, *89*(5), 755–768. https://doi.org/10.1037/0021-9010.89.5.755
Kahn, W. (2007). *Meaningful Connections, Positive Relationships and Attachments at Work*. Psychology Press.
Katz, D. (1978). *Social psychology of organizations.*
Kelly. (2012). *Better than human: Why robots will—and must—take our jobs.* .

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: how organizations can win over skeptical managers. *Strategy & Leadership*, *45*(1), 37–43. https://doi.org/10.1108/SL-12-2016-0085

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2), 717–734. https://doi.org/10.1108/IJCHM-07-2020-0789

Leetaru, K. (2016). Is Elon Musk right and will AI replace most human jobs? *Forbes*.

Lips-Wiersma, M., & Morris, L. (2009). Discriminating Between 'Meaningful Work' and the 'Management of Meaning.' *Journal of Business Ethics*, *88*(3), 491–511. https://doi.org/10.1007/s10551-009-0118-9

Lips-Wiersma, M., & Wright, S. (2012). Measuring the Meaning of Meaningful Work. *Group & Organization Management*, *37*(5), 655–685. https://doi.org/10.1177/1059601112461578

Littman-Ovadia, H., & Steger, M. (2010). Character strengths and well-being among volunteers and employees: Toward an integrative model. *The Journal of Positive Psychology*, *5*(6), 419–430. https://doi.org/10.1080/17439760.2010.516765

Lysova, E. I., Allan, B. A., Dik, B. J., Duffy, R. D., & Steger, M. F. (2019). Fostering meaningful work in organizations: A multi-level review and integration. *Journal of Vocational Behavior*, *110*, 374–389. https://doi.org/10.1016/j.jvb.2018.07.004

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Malhotra, N. D. N. D. F. B., Nunan, D., & Birks, D. (2017). *Marketing research an applied approach* (Fifth edition).

May, D. R., Gilson, R. L., & Harter, L. M. (2004). The psychological conditions of meaningfulness, safety and availability and the engagement of the human spirit at work. *Journal of Occupational and Organizational Psychology*, *77*(1), 11–37. https://doi.org/10.1348/096317904322915892

Mccarthy, J. (2007). *WHAT IS ARTIFICIAL INTELLIGENCE?* http://www-formal.stanford.edu/jmc/

Mihm, J., Loch, C. H., Wilkinson, D., & Huberman, B. A. (2010). Hierarchical Structure and Search in Complex Organizations. *Management Science*, *56*(5), 831–848. https://doi.org/10.1287/mnsc.1100.1148

Mintzberg, H. (1989). The Structuring of Organizations. In *Readings in Strategic Management* (pp. 322–352). Macmillan Education UK. https://doi.org/10.1007/978-1-349-20317-8_23

Mirbabaie, M., Brünker, F., Möllmann Frick, N. R. J., & Stieglitz, S. (2022). The rise of artificial intelligence – understanding the AI identity threat at the workplace. *Electronic Markets*, *32*(1), 73–99. https://doi.org/10.1007/s12525-021-00496-x

Misselhorn, C. (2018). Artificial Morality. Concepts, Issues and Challenges. *Society*, *55*(2), 161–169. https://doi.org/10.1007/s12115-018-0229-y

Morse, N. C., & Weiss, R. S. (1955). The Function and Meaning of Work and the Job. *American Sociological Review*, *20*(2), 191. https://doi.org/10.2307/2088325

Muijs, D. (2010). *Doing Quantitative Research in Education with SPSS* (Second edition).

Nadler, D. A., Tushman, M. L., & Nadler, M. B. (1997). *Competing by Design*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195099171.001.0001

Osborne, J. W. & Overbay, A. (2004). The power of outliers (and why researchers should ALWAYS check for them). *Practical Assessment, Research and Evaluation*, *9*(1), 1–8. https://doi.org/10.7275/qf69-7k43

Ramos, C., Augusto, J. C., & Shapiro, D. (2008). Ambient Intelligence—the Next Step for Artificial Intelligence. *IEEE Intelligent Systems*, *23*(2), 15–18. https://doi.org/10.1109/MIS.2008.19

Rodell, J. B. (2013). Finding Meaning through Volunteering: Why Do Employees Volunteer and What Does It Mean for Their Jobs? *Academy of Management Journal*, *56*(5), 1274–1294. https://doi.org/10.5465/amj.2012.0611

Rosso, B. D., Dekas, K. H., & Wrzesniewski, A. (2010). On the meaning of work: A theoretical integration and review. *Research in Organizational Behavior*, *30*, 91–127. https://doi.org/10.1016/j.riob.2010.09.001

Selenko, E., Bankins, S., Shoss, M., Warburton, J., & Restubog, S. L. D. (2022). Artificial Intelligence and the Future of Work: A Functional-Identity Perspective. *Current Directions in Psychological Science*, *31*(3), 272–279. https://doi.org/10.1177/09637214221091823

Smith, A. M., & Green, M. (2018). Artificial Intelligence and the Role of Leadership. *Journal of Leadership Studies*, jls.21605. https://doi.org/10.1002/jls.21605

Steger, M. F. (2016). Creating Meaning and Purpose at Work. In *The Wiley Blackwell Handbook of the Psychology of Positivity and Strengths&;#x02010;Based Approaches at Work* (pp. 60–81). John Wiley &;#38; Sons, Ltd. https://doi.org/10.1002/9781118977620.ch5

Steger, M. F., & Dik, B. J. (2009). If One is Looking for Meaning in Life, Does it Help to Find Meaning in Work? *Applied Psychology: Health and Well-Being*, *1*(3), 303–320. https://doi.org/10.1111/j.1758-0854.2009.01018.x

Steger, M. F., Dik, B. J., & Duffy, R. D. (2012). Measuring Meaningful Work. *Journal of Career Assessment*, *20*(3), 322–337. https://doi.org/10.1177/1069072711436160

Stein, M., Wagner, E. L., Tierney, P., Newell, S., & Galliers, R. D. (2019). Datification and the Pursuit of Meaningfulness in Work. *Journal of Management Studies*, *56*(3), 685–717. https://doi.org/10.1111/joms.12409

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., & Hager, G. (2016). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. *Stanford University*.

Susskind, D. (2020). *A World Without Work: Technology, Automation and How We Should Respond*. Penguin Books Ltd.

Tummers, L. G., & Knies, E. (2013). Leadership and Meaningful Work in the Public Sector. *Public Administration Review*, *73*(6), 859–868. https://doi.org/10.1111/puar.12138

Weeks, K. (2020). *The Problem with Work*. Duke University Press. https://doi.org/10.1515/9780822394723

Wisskirchen, G., Thibault Biacabe, B., Bormann, U., Muntz, A., Niehaus, G., Soler, G. J., & von Brauchitsch, B. (2017). *Artificial Intelligence and Robotics and Their Impact on the Workplace*.

Wright, S. A., & Schultz, A. E. (2018). The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, *61*(6), 823–832. https://doi.org/10.1016/j.bushor.2018.07.001

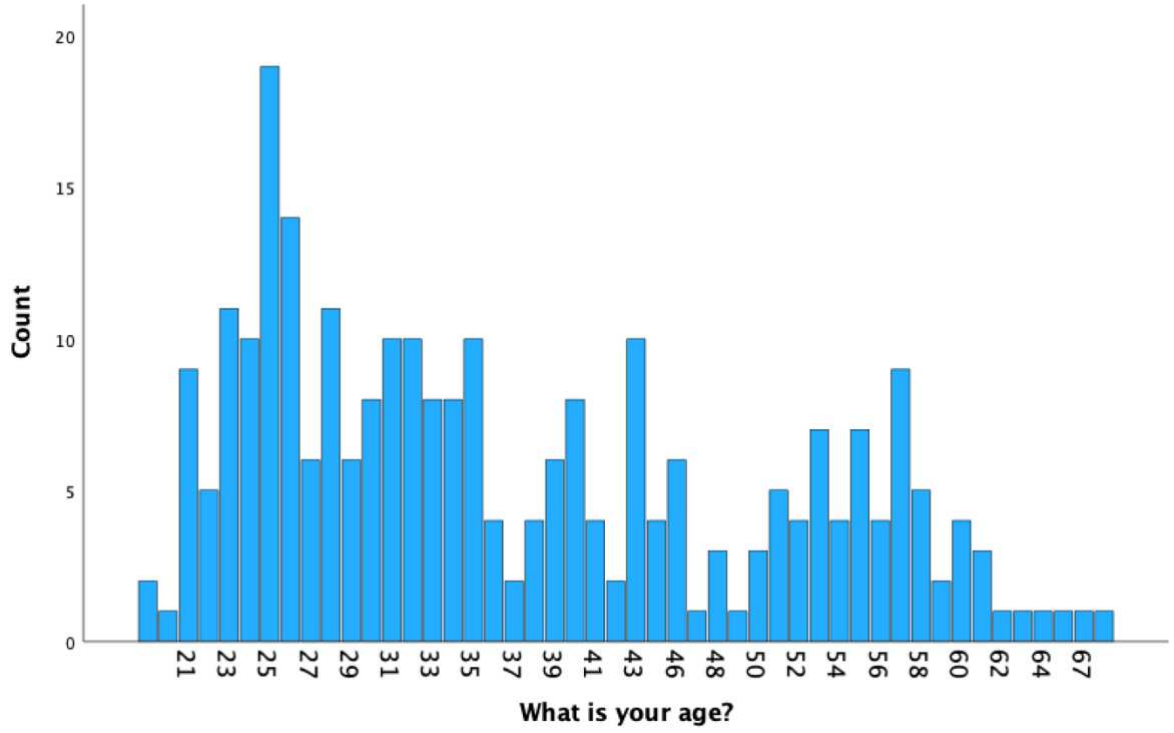
Wrzesniewski, A., Dutton, J. E., & Debebe, G. (2003). INTERPERSONAL SENSEMAKING AND THE MEANING OF WORK. *Research in Organizational Behavior*, *25*, 93–135. https://doi.org/10.1016/S0191-3085(03)25003-6

Xu, M., David, J. M., & Kim, S. H. (2018). The Fourth Industrial Revolution: Opportunities and Challenges. *International Journal of Financial Research*, *9*(2), 90. https://doi.org/10.5430/ijfr.v9n2p90

Appendix

Appendix A

Populations distribution of age



Appendix B

Survey

Welcome, and thank you for participating in this experiment on meaning at work. I, Aimée Gebben, am conducting this experiment as part of my Master Thesis at Católica Lisbon School of Business and Economics, under the supervision of Filipa de Almeida.

The purpose is to gain insight into meaning at work. Therefore, this survey is only intended for people who are currently working. It will take about 5 minutes to complete. Please answer as honestly as possible. All answers will be kept strictly confidentially and are anonymous. This means that there will be no way to link your responses to your identity. The data collected will be used for research purposes only.

There are no expected side effects of participating in this study. You may drop out at any point. If you have any questions about this study, please email s-agebben@ucp.pt. By continuing you agree to participate.

Thank you!

What is your gender?

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

What is your age?

_____

What is the highest level of education (or equivalent) you have completed?

- ○ Less than high school
- ○ High school
- ○ Intermediate vocational education (MBO)
- ○ Bachelor
- ○ Master
- ○ PhD

What is your current work status?

- ○ Student
- ○ Employed full time
- ○ Employed part time
- ○ Self-employed
- ○ Retired
- ○ Unemployed
- ○ Unable to work

What job sector do you work in?

- ○ Arts and creative
- ○ Business
- ○ Construction and property
- ○ Engineering
- ○ Finance
- ○ Healthcare and veterinary medicine
- ○ Hospitality and travel
- ○ IT and technology
- ○ Law
- ○ Media
- ○ Public sector and charity
- ○ Retail, buying and fashion
- ○ Science
- ○ Teaching and education
- ○ Other _____

What organizational (hierarchical) level are you in?

- ○ Strategic management. (Top management)
- ○ Tactical management. (Middle management)
- ○ Operating Core. (Operations, operational processes)

Please answer the following questions having in mind your current job.

	Absolutely untrue	Mostly untrue	Neither untrue nor true	Mostly true	Absolutely true
I have found a meaningful career.	○	○	○	○	○
I view my work as contributing to my personal growth.	○	○	○	○	○
My work really makes no difference to the world.	○	○	○	○	○
I understand how my work contributes to my life's meaning.	○	○	○	○	○
I have a good sense of what makes my job meaningful.	○	○	○	○	○
I know my work makes a positive difference in the world.	○	○	○	○	○
My work helps me better understand myself.	○	○	○	○	○
I have discovered work that has a satisfying purpose.	○	○	○	○	○
My work helps me make sense of the world around me.	○	○	○	○	○
The work I do serves a greater purpose.	○	○	○	○	○

To what extent are you aware of technological innovations in the field of artificial intelligence?

- ○ Very unaware
- ○ Somewhat unaware
- ○ Neither unaware nor aware
- ○ Somewhat aware
- ○ Very aware

Please read the following text attentively. You may be quizzed about it later.

'Artificial intelligence (AI) is a system or machine that mimics human intelligence to perform tasks. It can iteratively improve itself based on the information it collects. In a practical sense, this means that AI can already automate specific 'human' tasks, at the moment, this mainly concerns monotonous and repetitive tasks. However, AI is starting to surpass humans in more and more skills, even in understanding human emotions. It has been suggested that AI will be able to do more and more. Thus:

- AI may not only replace people's tasks, but it can also create new tasks for both people and AI to work on. As a result, people may have to retrain to perform the skills of the new position.
- Another option is to shift the job content of human workers more towards creative work (which is central to the human experience and needs the use of capabilities such as creativity and sensing emotions), as AI still needs to be developed more in this field.

An important question is how these developments in the AI field coexist with human needs. If AI can work alongside humans, as a colleague, how will humans feel at the workplace?

How does this scenario make you feel? Please name 3 emotions

- ○ Emotion 1 _____
- ○ Emotion 2 _____
- ○ Emotion 3 _____

Do you feel like the text has changed your perception on the influence of Artificial Intelligence at the workplace?

- ○ Definitely not
- ○ Probably not
- ○ Might or might not
- ○ Probably yes
- ○ Definitely yes

How much is AI currently part of your workplace?

- ○ Not at all
- ○ A little
- ○ Neither a little nor a lot
- ○ A high amount
- ○ Always

Now that you have contemplated this scenario (with AI in the workplace), please answer to the following questions imagining an AI agent works alongside you as your colleague, performing similar functions to yours. Imagine such is the case in your current job.

	Absolutely untrue	Mostly untrue	Neither untrue nor true	Mostly true	Absolutely true
I have found a meaningful career.	○	○	○	○	○
I view my work as contributing to my personal growth.	○	○	○	○	○
My work really makes no difference to the world.	○	○	○	○	○
I understand how my work contributes to my life's meaning.	○	○	○	○	○
I have a good sense of what makes my job meaningful.	○	○	○	○	○
I know my work makes a positive difference in the world.	○	○	○	○	○
My work helps me better understand myself.	○	○	○	○	○
I have discovered work that has a satisfying purpose.	○	○	○	○	○
My work helps me make sense of the world around me.	○	○	○	○	○
The work I do serves a greater purpose.	○	○	○	○	○

Thank you for your answers.
Please answer the following question.
The innovation of Artificial Intelligence is going to affect...

	Disagree	Slightly disagree	Neither disagree nor agree	Slightly agree	Agree
my job sector within 5 years.	○	○	○	○	○
my job within 5 years.	○	○	○	○	○
my job sector within 15 years.	○	○	○	○	○
my job within 15 years.	○	○	○	○	○

Thank you for your participation in this study. In this study we want to study how Artificial Intelligence influences employees' meaning at work. To research this, we measured your perception on Meaning before being exposed to information about AI and afterwards. This difference will inform us on how imagining working alongside an AI agent will impact one's job meaning. Thanks again!

Appendix C

Results of the question on job sector

Job sector	Frequency	Percentage
Arts and creative	8	3,01%
Business	25	9,40%
Construction and property	7	2,63%
Engineering	13	4,89%
Finance	18	6,77%
Healthcare and veterinary medicine	25	9,40%
Hospitality and travel	5	1,88%

IT and technology	33	12,41%
Law	4	1,50%
Media	2	0,75%
Public sector and charity	34	12,78%
Retail, buying and fashion	15	5,64%
Science	7	2,63%
Teaching and education	35	13,16%
Other	35	13,16%
Total	266	100,00%

Appendix D

Technical awareness	Frequency	Percentage
Very unaware	8	3,01%
Somewhat unaware	27	10,15%
Neither unaware nor aware	32	12,03%
Somewhat aware	148	55,64%
Very aware	51	19,17%
Total	266	100,00%

Appendix E

Cronbach's Alpha if item deleted

Question	Alpha
Q1	0.906
Q2	0.904
Q3	0.913
Q4	0.909
Q5	0.905
Q6	0.905
Q7	0.910
Q8	0.904

Q9	0.906
Q10	0.903

Inter-item correlations WAMI questions

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Q1	1	0.690	0.390	0.478	0.619	0.452	0.484	0.690	0.503	0.495
Q2		1	0.393	0.548	0.625	0.457	0.569	0.669	0.546	0.529
Q3			1	0.420	0.453	0.695	0.304	0.339	0.436	0.625
Q4				1	0.592	0.475	0.457	0.513	0.438	0.465
Q5					1	0.530	0.464	0.642	0.526	0.548
Q6						1	0.385	0.482	0.526	0.751
Q7							1	0.539	0.576	0.491
Q8								1	0.579	0.528
Q9									1	0.531
Q10										1

Appendix F

Results of the WAMI before the scenario per question

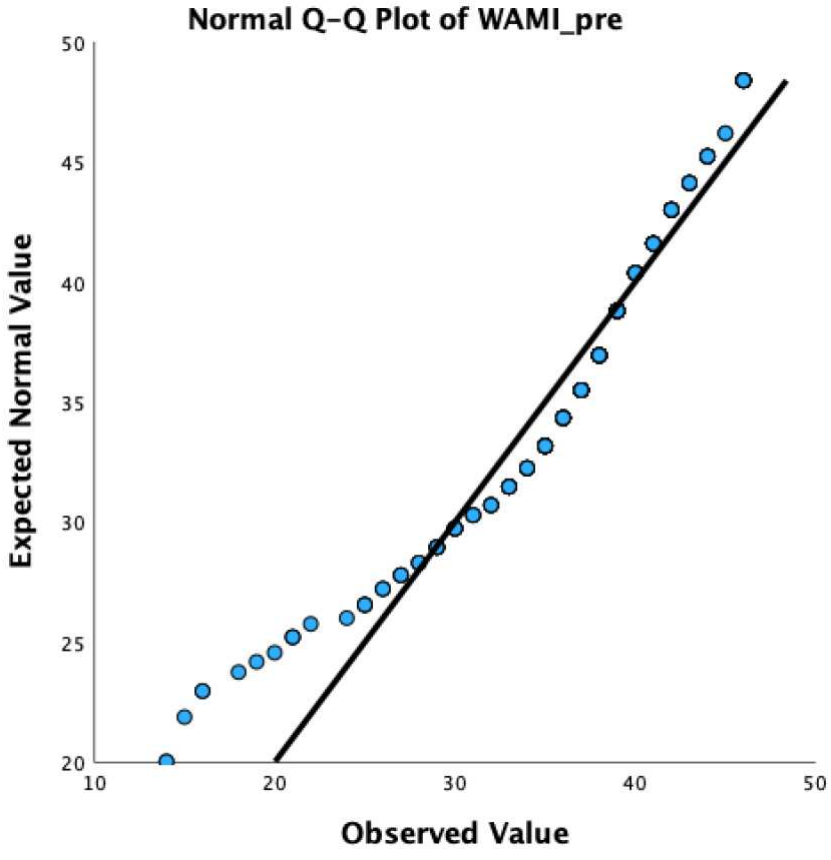
WAMI pre scenario	Mean	Standard Deviation
Q1	3.857	1.025
Q2	4.008	0.940
Q3	3.250	1.099
Q4	3.906	0.896
Q5	4.015	0.842
Q6	3.707	1.034
Q7	3.718	1.005
Q8	3.801	1.010
Q9	3.571	1.080
Q10	3.650	1.107

Results of the WAMI after the scenario per question

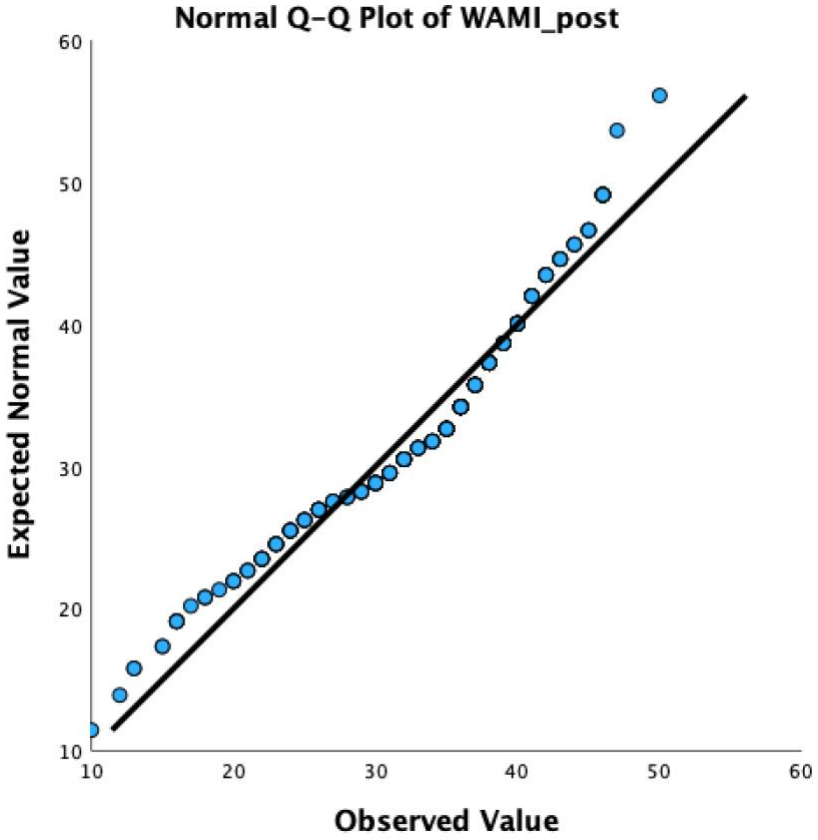
WAMI after scenario	Mean	Standard Deviation
Q1	3.35	1.156
Q2	3.43	1.118
Q3	2.58	1.164
Q4	3.50	1.036
Q5	3.66	1.071
Q6	3.49	1.113
Q7	3.44	1.142
Q8	3.44	1.145
Q9	3.42	1.044
Q10	3.45	1.139

Appendix G

Q-Q plot WAMI before scenario



Q-Q plot WAMI after scenario



Appendix H

Wilcoxon signed-rank test

H1

Means before and after the AI scenario

WAMI before	WAMI after	Z	Sig.
36.47 (6.27)	33.77 (7.95)	-6.96	<.001

A Wilcoxon signed-rank test showed that the AI scenario did statistically significant change in the WAMI scores ($Z = -6.96$, $p < 0.001$).

H2

	Before	After	Z	Sig.
Positive meaning	15.58 (3.14)	13.94 (3.93)	-7.78	<.001
Meaning-making	11.30 (2.55)	10.29 (2.94)	-6.72	<.001

Greater good	11.11 (2.89)	10.37 (2.80)	-5.02	<.001

The Wilcoxon signed-rank test showed that the AI scenario did statistically significant change in all the components of meaning at work.

H3

	Before	After	Z	Sig.
Strategic	40.09 (3.59)	36.94 (6.08)	-3.83	<.001
Tactical	37.91(4.57)	34.49 (7.05)	-3.92	<.001
Operational	34.04 (6.95)	31.87 (8.64)	-4.25	<.001

In this hypothesis the Wilcoxon signed-rank test showed that the AI scenario did statistically significant change the scores on meaning of the organizational levels. .

Appendix I

Wilcoxon signed-rank test on job sector question

AI going to affect one's job or job sector within 5 or 15 years. Scored in a 5-point Likert scale varying from 1 (Disagree) to 5 (Agree).

	Job			Job sector		
	M(SD)	Z	Sig.	M(SD)	Z	Sig.
5 years	2.94 (1.35)	-8.67	<.001	3.56 (1.32)	-5.91	<.001
15 years	3.66 (1.35)			4.00 (1.24)		

	Job 5 years		Job sector 5 years		Job 15 years		Job sector 15 years	
WAMI	Pearson	Sig.	Pearson	Sig.	Pearson	Sig.	Pearson	Sig.

Before	0.09	0.15	0.06	0.37	0.06	0.35	0.02	0.73
After	0.13	0.03	0.13	0.04	0.08	0.05	0.08	0.21