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MACHINE LEARNING IN EMPLOYMENT RESEARCH AND ALGORITHMIC MANAGEMENT

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Abstract This review looks at the implementation of artificial intelligence and machine learning into employment research. Based upon an extensive search of literature, the study aims to illustrate the main themes of algorithmic management, platform labor, occupational safety, and aesthetic work where model-building techniques such as neural networks and generative artificial intelligence are applied. An initial search concerning publications between 2014 and 2024 revealed 802 studies. Following a rigorous screening procedure according to the PRISMA guidelines, 25 articles were retained for detailed analysis. This review develops a comprehensive taxonomy of machine learning in employment research and demonstrates its role in modeling the employment quality and improving organizational productivity while affecting occupational safety. Furthermore, this study highlights the importance of explainability, transparency and fairness in machine learning applications for employment research in view of the new legal framework adopted by the European Union in 2024. Additionally, this review attempts to classify machine learning applications in employment research according to the new European regulation on artificial intelligence, introducing a conceptual framework to assess contemporary machine learning-enabled employment research for readiness in view of the new legislation. The results highlight the transformative aspects of artificial intelligence on the nature of work. The research contributes to the understanding of the impact of artificial intelligence and machine learning on employees and organizations, deepening the discourse on its implications in restructuring employment relations in the near future.

Keywords: machine learning, artificial intelligence, employment research, algorithmic management, occupational safety and health, XAI, deep learning, big data, data science.

AMS Mathematics Subject Classification: 68T01, 68T05.

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1 Introduction

Employment is vital for ensuring long-term economic stability and determining future growth prospects [1]. Economists and policymakers define employment at the macroeconomic level as the ratio of employed individuals to the working-age population in a specific country, region, industry, or area. From a macro standpoint, employment is expressed in relation to its complement, unemployment, which is defined as an economic indicator representing the number of individuals without jobs who meet job criteria and actively seek work during a given period [2]. In microeconomics, employment is viewed as the relationship between employees and firms that require labor to produce goods and services for market sale [3]. At the micro level, employment research concentrates on the voluntary choices made by job applicants (the supply side of the labor market) and employers (the demand side of the labor market). These choices are influenced by factors such as wage levels, working conditions, education, productivity, and job satisfaction levels. Applied machine learning (ML) research, as the core area of artificial intelligence (AI), now plays a growing role in employment research. It supports tasks such as hiring, performance evaluation, and employee retention. However, most

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studies focus on tools and outcomes rather than on how these technologies affect workers. Key issues such as fairness, bias, and transparency often remain underexplored. Little research examines the complete picture. This gap makes it necessary to initiate new research. A comprehensive review is needed to identify what has been accomplished, locate the gaps, and better understand how AI transforms the workplace. A fresh examination can help shape fairer and more effective practices.

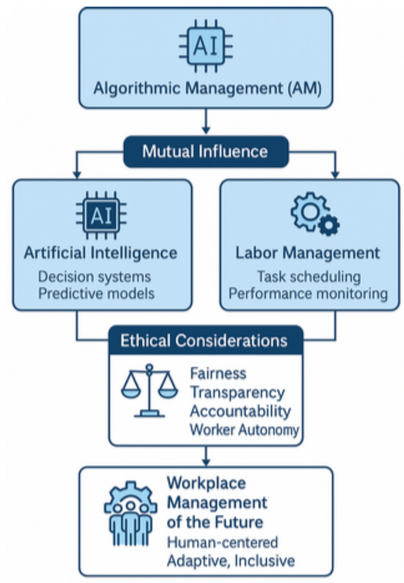

Figure 1: Relationship between AM, AI and labor management

Employment research is important at both the macro and micro levels for various reasons. Employment is recognized as a significant factor that impacts economic growth and serves as one of the cornerstones that can shape a sustainable future for society [1]. At the macroeconomic scale, the calculation and prediction of employment and unemployment rates can influence policymaker decisions. Employment data is considered fundamental for planning and implementing social policies, evaluating required public spending in critical industries, and designing mutually beneficial migration strategies [4][5]. At the micro level, companies can leverage employment data to improve their recruitment and talent management processes, optimize their organizational efficiency, and make informed business development decisions based on labor market density in specific industries or particular regions. The importance of employment research has been prominent since the introduction of Okun's Law, which proved that unemployment can be closely related to negative growth in real gross domestic product (GDP) [6]. Although direct correlation between employment and GDP growth remains debatable [2], scientific research has proved that unemployment and underemployment can produce negative effects on social stability and provoke drastic social tensions [7]. Employee productivity receives more attention than employment itself in labor research. It results from a combination of technology, skills, and motivation. Porter argued that skilled labor provides nations with a competitive edge, while unskilled labor only helps if workers are trained and remain open to new technologies [8]. However, even skilled workers now face pressure. As AI and robotics advance rapidly, they risk falling behind unless we invest in new skills and smart hiring in related fields [9]. The tech industry, which is known for skill development and retraining opportunities, experienced major layoffs after COVID-19 [10]. Meanwhile, Generation Z enters the workforce with new expectations. They expect employers to understand their values and motivations [11]. Psychology also highlights the need to build self-efficacy, hope, optimism, and resilience to keep employees engaged and secure at work [12]. This indicates that employment research must adapt to evolving workplace needs. Traditionally, economists used statistics and econometrics to track job trends and examine their connections to other factors. However, in the last 20 years, the statistics field has been criticized for slow adoption of AI and ML compared to other disciplines [13][14]. Athey and Imbens argue that economists focus more on how different factors interact, whereas ML models often do not emphasize the underlying complexities [14]. Nevertheless, many studies employ methods such as PLS-SEM, which relies on surveys, to examine AI's impact on jobs and performance [15][16][17][18][19][20]. Since Industry 4.0 began in the early 2010s [21], more researchers have started to use ML tools. This demonstrates a clear need for additional studies on how these models can help understand and predict job market trends.

AI is changing the job market, but it also provides researchers with better tools to understand employment trends. Studies show that using ML alongside traditional statistics can improve accuracy and predictions [22][23]. As AI becomes more common in labor research, interest in workplace process mining also grows [24]. This supports a broader concept known as algorithmic management (AM). AM uses technology to support or automate management tasks such as work assignment, performance tracking, and decision-making. It originated with ride-sharing companies such as Uber and Lyft [25], but now it is spreading to traditional industries [26]. AI is now considered a key component of AM, which helps boost efficiency and automation. However, this raises ethical concerns about transparency, accountability, and worker autonomy [27]. Despite these concerns, AI is expected to play a central role in AM. It helps with data-driven predictions and smarter decision-making. Figure 1 in the review shows how AI supports AM in labor management and affects talent practices and workplace ethics. Current AI tools still depend on human-defined rules and are limited in scope. However, future advancements could bring significant changes to work management approaches. These developments must focus on fairness and transparency to address the ethical issues that accompany increased automation. Since AM is a growing area in labor research, this review includes several studies on how AI supports AM.

There are various ways in which employment and labor management trends have been addressed through the use of ML and AI. Several studies aimed to evaluate and improve occupational safety and health (OSH) with AI by reviewing the role of AI in OSH [28][29], applying ML models [4][30], introducing a concept to support OSH risk analysis with deep learning (DL) [31], or combining DL with digital twins and industrial internet of things for better workplace security [32]. Moreover, AI was used to design smart helmets to identify workplace safety hazards [33]. Besides, we identified research aimed to combine AI-driven intelligent agents and intelligent systems with organizational knowledge sharing tools to improve workforce productivity [34]. Furthermore, we explored research focusing on the potential and current applications of AI-powered chatbots in personnel coaching [35]. In addition, we reviewed a number of articles introducing ML-based models to measure employee trust, job satisfaction and loyalty for organizational performance improvement [3][36][37]. The literature review also covers research that evaluates individual employees and job applicants against AI-generated standardized models of a "talented worker" in AM software [38]. In general, the applicability of ML models to the personnel selection process appears to be a widespread concept in modern employment research [39][40]. Prediction of student employability with ML models based on various factors related to students' university performance and skills [5], as well as more general-purpose ML-powered employability prediction models [41], are also notable concepts in modern employment research. We also reviewed how ML methods were used to predict social profiles of job applicants based on analysis of nonverbal signals collected from applicants during job interviews through a "virtual recruiter" [42]. Besides, we explored research aimed at unemployment detection through ML analysis of data collected by smart metering infrastructure [43]. Concurrently, a significant number of articles identified by this study are related to the broader discussion of how various applications of AI in the workplace can reimagine the future of work, AM, employer-employee relationships, and organizational performance in general through surveys performed in various industries [15][16][17][18][19][20].

The proposed method aims to create a comprehensive taxonomy of how ML and AI tools have been used in employment research in recent years and improve the general understanding of AI-driven employment research trends. Following the introductory section, the second section of our article describes PRISMA methodology used as the backbone of our literature review. The third section identifies the results of our study on how ML and AI tools and techniques were applied to various fields of employment research in the selected population of scientific papers with the most relevance to the subject. The fourth section calls for discussion of the results identified during this research. The fifth section contemplates our conclusion on potential future research in this area.

2 Methodology

This literature review is based on the adapted PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) used in previous similar studies [44][45]. In terms of our original screening for related articles, we concluded a comprehensive search in the Scopus database using the combination of the following keywords: ("algorithmic management" OR "organizational performance" OR employment OR "job quality" OR "aesthetic labor" OR "platform labor" OR "occupational safety") AND ("machine learning" OR "artificial intelligence" OR "neural network" OR "support vector" OR "deep learning" OR "generative AI"). Our analysis initially identified 802 articles published between 2014 and 2024 dedicated to potential application of AI and ML in employment research, AM and organizational performance, showing that scientific community attention to this field has been gradually increasing (Figure 2).

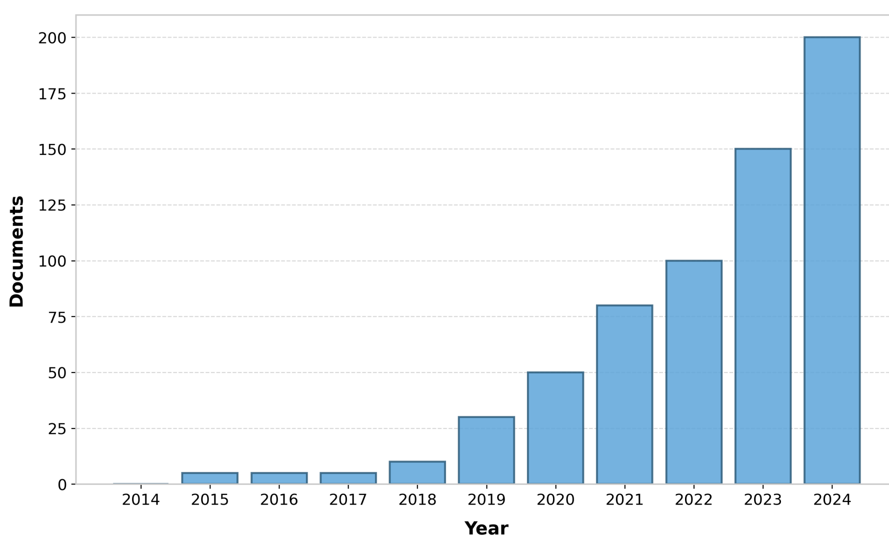

Figure 2: Progress of AI in employment research with 802 articles

After the initial analysis had been completed, the search results were examined through a comprehensive three-phase screening process. At Phase I the titles and abstracts of the identified articles were rigorously reviewed to extract the population of English language papers consistent with the research subject, as well as to remove duplicates and unverified sources. As a result of Phase I, we determined 47 articles for retrieval and full-text screening. Upon the original screening of the identified papers at Phase II, we selected 18 articles with the most relevance to the subject of this study where the full text was available for scrutiny. The subsequent review of secondary citations allowed us to retrieve 7 more articles that were ultimately included into the scope of this literature review, thus resulting in 25 selected papers for systematic consideration at Phase III. The 25 articles related to ML and AI applications in employment research identified as a result of Phase III were thoroughly inspected in terms of this study to indicate the domain of employment research they belong to, stipulate the primary research method used by the authors, as well as specify how ML and AI were applied by the researchers in terms of these studies to solve various problems arising in the field of employment research.

3 Results

Table I outlines the list of the 25 articles related to ML and AI applications in employment research identified as a result of Phase III of our screening process. In Table I, the titles of the reviewed papers are presented in descending chronological order, showing whether they were selected during the original screening or added to the population through secondary citations analysis. Our literature review identified several major domains related to employment research where the specified studies had been conducted, covering personnel development and selection, organizational performance (OP), algorithmic management (AM), occupational safety and health (OSH), employee satisfaction and unemployment prediction. Research methods determined in the reviewed selection of papers include design of conceptual frameworks, partial least squares structural equation modeling (PLS-SEM) based on surveys conducted in various employment areas, development of supervised and unsupervised ML models, systematic literature reviews of ML and AI applications in employment areas, as well as case studies and practical field experiments related to the subject.

Table 1: Selected articles on ML application in employment research

Ref.	Original Screening vs Added Citations	Title	Year	Domain	Research Method	Application
[35]	Original	AI coaching: redefining people development and OP	2024	Personnel Development	Conceptual Framework	Applying AI Chatbots to Organizational Coaching
[17]	Original	Applications of generative AI and future OP: the mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism	2024	OP	PLS-SEM	Impact Assessment of Generative AI Adoption on OP

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Table 1 – *Continued from previous page*

Ref.	Original Screening vs Added Citations	Title	Year	Domain	Research Method	Application
[4]	Original	Causal impact evaluation of occupational safety policies on firms' default using ML uplift modeling	2024	OSH	ML Model	Modeling Causal Effect of OSH Incentives on Corporate Success
[38]	Original	How does AI work in organizations? AM, talent and dividuation processes	2024	AM	Case Study	Reviewing AI Applications in AM Software
[20]	Original	AI competencies for OP: a B2B marketing capabilities perspective	2023	OP	PLS-SEM	Impact Assessment of AI Competences on OP and Competitiveness
[28]	Original	OSH equity impacts of AI: a scoping review	2023	OSH	Literature Review	Review of the Role of AI in OSH Equity Promotion
[41]	Added	ATOM - a flexible multi-method ML framework for predicting occupational success	2023	Personnel Selection	ML Model	Predictive Modeling of Applicant Employability
[3]	Original	Modeling OP with ML	2022	OP / Employee Satisfaction	ML Model	Applying ML to Predict OP and Employee Well-being
[33]	Original	Smart helmet-based proximity warning system to improve occupational safety on the road using image sensor and AI	2022	OSH	Field Experiment	Implementing Real-Time Image Recognition to Prevent Occupational Hazards
[32]	Original	Industrial internet of things and unsupervised DL enabled real-time occupational safety monitoring in cold storage warehouse	2022	OSH	ML Model / Field Experiment	Combining Unsupervised DL with Bluetooth Low Energy Signals and Digital Twin to Improve OSH
[19]	Original	Human resource AI implementation and OP in Malaysia	2022	OP	PLS-SEM	Impact Assessment of AI Implementation on OP
[34]	Original	AI and knowledge sharing: contributing factors to OP	2022	OP	Conceptual Framework	Combining AI with Knowledge Sharing to Improve Sustainable OP
[31]	Original	Concept for supporting occupational safety risk analysis with a ML tool	2022	OSH	Conceptual Framework	Introducing a Concept of ML-Enabled OSH Analysis

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Table 1 – *Continued from previous page*

Ref.	Original Screening vs Added Citations	Title	Year	Domain	Research Method	Application
[18]	Original	AI innovation related factors affecting OP	2022	OP	PLS-SEM	Impact Assessment of AI-Related Innovation on OP
[16]	Added	Human resource developments with the touch of AI: a scale development study	2022	AM	PLS-SEM	Assessing Recruiters' Perception of AI Usage in AM
[37]	Original	Exploring the relationship between abusive management, self-efficacy and OP in the context of human-machine interaction technology and AI with the effect of ergonomics	2022	Employee Satisfaction	ML Model	Evaluating Employee Job Satisfaction and Employee Performance
[39]	Added	ML in personnel selection	2022	Personnel Selection	Literature Review	Review of ML Trends in Personnel Selection
[36]	Original	A ML classification tree model of perceived OP in U.S. federal government health agencies	2021	OP	ML Model	Employee Classification by Perceived OP
[29]	Original	REDECA: a novel framework to review AI and its applications in OSH	2021	OSH	Literature Review	Review of AI Applications in OSH via Novel Conceptual Framework for Risk Assessment
[30]	Original	Utilization of ML in supporting OSH decisions in hospital workplace	2021	OSH	ML Model	Classification of Post-Incident Data and Prediction of Accidents
[40]	Added	Performance evaluation of ML predictive analytical model for determining the job applicants employment status	2021	Personnel Selection	ML Model	Predictive Modeling of Applicant Employment Status
[15]	Original	Moderating interact of AI use in the influences of recruitment, selection, and staffing on the OP in the UAE manufacturing industry	2021	OP	PLS-SEM	Impact Assessment of AI Usage in Employee Recruitment, Selection, and Staffing on OP
[43]	Added	A ML approach for detecting unemployment using the smart metering infrastructure	2020	Unemployment Prediction	ML Model	Unemployment Prediction with Smart Metering Data

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Table 1 – *Continued from previous page*

Ref.	Original Screening vs Added Citations	Title	Year	Domain	Research Method	Application
[42]	Added	A methodology for the automatic extraction and generation of non-verbal signals sequences conveying interpersonal attitudes	2019	Personnel Selection	Conceptual Framework/ Case Study	Designing a Virtual Recruiter Capable of Expressing Social Attitudes
[5]	Added	Proposing a ML approach to analyze and predict employment and its factors	2018	Personnel Selection	ML Model	Predictive Modeling of Student Employability

Table II represents ML models identified in the selected scientific papers in terms of our study. Summary provided in Table II addresses ML tasks related to the field of employment research that the authors were aiming to automate with AI technology in their studies, as well as outlines ML models that were implemented by the authors to solve these problems. The summary represents a notable variety of different ML models used in employment research, covering both supervised and unsupervised solutions. The majority of ML models identified in this study were supervised, namely LR, Regularized (Logistic/Lasso/Ridge) Regression, Naive Bayes and Bayesian Networks, K-Nearest Neighbors, SVM/SVC, Decision Trees/CART/RF, Gradient Boosting models, BART, Multilayer Perceptron / Deep NN, Distance-Weighted Discrimination. Unsupervised ML were represented by Hierarchical Clustering, Unsupervised DL NN and Stacked Auto-Encoder. Other models included Causal Uplift Modeling, Genetic Algorithms and Digital Twins.

4 Discussion

This literature review identified a variety of novel ways to apply ML and AI to employment research, following a rigorous article selection process. Out of the initial 802 articles determined in the Scopus database based on the keywords specified in this study and the subsequent secondary citation analysis, 25 articles were selected for scrutinous review and categorization. The results of our analysis suggest that from 2014 through 2024 there has been a growing attention to the application of AI, and ML models in particular, to various domains of employment research. As represented in Figure 3, the majority of the selected papers belong to ML and AI applications in employment research related to OP, closely followed by OSH and personnel selection. The minority of the selected articles belong to other domains of employment research, i.e. employee satisfaction, AM, personnel development and unemployment prediction.

Development of supervised and unsupervised ML models and their application to various problems related to employment is the major research method utilized in the selected collection of scientific articles (Figure 4). At the same time, a noteworthy quantity of AI-related articles in employment research seems to be focusing on the discussion of AI applicability to employment problems, rather than on the actual ML implementation, with PLS-SEM based on surveys on AI applicability being one of the dominant research methods. This study also identified several conceptual frameworks and systematic literature reviews focusing on various aspects of AI application in employment research, thus highlighting the growing scientific interest in this field. However, only a minority of the identified articles feature practical case studies or field experiments of real-world ML applications in the workplace. This limitation

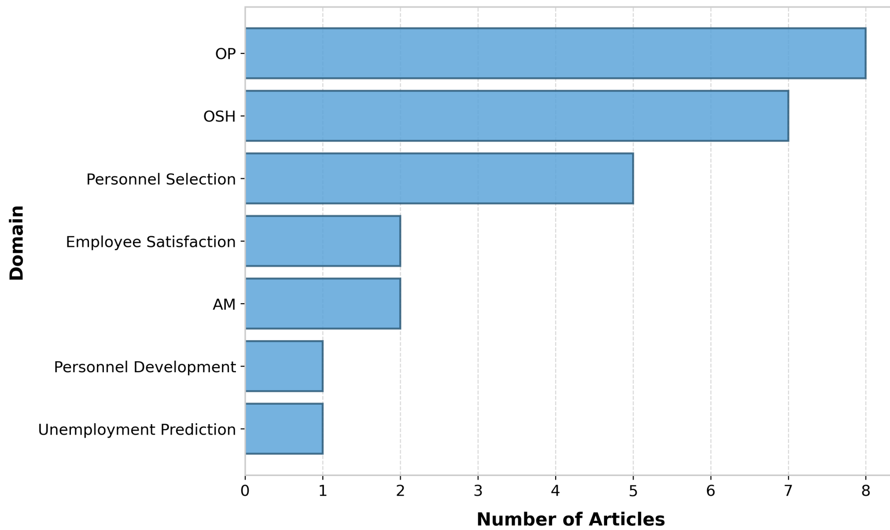

Figure 3: Distribution of selected articles by Domain

can be partially explained by the fact that employment data is often sensible, whereas scientific access to real-world workplace settings without constraints is not always allowed and requires solid cooperation with public or private third-party organizations.

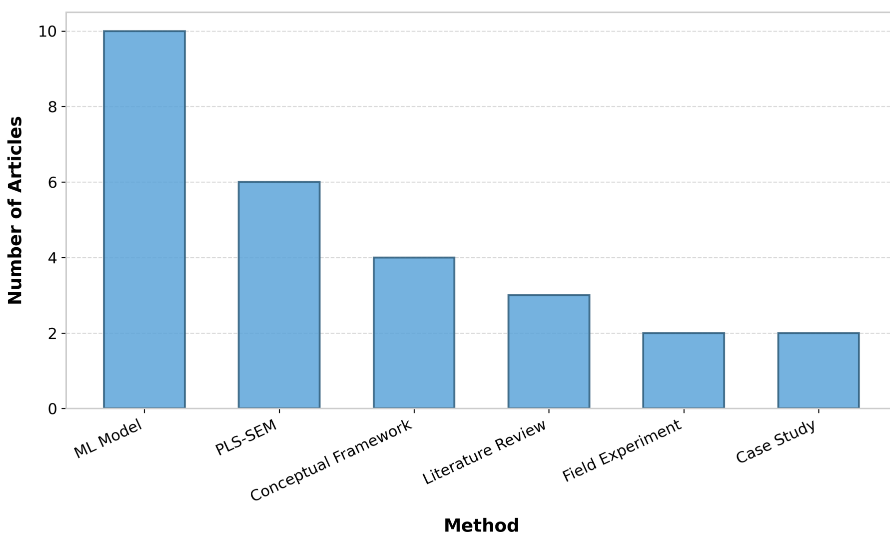

Figure 4: Distribution of selected articles by Method

Incorporation of ML within job studies, as shown in Figure 5, can be classified and discussed in three main fields, i.e., Human Resource Management, Algorithmic Management, and Job Quality Applications. Within human resource management, ML supports a range of functions such as employee growth, HR management software, and influence on factors analysis. It also includes ML techniques used for forecasting talent and monitoring performance. These programs facilitate more accurate recruitment and personalized employee training, resulting in employee retention and development [46][47][48]. Additionally, ML facilitates the reduction of bias through the creation of inclusive hiring processes [49][50][51][52]. In the context of AM, ML automatizes managerial and decision-making functions. As shown in Figure

Table 2: Summary of ML applications

Ref.	ML Tasks	Models
[4]	Firm Classification, Survival Prediction	Causal Uplift Modeling, Lasso and Ridge Regression, RF, SVM, Gradient Boosting (LightGBM, XGBoost, CatBoost)
[41]	Recruitment Decision Support	LR, Regularized LR, SVC, RF, AdaBoost, Multilayer Perceptron
[3]	Firm Performance / Employee Well-being Prediction	Genetic Algorithm, Bayesian Additive Regression Trees (BART)
[32]	Occupational Safety Monitoring	Unsupervised DL NN, Stacked Auto-Encoder (SAE), Digital Twin
[37]	Employee Satisfaction / Performance Analysis	DL Back Propagation NN, SVM Regression Model
[36]	Worker Classification by Perceived OP	Decision Tree Classifier
[30]	Workplace Incident Classification and Prediction	Naive Bayesian Classifier, Bayesian Network, K-Nearest Neighbors Classifier, Multilayer Perceptron
[40]	Job Applicant Classification	Naive Bayes, Logistic Regression, SVM Classifier, RF, Decision Tree
[43]	Unemployment Prediction based on Smart Meter Data Analysis	Lasso and Ridge Regression, Classification and Regression Trees (CART), RF, Stochastic Gradient Boosting, Multilayer Perceptron, Distance Weighted Discrimination with Polynomial Kernel
[5]	Employability Prediction	RF Classifier, Hierarchical Clustering

5, these include operational decision-making and staff training based on algorithmic output. While these kinds of systems can promote efficiency, they can also compromise transparency and alter power dynamics at work [53]. In job quality applications, ML promotes data-driven decision-making in work-life balance and job satisfaction. These include ongoing monitoring of wellness markers and the generation of personalized interventions [54][55][56]. The figure also, though, depicts the dangers of ethical governance and equity, and the need for urgent regulation. Accordingly, while ML-based work systems bring measurable benefits to various HR domains, they must be introduced with strong safeguards for equity and accountability [53][57].

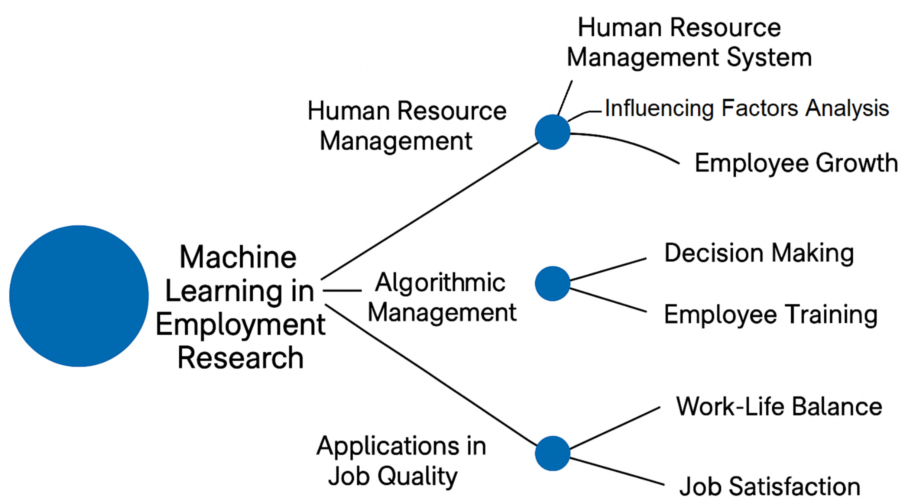

Figure 5: Taxonomy-concept map of ML in employment research

Modern expectations towards responsible use of AI (collectively addressed as "explainable AI", or XAI) encourage ML developers to implement frameworks improving transparency, traceability and interpretability of the models and their output [58]. Our research, however, showed that XAI-themed modeling considerations were mostly out of focus in the selected articles, suggesting a notable gap in ML modeling for employment research that should be addressed in further studies. Figure 6 shows that only one paper in the selected ML applications explicitly declared a white box approach [5]. Another paper declared using SHAP-value method to improve attribution and interpretability of the model [41]. The majority of the papers only hinted XAI-themed topics of model interpretability, transparency, sensitivity and causal interpretation without direct focus on the matter (illustrated with dashed lines in Figure 6). Such key XAI topics as traceability, auditing and user satisfaction were not represented in the selected collection of research papers. Although Figure 2 highlights a substantial growth in the number of studies on AI in employment research, this trend mainly reflects the general adoption of AI tools rather than a deliberate focus on ethical or responsible AI. Most of these studies assess the technical performance of algorithms or their application in organizational settings, while questions of fairness, transparency, accountability, and bias mitigation remain less frequently addressed. For instance, Chen et al. (2023) conducted a widely cited literature review on discrimination in AI-enabled recruitment and highlighted algorithmic bias across gender, race, and personality traits, proposing both technical and managerial governance measures [60]. Similarly, Ferrara (2024) offers a comprehensive survey of bias in AI systems and mitigation strategies, extending into the emerging domain of generative AI bias [61]. Another influential overview by Mujtaba and Mahapatra (2024) outlines definitions and methods for fairness in AI-driven recruitment, reviews fairness metrics, tools for auditing, and outlines future research directions [62]. These studies go beyond simple deployment of AI, illustrating a shift towards socially and ethically grounded research [63]. This distinction is important because the rising volume of publications does not necessarily mean that research outcomes align with responsible AI principles. Systematic analyses that explicitly evaluate how ethical and responsible AI practices are embedded in these studies would therefore complement the current picture and could even produce a separate trend analysis parallel to the general one presented in Figure 2.

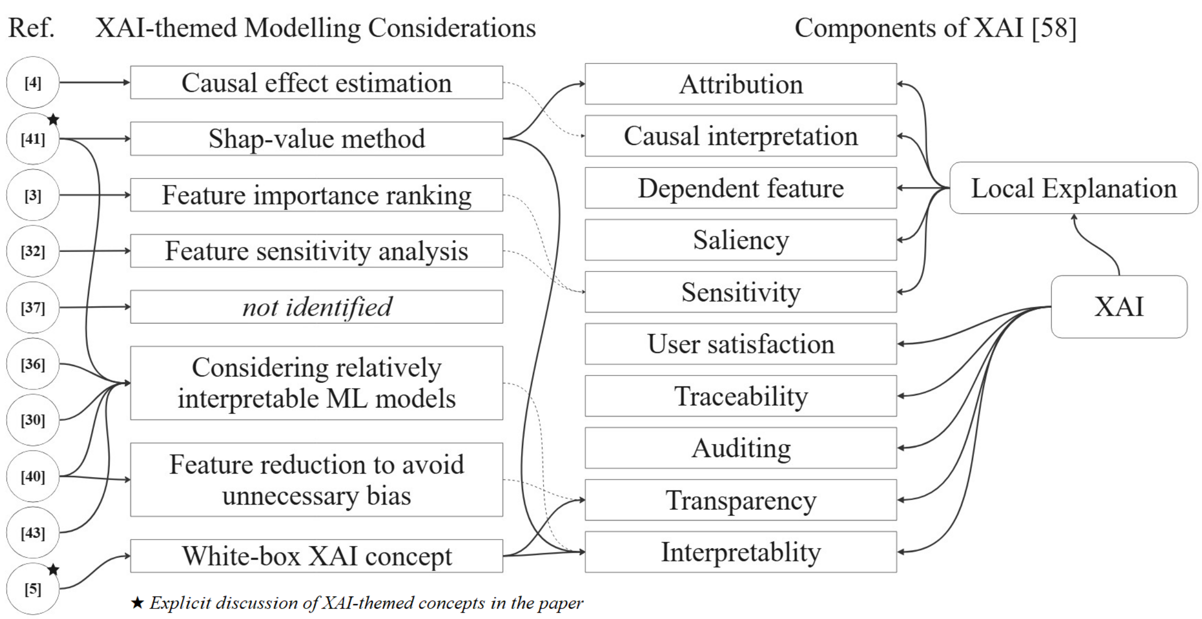

Figure 6: XAI-themed modeling considerations in selected articles

Moreover, considering XAI concepts in employment-related ML research is crucial in the wake of the new EU AI Act, the first structured legal framework adopted by the European Union in August 2024 to govern AI applications on the statutory level and expected to become fully applicable in August 2026 [59]. The EU AI Act outlines several broad categories of risks stemming from AI applications, imposing strict XAI-themed obligations for high-risk AI systems and fully prohibiting AI applications in the "Unacceptable risk" category in the EU. This research makes a high-level attempt to categorize the practical ML/AI applications from the selected papers based on their potential treatment under the EU AI Act (Figure 7). Although it must be highlighted that each application should undergo a more thorough analysis before it can be accurately placed under one of the EU AI Act risk categories, we would like to emphasize that the Act can prohibit emotion recognition in workplaces and place strict requirements for AI applications in AM, personnel selection and OSH. Other employment-related AI applications involving chatbots or, for example, dealing with sensitive data may require more transparency, whereas ML-powered OP modeling or applications unrelated to decision-making and safety in the workplace may be considered less risky by the regulators. For future assessment of AI/ML applications in employment research in view of their readiness for the EU AI Act, we suggest the conceptual framework outlined in Figure 8.

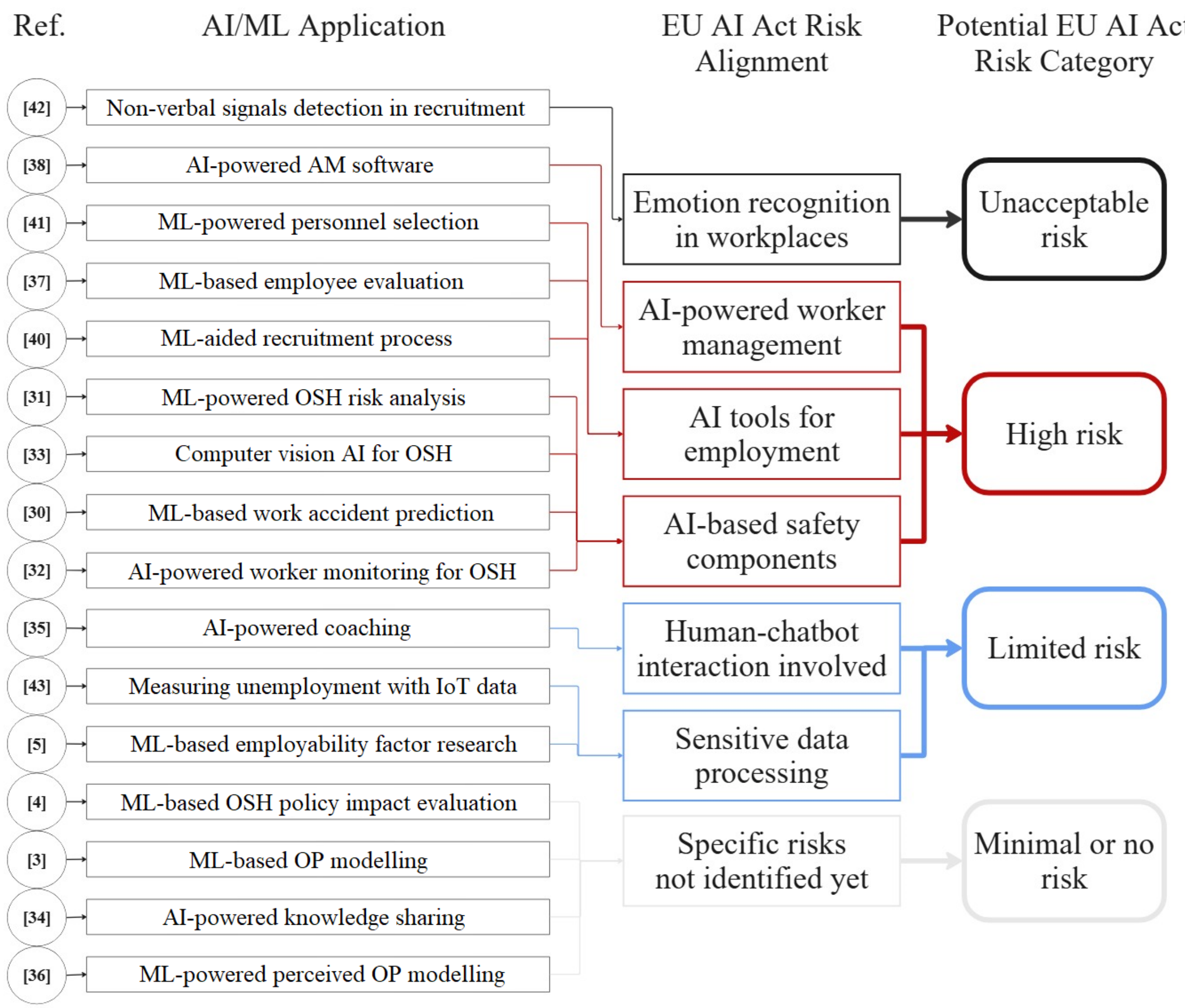

Figure 7: Potential EU AI Act [59] risk category representation

This study, however, has several limitations in scope and analytical depth. The time frame of the study was limited to October 2024, when the authors conducted the article search in

Scopus. Adding more recent articles into the scope of the literature review would provide more insights into the current state of ML application in employment research. Broadening the list of keywords for the initial screening and expanding the search to other databases apart from Scopus could also provide a more diverse selection of papers. Future research should put more emphasis on real-world field experiments and case studies of ML application in the workplace, providing more empirical data needed for further XAI and EU AI Act-related research. Future ML applications in employment research should encourage more transparency and better interpretability of ML models, diving into design frameworks for traceability, auditing and user satisfaction. ML-powered employment research representation under EU AI Act also remains a novel topic for future scientific analysis. Moreover, considering the lack of practical ML solutions based on large language models in the papers selected for this literature review, for future workplace studies we suggest leveraging generative AI as foundation models to reuse code and optimize the resources required for training ML models in employment-related research.

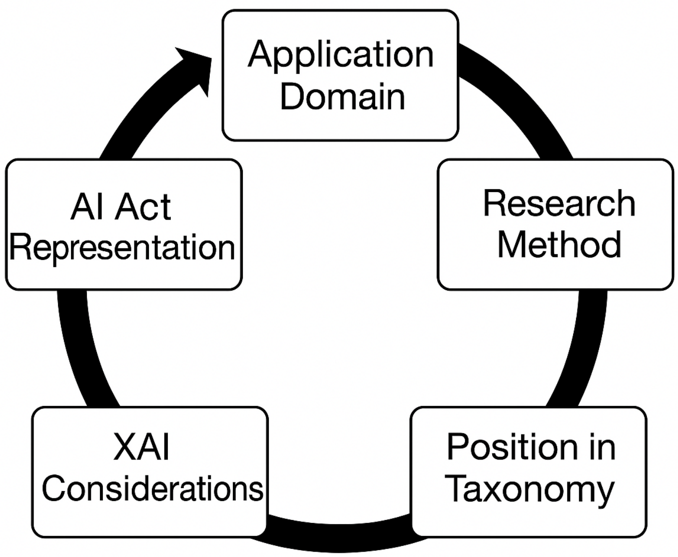

Figure 8: Conceptual framework for EU AI Act readiness assessment in employment research

5 Conclusion

AI reshapes employment research through practical applications in job quality and algorithmic management. These technologies already predict employee performance, reduce turnover, personalize education, and improve recruitment efficiency. AI replaces repetitive tasks and generates actionable insights on satisfaction and risk of exit. At the same time, their use introduces new challenges related to bias, data privacy, and transparency. In current practice, these concerns receive increasing attention, with efforts to improve fairness and accountability. AI-driven workforce management now reflects a shift toward data-informed, efficient, and adaptive employment systems.

Applied ML provides promising tools that solve a wide variety of employment-related problems. This study provided insights into the growing field of research on application of ML models to a diverse array of underlying domains, considering the implementation of AI into employment-related OP, OSH, personnel selection, employee satisfaction, AM, personnel development and unemployment prediction. This paper introduces the taxonomy concept for ML applications in employment research, discusses the growing focus on XAI frameworks accelerated by the adoption of the EU AI Act, as well as suggests the conceptual framework for EU AI Act readiness assessment in employment research. Whereas the number of publications on the subject is growing, we suggest that the scientific community should place more importance on real-world case studies and field experiments, implement XAI concepts in future ML models for the workplace, lead the discussion around the potential impact of the EU AI Act on ML applications in employment research, as well as consider leveraging generative AI to make use of the available foundation models as the backbone of further research.

Novel applications of ML and AI in employment research, both on the macroeconomic and microeconomic level, can revolutionize the workplace and refine the employer-employee relationship towards a more sustainable future. Beyond the scope of AI in general, future studies should specifically examine the extent to which ethical and responsible AI principles - such as fairness, accountability, transparency, and sustainability - are integrated into employment-related AI applications. As suggested by the growing policy and research discourse, this perspective could complement the analysis presented in Figure 2 by distinguishing between the simple use of AI and the adoption of ethical AI practices. Mapping the trend of responsible AI would help identify whether recent developments move beyond technical optimization towards approaches that are socially responsible, legally compliant, and aligned with human-centered values.

Abbreviations

AI Artificial Intelligence
AM Algorithmic Management
BART Bayesian Additive Regression Trees
DL Deep Learning
GDP Gross Domestic Product
IoT Internet of Things
LR Logistic Regression
ML Machine Learning
NN Neural Network
OP Organizational Performance
OSH Occupational Safety and Health
PLS Partial Least Squares
PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF Random Forest
SEM Structural Equation Modeling
SVC Support Vector Classifier
SVM Support Vector Machine
XAI Explainable AI

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typographical error detection. All scientific reasoning, methodological design, and conclusions were developed entirely by the authors. An author is in the editorial board of the journal.

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