Journal of Human Resource Management
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HR Advances and Developments

ISSN 2453 – 7683 www.jhrm.eu

# Unlocking the Path to AI Adoption: Antecedents to Behavioral Intentions in Utilizing AI for Effective Job (Re)Design

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ABSTRACT

**Purpose** – The study attempts to shed light on the level of adoption of artificial intelligence (AI) in the human resource (HR) departments for the purposes of designing jobs through assessment of the willingness and utilization of the employees in the said departments.
**Aim(s)** – The objective is to identify the primary antecedents that influence the behavioral intentions of employees in HR departments to use AI specifically for the HR function of job design.
**Design/methodology/approach** – The study uses a multiple linear regression method grounded in a survey based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The purposive sample consisted of 107 HR professionals working in companies in the Republic of North Macedonia.
**Findings** – The results from the regression analysis revealed that performance expectancy, social influence, and facilitating conditions positively influence the behavioral intentions of HR professionals toward AI adoption in job design activities.
**Limitations of the study** – Future studies could address the limitations of our research endeavor by broadening the sample size, assessing the opportunity for adopting AI in other HR functions, and including more countries in the sampling and analysis.
**Practical implications** – The study points out several recommendations to HR managers, business leaders, and policy-makers regarding the effective and ethical utilization of AI for designing and redesigning jobs in the contemporary business environment to make the workforce more satisfied, engaged, and productive.
**Originality/value** – This study represents one of the first research endeavors on the application of AI for the particular HR function of job design, considering its previous wider adoption in HR functions like recruitment and payroll, which is heavily researched. It further contributes to the discussion of if and to what extent HR professionals tend to use AI.

KEY WORDS

artificial intelligence, human resource management, job design, UTAUT, industry 4.0

JEL Code: M12
DOI: 10.46287/OTTP6295

## 1 INTRODUCTION

Since the beginning of the new decade, organizations have faced the dawn of a new AI spring. The introduction of the generative artificial intelligence (AI) chatbot – ChatGPT has opened the doors for what AI can be and how a single tool can upend current business practices (Pratiwie, 2023). ChatGPT has brought the wider topic of AI in the workplace into mainstream everyday discussion and scientific discourse. This led to many scholars calling the current evolutionary development of technology the Fifth Industrial Revolution, where AI takes the central stage even though it was championed as a pillar of the Fourth one (Podhorcová et al., 2023; Eftimov & Kitanovikj, 2023).

Rapid digitalization, the rise of human-robot teams, new technological advancements like AI and robotics, and contemporary flexible work arrangements have deeply influenced the workplaces as we know them (Štaffenová & Kucharčíková, 2021). It is up to human resource (HR) professionals to rise to the occasion and find the most efficient solutions for managing these changes. Subsequently, all these changes have resulted in growing rates of employee disengagement, burnout, low rates of satisfaction, and similar potentially disruptive effects (Parker, 2014). Yet, it has been found that the root cause of employee disengagement and work stress is mostly related to how the organization designed the jobs of its workforce (Parker et al., 2019). As organizations manage change, jobs should change, too, popularizing the process of job redesign, too, in a way to recraft jobs to reflect new business surroundings (Chen, Y., & Reay, T. (2021). Moreover, there is a strong link between destructive employee outcomes, on the one hand, that include high turnover rates, decreased productivity and satisfaction, impaired learning and development, and increased mental strain, as well as poor work design on the other hand (Parker et al., 2019).

Yet, many HR and operational managers, who are in charge of designing jobs, often don't fully comprehend the process of designing high-quality jobs, considering that job quality lies in the essence of the process (Parker et al., 2019). To mitigate this situation, AI-based software and technologies can potentially help to bridge the gap between the current state of managers' knowledge and high-quality work for their employees that brings gains to both organizations and their workforce. To understand how AI can help or hinder the job design process, we believe HR managers and professionals should be aware of its potential, opportunities, and challenges.

This motivated us to research the current state of HR professionals' willingness to adopt AI for crafting high-quality jobs with the help of AI. Additionally, after a search of the Scopus database, which indexes global, scientific literature, we detected a gap in the existing literature concerning an assessment of the intentions of HR professionals to use such a technology as a tool for crafting quality jobs more effectively. As a result, our research objective is to identify the primary antecedents that influence the behavioral intentions of employees in HR departments to use AI specifically for the HR function of job design. We plan to fulfill this research objective by answering these research questions (RQ):

*RQ1*: How can AI be adopted in human resource management (HRM) for job (re)design purposes?

*RQ2*: What antecedents influence the intentions of HR professionals to use AI for quality job (re)design?

The article is structured in a way that begins with the introduction, followed by a review of the literature and theoretical background related to the wider application of AI in the HR function of organizations, the concept of job design and redesign, and the theoretical foundations. The third section of the article is dedicated to methodology, and then it moves on to presenting the main findings and discussing them in the fourth section. Eventually, the article wraps up with the primary conclusions, addressing some research limitations, and identifying pathways for future research and practical implications for HR professionals, managers, and policy-makers.

## 2 LITERATURE REVIEW

### 2.1 AI – THE NEW COLLEAGUE IN THE HR DEPARTMENT

To define AI, one can view it as the field of computer science, which focuses on simulating intelligent computer behavior or machines' ability to reproduce human intelligent behavior (Zhang & Lu, 2021). We believe the latter definition gains ground, especially in the context of social and organizational sciences, where AI is becoming more and more applicable by the day. Considered the backbone of Industry 4.0, AI revolutionizes how the HR function is done nowadays, resulting in alterations in business processes, overall organizational profitability, and competitiveness.

Considering this, AI refers to intelligence that can recognize, interact with, evaluate, learn, and mimic human-like intelligent actions for managing complex activities without the help or support of humans whatsoever (Davenport, 2018). As a wide field, it incorporates the use of various technologies, including algorithm designs, Bayesian networks, Brain-Computer Interfaces (BCIs), data analytics, machine learning (ML), natural language processing (NLP), and robotics (Bruun & Duka, 2018). Even though all these technologies find applications in a range of industries like healthcare, finances, marketing, and similar, we believe that not all of them are relevant for the purposes of HRM; robotics or BCI tend to have very little significance and impact on the HR function (Budhwar et al., 2023).

AI's highlight advantages are linked to boosts in productivity, cost savings, swifter and more informed decision making, automating mundane and repetitive tasks, faster completion of complex tasks, lowering the level of human error and bias, real-time services, and more (Vrontis et al., 2022; Pereira et al., 2023). On the other hand, there are persistent worries about ethical implications (Rodgers et al., 2023), the danger of over-dependence on AI systems (Tambe et al., 2019), algorithmic prejudice (Chen, 2023), errors in the system (Tambe et al., 2019), and similar. Even though in our opinion, AI can't completely replace the work of an HR professional, experts are right to question how much AI can or potentially could automate HR functions like recruitment and selection (Hmoud & Laszlo, 2019) or smaller HR-related tasks (Pérez & Falótico, 2019; Charlwood & Guenole, 2022).

The phenomenon of AI isn't anything new with the first studies appearing around the middle of the twentieth century when McCulloch and Pitts (1943) introduced an artificial neuron model, representing the first computer with a neural network. Significant early contributions to AI are associated with the father of computer science, Alan Turing, who wrote the article "Computing Machinery and Intelligence" (Russel & Norvig, 2010). Afterward, IBM popularized the term even more with the launch of its AI-based software Deep Blue and the groundbreaking win of its computer system Watson on the TV gameshow Jeopardy (Zhang & Lu, 2021).

Since the 1950s, AI's popularity has wavered twice in a period known as AI winters, which were marked by a lack of interest from both researchers and practitioners and a lack of funding for AI projects (Chowdhury et al., 2023). Yet, in the past decade, AI has regained its place in the spotlight, penetrating a variety of industries, sectors, functions, and operations, including HR.

Implementation of AI is found in 1) *recruitment and selection*, where AI applications can scan, assess, and accept or reject candidates' resumes and chatbots can answer queries (Bhardwaj et al., 2020), 2) *training and development*, through custom-tailoring training programs, providing recommendations and text-to-visual outputs (Chowdhury et al., 2023), 3) *performance management*, through assessing continuous matching of the employees' work with the organization's objectives, forecasting performance indicators and potential turnover, identifying top performers, and similar (Vrontis et al., 2022), 4) *employee retention*, by forecasting employee requirements and actions of individual employees (Bhardwaj et al., 2020), and other HR functions. In our view, AI is and will be adopted in every HR function with various degrees of usage. This includes job design and analysis, which can make the process of determining employees' duties and responsibilities, including them in their roles, and assigning adequate employees to adequate jobs more efficient and effective. AI has become more accessible for HR professionals with the rise of generative AI and AI-based chatbots like ChatGPT, providing helpful textual results to questions, queries, and carefully crafted prompts (Budhwar et al., 2023).

### 2.2 JOB (RE)DESIGN

In a broader sense, the conceptualization of job design implies cognitive or operational modifications in the professional tasks and relationships at work for the benefit of the employees themselves and the organizational performance (Wrzesniewski & Dutton, 2001). In other words, it refers to the HR activity that means striking a balance between the needed resources for the task and the employees' capacities for action.

Its objective is to aid HR professionals in developing effective and efficient jobs that contribute to the maximization of the workforce's performance and employee engagement and avoid the creation of repetitive and monotonous tasks (Oldham & Fried, 2016). This isn't a finite process, giving rise to the term job redesign of reconfiguring jobs when they prove themselves inefficient after the initial job design is concluded (Rai, 2018).

Contemporary job design goes beyond the main facets of job (re)design, which include job simplification, job enrichment, job rotation, and job enlargement (Tims & Bakker, 2010). Newest trends suggest that job design – or job crafting for that matter – can happen on 1) *an individual level* (prioritizing new forms of job crafting that include remote work and a focus on work-life balance, and searching for a deeper personal understanding of the process), 2) *team level* (reviving the focus on team outcomes and collaborative job crafting, as well as developing social relationships for collaborative crafting), and 3) *social level* (considering the others' points of view on job crafting and inserting personal job design in the given social surroundings) (Tims et al., 2022).

This is where AI comes in. This technology can determine the optimal blend of responsibilities, duties, and possible incentives for all job positions using predictive modeling, ML, and data analytics (Oldham & Fried, 2016). To illustrate, AI can recommend flexible working schedules for certain jobs, and individual learning plans, scan and evaluate job descriptions, resumes, and performance evaluations to assess the right job fit (Xu & Li, 2020). With the use of regression analyses and neural networks, AI-based software can compare job profiles and market data, based on data that includes levels of skills, task complexity, job demand, and impact, thus suggesting adequate wage ranges and benefits packages (Bhardwaj et al., 2020). AI can be adopted for the job-matching aspect of job design, too. The software can identify and choose the most qualified individuals for a certain job thanks to semantic matching and deep learning and makes use of voice assistants and chatbots to aid the process (Xu & Li, 2020). Throughout the job design process, it is integral for HR professionals to maintain fairness, and high ethical standards and prevent bias. AI technology has been used for job (re)design in an exploratory way in healthcare. Tursunbayeva and Renkema (2022) have found that some of the job design dimensions, which were significantly impacted by AI included job autonomy and control, the use of skills and the required variety of skills, job feedback, social relations in the workplace, and job demands.

We argue that once a job is tailored to the individual capabilities, interests, and objectives of each employee, the workplace can enjoy the benefits of increased employee motivation, performance, and overall satisfaction.

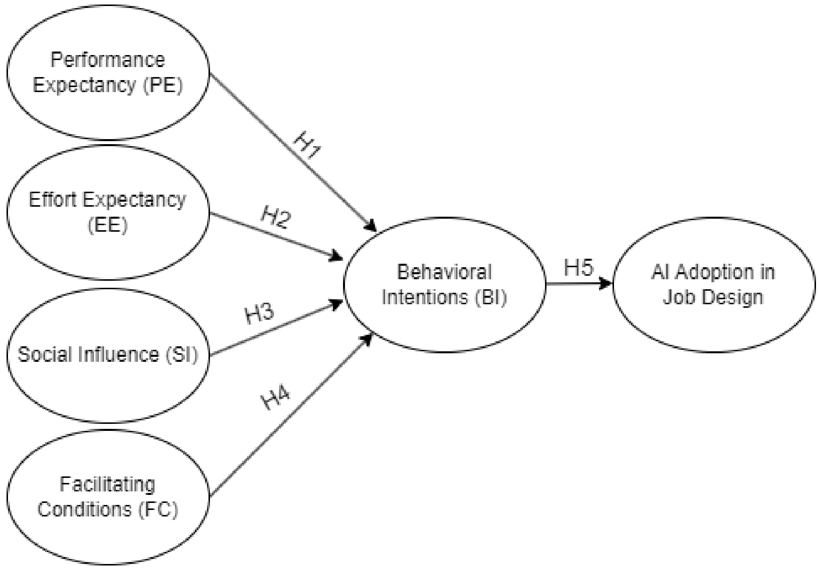
### 2.3 ANTECEDENTS OF TECHNOLOGY ADOPTION

The study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) theoretical model as one of the foundational frameworks for the identification and exploration of antecedents to technological adoption such as AI in our case (Venkatesh et al., 2003). Transcending the organizational context, on which previous models like the Technology Acceptance Model (TAM) heavily relied (Legris et al., 2003), UTAUT stems from a thorough overview of models for technological adoption and has a more widespread use (Dwivedi et al., 2019). Besides that, the model has been used by other proponents and researchers in the field of HRM (Theres & Strohmeier, 2023) and management (Chang, 2012) in general to determine the behavioral intentions for using a certain technology.

The model comes with some limitations such as a focus on self-reported usage or intended behaviors instead of assessment of the actual usage, cross-sectional character that measures the constructs at only one point in time, self-selection bias, and similar (Dwivedi et al., 2011). Yet, UTAUT remains one of the most applied new models for assessing the willingness of a certain category to implement a new technological form (Chang, 2012). This is likely due to its extremely high explanatory power and transferability to various cultures and different technologies (Blut et al., 2021).

We recognize four factors as antecedents to technological adoption based on the theoretical framework: 1) *performance expectancy (PE)*, meaning the anticipated results thanks to the utilization of the technology, 2) *effort expectancy (EE)*, or the amount of effort the user has to put in to make the use of the technology worthwhile, 3) *social influence (SI)*, which refers to the level of the technology's adoption in the social surroundings of the particular user, and 4) *facilitating conditions (FC)* or the factors that encourage or hinder the use of the technology (Venkatesh et al., 2003). As an outcome of the model, we consider the explicit *behavioral intentions (BI)* of users to implement the technology for their purposes, which for the context of the study are their intentions to use AI for job design as one of the key HR activities.

Fig 1. Theoretical model for adopting AI for job design purposes based on the UTAUT model




*source: Venkatesh et al., (2003).*

Performance expectancy (PE) represents a vital operational variable in the organization with the goal of aiding employees to enhance their performances individually (Dwivedi et al., 2011). Thus, we define performance expectancy as the extent to which HR professionals believe that using AI will help them satisfy their work-related needs. Connected to this, past literature demonstrated a strong link between AI and an increase in performance (Ransbotham et al., 2018). We believe that an effectively designed performance expectancy system can increase the capacities of HR professionals to use AI-based solutions for designing and redesigning jobs in their organizations. Performance expectancy relies on the users' perceived usefulness, relative perks, expectations for the outcomes of the implementation, external motivation, and fitness for the job (Theres & Strohmeier, 2023).

*Hypothesis 1: Performance expectancy (PE) positively affects behavioral intentions (BI) for adopting AI for job design purposes of HR.*

Defined as the extent users believe the technology is easy to use, the effort expectancy (EE) is a complex factor, often demanding the use of high, state-of-the-art technology for improving innovation platforms (Dwivedi et al., 2019). Blut et al. (2021) point out that the variable can be explained by the general effort one would use to master the use of the technology, represented through the user's perceived learning curve or other parameters. This study identifies EE as the difficulty or ease of HR professionals to operate AI-powered tools for work (re)design.

*Hypothesis 2: Effort expectancy (EE) positively affects behavioral intentions (BI) for adopting AI for job design purposes of HR.*

The social influence (SI) as a factor relies on the users' perception of how much they will make use of AI for this HR purpose. Additionally, this perception is impacted by an assessment of the behaviors of other members of the direct social environment toward the use of technology (Venkatesh, 2022). In our research, we consider SI as the level of influence on HR professionals' perception of AI and its usage by their social environment, including peers, management, and seniors. In the initial stages of implementation, this influence on others' behavior can be the outcome of compliance or the fear of missing out (Blut et al., 2021). The social influence shouldn't be underplayed as it can include social factors, the users' image, and their subjective norms, contributing to the workplace's social dynamics and behaviors (Chang, 2012).

*Hypothesis 3: Social influence (SI) positively affects behavioral intentions (BI) for adopting AI for job design purposes of HR.*

One can view facilitating conditions (FC) as the required level of support of both organizational and technological infrastructure for successfully implementing the new system based on the analyzed technology (Thomas et al., 2013). We believe that when an organization has adequate conditions to support the introduction of AI into the present work, the influence of the new technology will be positive towards the behaviors and attitudes of the workforce. On one hand, the facilitating conditions in the technological context can include the barriers and encouraging factors for adoption, the usage of related technologies, the external environment, the already established infrastructure, and others, while the organizational context factors can refer to the support from the top management and the CEO, limitations in the budgets, the workforce's capacities and attitudes towards technology and information systems in general, and similar (Menant et al., 2021).

*Hypothesis 4: Facilitating conditions (FC) positively affect behavioral intentions (BI) for adopting AI for job design purposes of HR.*

The workforce's behavioral intention (BI), which can be defined as an indication of how ready an individual is to exhibit a particular behavior, plays a vital role in the eventual adoption of the new technology (Ajzen, 2002). This behavior can be reflected in an active usage of the technology, thoughts about future implementation of the technology, willingness to share it with other colleagues, positive emotions at work, and similar (Ajzen, 2002). In other words, if employees in an organization display intentions to utilize new technology such as AI for their job design activities, they will most likely behave in a way that accepts the actual initial deployment of the new technology and vice versa. If employees have a negative attitude toward this technology and don't display intentions to use it, this will more likely result in them rejecting the implementation or simply not accepting it into their work (Menant et al., 2021).

*Hypothesis 5: Behavioral intentions (BI) positively affect AI adoption in job design.*

## 3 METHODOLOGY

To empirically explore the antecedents to AI adoption in job design activities as an integral part of the HR function, we use a quantitative research method based on the UTAUT model. We employed purposive sampling with the determined population being HR professionals and business leaders in the Republic of North Macedonia. An online survey was distributed to a database of contacts of the authors who work in HR. Additionally, the survey was sent to the contacts in the database of HR professionals who are at the same time members of the Macedonian Human Resource Association (MHRA). This resulted in a total of 107 respondents fully filling in the survey. We believe this is an adequate sample size as some recommendations point out that the sample size should be around 15 to 20 observations per construct for generalizability (Hair et al., 2006). The study analyzes six constructs, including the adoption of AI in job design.

The responses from the survey were then subject to a multiple linear regression using the SPSS statistical software. We chose this method for data analysis as regression analysis is one of the most used ones for verifying the theoretical UTAUT model (Khechine et al., 2016; Theres & Strohmeier, 2023). The multiple linear regression analysis was employed to approximate the linear relationships between the independent variables and the dependent one, thus investigating if the constructs' variables significantly and positively influence behavioral intentions. Also, the analysis enabled us to uncover the constructs with the highest impact.

The survey consisted of 23 questions out of which five of them referred to the demographic characteristics, while the rest of the questions related to the outlined dimensions of the UTAUT model for identification of the primary antecedents to AI adoption in job design. Each dimension was presented with three statements, which respondents answered on a five-point Likert scale (1 – strongly disagree, 5 – strongly agree). The survey was designed to be answered anonymously to ensure that the answers were more honest and free of prejudice or fear from the respondents' side. The respondents were made aware of the survey's anonymity and were additionally provided with a description of the study, and its objective, as well as a definition of job design and short sample case studies of how AI is used for this HR function.

Regarding the characteristics of the sample, most of the respondents identified as female (81%), a smaller portion as male (16%), and 3% didn't want to disclose their gender. Furthermore, the majority of respondents (73.5%) were between 25 and 44 years old and worked in organizations that employ more than 50 employees (53%). This supports previous findings that AI is predominantly used in large organizations rather than smaller ones (Benbya et al., 2020). Further, the specific roles that the respondents provided principally include HR manager, HR assistant, talent acquisition specialist, HR specialist, HR professional, recruiter, and talent manager. Regarding the industry and the economic sector of their organizations, most of the respondents work in the information and communications technology (ICT) sector (32%), banking and finances (21%), and professional services and consultancy (18%). The respondents answered about their job tenure with 38% of them employed for one to three years, 25% of them for less than a year, 14% of them having a working experience from four to six years, 13% of them worked from seven to ten years, and 10% for more than ten years.

# 4 RESULTS AND DISCUSSION

## 4.1 ASSESSMENT OF RELIABILITY AND CONSTRUCT VALIDITY

We investigated the construct validity to confirm the factors, which are already conceptualized in the literature, by conducting an exploratory factor analysis utilizing a principal component analysis with varimax rotation. The minimum factor loading criteria was set to 0.5. Additionally, all communalities were above 0.5.

To measure the significance of the correlations among some of the components of the correlation matrix as well as to assess the suitability of the data for factor analysis, we conducted a Bartlett's Test of Sphericity and a Kaiser-Meyer-Olkin Measure. According to Bartlett's Test of Sphericity, the results were significant, x2 (n=107) = 743.332 ($p<0.001$), indicating a suitability for factor analysis. Considering the values of the Kaiser-Meyer-Olkin Measure of Sampling Adequacy should be above 0.800 to be deemed appropriate (Hair et al., 2010), the result from the test was 0.828, which makes it suitable for further analysis. From the initial exploratory factor analysis, two items ("PE3: I can get accurate answers using AI-powered chatbot technology."; "EE3: If I know basic AI technology, I can easily learn other AI-based applications.") were removed since they failed to load on a dimension significantly. The factor loadings are presented in Table 1.

Table 1. Results of exploratory factor analysis, factor loadings (N=107)

| No. | Items | Factor | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 |
| | Performance Expectancy (PE) | | | | | | |
| 1. | It will be easy to apply a perfect AI application catering to the needs of HR for redesigning jobs. | .681 | | | | | |
| 2. | AI will enhance the efficiency of the HR function, in particular job design and redesign. | .728 | | | | | |
| | Effort Expectancy (EE) | | | | | | |
| 1. | AI technology is easy to learn. | | .874 | | | | |
| 2. | I need to put a little effort into learning AI technology. | | .816 | | | | |
| | Social Influence (SI) | | | | | | |
| 1. | If the public supports the use of AI, I will intend to use it. | | | .755 | | | |
| 2. | The use of AI for job design purposes connotes being able to keep up with the trends. | | | .691 | | | |
| 3. | Many friends and colleagues use AI for job design, so I feel I should use it, too. | | | .811 | | | |
| | Facilitating Conditions (FC) | | | | | | |
| 1. | My organization has all the necessary resources to use AI technology for job simplification, rotation, enlargement, and enrichment. | | | | .795 | | |
| 2. | Our offices are equipped with the necessary devices for using AI technology for HR purposes. | | | | .686 | | |
| 3. | My organization encourages its staff to use modern technology. | | | | .798 | | |
| | Behavioral Intentions (BI) | | | | | | |
| 1. | I am willing to use AI technology for designing jobs more efficiently and effectively. | | | | | .740 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2. | I shall recommend all the stakeholders explore AI technology for their HR purposes. | | | | | .753 | |
| 3. | I intend to use AI technology for job design in the next couple of years. | | | | | .808 | |
| | Adoption of AI in Job Design (AAJD) | | | | | | |
| 1. | The adoption of AI in job design processes is good for the business. | | | | | | .694 |
| 2. | The adoption of AI in job design will make it cost-effective. | | | | | | .636 |
| 3. | The adoption of AI in job design will make defining how work will be performed and what tasks will be required more interesting. | | | | | | .750 |

*source: Authors' calculations.*

Additionally, Cronbach's alpha coefficient for the constructs is 0.831, which confirms the internal reliability of the scales, keeping in mind it is above the threshold value of 0.7 (Hair et al., 2010).

### 4.2 RESULTS OF THE MULTIPLE LINEAR REGRESSION METHOD

To assess the impact of the behavioral intentions of HR professionals to implement AI in their job design activities, through the intentions' four dimensions, we employ a multiple linear regression method. The used equation is presented as follows:

$$Y = \beta0 + \beta1x1 + \beta2x2 + \beta3x3 + \beta4x4 + \varepsilon \quad (1)$$

In the equation, Y = behavioral intention; x1 = performance expectancy; x2 = effort expectancy; x3 = social influence; x4 = facilitating conditions; ε = standard error.

The multiple linear regression to analyze the established hypotheses was used at 95% confidence intervals. Moreover, the analysis showed that the model is statistically significant. The model summary is presented further: $P < .001$, $R2 = 0.273$, Adj. $R2 = 0.245$, R2 Change = 0.273. Additionally, the constructs meet the recommended values for Tolerance and VIF (Hair et al., 2010), which can be seen in Table 2. The Durbin-Watson test signifies that there isn't autocorrelation in the residuals from the multiple linear regression analysis (Table 3) (Durbin & Watson, 1971). Furthermore, the R square and Adjusted R square values signify that performance expectancy, effort expectancy, social influence, and facilitating conditions explain 27.3% and 24.5% variations in HR professionals' intent to implement AI for job design activities respectively (Table 3).

Table 2. Coefficients of a multiple linear regression model

| Independent Variables | Standard Coefficients | Sig. | Collinearity Statistics | |
|---|---|---|---|---|
| | | | VIF | Tolerance |
| (Constant) | | .001 | | |
| Performance Expectancy | .211 | .019 | 1.104 | .906 |
| Effort Expectancy | -.173 | .052 | 1.087 | .920 |
| Social Influence | .228 | .015 | 1.206 | .829 |
| Facilitating Conditions | .305 | .001 | 1.217 | .822 |

*source: Authors' calculations.*

Table 3. Summary of the model

| R Square | Adjusted R Square | p-value | Durbin-Watson |
|---|---|---|---|
| .273 | .245 | .000 | 1.974 |

*source: Authors' calculations.*

Following the multiple linear regression, the results show that performance expectancy, social influence, and facilitating conditions positively influence the behavioral intentions of HR professionals toward AI adoption in job design activities ($p<0.05$). This confirms H1, H3, and H4. By looking at the standardized beta coefficients, it's evident that the facilitating conditions (0.305) have the strongest positive impact on the behavior of HR professionals, with the social influence (0.228) and performance expectancy (0.211) following closely behind. On the other hand, effort expectancy negatively affects the behavior of HR professionals toward adopting this modern type of technology in the analyzed HR function. Thus, H2 is rejected. Subsequently, research has found that behavioral intentions later transfer into a real-world implementation of the technology in question. This study's results are in line with these prior findings, so H5 is confirmed, too. In other words, behavioral intentions have a positive effect on the actual adoption of AI for job design purposes ($\beta = 0.670$, $t = 9.241$, $P < .001$). Considering this interpretation, we believe that the multiple linear regression method was adequate for analyzing the data from the disseminated survey as the findings are logical and in line with the published literature.

While these findings are similar to those of previous studies, they can still be differentiated due to the different contexts and the field where AI is adopted. Illustratively, Chatterjee and Bhattacharjee (2020) have found that effort expectancy has a positive impact on the attitude and behavioral intentions when it comes to using AI in higher education, while performance expectancy doesn't have a significant impact on the attitude, and thus the behavior. This is why analyzing the adoption of AI in the specific HR function fills a gap in the existing literature. Other studies have demonstrated that the facilitating conditions, or in other words, the supportive environment and motives can make people see the benefits of using such a technology (Grover et al., 2022).

AI has a wide range of applications in work design and job redesign. An AI-mediated job design process can help HR managers tailor the jobs to a person's abilities, interests, and goals, influencing job satisfaction, motivation, and performance (Afzal et al., 2023). To more efficiently create job specifications and allocate the right people to the right jobs, AI's ML and NLP techniques can scan and evaluate job descriptions, resumes, performance evaluations, and other relevant data (Roy et al., 2020). This contributes to more efficient job matching through semantic learning and deep learning (Wei & Jin, 2021). Undeniably, the discussion about which tasks and jobs can be automated by AI persists (Kusý, 2021), as this dramatically upsets the current job landscape and how HR professionals will design the jobs in the future.

With that in mind, the results of this study can be used in practice to widen the application of AI in HRM functions and the tasks of the job (re)design function. AI-powered algorithms can influence several aspects of the job design process, including characteristics related to the task, required knowledge, social support, and job demands (Parent-Rocheleau & Parker, 2022). Illustratively, AI has been found to decrease autonomy and job complexity (Heiland, 2021), while positively impacting emotional demands and role clarity (Adams-Prasll, 2019) across different types of jobs. Knowing AI's effect on work design, business leaders and HR managers can make decisions about which job characteristics and tasks would require more or less interference from AI algorithms.

Considering the findings pointed out that the facilitating conditions influence HR professionals' behavioral intentions, the management of organizations can ensure that these facilitating conditions are met, such as nurturing culture and leadership, setting up technological infrastructure, providing support, and focusing on other socio-technical moderators. Socio-technical moderators include human influence, system transparency, and system fairness (Parent-Rocheleau & Parker, 2022). As a result, practitioners can make sure that the AI-powered software is transparent and fair to enhance workers' feelings of autonomy and control over their jobs (Heiland, 2021; Wang et al., 2020). Additionally, job design features like task variety and job complexity will likely be maintained or even boosted if business leaders and HR managers invite employees to contribute to the AI-powered system and keep the human influence in the loop (Grønsund & Aanestad, 2020). As the findings also stress that performance expectancy and social influence positively affect HR professionals' behavior, the management can provide more training and increase the understanding of the HR staff that using AI in their work can result in better performance, efficiency, and productivity, while eliminating repetitive tasks and automating simple and manual ones.

## 5 CONCLUSION

With our research endeavor, we set out to fulfill the objective of identifying the primary antecedents that significantly impact the behavioral intentions of employees in HR departments to use AI for the HR function of job design. Grounded in the UTAUT theory, which is proven to efficiently assess the willingness to accept and utilize a certain type of technology, the research used a multiple linear regression model from data acquired through a questionnaire.

It was found that performance expectancy, social influence, and facilitating conditions positively affect the behavior mindset of HR professionals towards AI adoption in the HR function of job design, while effort expectancy negatively affects this behavior mindset. This can be explained by the claim that if HR professionals feel that the adoption of AI will further overburden them and require additional effort, they will more likely leave AI off their agenda.

Although the results of this research endeavor attempt to significantly contribute to the scientific discourse on the topic, and provide recommendations for HR managers, business leaders, and policymakers, it still has some constraints, which can be addressed by future studies. The UTAUT model or other versions of it can be utilized to assess the willingness of HR professionals to adopt AI in other HR functions besides job design. This may include performance management, stress management, employee engagement, onboarding, and similar. Additionally, this study can be replicated in other contexts and compared to the findings of our study, enabling an easier cross-country comparison. As stated, the sample size of at least five times as many observations as the number of analyzed constructs is adequate (Hair et al., 2010), yet input from more respondents may positively contribute to higher generalizability of the research findings.

Nevertheless, the findings have significant practical implications for HR professionals and managers on the one hand and decision-makers on the other hand. Firstly, HR professionals and managers can use these findings to make sure the needed facilitating conditions are met for implementing innovative technologies in the daily work of HR departments. The introduction of new AI tools and software solutions warrants potential upskilling and reskilling of the current workforce. Moreover, the wider adoption of AI in job crafting makes ethical and legal compliance a top priority, ensuring workplaces are safe, unbiased, transparent, equitable, and diverse. 2023 has been dubbed the year of the AI Act (Helberger & Diakopoulos, 2023), so policymakers can benefit from research that puts the spotlight on applying AI in contemporary work settings. Subsequently, regulators should govern the use of AI in job design to protect employees' rights and ensure fair and ethical practices.

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