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Systematic Review

The Impact of Artificial Intelligence on Industrial-Organizational Psychology: A Systematic Review

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Abstract

Current trends indicate that the pace of artificial intelligence and machine learning technology innovations will continue to increase in the foreseeable future. The objective of this study was to conduct a systematic review of the relevant literature as well as a qualitative meta-analysis of recent studies on the impact of artificial intelligence and big data on industrial-organizational psychology. Following the guidelines for preferred reporting items for systematic reviews (PRISMA) and meta-analyses, the researcher conducted a literature search within various main electronic databases. The results of the meta-analysis showed a positive association between artificial intelligence and different aspects of industrial-organizational psychology. In addition, results showed that artificial intelligence-enabled automation and robotics are going to play a great role in the future. Furthermore, this study provides several directions for future studies and discussion on both academic and professional implications.

Due to the rapid increase in the technology inventions and information systems, big data have become one of the most critical challenges that face organizations, as the need to coordinate and connect those huge sets of data across different sources is increasing as well (Pietsch, 2021). According to Sheoran and Parmar (2022), data cleaning is considered as the most time-consuming and financially costly phase in data analysis. Machine learning (ML) and artificial intelligence (AI) could use those huge datasets to conduct automated analysis and make decisions. Artificial intelligence is widely regarded as an important innovation that will fundamentally change how humans perform their day-to-day workplace activities, with special implications for several service and industrial sectors (Clifton et al., 2020). Artificial intelligence can be defined as the process of making machines intelligent, where intelligence is the property that allows an object to function appropriately and predictably in its surroundings (Boddu et al., 2022). Artificial intelligence has become increasingly visible in the society and the economy. Artificial intelligence is an umbrella concept that subsumes an entirely new generation of technologies that can interact with the external environment in ways that increasingly simulate human intelligence naturally (Glikson & Woolley, 2020). Therefore, successful implementation of AI into organizational computer networks is inextricably tied to human trust in AI technologies. Artificial intelligence technologies are situated at the foundation of what has been termed the “fourth industrial revolution” by some authors (Hassoun et al., 2022; Tortorella et al., 2021; Malomane et al., 2022). The basic transfer of individual agency and autonomy from human beings to some type of computer-assisted technology represents the core of the process (Glikson & Woolley, 2020). Although a growing number of enterprises of all sizes and types of report using AI and ML algorithms to solve a wide range of organizational problems based on their ability to formulate accurate predictions by analyzing big data, there remains an urgent need to investigate further the impact of AI in various industrial settings to determine its effect on human-technology interactions.

Industrial-organizational psychology (IOP) is uniquely positioned to offer guidance about how current AI implications and future AI development could impact and employees by providing evidence for investigating the opportunities and challenges of such technology. Industrial-organizational psychology is a psychological subfield that studies individual, team, and organizational issues in the workplace context using psychological theories and methods (Spector, 2021). Industrial-organizational psychologists can be found in organizations performing different jobs. For example, they act as human resources managers, behavioral analysts, and organizational effectiveness consultants (Kumar et al., 2018). Current literature has many studies on conceptual (Dessein et al., 2022; Hüffmeier & Zacher, 2021; Lefkowitz, 2021; Moses et al., 2022) and meta-analytic (Bartlett et al., 2019; Donaldson et al., 2019; Guzeller & Celiker, 2020; Cabello et al., 2020) IOP. However, as the field of IOP has grown rapidly in the past decade, there is a need for an update to cover the crucial findings on evolving trends and issues in the contemporary empirical research. While the previous studies have provided useful information about the advancement of IOP and AI, their focus was on specific IOP functions or practices; to the best of the researcher's knowledge, no study has reported a comprehensive review on the impact of AI on IOP. Thus, to address this research gap, the purpose of this study was to conduct a systematic review of the relevant literature as well as conduct a qualitative meta-analysis of recent studies on AI related to IOP. In addition, this review provides implications and suggestions that support the organizational research and practice community.

Methods

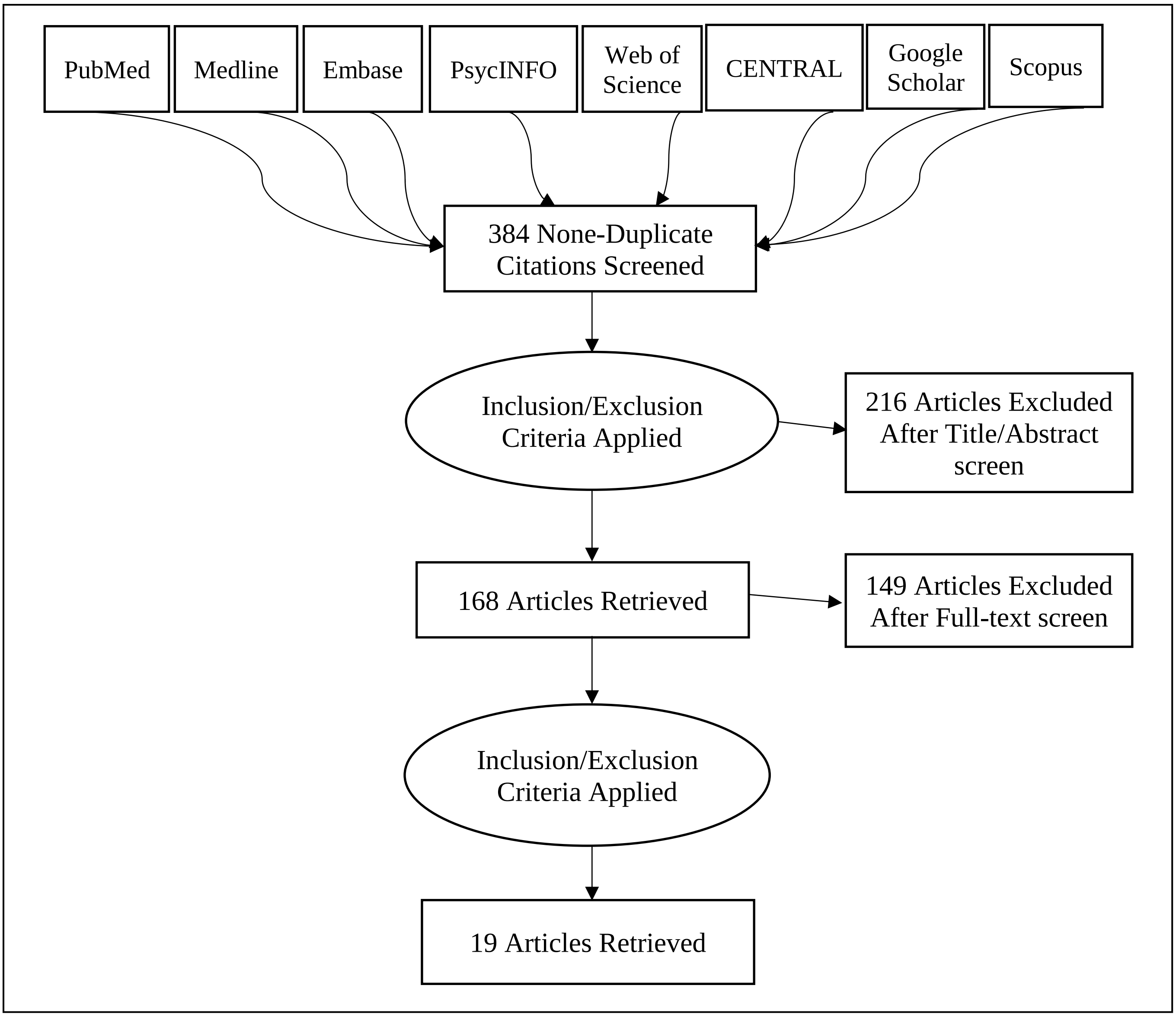
This study is reported in compliance with the preferred reporting items for systematic reviews and meta-analyses (PRISMA) reporting guidelines. According to (Moher et al., 2016) PRISMA has become one of the most-used systematic reviews guidelines by scholars in different fields (Caulley et al., 2020; Page & Moher, 2017). The PRISMA guidelines are a practical set of suggestions proposed to encourage transparent and comprehensive reporting of systematized review research (Sarkis-Onofre et al., 2021). The scope of this study is a comparative systematic review that addresses the population, intervention, control, and outcomes (PICO) framework (Morgan et al., 2018), including study design, participants, interventions, comparators, and outcomes, for eligibility. As for the study design, prospective field research reporting links between AI and IOP was eligible. This study included all types of adults in different occupations, sectors, and employment, including unemployed individuals. In addition, studies examining a wide range of work- and employment-related elements, such as working time, compensation, and mental and physical demands, were eligible. The comparator group was made up of subjects who had not been exposed to a certain working condition/had been exposed to a lesser amount or who were not exposed to a specific workplace intervention/or had been exposed to a different intervention, as appropriate. Thus, all outcomes of interest affecting the psychological status of the study sample upon interaction with, or implementation of AI were eligible. Furthermore, articles from peer-reviewed journals published in English were eligible for inclusion, while conference proceedings, dissertations, and these-related manuscripts were excluded.

The major source was a structured search of various electronic databases, including PubMed/MEDLINE, Embase, PsycINFO, Web of Science, Google Scholar, and the Cochrane Central Register of Controlled Trials (CENTRAL), for relevant material. Third-party inspection (TPI) searched the reference lists of included research and pertinent reviews by hand (Neuman, 2014). Professors and librarians with expertise in the topic were contacted and consulted. Keyword search terms included "I-O psychology," "big data," "artificial intelligence," and "machine learning," as well as various combinations thereof. The key findings were organized thematically.

The first stage in the screening process was to load the articles into the EndNote X8 software developed by Thomson Reuters. Then, all generated articles were examined for relevancy, and an online and mobile application was used to conduct the screening procedure (Ouzzani et al., 2016). Studies not included in the analysis were recorded. All stages were checked prior to study selection to discover any potential misunderstandings among the reviewers about the eligibility criteria or the software interface. Figure 1 shows a flow diagram depicting the study selection process.

Figure 1

PRISMA Flow Chart of the Article Review Process in the Study



The researcher extracted data and put it into an Excel sheet. This stage was piloted with five articles to ensure that it was feasible and comprehensive. Many broad categories and individual data were retrieved (see Table 1). Next, the researcher performed a criteria-based classification of emerging themes in AI and IOP. These themes were created based on a prior literature review. Three themes were employed to filter and classify the articles chosen for inclusion: (1) artificial intelligence and big data, (2) the impact of AI-enabled technologies on the workplace, and (3) the impact of AI-enabled technologies on employees.

The grading of recommendations assessment, development, and evaluation (GRADE) approach was used to provide a structured method for the assessment of certainty (Brozek et al., 2021). In addition, a standardized risk-of-bias evaluation was used to examine the methodological quality of all relevant studies and any validity issues. The Cochrane risk-of-bias tool (RoB 2) was utilized for randomized controlled trials (Corbett et al., 2014). Furthermore, the risk of bias in non-randomized studies of interventions (ROBINS-I) (Sterne et al., 2019) tool was used for non-randomized intervention studies. Finally, a checklist reporting the quality of observational longitudinal research was used for prospective observational research (Tooth et al., 2005).

The search in PubMed/MEDLINE, Embase, PsycINFO, Web of Science, CENTRAL, and Google Scholar yielded 437 articles. These were analyzed for repeats, and 53 articles were dropped. The remaining 384 articles were analyzed based on title and abstract to determine their relevance to the study. A total of 216 articles were dropped. The remaining were then analyzed on a whole-text basis to determine their relevance to the purpose of the current study; a further 149 articles were dropped. The remaining 19 articles were then selected for inclusion in the current review (see Table 1).

Thematic Analysis and Discussion

Table 1

Articles Selected for this Systemic Review

Author(s) and date	Objective(s)/purpose	Study design	Anchored theory	Outcome
(Feinzig, 2022)	To investigate the benefits of using A.I. on improving the different HR functions.	Explorative study	N/A	A.I. can benefit the talent lifecycle, increased quality of hiring, and increased HR efficiency and effectiveness.
(Shaohua & Shorey, 2021)	To see how successful psychosocial therapies reduce depression, anxiety, and sorrow in parents who have experienced perinatal loss.	Exploratory systematic review study design	Social support theory	The use of AI-enabled technologies holds the promise of helping people cope with various types of loss.
(Braganza et al., 2021)	This study looks at the conflict between the U.N.'s Sustainable Development Goal 8 (SDG 8), promoting productive employment and dignified work with artificial intelligence (A.I.) deployment.	Exploratory study design	Psychological contract theory	Psychological contracts have a large, beneficial influence on job engagement and trust. However, when A.I. became more prevalent, the impact diminished considerably.
(Koo et al., 2021)	Investigate hotel employees' perceptions of A.I. and its influence	An explanatory sequential mixed methods design	Self-determination theory	A.I. caused job insecurity, which leads to more turnover and job stress
(Mikalef & Gupta, 2021)	Investigates the relationship between an A.I. capability and organizational creativity and performance.	Exploratory study	Resource-based theory	A.I. capability increases organizational creativity and performance.

Table 1 *(Continued)*

Author(s) and date	Objective(s)/purpose	Study design	Anchored theory	Outcome
(Pizzi et al., 2021)	Investigate how are customers react to assistants' appearance and level of activation	Cross-section study design	Consumer behavior theory	Digital assistants are linked to higher psychological reactivity.
(Wu et al., 2021)	Examine the relationship between Enterprise Service Management (ESM) use and job performance.	Cross-sectional design	Information sharing theory	There is a strong positive connection between ESM use and job performance.
(Obschonka et al., 2020)	To determine if A.I. models based on publicly available Big Data can detect changes in entrepreneurial mentality or culture between geographies.	Cross-sectional study design	The theory of economic development	The Twitter-based personality estimates show significant relationships to county-level entrepreneurship activity.
(Kaltenegger et al., 2020)	To see if there was a link between employees' working environment and systemic inflammation.	Exploratory study design	The cultivation analysis theory	Provided a synthesis of studies evaluating the association of working conditions and systemic inflammation.
(Lee et al., 2020)	Explains how machine learning approaches may inform predictive and causal models of leadership effects.	Exploratory study design	N/A	the research recommends merging machine learning with experimental designs to make causal inferences.
(Sun et al., 2020)	Examines the impact of cultural values on hotel technology	Exploratory study design	The theory of reasoned action	validating the seven-factor construct (i.e., perceived ease of use, usefulness, and usefulness).
(Schepers & Borgh, 2020)	The moderating influences of national culture on the front-line role process are explored in this meta-analysis.	Explorative meta-analysis study design	N/A	Customer expectations are the strongest antecedent to both in-role and extra-role behavior, revealing that the front-line role process differs between cultures.
(Singh et al., 2019)	Provide guide to future research and practice in sales management, related to digitization and artificial intelligence technology.	Exploratory study	N/A	The impact of sales digitalization technologies is projected to be greater and more widespread than earlier.

Table 1 *(Continued)*

Author(s) and date	Objective(s)/purpose	Study design	Anchored theory	Outcome
(Mfanafuthi et al., 2019)	Answering whether artificial intelligence and robotics will eventually replace human labor.	Exploratory study design	The labor theory of value	Computerization will replace human labor, particularly in occupations involving routine tasks.
(Reis et al., 2019)	Examine the impact of A.I. on the governmental context.	Cross-sectional study design	N/A	A.I. is likely to have a substantial impact on public jobs.
(Trang & Brendel, 2019)	Analyzes the relevance of deterrence theory in information security policy	Exploratory meta-analysis study	Deterrence theory	punishments have a broad impact on aberrant conduct.
(Damianidou et al., 2019)	Reexamine the impact of technology on employment-related outcomes	Exploratory meta-analysis study design	N/A	A.I. can help people with intellectual and developmental disabilities achieve better work outcomes.
(Feng et al., 2018)	Investigate why users display resistance to self-service technologies (SSTs).	Observed exploratory study	Psychological reactance theory	Users are more likely to regard forced adoption as a danger to their freedom in a forced setting, resulting in negative emotions and perceptions of SSTs.

Theme 1: Artificial Intelligence and Big Data

Lee et al. (2020) examined the potential effects of AI, the so-called "big data" generated by social media platforms on human–technology interactions. The cost effectiveness of this approach over conventional marketing research and analysis is clear, but important issues related to the Lee et al. study warrant noting. For instance, the findings by Lee and his associates were regarded as especially trustworthy given that the study's results were based on an ML model that examined 1.5 billion tweets made by 5.25 million Twitter users to provide an estimation of the big five personality traits (extraversion, agreeableness, openness, conscientiousness, and neuroticism) to create an entrepreneurial profile for 1,772 counties in the United States. The results of their study indicate that AI applied to the big data available through social media platforms can provide IOP researchers with timely and valuable insights into personality and culture that would not be otherwise available using conventional survey-based personality tests.

The ability to facilitate knowledge sharing, information exchange, and work collaboration has fueled a growing interest in big data generated by enterprise social media (ESM) and the big data it can generate (Wu et al., 2021). Business leaders have widely embraced these technologies to improve job performance; however, with deepening empirical research and practice, ESM usage has also yielded various negative outcomes, such as information overload, privacy invasion, turnover intention, and work–life conflicts. Over time, these negative outcomes may result in diminished job performance and employee morale (Wu et al., 2021). The outcome of this study indicates that there is a significant positive correlation between ESM usage and job performance as mediated by several factors, including the level of the job (i.e., front-line or manager) as well as gender-related differences and differences in acceptance levels for new technologies, which were attributable to the national setting (i.e., developed versus developing economy). These findings have several important implications for IOP practitioners and provide a foundation for additional research in this area.

Pizzi et al. (2021) reported that AI can help in analyzing big data by (1) gathering information from outside (including from natural language) or other computer systems; (2) interpreting this information, recognizing patterns, inferring rules, or predicting events; (3) generating results, answering questions, or giving instructions to other systems; and (4) evaluating the results of actions and improving decision systems to achieve specific objectives. While the interactional characteristics of AI have been shown to facilitate ML, these technologies also cause corresponding changes in behavior that result from external environmental stimuli in ways that resemble and even mimic the way humans learn. These findings suggest that AI will continue to increase its capabilities, limited only by computer processing speeds that have roughly maintained pace with Moore’s law and by the humans who design these systems. These findings also underscore the need for continuing research regarding the effects of these trends on the human beings that use them.

Theme 2: Impact of AI-enabled Technologies on The Workplace

Likewise, Singh et al. (2019) cited the proliferation of AI-enabled technologies, which they noted as having a profound impact on the different levels of IOP with a virtually limitless future in store. The key findings from this study included increasing potential for AI to automate organizational processes from start to finish, including customer acquisition and retention strategies, in ways never before possible. In addition, Singh et al. (2019) concluded that the extent to which companies succeed in leveraging their AI resources to automate the retail sales process will likely be the extent to which they can develop and sustain a competitive advantage in an increasingly globalized marketplace.

The findings by Singh et al. (2019) served as a useful background for a subsequent study by Schepers and Borgh (2020), which was an ambitious meta-analysis of 105 articles from 35 countries that found customer expectations are the strongest antecedents to IOP by front-line customer service employees, but these expectations differ significantly across cultures. The authors cited various examples of front-line personnel going above and beyond for customers, including financial service professionals supporting clients in choosing party venues and an airline ticket agent rushing to place a hold on an airliner to accommodate late passengers. Although rare in the real-world workplace, these types of customer-directed extra-role behaviors can be facilitated by automated technologies. However, they will still have the bottom-line effect of promoting customer goodwill and loyalty (Schepers & Borgh, 2020).

Because AI-enabled technologies do not require coffee breaks, vacations, or sick days, it is little wonder that their use has become increasingly commonplace in many manufacturing settings; however, these same benefits can also be achieved in other workplace settings, including among various service employees whose roles were limited to humans until the recent past (Feng et al., 2018). Many service industries have provided employees with self-service technologies (SSTs) to reduce costs and increase efficiency in response to these trends. Not surprisingly, the humans who survive this replacement process may become modern-day Luddites that resist the use of SSTs in ways that sabotage their effectiveness and limit the ability of companies to achieve the full range of benefits these technologies can otherwise provide. Therefore, this potentially powerful constraint to human interactions with AI-enabled technologies must be considered during any implementation of SSTs in customer service settings. An especially significant finding to emerge from the Feng et al. (2018) study is that negative reactions to SSTs are a universal human response to perceived threats. These responses vary from one individual to another. Still, they typically include negative emotions and perceptions toward the SSTs and their further adoption in the workplace since this would be regarded as yet another threat (Feng et al., 2018).

In sharp contrast to the potential Luddite-like reaction to AI-enabled technologies, a study by Mfanafuthi et al. (2019) cited the lengthy historical record confirming that automation will continue to replace human labor wherever feasible, especially for jobs that involve repetitive tasks. The studies indicate that AI and robotics are already having a profound effect on these types of traditional occupations. It is reasonable to posit that these trends will accelerate well into the foreseeable future as the fourth industrial revolution continues to redefine human jobs. Certainly, other sectors are also already benefiting from AI-enabled technologies. The number of organizations implementing AI has grown 270% since 2017 and tripled since early 2020 (Mikalef & Gupta, 2021). However, Mikalef and Gupta (2021) found that the proliferation of these automated strategies has been limited due to problems associated with their implementation and the need for fundamental organizational restructuring to achieve optimal outcomes. Therefore, organizations must also invest in complementary resources to realize the maximum return on their AI investments and reap the benefits of increasingly accessible big data resources. Because every organization is unique, complementary resources will also differ, but properly implemented and administered, AI can increase organizational creativity and performance (Mikalef & Gupta, 2021). A study by Reis et al. (2019) also investigated which sectors AI would likely have the most impact on in the coming years. Based on their findings, these researchers concluded that the transport sector will likely experience the most significant increases in the use of AI-enabled technologies. This potentially prescient prediction is based on current trends toward the commercialization and proliferation of autonomous vehicles and the corresponding uptake by the public concerning these technologies. These trends, combined with the potential for AI and big data analyses, may help identify opportunities to improve workers' acceptance of these technologies in the future in transport and other sectors (Reis et al., 2019). In addition, rather than using wholesale, across-the-board downsizing approaches to accommodate the proliferation of AI-enabled technologies, Reis et al. (2019) recommended that employees be retrained for the new types of jobs that will emerge following additional automation of existing processes.

Theme 3: Impact of AI-enabled Technologies on Employees

Braganza et al. (2021) noted the rapid proliferation of AI-enabled technologies in recent years, which is already having broad-based effects on workplace settings at the global level. Still, these researchers cautioned that improvements in organizational productivity and efficiencies will invariably carry a heavy price tag regarding their impact on employee morale and loyalty. Nevertheless, current estimates indicate that investments in AI will keep increasing over the next few years (Braganza et al., 2021). These investments also mean that unlike workplace settings in the recent past, where psychological contracts positively affected employee job engagement and trust, the proliferation of AI technologies has introduced a new type of psychological contract, termed "alienation," that has special implications for IOP practitioners. The researchers posited that the adoption has harmed modern psychological contracts that diminish employee performance in yet undetermined ways (Braganza et al., 2021). The notion of alienation responses to AI-enabled technologies was also the focus of a study by Koo et al. (2021). This mixed-methods study demonstrated that perceived job insecurity due to the implementation of AI-enabled technologies significantly affected perceived job insecurity and perceived job engagement, which indirectly affected turnover intention through an intermediary variable of perceived job engagement. The implications of these findings are significant concerning the special influence of AI on employees and their organizations (Koo et al., 2021).

The major results that emerged from Sun et al. (2020) study were the profound dearth of studies that have taken individual-level cultural values that affect employee acceptance levels of industrial technology adoption. This study drew on Hofstede's cultural dimensions to identify these cultural values, which were confirmed to play an important role in employee acceptance of AI-enabled technologies. The main practical implication of this study concerns the critical importance of considering individual-level cultural values when implementing new industrial technologies to facilitate their successful adoption. However, recently, facilitating the successful adoption of AI-enabled technologies has been particularly challenging. Indeed, IOP professionals have been confronted with some especially significant constraints to successful implementations in recent months, including developing viable responses to an ongoing global pandemic and ensuring employee safety while maintaining competitiveness and promoting organizational efficiency. Vendors have introduced hundreds of new AI-enabled IOP applications in recent years, and their use by organizations of all sizes and types has continued to increase. As this trend accelerates, Feinzig (2022) cautioned that IOP practitioners must also understand the limitations and risks associated with AI-enabled technologies to maximize the return on investments and mitigate their adverse effects. Yet another key finding that emerged from the study by Feinzig (2022) concerned the significance of recent trends in integrating various AI-enabled technologies to assist IOP practitioners in reducing recruiting time and costs and improving the quality of new hires in ways that contribute to the achievement of organizational goals. Based on his analysis, the author concluded that AI and ML can bring measurable value across the talent lifecycle. This conclusion, though, assumes that IOP practitioners accept the guidance to become more familiar with the pros and cons of AI-enabled technologies.

The downsides to implementing AI-enabled technologies were the focus of an interesting tangential quantitative meta-analysis by Trang and Brendel (2019), which sought to determine how employees tended to engage in deviant workplace behaviors when different types of AI-enabled computer-security protocols were in place. Drawing on Geert Hofstede's cultural dimension analyses, these researchers concluded that employer sanctions affect deviant behavior. Still, this dampening effect is mediated by various cultural dimensions, including power distance and uncertainty avoidance. The relationship between organizational performance and effective leadership is well documented. The integration of AI-enabled ML technologies has potential for improving this relationship in new ways (Obschonka et al., 2020). According to Obschonka et al. ML technologies provide new opportunities for organizational leadership research that has significant implications for IOP practitioners. Based on the novel and dynamic nature of the current AI landscape, the researchers also advocated the use of ML in experimental designs to identify causal inferences through the introduction of a recently developed technique to isolate "heterogeneous treatment effects" and to provide step-by-step guidance on designing studies that combine field experiments with the application of ML to identify such causal relationships. Citing relevant examples from the scholarly leadership literature, Obschonka et al. (2020) described a recommended approach to examining the impact of leadership behavior on follower outcomes and how ML can be used to advance leadership research from theoretical, methodological, and practical perspectives.

A systematic review by Kaltenegger et al. (2020) evaluated the association between working conditions in general and digital technology usage and their effects on the human immune system's response to systemic inflammatory stimuli. The main finding that emerged from this study concerned the potential additional stressors that advanced technologies such as AI may have on working environments in the future and their corresponding risks for exacerbating employee stress levels. These researchers made an important point that work stress caused by AI-enabled technologies has been associated with several health-related problems among human workers, including inflammatory processes and immune function. Although not specifically addressed, these findings have special implications during the ongoing Covid-19 pandemic that will likely endure after its resolution. In addition, the author notes that the relationship between stress exposure and chronic illness is well documented and warrants additional research.

A study by Shaohua and Shorey (2021) focused on how perinatal loss can adversely affect employee morale and performance. Citing a long list of negative psychological and physical consequences, including depression, anxiety, and grief, these researchers concluded that perinatal loss could have a devastating effect on parents, which invariably translates into diminished performance and effectiveness in the workplace. Although people will experience loss in different ways and for different lengths of time, these researchers emphasized that the use of AI-enabled technologies holds the promise of helping people cope with various types of loss.

Finally, a meta-analysis by Damianidou et al. (2019) expanded on a previous meta-analysis to analyze the effects of technology on employment-related outcomes for people with intellectual and developmental disabilities. The results of this ambitious follow-up meta-analysis were generally consistent with those of the original meta-analysis concerning applied cognitive technology effectively supporting employment-related outcomes for people with these disabilities. Nevertheless, significant differences in the intervention effects were identified (a) between groups of individuals with varying levels of disability and (b) between interventions utilizing technology with and without universal design features.

Results of Meta-Analysis

Most of the studies concurred that AI holds special implications for the future of IOP. It has already significantly influenced numerous workplace settings in various commercial sectors. Moreover, several researchers also cited the potential for big data and AI to generate new insights concerning how employees make workplace decisions (Obschonka et al., 2020; Pizzi et al., 2021; Wu et al., 2021). An especially interesting finding concerned the geographic differences that affected these decision-making processes globally (Braganza et al., 2021). In addition, the findings of the meta-analysis were also consistent in showing that AI-enabled automation and robotics are going to play an even greater role in the future, including in areas that have traditionally and historically been limited by technological capabilities, most especially in manufacturing, transport, and service industries as well as conventional workplace administration (Mfanafuthi et al., 2019; Schepers & Borgh, 2020; Singh et al., 2019). Finally, another key finding that emerged from the meta-analysis concerned the potential health hazards associated with AI (Kaltenegger et al., 2020). Besides the veritable universal calls for additional research, some other areas of consensus were identified in the meta-analysis. The findings of this research have specific limitation and implications for IOP practitioners as discussed below.

Limitations of Evidence

The primary limitation of the data included in this study is that it is secondary data and not primary data being collected from other studies. Even though it is a summary of various studies, the same evidence could be considered high quality if the same study was done at the field level involving various organizations that have implemented AI and considering the impact on IOP among employees and organizations.

Implications of the Study

Industrial-organizational psychology professionals and people in charge of various human resources tasks, such as recruitment, remuneration, well-being, labor relations, planning, training, and performance management, may find this research relevant. With the help of AI, organizations have the opportunity to learn from their data overtime to achieve their competitive advantage (Crowston & Bolici, 2019; Mikalef & Gupta, 2021; Pumplun et al., 2019; Rzepka & Berger, 2018). For example, IOP professionals in recruiting and selection can think about using data mining techniques to be more comprehensive in their search for the right individuals and analyze candidate profiles to ensure a perfect fit between candidate and firm. Furthermore, compensation professionals could use algorithms at work to determine the most effective payment formula that optimizes the balance between individual performance and compensation. Managers in charge of training and development, on the other hand, may use ML and deep learning to create tailored methods for staff training.

The adaptation of AI in organizations does not only depend on their technology readiness, but also from organizational factors such as management support (Jöhnk et al., 2021; Kelley, 2022; Shah et al., 2021), organizational culture (Behl et al., 2022; Bley et al., 2022; Dabbous et al., 2022), and organizational structure (Rieder & Skop, 2021; Shrestha et al., 2019). The effectuality of an AI system is based on the input of data which has to be carried by the employees over time (Crowston & Bolici, 2019). Thus, organizations are suggested to create an innovative culture that motivate the employees and increase their willingness to use technology to improve the quality and decisions made by AI system. In addition, the implementation of any AI system needs the support of top management and to facilitate the process and communicated down to their employees. As a result, organizations might need to be restructured to serve purposes of the proposed organizational change. Finally, by examining the IOP professionals' roles in which AI is used, this systematic literature review gives a complete overview and critical analysis of the state-of-the-art AI research and employee/organizational outcomes.

Conclusion

This study was able to: a) provide an integrative, multi-dimensional framework that encapsulates and provides a better understanding of current literature; and b) identify several research streams of how future research could further enhance the conceptual basis of this research domain by suggesting and stimulating theoretical and conceptual inputs from various fields. It is intended that this thorough and timely analysis will serve as a foundation for new and innovative research in this field, which will be of interest to a wide spectrum of academics and practitioners.

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