EFFECTS OF ARTIFICIAL INTELLIGENCE AND AUTOMATION ON THE LABOR MARKET

AYŞE NUR ERTEM

BOĞAZİÇİ UNIVERSITY

2024

EFFECTS OF ARTIFICIAL INTELLIGENCE
AND AUTOMATION ON THE LABOR MARKET

Thesis submitted to the

Institute for Graduate Studies in Social Sciences

in partial fulfillment of the requirements for the degree of

Master of Arts

in

Management

by

Ayşe Nur Ertem

Boğaziçi University

2024

Effects of Artificial Intelligence and Automation on the Labor Market

This thesis of Ayşe Nur Ertem

has been approved by:

Assoc. Prof. Yavuz Acar __________________________
(Thesis Advisor)

Assoc. Prof. Özgün Burcu Rodopman Acar __________________________

Assist. Prof. Alev Özer Torgalöz __________________________
(External Member)

September 2024

DECLARATION OF ORIGINALITY

I, Ayşe Nur Ertem, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

Signature ______________________

Date ______________________

ABSTRACT

Effects of Artificial Intelligence and Automation on the Labor Market

In recent years, the integration of artificial intelligence (AI) and automation has significantly impacted the labor market, creating new job opportunities, transforming existing roles, and raising concerns about potential job displacement. As the previous studies regarding AI driven automation, and its effects on workplaces are rather limited and fragmented, this research has been found necessary to detect the outcomes of inevitable integration of artificial intelligence and automation to work life and make use of it efficiently. The objective of this study is to find out the effects on AI driven automation on the organizational commitment, job performance and turnover intention. In conclusion, to this research, it is found out that AI literacy and perceived automatability has a positive relationship with automation-related performance optimism, which has a significant positive relationship with job performance and organizational commitment while having a negative relationship with turnover intention.

ÖZET

Yapay Zeka ve Otomasyonun İşgücü Piyasasına Etkileri

Son yıllarda, yapay zeka (AI) ve otomasyonun entegrasyonu iş gücü piyasasını önemli ölçüde etkilemiş, yeni iş fırsatları yaratmış, mevcut rolleri dönüştürmüş ve potansiyel iş kaybı konusunda endişelere yol açmıştır. Yapay zeka destekli otomasyon ve işyerleri üzerindeki etkileriyle ilgili önceki çalışmalar oldukça sınırlı ve parçalı olduğundan, yapay zeka ve otomasyonun iş hayatına kaçınılmaz entegrasyonunun sonuçlarını tespit etmek ve bundan verimli bir şekilde yararlanmak için bu araştırmanın gerekli olduğu tespit edilmiştir. Bu çalışmanın amacı, AI destekli otomasyonun örgütsel bağlılık, iş performansı ve işten ayrılma niyeti üzerindeki etkilerini bulmaktır. Bu araştırmanın sonucunda, AI okuryazarlığı ve algılanan otomasyona yatkınlığın otomasyonla ilgili performans iyimserliği ile pozitif bir ilişkiye sahip olduğu, bunun da iş performansı ve örgütsel bağlılıkla anlamlı pozitif bir ilişkiye sahipken, işten ayrılma niyetiyle negatif bir ilişkiye sahip olduğu bulunmuştur.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Recently, AI have been embraced by organizations globally to facilitate digital transformation and obtain agile response strategies to improve organizational performance (Aldoseri et al., 2024). AI enables manufacturers to adapt to dynamic market demands, meet production targets and achieve performance goals (Haenlein and Kaplan, 2019). Application of AI and automation is not only limited to manufacturing sector, it has been also widely applied in other areas as well, such as healthcare, law, and education (Yarlagadda, 2017) For instance, machine learning enables doctors to diagnose diseases within a short period of time. Chatbots provide an effective solution for appointment scheduling, managing accounting processes, tracking patient’s experince.

AI and automation is an effective solution to grade assignments and exams automatically, assisting instructors and student’s needs and making sure, they are on the right track. Legislators can process and access huge volume of data regarding legal documents easily and quickly in the law sector (Coeckelbergh, 2015). Robots can produce in mass amounts in a shorter period with less errors compared to humans in industrial processes. In today’s business environment, economic systems, job definitions, work processes and remuneration systems are likely to undergo huge transformations. (Nof, 2009).

Given their advantages, AI and automation also presents new challenges as a factor of rapid technological advancements that organizations, employers and employees struggle to cope with. Therefore, this research paper seeks to unveil the effects of AI and automation on the labor market by analyzing survey data of workers from various sectors and organizations.

CHAPTER 2

LITERATURE REVIEW

2.1 AI and the labor market

The world is experiencing the start of a new industrial revolution nowadays, which is projected to have a significant impact on industries worldwide (Pereira et al., 2023). This marks a new era in integrating the physical and digital worlds, enhancing human-machine interactions, and promoting automation through the integration of smart machines and intelligent software (Ibarra, Ganzarain & Igartua, 2018). Artificial intelligence, rooted in philosophy, computation, psychology, mathematics, and neuroscience, is having more and more interaction with both manufacturing and service industries. AI aims to enable machines to think like humans while challenging human capabilities by autonomously gathering and processing information from their environment to make decisions where human reasoning is required. Its incorporation at work aims to enhance task execution and performance through computer-based systems involving machine learning, soft computing, smart robots, and virtual/augmented reality (Liu, Shi & Liu, 2017).

While AI and automation is getting an indispensable and inseparable part of the work processes, it is of utmost importance to predict and manage their effect on the human resource for organizations to survive and thrive. The role of human resource management (HRM) within an organization plays a major part in effectively integrating AI at work. Integrating HRM processes with artificial intelligence can yield various benefits for an organization such as improved decision-making, streamlined employee recruitment processes, higher workplace learning effectiveness, employee engagement, and employee retention ratios. So, Pereira et al. focused on utilizing from AI in HRM processes to maintain their tasks more affectively and achieve a more solid decision making process.

Webb (2019) developed a method to measure the exposure of tasks to automation with an aim to assess the impact of artificial intelligence on the labor market. Webb applied his method to previous cases, e.g. software and robots. Occupations that were found to be exposed to these technologies recorded declines in employment and salaries. To be able to foresee the impacts of AI, fitted parameters from these case studies are utilized. As a result, unlike software and robots, AI is expected to dramatically affect high-skilled tasks. Within the condition that the effects will be valid in the long run, AI can play a role in reducing income inequality by decreasing the wage gap. However, the prediction suggests that the top 1% will not be affected.

The adoption of artificial intelligence by organizations is a subject evaluated skeptically by many scholars (e.g., Acemoglu & Restrepo, 2020; Choi & Kang, 2019). They underlined the risks and negative aspects that might be caused by the usage of AI in the workplace, e.g. people having less amount of role in the manufacturing of goods and providing services, or decreased labor in sectors with low labor productivity levels. Even middle-skill jobs requiring a high level of cognitive capabilities might be replaced fully or partially by AI (David, 2015). A disadvantage of using AI in organizations is that many managers and employees have a lack of trust and approach negatively to automation and AI (Frey, Osborne, 2017).

Employees have a fear that AI might take away their jobs from their hands (Makarius, Mukherjee& Fox, 2020). Therefore, taking advantage of AI within organizations is considered as a potential cause of higher employee stress, lower organizational commitment, even decreased productivity (Brougham & Haar, 2018).

Afterward, recent research has emphasized the need for a deeper comprehension of the influence of AI on workers and the workplace to help companies address some of the challenges associated with AI implementation. Pereira et al. (2023) responds to this call by conducting a comprehensive review of how AI impacts workplace results and by suggesting future paths for both research and application that can facilitate a smoother organizational transition into Industry 4.0. To accomplish this, they approach the issue from the viewpoint of human resource management (HRM), which has been highlighted as crucial for supporting the successful integration of artificial intelligence technologies in workplaces (Cheng & Hackett, 2019; Tambe et al., 2019). While HRM influences employee and organizational outcomes, its function is vital in comprehending how organizations can effectively embrace AI while minimizing risks and maintaining positive results for employees.

A previous research (Prentice et. al., 2020) focused on how human (emotional intelligence) and machine intelligence (artificial intelligence) affect employee churn, and internal and external service performance of employees. In result, their finding shows that EI has a significant effect on both retention and performance. On the other hand, AI has a moderating role in the relationship between EI and the proposed outcome variable. Therefore, AI plays a buffer role in employee performance. So, an employee with a higher level of AI performs better when AI is rated lower. Similarly, an employee who rated high on AI and low on EI does not perform better than an employee who rated low on AI and high on EI. The findings corroborate the assertions made in studies suggesting that artificial intelligence is improbable to supplant human responsibilities (Bowen, 2016; Mohanty, 2018). The consulting company Gartner underlines that AI creates more jobs than it eliminates. Likewise, Pew Research Centre discusses that AI might only replace low-level human jobs.

2.2 Automation and the labor market

Pouliakas (2018) mentions a term called ‘automatability risk ’and aims to identify the determinants of this risk. He refers to automatability risk as a job with a high risk of substitution by machines or robots while aiming to reveal its impact on the labor market. A research conducted in the European Union by European Centre for the Development of Vocational Training (Cedefop, 2018) highlights that nearly 43% of adult employees in the EU labor market went through disruptive technological changes in their workplaces during last five years such as new ICT systems or machinery.

Frey and Osborne (2013) state that almost 50% of jobs in advanced economies are vulnerable to automation by process automation and other developing technologies. Their statement underline the fact that societies and economies are on the verge of a critical point in which technological developments like machine learning, AI, visual-space perception, 3D-printing, nanotechnologies, bioengineering, language processing models are expected to cause a major transformation in the upcoming years among all technological advancements (Brynjolfsson and McAfee, 2014). Nevertheless, proponents of the positive results of technical progress evaluate the situation in a way that embodied technical change to bring out a labor market balance and a net employment (Vivarelli, 2014; Bessen, 2016).

Further capital investment expenditure by companies after the integration of a new technology is not an irreversible situation as well (DeCanio, 2016). While innovation cycles and their commercial applications in industry are shortening, particularly through rapid prototyping, the labor-disrupting diffusion of new technologies within firms can take time and be uncertain. Additional to considering the relative cost of human and capital factor inputs according to their marginal productivity to decide the degree of substitutability of labor for capital, many organizations recognize that their human capital constitutes a source of income in the global economic environment providing a competitive advantage. Rapid replacement of the workforce with machines can often result in a critical loss of organizational creativity, innovation and employee motivation as Pouliakas suggests (2018).

Gomes and Seruca (2023) analyzes a global company based in Portugal to assess employees 'perception of robotic process automation (RPA) which is using a software to automate repetitive and routine tasks which allows replicating human actions. RPA handles many time consuming tasks without any need of human intervention. Since it enables higher productivity and reduces costs and errors, this automation feature has received lots of attention. It is highlighted as one of the most relevant concepts in the current business context and has lots of room to grow within organizations (Sobczak, 2021; Siderska, 2020; Ivancic et al., 2019)

Notwithstanding, companies needs to put much effort to discover all the opportunities provided by automation, and there stands a large margin for progress. According to Gartner's prediction (2020), 90% of large organizations worldwide are expected to utilize RPA by 2022, large companies will increase their RPA usage by %200 until 2024. Another study conducted by Fortune Business Insights (Fernandez, 2020) expects the global RPA market to hit approximately $7 billion by 2026. Beyond RPA being an area of increasing commercial interest, it has also created academic interest as a highly trending topic. Nonetheless, the literature on RPA is quite limited due to the emergent nature of technology. In this regard, Nauwerck and Cajander (2019) highlight that research on RPA is very limited and do not reflect the perspective of employees; Enriquez et al. (2020) aimed to reveal the effects of RPA on companies and employees; and Hofmann et al. (2020) underline the existing gap with the need to comprehend not only the effects but also perception of employees regarding RPA.

Gomes and Seruca (2023) suggest that their underlying argument is that it is crucial for organizations to understand perception of RPA implementation by managers and employees to establish better solutions and crate strategies for communication which enables the acceptance and effectiveness of this technology. To close this gap between the perceptions of managers versus employees, the organizations are advised to distribute more information regarding the robotic automation of processes adopted in the company through newsletters or experience sharing sessions, to announce the performance and results achieved with the robots to employees, to adopt initiatives to facilitate the positive image that RPA currently has on employees (to maintain and enhance the actions to robotize processes in the organization). These kind of initiatives may contain innovation awards that celebrates innovative ideas for process automation and improvement.

2.3 The future of labor market

Tasks associated with knowledge labor are vulnerable to automation. Though it will be marginal, some knowledge workers will lose their jobs. Instead of ten, there will be eight attorneys. Nobody is sure how many occupations there will be that involve interacting with intelligent machines. Significant increases in productivity is expected, allowing organizations retrain and reallocate personnel as needed. However, there is no space for complacency.

When the effect of new technologies on productivity and labor market outcomes is analyzed, and the concern of new technologies to displace labor is seen at the forefront.

A rise in computer capital is linked to an increase in labor input for non-routine cognitive tasks and a decrease in labor input for routine cognitive and routine manual jobs. A conceptual framework that shows how automation might result in a decrease in the labor share, employment, and wages is developed in which machines take the place of human labor (Acemoglu & Restrepo, 2018b). Another theoretical research on the loss of jobs related to automation was performed by Acemoglu and Autor (2011), who found that the use of technology in support, office, and administrative jobs increases employment and wages for the general public.

Due to technology and global commerce, the nature of work has changed, particularly for professions requiring non-college occupational skills. As a result, urban labor markets have become more polarized. There is currently little empirical data regarding how AI affects labor and productivity. Evidence about the impact of advancements in nine different AI applications on earnings and employment was presented by Felten, Raj, and Seamans (2019). They discovered that while there is a positive association between AI and pay growth, there is no discernible relationship between AI exposure and employment growth. Although there is a favorable correlation between AI and business market values, there is no conclusive proof that investing in AI increased enterprises' productivity.

Another finding is that organizational changes decrease the demand for unskilled workers. MacCrory et al. (2014) stated that demand for skills that compete with machines declines, whereas more skills which complement machines are required. Manual-routine jobs are being replaced my machines, while upskilling is seen in cognitive-routine jobs (Hershbein & Kahn, 2018)

The report "The Skills Revolution and the Future of Learning and Earning" (2023) by McKinsey & Company states that as automation becomes more prevalent, millions of workers worldwide will have to shift their line of work. The need for higher order cognitive abilities, social and emotional intelligence, and both fundamental and sophisticated digital skills will increase. The world of work is changing as a result of the rapid advancements in technology, which are bringing with them new difficulties as well as new efficiency, increased innovation, and new products and services.

The skills revolution is one of the most significant of these challenges; basic digital competencies are now required in a variety of professions, from truck driving to nursing. New and more advanced skills, such as social and emotional skills, higher cognitive skills, and technological skills, are getting increasingly important. It is now essential for players in the public and private sectors worldwide to rethink the learning and earning core of the global labor market and to invest in the changes required to equip individuals with the skills of the future.

A study by Wharton School (2024) focuses on the effects of large language models (LLMs) by evaluating the exposure of tasks to the technology and potential of tasks to be transformed by AI. The results indicate that the impact of LLMs on labor market will take a long time since software, training and change management are required to catch the opportunities. And the impact depends on the potential of tasks to be automated, such as cooks and carpenters are not expected to impacted by LLMs whereas interpreters and proofreaders may lose their jobs. Either way, new policies are crucial both organizational and governmental to facilitate training, integration, and assistance for displaced workers.

Technology adoption may result in the loss of many employment, the creation of many more, and a change in practically all jobs. In order to fully reap the benefits of the productivity boost provided by new technology, businesses will need to carefully manage these changes and make sure that all employees are equipped with the skills necessary to succeed in an evolving work environment. A review of data on eight nations suggests that, globally, up to one in sixteen people may need to change careers by 2030 in order to adapt to the shifting demands of the labor market (McKinsey Global Institute, 2021). According to a different study done on 46 nations, half of all work activities could be automated (McKinsey, 2018).

The workforce will undergo a dramatic skill transition in the future due to automation and artificial intelligence. There will probably be a greater and quicker transition than in the past. Technological skills, social and emotional abilities, and higher-level cognitive skills rank first through third in terms of predicted demand. The need for social and emotional competencies, like managing people and exercising leadership, will only increase in our increasingly digitalized society. These are innate human abilities that are difficult for robots to imitate.

2.4 Employee reactions to automation and AI

Various studies have been conducted to examine the conditions for employees to trust and adopt new technologies at workplaces (Langer and Landers, 2021; Parasuraman and Riley, 1997). These research mainly focus on the types on technology, demographics of the employee and context that effects the use of that technology. However, there was a lack of research focusing on the perceptions of automation processes and consequences of these perceptions regarding employee behavior. Gödellei and Beck (2023) contributed to close this gap by establishing a model based on employees ’optimistic and pessimistic perceptions of their jobs automatability by taking perceived control into consideration as a moderating factor to discover the effects of automation on employee engagement and turnover intentions. We aim to make contribution to literature of employee behavior regarding their perceptions of automation and AI, by incorporating applying AI, organizational commitment, job performance into our model (see Figure 1). Perceived automatability is an evaluation related with the capabilities of technologies, instead of an evaluation of the effect of technologies on employees. This research sheds light to the relationship between perceived automatability and automation-related performance optimism. This relationship has been found significant ($p<.001$ and correlation is .66) in Gödellei and Beck’s model as well (2023), they established a SEM construct to make analysis.

H1. There will be a positive relationship between AI literacy and automation-related performance optimism.

H2. There will be a positive relationship between perceived automatability and automation-related performance optimism.

2.5 Social exchange theory

Social exchange theory (Blau, 1964) explains the nature of exchange relationships between employees and its eventual effect on their attitudes and behaviors. Based on this theory, employees working in an organization have positive and negative feelings towards their organization, which causes them to be committed or dissatisfied with the particular organization (Nawaz & Pangil, 2016). Rehman et al. (2022) utilized this theory to investigate the mediating role of organizational commitment in the relationship between workplace incivility and turnover intention. Li et al. (2021) also used the social exchange theory to explain the relationship between organizational commitment and turnover intention with the aim of describing factors related with organizational commitment to help decrease turnover intention of employees to within their organization.

The social exchange theory implies that employees who are satisfied with what they organizations provide for them (e.g., salary, side benefit) are likely to have strong organizational commitment. This commitment includes forming higher emotional attachment (affective commitment), establishing a feeling of obligation due to good treatment by organization resulting as less inclination to search other employment outside of organization (continuance commitment) (Williamson et al., 2009).

Since organizational commitment performed such significant relationship between income and turnover intention, researchers suggested to locate organizational commitment as a mediator. Many research indicates that income and organizational commitment were negatively correlated with turnover intention, and organizational commitment mediates the effect of income on turnover intention (Joarder et al., 2011, Li et al., 2021, Nawaz and Pangil, 2016, Zhang, 2014).

As social exchange theory is one of the most influential theories to comprehend workplace behavior (Cropanzano and Mitchell, 2005), it has been utilized to address the relationship between the attitudes and behaviors of employees (e.g., job satisfaction, organizational commitment, job performance). This theory suggests a reciprocity principle which states that employees feel obliged to organizations when they are treated fairly and positively and they respond kindly and perform well (Dinc, 2017). Therefore, the exchange ideology of employees enhances their job satisfaction (Witt, 1991), organizational commitment (Andrews, Witt, & Kacmar, 2003) and job performance (Orpen, 1994).

2.6 Downstream effects on job performance and organizational commitment

As mentioned by Gödellei and Beck (2023), based on the transactional theory of stress, automatability of a job can be considered as an environmental stressor since it may have disruptive effects on the future on an individual's job and its features. In parallel with the threat and challenge appraisals in this theory, Gödellei and Beck (2023) discusses that perceived automatability can be regarded in both optimistic and pessimistic ways by employees, these perceptions of employees are categorized as automation-related performance optimism and automation-related job insecurity respectively. In our study, we integrated the measure of automation-related performance optimism into our model, expecting that there will be a significant and positive relationship between (1) automation-related performance optimism and organizational commitment, (2) automation-related performance optimism and job performance.

H3. There will be a positive relationship between automation-related performance optimism and organizational commitment.

H4. There will be a positive relationship between automation-related performance optimism and job performance.

2.7 Mediating effect of organizational commitment

Organizational commitment describes the relationship between employees and the organization (Bhende et al., 2020). An employee who is highly committed to the organization has a high loyalty; therefore, this employee will make an effort as much as possible to align with and contribute to accomplish the goals of the organization. Not surprisingly, it is usually described as employee loyalty (Sumarsi, 2020). If an employee feels and acts in a way that he is at the same side with the organization and shares the commons goals with the organization where the employee works and intends to continue his membership, then it is defined as organizational commitment as well (Tripathy, 2017). Conceptualized organizational commitment as an attitudinal approach, where organizational commitment is stated as 1) a strong will to stay a member of the company, 2) the will to strive according to the desires of the organization, 3) believing in and approving of the values and goals of the company.

Organizational psychology deals with commitment in various ways while conceptualizing and measuring it. A general approach to commitment found in the literature focuses on turnover rate, meaning that employees who are more committed to their organization are less likely to leave their firm. A model of commitment developed by Meyer & Allen (1987), three approaches were named as affective, continuance, and normative commitment. Even though similar to the previous literature, a link between the employees and organization that decreases the likelihood or turnover, the type and construct of that link is different. To be more precise, strong affective commitment means that an employee with a solid affective commitment remains because he/she wants to. On the other hand, an employee with a strong continuance commitment stays within the company because he/she needs to. Lastly, an employee with a strong normative commitment does not leave his/her company because he/she feels he/she ought to do so.

As stated by Meyer and Allen in their study (1990), affective, continuance, and normative commitment can be seen as distinguishable components of attitudinal commitment rather than types of it. Therefore, employees can experience these psychological states to various degrees. Even if the degree of each component can vary, the net sum of an employee's commitment to the organization can be derived from each of these separable states.

In this study, affective commitment scale items developed by Meyer and Allen (1990) are adopted. As these three forms, i.e., affective, continuance, and normative commitment, focus on different aspects of commitment of an employee, affective commitment focuses on whether an employee wants to stay at the organization. Where continuance commitment evaluates whether an employee needs to continue the organization's membership. Finally, normative commitment examines whether an employee stays at the organization because he/she feels he/she ought to do so. In the scope of this research, the willingness of an employee to stay at his/her organization is the subject of concern.

H5. There will be a negative relationship between organizational commitment and turnover intention.

H6. There will be a positive relationship between organizational commitment and job performance.

H7. Organizational commitment mediates the relationship between automation-related performance optimism and turnover intention.

In the research conducted by Li and Guo (2021), which focused on preschool educators in mainland China, the study aimed to explore the direct correlation between income and turnover intention, as well as the indirect relationship mediated by work–family conflict and organizational commitment. The findings indicated that organizational commitment served as a mediator in the relationship between income and turnover intention. We anticipate that our results will similarly demonstrate that organizational commitment mediates the relationship between automation-related performance optimism and turnover intention.

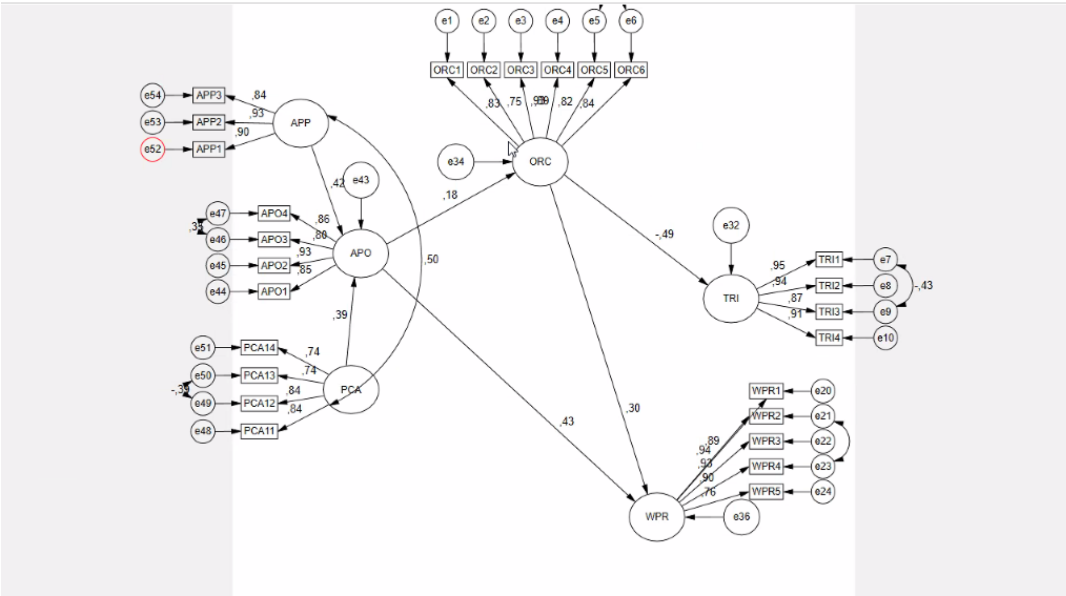

Figure 1. Hypothesized model (APP: Applying AI, ORC: Organizational commitment, APO: Automation-related performance optimism, PCA: Perceived automatability, TRI: Turnover intention, WPR: Job performance)

CHAPTER 3

METHODOLOGY AND DATA ANALYSIS

To be able to gather required quantitative and qualitative data from the market, an online survey is conducted. Complete list of the survey questions can be found in Appendix A (List of Measures) and Appendix B (Demographic and Job-Specific Questions). After the survey, collected data is analysed on Microsoft Excel, IBM SPSS and AMOS software.

3.1 Measures

Extensive literature review in conducted to synthesize the measures for similar constructs Five-point Likert scale is applied to assess the degree of agreement, 1 referring to “strongly disagree” and 5 referring to “strongly agree”.

Perceived Automatability. There are four statements assessing the individual’s level of agreement such as “AI automation will change how this job is performed in the future.” adapted from the research of Gödöllei & Beck (2023). We removed 2 reverse items from the scale for a simplicity purpose. Items were written to measure the degree of which employees believe that dimensions of their job are vulnerable to automation.

Automation-related Performance Optimism. This six-item scale is developed by Gödöllei and Beck (2023) to find out the degree of which people believe that automation will improve their capability to perform better. For instance, “AI Automation will enhance my work performance.”.

AI-literacy. Applying AI and *Understanding AI* scales are adapted from Ng et al. (2022), three-item scale is utilized for *Applying AI* and *Understanding AI* (e.g., I can use artificial intelligence meaningfully to achieve my goals). In this research, for the simplicity and meaningfulness purpose, we used the term “AI-literacy” while interpreting the results related with the scale *Applying AI.*

Organizational Commitment. Organizational commitment describes the relationship between employees and the organization (Bhende et al., 2020). In this study, affective commitment scale items developed by Meyer and Allen (1990) are adopted. As these three forms, i.e., affective, continuance, and normative commitment, focus on different aspects of commitment of an employee, affective commitment focuses on whether an employee wants to stay at the organization. Where continuance commitment evaluates whether an employee needs to continue the organization's membership. Finally, normative commitment examines whether an employee stays at the organization because he/she feels he/she ought to do so. In the scope of this research, the willingness of an employee to stay at his/her organization is the subject of concern, one of the items is as follows “I really feel as if this organization's problems are my own”.

Job Performance. We adapted 5-items from the 21-items scale developed by Williams and Anderson (1991) to measure performance. One of the items is “Fulfills responsibilities specified in job description”. The 21-items scale have three distinct types of performance, IRB (in-role behavior), OCBI (behaviors which provides benefit for individuals and indirectly contribute to the company), OCBO (behaviors that benefit the organization in general). We decided to use IRB which is a 7-items scale, and removed the reverse items, since IRB is defined as the behaviors which are defined by official reward systems and part of the necessities as defined in job descriptions.

Turnover Intentions. (adapted from Kelloway et al., 1999, also used by Gödöllei & Beck, 2023) We utilized 4-item scale developed by Kelloway et al. (1999) to evaluate individual's turnover intentions which was also used by Gödöllei & Beck (2023) to assess the negative effect of automation-related job insecurity on turnover intentions.

3.2 Results

3.2.1 Statistical techniques used in data analysis

In this research, the survey data collected from 220 participants were examined utilizing SPSS for Windows version 25.00 and AMOS version 24.0. The comprehensive frequency analysis of the sample presents demographic characteristics and descriptive information regarding work life in tabular form, accompanied by percentage values. A confirmatory factor analysis was conducted for the constructs included in the survey, such as AI literacy, perceived automatability, automation-related performance optimism, organizational commitment, job performance, and turnover intentions. The validity and reliability of these constructs were assessed through the calculation of Cronbach's alpha and the Average Variance Explained (AVE) values.

Examining discriminant validity among the variables assessed whether the distinction between the variables was adequate for structural equation modeling (SEM).

This model explored the influence of the variables Applying AI and perceived automatability on automation-related performance optimism. It also investigated the indirect impact of automation-related performance optimism on turnover intentions through organizational commitment and the direct effect of organizational commitment on turnover intentions. Additionally, the analysis included the indirect effect of automation-related performance optimism on job performance through organizational commitment, along with the indirect influence of Applying AI and perceived automatability on job performance via automation-related performance optimism.

Table 1. Demographic Characteristics of the Sample

		n	%
Gender	Female	77	35,0%
	Male	143	65,0%
Age group	21-25	29	13,2%
	26-30	62	28,2%
	31-35	47	21,4%
	36-40	27	12,3%
	41-45	16	7,3%
	46+	39	17,7%
Education	Less than a High School Diploma	2	0,9%
	High School Diploma (or High School Equivalence Certificate)	12	5,5%
	Bachelor's Degree	119	54,1%
	Master's Degree	71	32,3%
	Doctoral Degree	16	7,3%

3.2.2 Confirmatory factor analysis of the measures in the model

In confirmatory factor analysis, an increase in sample size, particularly in samples exceeding 200, results in a higher Chi-Square (χ^2) value, while the statistical significance level of the Chi-Square (χ^2) test diminishes (Bollen, 1989). The assessment of the measures employed in the research and the appropriateness of the tested models is determined by analyzing the Chi-Square (χ^2) value adjusted for degree of freedom (Chi-Square value/Degree of freedom), along with other goodness-of-fit indices and the standardized residual covariance matrix.

Table 2. Goodness of Fit Indexes Utilized in the Confirmatory Factor Analysis

Index	Good fit	Acceptable fit
x^2 / df	$0 \leq \chi 2/df \leq 2$	$2 < \chi 2/df \leq 3$
GFI	$\geq 0,85$	0,85-0,89
CFI	$\geq 0,97$	, $\geq 0,95$
SRMR	$\leq 0,05$	,06 $\leq$ SRMR $\leq$,08
RMSEA	$\leq 0,05$	,06 $\leq$ RMSEA $\leq$,08

(GFI: Goodnes of fit, CFI: Comparative fit, SRMR: Standardized Root Mean Square Residual, RMSEA: Root Mean Squared Error)

*Meydan, 2011

3.2.3 Confirmatory factor analysis for applying understanding AI

In the confirmatory factor analysis conducted on a measure comprising six items across two dimensions, the standard factor loadings ranged from .85 to .93 for the Applying AI dimension, and from .76 to .89 for the Understanding AI dimension. A positive and significant covariance of .71 was observed between the Applying AI and Understanding AI dimensions. Applying AI dimension was picked to be used in our model, since there is a relatively high covariance between Applying AI and Understanding AI.

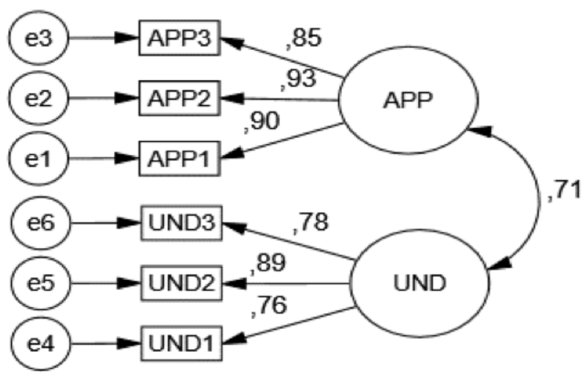

Figure 2. Confirmatory factor analysis dimension structure of applying and understanding AI measure

In the confirmatory factor analysis, the model index values are calculated as x^2 (12.537), x^2/df (.129) given that (P>0.05) indicates that the analysis is significant. The fit index values of the model (GFI (.982), CFI (.995), SRMR (.0207), and RMSEA (.050)), fall within the acceptable range for good fit, thereby confirming the structural validity of the measure. Table 3 shows the standard factor loadings and significance values derived from the confirmatory factor analysis.

Table 3. Confirmatory Factor Analysis Parameter Table of Applying AI and Understanding AI Measure

Componenet		İtem	Estimate	Std. estimate.	Z	P
APP	→	APP1	1,000	,896	-	-
APP	→	APP2	1,163	,927	20,328	***
APP	→	APP3	1,020	,848	17,346	***
UND	→	UND1	1,00	,760	-	-
UND	→	UND2	1,023	,894	12,669	***
UND	→	UND3	,843	,776	11,419	***

****p<0,001 **p<0,01*

The standard factor loadings for all items in the measure found higher than (0.50) and significant (p<0.05). These results indicate that the Applying Understanding AI measure is valid for our sample.

3.2.4 Confirmatory factor analysis for perceived automatability

In the confirmatory factor analysis run for Perceived Automatability (PCA), which includes four items within a single dimension, due to the presence of satisfactory factor loading values (FY>0.5) all items are decided to be remained. The factor loading values observed in this analysis ranged from .71 to .85. To enhance the model parameters, a modification was made between the second and third items, which are identified as evaluating the future prospects of jobs in relation to AI-driven automation and the potential for these jobs to be automated by AI.

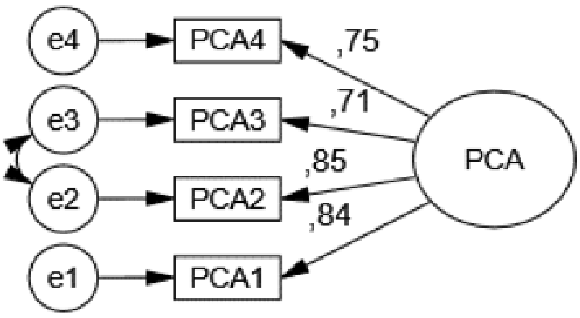

Figure 3. Confirmatory factor analysis dimension structure of perceived automatability measure

The model fit values derived from the confirmatory factor analysis indicate significance, as evidenced by P>0.05, with x^2 (.685) and x^2/df (.685). Furthermore, the fit index values of the model, including GFI (.998), CFI (1.00), SRMR (.0082), and RMSEA (.000), fall within the acceptable range for good fit. This suggests that the structural validity of the scale for the research sample is confirmed. The standard factor loadings along with their significance values obtained from the confirmatory factor analysis are detailed in Table 4.

Table 4. Confirmatory Factor Analysis Parameter Table of Perceived Automatability Measure

Component		Item	Estimate	Std. estimate.	Z	P
PCA	→	IT1	1,000	,840	-	-
PCA	→	IT2	1,068	,849	12,825	***
PCA	→	IT3	,759	,708	10,206	***
PCA	→	IT4	,997	,749	12,405	***

***p<0,001 **p<0,01

The standard factor loadings of the items in the analysis were found to be higher than (0.50) and significant (p>0.05). According to the results achieved, it can be stated that the Perceived Automatability measure is valid for the sample.

2.5 Confirmatory factor analysis for automation-related performance optimism (APO)

In the confirmatory factor analysis conducted on the Automation-related Performance Optimism measure (APO), which consists of four items and is recognized as a one-dimensional scale in existing literature, no items were removed from the analysis due to their standard factor loading values (FY>0.5). The analysis was completed with all four items retained. The factor loading values observed in the analysis ranged from (.79 to .93). To enhance the model parameters, a modification connection was established between the third and fourth items, which emphasize the advantages of artificial intelligence, such as allowing workers to concentrate on more critical tasks and augmenting their skill sets.

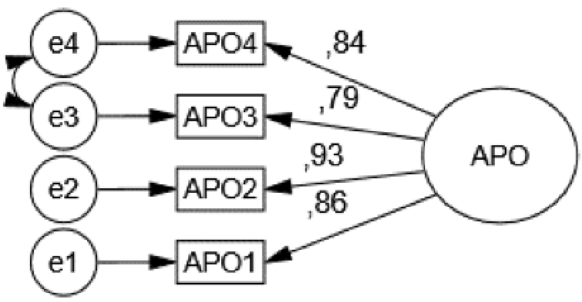

Figure 4. Confirmatory factor analysis dimension structure of automation-related performance optimism measure

In the confirmatory factor analysis, the model fit values indicate significance, with P<0.05, and the results show x^2 (.941) and x^2/df (.941). The fit index values for the model are GFI (.998), CFI (1.00), SRMR (.0046), and RMSEA (.000), all of which fall within acceptable limits for a good fit. This suggests that the structural validity of the measure is confirmed for the research sample. The standard factor loadings and their corresponding significance values derived from the confirmatory factor analysis are detailed in Table 5.

Table 5. Confirmatory Factor Analysis Parameter Table of Automation-Related Performance Optimism Measure

Component		Item	Estimate	Std. estimate.	Z	P
APO	→	APO	1,000	,860	-	-
APO	→	APO	1,035	,932	18,103	***
APO	→	APO	,869	,793	14,293	***
APO	→	APO	,872	,845	15,921	***

****p<0,001 **p<0,01*

The standard factor loadings of the items in the analysis were found to be higher than (0.50) and significant (p<0.05). According to the results achieved, it can be stated that the Automation-related Performance Optimism measure is valid for the sample.

3.2.6 Confirmatory factor analysis for organizational commitment (ORC)

In the confirmatory factor analysis performed for the Organizational Commitment scale (ORC), which consists of six items and is recognized as a unidimensional scale in the literature, no items were removed from the analysis due to their standard factor loading values (FD>0.5). The analysis was completed with all six items retained. The factor loading values observed in the analysis ranged from .75 to .89. To enhance the model parameters, a modification connection was established between the fifth and sixth items. These items evaluate the extent to which an employee feels a sense of belonging within the organization and the personal significance it holds for them; consequently, they are perceived as closely related by the participants.

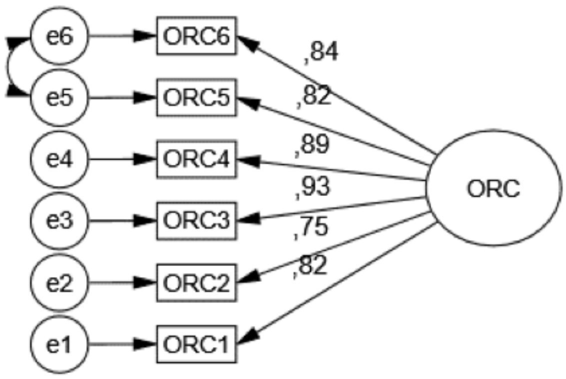

Figure 5. Confirmatory factor analysis dimension structure of organizational commitment measure

In the confirmatory factor analysis, the model fit values indicated significance, with P<0.05, and the results were x^2 (17.086) and x^2/df (2.136). The fit index values for the model, including GFI (.977), CFI (.992), SRMR (.01556), and RMSEA (.072), fall within the acceptable limits, confirming the structural validity of the scale for the research sample. The standard factor loadings and their corresponding significance values derived from the confirmatory factor analysis are detailed in Table 6.

Table 6. Confirmatory Factor Analysis Parameter Table of Organizational Commitment Measure

Component		Item	Estimate	Std. estimate.	Z	P
ORC	→	ORC1	1,000	,824	-	-
ORC	→	ORC2	,891	,752	12,807	***
ORC	→	ORC3	1,087	,929	17,674	***
ORC	→	ORC4	1,067	,890	16,526	***
ORC	→	ORC5	,991	,818	14,449	***
ORC	→	ORC6	,967	,840	15,058	***

***p<0,001 **p<0,01

The standard factor loadings of the items in the analysis were found to be higher than (0.50) and significant (p<0.05). According to the results achieved, it can be stated that the organizational commitment scale is valid for the sample.

3.2.7 Confirmatory factor analysis for job performance (WPR)

In the confirmatory factor analysis performed for the Job Performance measure (WPR), which consists of a five-item, one-dimensional scale recognized in the literature, no items were removed from the analysis due to their standard factor loading values (FD>0.5). The analysis was completed with all five items retained. The factor loading values were observed to range from (.75 to .95). To enhance the model parameters, a modification connection was established between the second and fourth items. These two items evaluate the extent to which employees meet their job responsibilities and requirements, leading participants to perceive them as closely related.

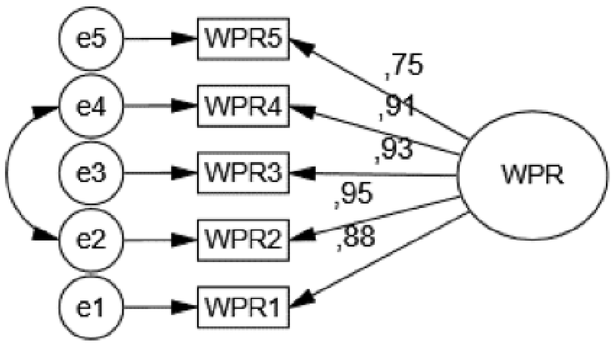

Figure 6. Confirmatory factor analysis dimension structure of job performance measure

In the confirmatory factor analysis, the model fit values indicated significance, with P<0.05, and the results were x^2 (5.460) and x^2/df (1.365). The fit index values for the model, including GFI (.990), CFI (.999), SRMR (.0108), and RMSEA (.041), fell within the acceptable range for good fit, demonstrating that the structural validity of the scale was established for the research sample. The standard factor loadings and their corresponding significance values derived from the confirmatory factor analysis are detailed in Table 7.

Table 7. Confirmatory Factor Analysis Parameter Table of Job Performance Measure

Component		Item	Estimate	Std. estimate.	Z	P
WPR	→	WPR1	1,000	,885		
WPR	→	WPR2	1,081	,947	22,446	***
WPR	→	WPR3	1,016	,929	22,087	***
WPR	→	WPR4	1,103	,905	19,991	***
WPR	→	WPR5	,899	,754	14,368	***

***p<0,001 **p<0,01

The standard factor loadings of the items in the analysis were found to be higher than (0.50) and significant ($p<0.05$). According to the results achieved, it can be stated that the job performance measure is valid for the sample.

3.2.8 Confirmatory factor analysis for turnover intention (TRI)

In the confirmatory factor analysis performed for the Turnover Intention measure (TRI), a one-dimensional scale consisting of four items, no items were removed from the analysis due to satisfactory standard factor loading values (FY>0.5). The analysis ultimately included four items. The factor loading values were observed to range from .87 to .95. To enhance the model parameters, a modification connection was established between items 1 and 3.

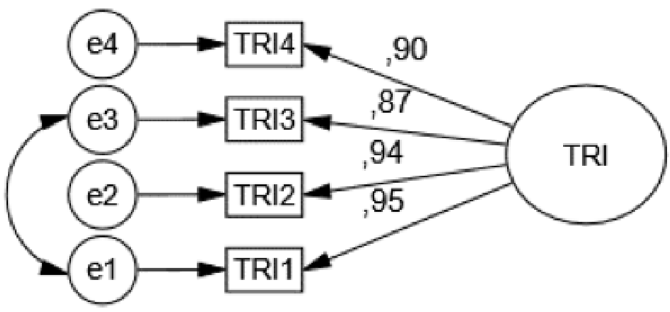

Figure 7. Confirmatory factor analysis dimension structure of turnover intension measure

In the confirmatory factor analysis, the model fit values ($P>0.05$) are indicated as x^2 (.363) and x^2/df (.363), demonstrating that the analysis is statistically significant. The fit index values for the model, including GFI (.999), CFI (1.00), SRMR (.0026), and RMSEA (.000), fall within the acceptable range for good fit, confirming the structural validity of the scale for the research sample. The standard factor loadings and their corresponding significance values derived from the confirmatory factor analysis are detailed in Table 8.

Table 8. Confirmatory Factor Analysis Parameter Table of Turnover Intension Measure

Component		Item	Estimate	Std. estimate.	Z	P
TRI	→	TRI1	1,000	,953	-	-
TRI	→	TRI2	,978	,939	27,993	***
TRI	→	TRI3	,920	,868	18,590	***
TRI	→	TRI4	,953	,905	24,565	***

***p<0,001 **p<0,01

The standard factor loadings of the items in the analysis were found to be higher than (0.50) and significant ($p<0.05$). According to the results achieved, it can be stated that the turnover intention measure is valid for the sample.

3.2.9 Confirmatory factor analysis for the measurement model including all variables

The measurement model, comprising 26 items across 6 dimensions, demonstrated standard factor loading values (FD>0.5) during the confirmatory factor analysis, resulting in no items being removed from the analysis. The factor loading values were observed to range from .74 to .95. The graphical representation of the model is illustrated in Figure 8.

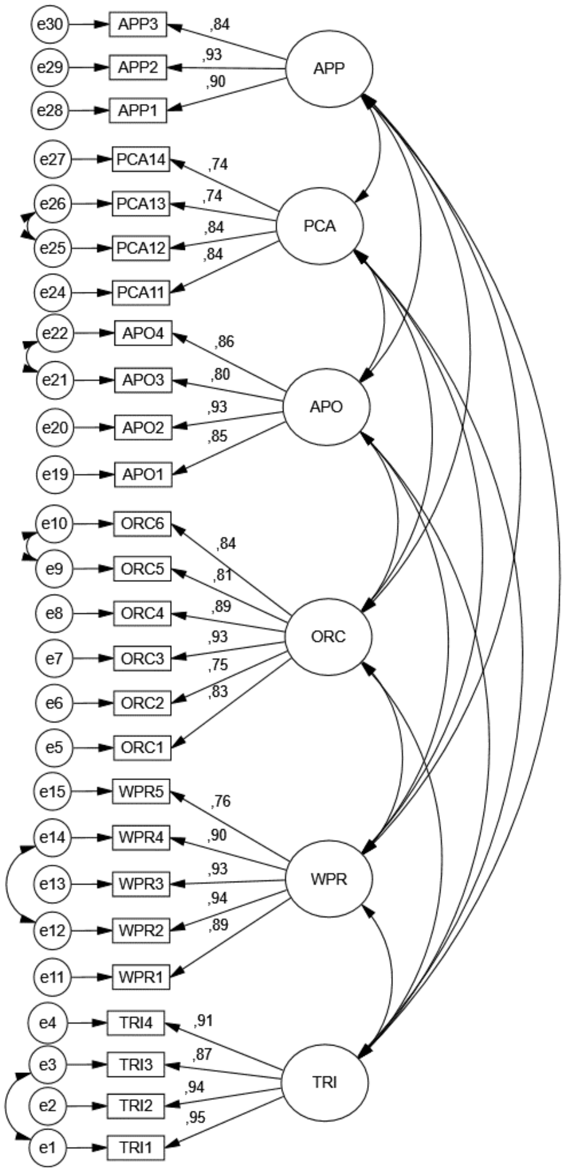

Figure 8. Confirmatory factor analysis for the measurement model including all variables x^2

In the confirmatory factor analysis of the measurement model, the model fit values indicated significance, with P>0.05, which were recorded at x^2 (424.346) and x^2/df (1.521). This suggests that the confirmatory factor analysis is statistically significant. Furthermore, the fit index values for the model, (GFI (.876), CFI (.972), SRMR (.0479), and RMSEA (.049)), resulted within the acceptable limits, therefore we confirm the structural validity of the model for our sample. The standard factor loadings along with their significance values calculated from the confirmatory factor analysis are listed in Table 9.

Table 9. Confirmatory Factor Analysis Parameter Table for the Model

Component		Item	Estimate	Std. estimate.	Z	P
TRI	→	TRI1	1,000	,949		
TRI	→	TRI2	,986	,942	28,138	***
TRI	→	TRI3	,921	,865	18,578	***
TRI	→	TRI4	,960	,907	24,604	***
ORC	→	ORC1	1,000	,832		
ORC	→	ORC2	,882	,751	12,956	***
ORC	→	ORC3	1,074	,927	18,055	***
ORC	→	ORC4	1,056	,889	16,838	***
ORC	→	ORC5	,976	,814	14,556	***
ORC	→	ORC6	,956	,839	15,292	***
WPR	→	WPR1	1,000	,887		
WPR	→	WPR2	1,073	,942	22,378	***
WPR	→	WPR3	1,018	,932	22,353	***
WPR	→	WPR4	1,098	,903	20,053	***
WPR	→	WPR5	,904	,759	14,543	***
APO	→	APO1	1,000	,852		
APO	→	APO2	1,043	,931	18,298	***
APO	→	APO3	,882	,797	14,308	***
APO	→	APO4	,891	,855	16,109	***
PCA	→	PCA1	1,000	,837		
PCA	→	PCA2	1,058	,838	13,360	***
PCA	→	PCA3	,796	,740	11,271	***
PCA	→	PCA4	,990	,741	12,335	***
APP	→	APP1	1,000	,901		
APP	→	APP2	1,157	,928	20,631	***
APP	→	APP3	1,005	,840	17,227	***

***p<0,001 **p<0,01 *APP: Applying AI PCA: Perceived Automatability APO: Automation-related Performance Optimism ORC: Organizational Commitment WPR : Job Performance TRI: Turnover Intention*

The standard factor loadings of the items in the model were found to be higher than (0.50) and significant (p<0.05). These results indicate that the measurement model is valid for our sample.

3.2.10 Convergence and discriminant validity for measure sub-dimensions

Composite reliability (CR) values are derived from the factor loadings obtained through confirmatory factor analysis of the model. Composite reliability is satisfied if CR found as ≥0.70 (Raykov, 1997).

Convergence validity is confirmed by AVE≥0.50 (average variance explained). However, when overall CR is found as ≥0.70, AVE≥0.40 can be accepted. The square root of AVE must be higher than the correlation values present in the same row and column (Fornell and Larcker, 1981) for discriminant validity to be confirmed.

Table 10. Convergent and Discriminant Validity Values Calculated From Standard Factor Loadings

Component	x	SD	APP	PCA	APO	ORC	WPR	TRI
APP	4,10	,79	(,890)					
PCA	3,82	,83	,452**	(,790)				
APO	4,00	,82	,560**	,527**	(,860)			
ORC	3,46	,98	,242**	,142*	,149*	(,887)		
WPR	4,14	,70	,515**	,376**	,452**	,375**	(,843)	
TRI	2,52	1,10	,104	,134*	,110	-,474**	,006	(,916)
Cronbach's Alpha			,918	,855	,924	,938	,943	,951
CR			,920	,869	,919	,948	,937	,954
AVE			,793	,625	,740	,787	,712	,840

****p<0.001 **p<0.01 *p<0.05   APP: Applying AI PCA: Perceived Automatability APO: Automation-related Performance Optimism   ORC: Organizational Commitment WPR : Job Performance TRI: Turnover Intentions*

The reliability coefficients of the scales utilized in the study for the sample were identified as follows: the applying AI variable recorded a value of (.912), the perceived automatability variable was (.855), the automation-related performance optimism variable achieved (.924), the organizational commitment variable reached (.938), the job performance variable was (.943), and the turnover intention variable was (.951). Consequently, all measures demonstrated a high degree of reliability (Alpha ≥ 0.80). The CR values were found as follows: (.920) for the applying AI variable, (.869) for the perceived automatability variable, (.919) for the automation-related performance optimism variable, (.948) for the organizational commitment variable, (.937) for the job performance variable, and (.954) for the turnover intention variable.

The computed coefficients for all scales indicate that the composite reliability values (CR≥0.70) are satisfactory, confirming that the condition for composite reliability is fulfilled. Additionally, the AVE for all variables found as ≥0.50, therefore the requisite condition for convergent validity is satisfied. The square root results of AVE values, which are essential for assessing discriminant validity, are presented in parentheses. As these values are higher the correlation values in the corresponding rows and columns, it can be concluded that discriminant validity is achieved.

3.2.11 SEM path analysis applied to the observed values of the research model

For structural equation modeling (SEM), models serve as foundational elements which are designed to assess the presence of mediator or moderator variables (Kline, 2005). Lately, practices have shifted towards evaluating their statistical significance through the bootstrapping method, which typically involves a minimum of 2000 resamples to establish a 95% Confidence Interval (CI), rather than relying on the Sobel test (Preacher and Hayes, 2008); since the indirect effects within these models frequently do not comply with the assumption of normal distribution.

In the model, the effects of the *applying AI* and *perceived automatability* variables on the *automation-related performance optimism* variable, the indirect effect of the *automation-related performance optimism* variable on the *turnover intention* variable via *organizational commitment*, and the direct effect of the *organizational commitment* variable on the *turnover intention* variable were examined. The indirect effect of the *automation-related performance optimism* variable on the *job performance* variable via the *organizational commitment* variable and the indirect effect of the *applying AI* and *perceived automatability* variables on the *job performance* variable via the *automation-related performance optimism* variable were also investigated in the model. The graphical structure of the model drawn in the AMOS program is given in Figure.

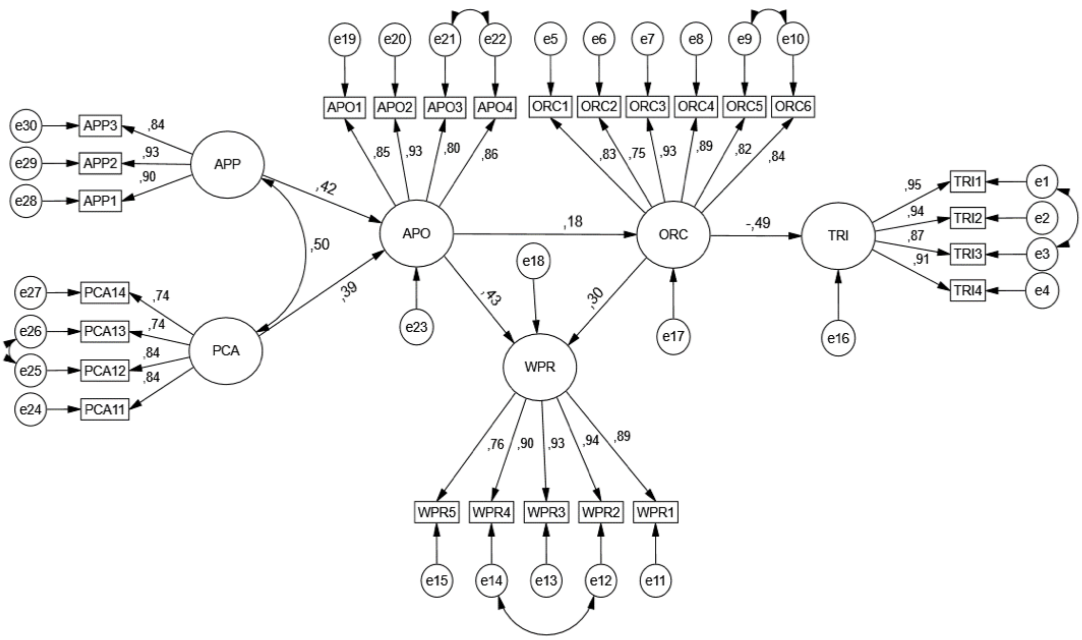

Figure 9. Mediator model path analysis with latent variables (bootstrap n=5000)

In the model where latent variables are used, the model test values (given that $p<0.05$) are found as x^2 (474.863), x^2/df (1.655), therefore it is concluded that the model is significant. Since the fit index values of the model GFI (.862), CFI (.964), SRMR (.0761), RMSEA (.0550) are within the acceptable fit limits, it is confirmed that the model is valid. The model regression parameters are given in Table 11, and the detailed values related to the mediator hypotheses are given in Table 12.

Table 11. Significance Test of Direct Regression Coefficients in the Model

Exogen		Endogen	Estimate	Std. estimate	Z	P	Hypothesis
PCA	→	APO	,392	,394	5,609	***	Accept
APP	→	APO	,474	,417	6,050	***	Accept
APO	→	ORC	,209	,179	2,485	,013*	Accept
ORC	→	TRI	-,570	-,486	-7,282	***	Accept
ORC	→	WPR	,211	,297	4,744	***	Accept
APO	→	WPR	,356	,430	6,604	***	Accept

***p<0,001 **p<0,01 *p<0,05 *APP: Applying AI PCA: Perceived Automatability APO: Automation-related Performance Optimism ORC: Organizational Commitment WPR : Job Performance TRI: Turnover Intentions*

In Table 11, where the impacts of direct regression are examined in the path analysis model with observed variables, it was determined that all direct effects are significant ($p<0.05$). Accordingly, the effect of *perceived automatability* on *automation-related performance optimism* (β=, 394; $p<0.05$) was found positive and significant. Therefore, the increase in *perceived automatability* directly increases *automation-related performance optimism*.

The effect of *applying AI* on *automation-related performance optimism* (β=, 417; $p<0.05$) was found positive and significant. Therefore, the increase in *applying AI* directly increases *automation-related performance optimism*.

The effect of *automation-related performance optimism* on *organizational commitment* (β=, 179; $p<0.05$) was found positive and significant. Therefore, the increase in *automation-related performance optimism* directly increases *organizational commitment*. The effect of *organizational commitment* on *turnover intention* (β=-

.486; $p<0.05$) was found negative and significant. Therefore, the increase in *organizational commitment* has a direct decreasing effect on *turnover intention*.

The effect of *organizational commitment* on *job performance* (β=.297; $p<0.05$) was found positive and significant. Accordingly, the increase in *organizational commitment* directly increases *job performance*.

The effect of *automation-related performance optimism* on *job performance* (β=.430; $p<0.05$) was found positive and significant. Accordingly, the increase in *automation-related performance optimism* directly increases *job performance*.

Table 12. Significance Test of Indirect Effects (Mediation) in the Model

Pattern	Indirect effect	Std. indirect effect	P	Hypothesis
APP→APO→WPR	,190	,201	,003**	Accept (FM)
APP→APO→ORC	,099	,085	,047*	Accept (FM)
PCA→APO→WPR	,157	,190	,006**	Accept (FM)
PCA→APO→ORC	,082	,091	,024*	Accept (FM)
APO→ORC→WPR	,054	,072	,030*	Accept (PM)
APO→ORC→TRI	-,119	-,103	,014*	Accept (FM)

***p<0,001 **p<0,01 *p<0,05 *FM:Full mediating PM:Partial mediating APP: Applying AI PCA: Perceived Automatability APO: Automation-related Performance Optimism ORC: Organizational Commitment WPR : Job Performance TRI: Turnover Intention*

In the model, the indirect effect of *automation-related performance optimism* on *turnover intention* via *organizational commitment*, the indirect effect of the *automation-related performance optimism* on *job performance* via *organizational commitment*, and the indirect effects of *applying AI* and *perceived automatability* on *job performance* via *automation-related performance optimism* were investigated. The bootstrap method (n=5000) was preferred to examine the mediation hypotheses. All six mediation hypotheses tested in the model were confirmed.

The indirect effect of the *applying AI* on the *job performance* via *automation-related performance optimism* (β= .201; $p<0.05$) was found to be positive and significant. Accordingly, *automation-related performance optimism* plays a full mediator role in the effect of *applying AI* on *job performance*.

The indirect effect of the *applying AI* variable on the *organizational commitment* variable via the *automation-related performance optimism* variable (β= .085; $p<0.05$) was found to be positive and significant. Accordingly, the *automation-related performance optimism* plays a full mediator role in the effect of the *applying AI* variable on the *organizational commitment* variable.

The indirect effect of the *perceived automatability* variable on the *job performance* variable via the *automation-related performance optimism* variable (β= .190; $p<0.05$) was found to be positive and significant. Accordingly, the *automation-related performance optimism* variable plays a full mediator role in the effect of the *perceived automatability* variable on the *job performance* variable.

The indirect effect of the *perceived automatability* variable on the *organizational commitment* variable via the *automation-related performance optimism* variable (β= .091; $p<0.05$) was found to be positive and significant. Accordingly, the *automation-related performance optimism* variable plays a full mediator role in the effect of the *perceived automatability* variable on the *organizational commitment* variable.

The indirect effect of the *automation-related performance optimism* variable on the *job performance* variable via the o*rganizational commitment* variable (β= .072; $p<0.05$) was detected as positive and significant. Accordingly, the o*rganiza-*

tional commitment variable plays a partial mediator role in the effect of the a*utomation-related performance optimism* variable on the *job performance* variable. (Partial since APOWPR is significant).

The indirect effect of the *automation-related performance optimism* variable on the *turnover intention* variable via the *organizational commitment* variable (β= -.103; $p<0.05$) was detected as negative and significant. Accordingly, the *organizational commitment* variable plays a full mediator role in the effect of the *automation-related performance optimism* variable on the *turnover intentions* variable.

CHAPTER 4

CONCLUSION

This study is made based on the survey data collected from 220 participants from various sectors, backgrounds, departments, organizations, ages, genders to understand the perceptions of employees of AI driven automation and their behavioral reactions to it in a better and deeper way through examining the relationships between AI-literacy, perceived automatability, automation-related performance optimism, organizational commitment, job performance and turnover intention. We tested our hypotheses and SEM model, all of the hypotheses have been accepted and the model has been found meaningful, thus all dimensions in the model have functioned properly and distinctively. Six mediating roles have been found, five of them confirmed as full moderating effect and one of them is partial moderating effect. 6 direct relationships have been found significant as well.

In conclusion, we found out that perceived automatability (PCA) has a positive and significant relationship with automation-related performance optimism (APO) ($p<0.001$). These results conform with previous research (Gödellei & Beck, 2023), we decided it will be useful to examine the relationship between AI-literacy (APP) and automation-related performance optimism (APO), since understanding this relationship will shed light to employees' approach to AI, and it will enlighten a path for organizations to shape the experience of employees through training and innovation competitions to scale up employees knowledge and ability to interact with AI through their work processes. As we expected, AI-literacy (APP) has a positive and significant relationship with automation-related performance optimism (APO) ($p<0.001$). These findings are helpful to better understand the factors contributing employees' performance optimism regarding automation especially from managerial perspective and viewpoint of human resources management.

We incorporated organizational commitment (ORC) into our model since it's defined as an important factor of psychological state of an employee. Such that, employees who displays high organizational commitment are expected to be beneficial to their organization by engaging in behaviors like high performance and citizenship activities (Jaros, 1997). We found that there is a significant and positive relationship between automation-related performance optimism (APO) and organizational commitment (ORC) ($p<0.05$). On the other hand, the relationship between organizational commitment (ORC) and turnover intention (TRI) found to be significant and negative ($p<0.001$). We utilized social exchange theory (Blau, 1964) to explain the relationship between organizational commitment (ORC) and turnover intention (TRI), since this theory states that if employees are satisfied with their organizations in terms of benefits provided for them, they tend to have higher organizational commitment and they want to reciprocate what they received from the organization. Previous research include example of incorporating social exchange theory to understand the relationship between organizational commitment and turnover intention (Li et al., 2021). The full moderating effect of organizational commitment (ORC) found on the relationship between automation-related performance optimism (APO) and turnover intention which is in negative direction. Similarly, previous studies discovered that organizational commitment has a partial moderating effect on the relationship between income and turnover intention (Li, 2018). Also, we found that organizational commitment (ORC) has a partial moderating effect on the relationship between automation-related performance optimism (APO) and job performance (WPR).

Also, we examined the relationship between organizational commitment (ORC) and job performance (WPR) which has been found significant and positive ($p<0.001$). These results conform with the social exchange theory as well, and it is consistent with the previous research (Meyer et al., 1989, Rafiei et al., 2014). Another finding is that there is a positive and significant relationship between automation-related performance optimism (APO) and job performance (WPR), which we believe will be very insightful for organizations to focus more on the employees' view on AI driven automation to increase job performance.

Without any doubts, automation-related performance optimism (APO) plays a substantial role in our model. Four of the six moderating roles are performed by automation-related performance optimism APO, and the moderating effect is full moderation. These relationships are listed as: (1) the relationship between AI-literacy (APP) and job performance (WPR), (2) the relationship between AI-literacy (APP) and organizational commitment (ORC), (3) the relationship between perceived automatability (PCA) and job performance (WPR) and (4) the relationship between perceived automatability (PCA) and organizational commitment (ORC). These results again emphasize the importance of performance optimism of employees regarding automation due to their effect on job performance and organizational commitment.

These results shed light to the perceptions and emotional and behavioral reactions of employees as they encounter with AI driven automation within their organization.

Further study can be made on sector-specific and longitudinal effects of AI and automation applications as current studies usually generalizes findings across industries and are cross-sectional. Few studies have examined interventions or organizational strategies that can mitigate the negative effects of perceived automation risks on employee commitment (Dabbous et al., 2022; Vishwanath & Vaddepalli, 2023), e.g. include training programs, communication strategies, or employee involvement initiatives; however, there is still a need to understand the effects of interventions by organizations more comprehensively.

APPENDIX A

LIST OF MEASURES

AI for Process Automation (adapted from Yu et al., 2024).

Please indicate the degree of your consent about the AI applications for process automation in your company, for instance, intelligent optimization of business processes, robotic automation of workflows, smart copywriting, etc.

1. Faster adaptation to changes toward more efficient workflow processes by AI
2. Quickly transferring and integrating data across different boundaries (e.g., organizations, departments, and systems) by AI
3. Enabling efficient collaboration between people, between systems, or between people and systems by AI
4. Facilitating seamless connection between different business processes through AI

Perceived Automatability (adapted from Gödöllei & Beck, 2023).

1. AI automation will change how this job is performed in the future.
2. In the future, this job will look very different because of AI automation.
3. Some of the tasks performed on this job can be AI automated.
4. Many aspects of this job can be automated by AI.

AI Automation-related Job Insecurity (adapted from Brougham & Haar 2018)

1. I think my job could be replaced by AI automation.

2. I am personally worried that what I do now in my job will be able to be replaced by AI automation.

3. I am personally worried about my future in my organization due to AI automation replacing employees.

4. I am personally worried about my future in my industry due to AI automation replacing employees.

Automation-related Performance Optimism (adapted from Gödöllei & Beck, 2023).

1. AI Automation will enable me to perform my job better.

2. AI Automation will enhance my work performance.

3. AI Automation will enable me to focus on the more important parts of my job.

4. AI can complement my current skill set to enable me to work better.

Applying AI (adapted from Ng et al., 2022)

1. I can use AI applications to make my life easier.

2. I can use artificial intelligence meaningfully to achieve my goals.

3. I can interact with AI in a way that makes my tasks easier.

Understanding AI (adapted from Ng et al., 2022)

1. I know the most important concepts in artificial intelligence.

2. I can assess what advantages and disadvantages the use of an artificial intelligence entails.

3. I can imagine possible future uses of AI

AI Automation Risk

My organization is facing the risk of AI automation.

My occupation is facing the risk of AI automation.

My job is facing the risk of AI automation.

Job Satisfaction (adapted from Camman et al., 1979).

1. All in all, I am satisfied with my job.

2. In general, I don't like my job.

3. In general, I like working here.

Organizational Commitment (adapted from Allen & Meyer, 1990)

1. I would be very happy to spend the rest of my career with this organization.
2. I really feel as if this organization's problems are my own.
3. I feel a strong sense of "belonging" to my organization.
4. I feel "emotionally attached" to this organization.
5. I feel like "part of the family" at my organization.
6. This organization has a great deal of personal meaning for me.

Occupational Commitment (adapted from Meyer et al., 1993)

1. This occupation is important to my self-image.

2. I am happy to have entered this occupation.

3. I am proud to be in the field of this occupation.

4. I like being in this occupation.

5. I strongly identify with this occupation.

6. I am enthusiastic about this occupation.

Original:

1. Nursing is important to my self-image.

2. I regret having entered the nursing profession. (R)

3. I am proud to be in the nursing profession.

4. I dislike being a nurse. (R)

5. I do not identify with the nursing profession. (R)

6. I am enthusiastic about nursing.

Job Performance (adapted from Williams and Anderson, 1991)

1. I adequately complete assigned duties at the unit I'm working at.

2. I fulfill responsibilities specified in job description.

3. I perform tasks that are expected of me.

4. I meet formal performance requirements of the job.

5. I engage in activities that will directly affect my performance evaluation.

Turnover Intentions (adapted from Kelloway et al., 1999)

1. I am thinking about leaving this organization.

2. I am planning to look for a new job.

3. I intend to ask people about new job opportunities.

4. I don’t plan to be in this organization much longer.

APPENDIX B

DEMOGRAPHIC AND JOB-SPECIFIC QUESTIONS

1. What is your gender? Male / Female

2. Please indicate your age.

3. Indicate the highest level of education that you have completed (please check only one box):

Less than a High School Diploma

High School Diploma (or High School Equivalence Certificate)

Bachelor's Degree

Master's Degree

Doctoral Degree

4. Please specify the business sector in which your firm operates (please tick one box only).

Agri/Food

PharmaChem

Medical Devices

Aerospace

Education

Healthcare Provision

Information Communications Technology

Telecommunications

Financial Services/Banking

Business Services/Consulting

Social/Community Services

Retail and wholesale

Hotels and restaurants (tourism-dependent, hotels, catering)

Arts & Culture

Transport and distribution (transport, storage)

Construction

Electrical/household appliances

Other (please specify)

5. Which of the following business functions best describes where you primarily work?

Manufacturing/operations

Frontline service delivery

Customer/shared services

Logistics/supply chain

Sales/marketing

Product management

Project management

Research & development

Finance

IT

Legal/regulatory/quality

Human resources

Business strategy/corporate development

Environment/sustainability/health & safety

Other (Please specify)

6. How many people in total work at your workplace, that is at the local site where you work?

1-9

10-49

50-99

100-249

250-499

500 and over

7. How long have you worked at this job (in years)?

8. Are you working in a managerial position? Yes / No

REFERENCES

Acemoglu, Daron, & David Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of labor economics*. Vol. 4, 1043–1171.

Acemoglu, Daron, and Pascual Restrepo. 2018a. "Artificial intelligence, automation and work." *National Bureau of Economic Research*.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). AI-Powered innovation in digital transformation: Key pillars and industry impact. *Sustainability*, *16*(5), 1790.

Alekseeva, L., Azar, J., Gine, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, *71*, 102002. https://doi.org/10.1016/j.labeco.2021.102002

Allen, N. J., & Meyer, J. P. (1990). The measurement and antecedents of affective, continuance and normative commitment to the organization. *Journal of occupational psychology*, *63*(1), 1-18.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2017. "Revisiting the risk of automation." *Economics Letters*, *159*: 157–160.

Bessen, J.E. (2016), "How computer automation affects occupations: Technology, jobs, and skills", Boston University School of Law, *Law & Economics Working Paper* No. 15-49, Boston University.

Blau, P. (1964). *Exchange and power in social life*. New York: Wiley

Blau, G. (1985). The measurement and prediction of career commitment. *Journal of Occupational Psychology*, *58*, 277–288.

Blau, G. (2003). Testing for a four-dimensional structure of occupational commitment. *Journal of Occupational and Organizational Psychology*, *76*(4), 469-488.

Bowen, D. E. (2016). The changing role of employees in service theory and practice: An inter-disciplinary view. *Human Resource Management Review*, *26*(1), 4–13.doi:10.1016/j.hrmr.2015.09.002

Bresnahan, Timothy F, and Manuel Trajtenberg. 1995. "General purpose technologies 'Engines of growth'?" *Journal of Econometrics*, *65*(1): 83–108.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company: NY.

Cedefop (2018). *Insights into skill shortages and skill mismatch: learning from Cedefop's European skills and jobs survey*. Luxembourg: Publications Office. Cedefop reference series; No 106. http://www.cedefop.europa.eu/en/publications-and-resources/publications/3075

Cheng, M. M., & Hackett, R. D. (2019). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review*, 100698.

Choi, D. Y., & Kang, J. H. (2019). Net job creation in an increasingly autonomous economy: The challenge of a generation. *Journal of Management Inquiry*, *28*(3), 300–305.

Colombo, E., Mercorio, F., & Mezzanzanica, M. (2019). AI meets labor market: Exploring the link between automation and skills. *Information Economics and Policy*, *47*, 27-37.

Dabbous, A., Aoun Barakat, K., & Merhej Sayegh, M. (2022). Enabling organizational use of artificial intelligence: an employee perspective. *Journal of Asia Business Studies*, *16*(2), 245-266.

Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. New York: Harper Business.

David, H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/ 10.1257/jep.29.3.3.

DeCanio, S.J. (2016). "Robots and humans-complements or substitutes", *Journal of Macroeconomics*, Vol. 49, pp. 280-291.

Dinc, M. S. (2017). Organizational commitment components and job performance: Mediating role of job satisfaction. *Pakistan Journal of Commerce and Social Sciences* (PJCSS), *11*(3), 773-789.

Felten, Edward W, Manav Raj, and Robert Seamans. 2018. "A method to link advances in artificial intelligence to occupational abilities." *AEA Papers and Proceedings*, *108*: 54–57

Fornell, C., Larcker, D. F. (1981) "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, pp. 39-50

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.

Frey, C. and Osborne, M. (2013). *The future of employment: How susceptible are jobs to computerization*. University of Oxford.

Hershbein, Brad, and Lisa B Kahn. 2018. “Do recessions accelerate routine-biased technological change? Evidence from vacancy postings.” *American Economic Review, 108*(7): 1737–72

Jaros, S. (1997) “An assessment of Meyer and Allen’s (1991) Three-Component model of organizational commitment and turnover intentions” *Journal of Vocational Behavior*, *51*, 319-337

Kline, RB (2005) *Principles and Practice of Structural Equation Modelling*. New York: The Guilford Press.

Lee, K., Carswell, J., & Allen, N. (2000). A meta-analytic review of occupational commitment: Relations with person and work-related variables. *Journal of Applied Psychology*, *85*, 799–811.

Li, X., Guo, Y., & Zhou, S. (2021). Chinese preschool teachers ’income, work-family conflict, organizational commitment, and turnover intention: A serial mediation model. *Children and Youth Services Review*, *128*, 106005.

Frank, M., Westerman, G., Alhammadi, Y., Brynjolfsson. E. (2014). “Racing with and against the machine: Changes in occupational skill composition in an era of rapid technological advance.”

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.

McKinsey Global Institute (2018). *The future of jobs in the Middle East*

McKinsey Global Institute (2021). *The future of work after COVID-19*

McKinsey & Company (2023). *The skills revolution and the future of learning and earning*

Maduravoyal, C. (2018). Artificial intelligence in human resource management. *International Journal of Pure and Applied Mathematics*, *119*(17), 1891–1895.

McKendrick, J. (2018, August 14). *Artificial intelligence will replace tasks, not jobs*. Forbes

Meyer, J. P., Paunonen, S. V., Gellatly, I. R., Goffin, R. D., & Jackson, D. N. (1989). Organizational commitment and job performance: It's the nature of the commitment that counts. *Journal of applied Psychology*, *74*(1), 152.

Meyer, J. P. & Allen, N. J. (1987 *a). Organizational commitment: Toward a three-component model.* Research Bulletin No. 660. The University of Western Ontario, Department of Psychology, London.

Meyer, J., & Allen, N. (1991). A three-component conceptualization of organizational commitment. *Human Resource Management Review*, *1*, 61–89.

Meyer, J., & Allen, N. (1997). *Commitment in the workplace: Theory, research and application.* Thousand Oaks, CA: Sage.

Meyer, J., Allen, N., & Smith, C. (1993). Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of Applied Psychology*, *78,* 538–551.

Meyer, J., & Herscovitch, L. (2001). Commitment in the workplace: Toward a general model. *Human Resource Management Review*, *11*, 299–326.

Meyer, J. P., & Topolnytsky, L. (2000). *Best practices: Employee retention.* Toronto, Canada: Carswell.

Mohanty, P. (2018, July 6). *Do you fear artificial intelligence will take your job?* Forbes.

Nawaz, M., & Pangil, F. (2016). The relationship between human resource development factors, career growth and turnover intention: The mediating role of organizational commitment. *Management Science Letters*, *6*(2), 157-176.

Parameshwaran, S. (2024) *How large language models could impact jobs,* https://knowledge.wharton.upenn.edu/article/how-large-language-models-could-impact-jobs

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023, March 1). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Elsevier BV*, 33(1), 100857-100857. https://doi.org/https://doi.org/10.1016/j.hrmr.2021.100857

Pouliakas, K. (2018). Determinants of automation risk in the EU labour market: A skills-needs approach.

Preacher, KJ, Hayes AF (2008) Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behav Res Methods *40*: 879-91.

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). Emotional intelligence or artificial intelligence–an employee perspective. *Journal of Hospitality Marketing & Management*, *29*(4), 377-403.

Rafiei, M., Amini, M., & Foroozandeh, N. (2014). Studying the impact of the organizational commitment on the job performance. *Management science letters*, *4*(8), 1841-1848.

Raykov, T.(1997) Estimation of composite reliability for congeneric measures. *Applied Psychological Measurement*, *21*, 173-184

Rehman, Z. U., Ziaullah, M., Mehmood, S., Buzdar, A. D., & Kashif, M. (2022). Exploring the relationship of workplace incivility, organizational commitment and turnover intention in the perspective of social exchange theory. *Indian Journal of Economics and Business*, *21*(3), 189-202.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42.

Vishwanath, B., & Vaddepalli, S. (2023). The future of work: Implications of artificial intelligence on HR practices. Tuijin Jishu/*Journal of Propulsion Technology*, *44*(3), 1711-1724.

Vivarelli, M. (2014). “Innovation, employment and skills in advanced and developing countries: a survey of the literature”, *Journal of Economic Issues*, Vol. 48 (1), pp. 123-154.

Webb. M. (2019). The impact of artificial intelligence on the labor market.

Williamson, C. E., Saros, J. E., Vincent, W. F., & Smol, J. P. (2009). Lakes and reservoirs as sentinels, integrators, and regulators of climate change. *Limnology and oceanography*, 54(part2), 2273-2282.

Yarlagadda, R. T. (2017). AI automation and it's future in the United States. *International Journal of Creative Research Thoughts* (IJCRT), ISSN, 2320-2882.