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IMPACT OF ARTIFICIAL INTELLIGENCE IN MANPOWER BASED INDUSTRIES

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Abstract— this research aims to provide a practical understanding of the positive and negative employee experiences caused by the adoption of artificial intelligence (AI) and the creation of techno stress. It explains the difficulties of human resource development with the advent of Industry 4.0. Recent evidence suggests an increase in artificial intelligence and robotics (AI) patenting activity in recent years, implying that AI-based solutions may have begun to have an impact on the economy. We test this hypothesis using a global sample of 5257 companies that submitted at least one AI-related patent between 2000 and 2016. After controlling for other patenting activities, our analysis demonstrates that AI patent applications have an extra-positive impact on company labor productivity. The influence primarily affects SMEs and the services sector, indicating that the ability to swiftly adapt and integrate AI-based applications into the production process is a key factor in the impact of AI so far.
Keywords— Impact of Artificial Intelligence, Manpower Based Industries, SMEs, Patenting Activities.

INTRODUCTION

A leverageable competitive advantage in the shape of human resources is a key factor in an organisation's success. Combining these human resources with operational skills enables organisations to get the most out of their human capital. (Bag and Gupta, 2019). A paradigm shift in business procedures has been brought about by the fourth industrial revolution (I4.0). But it also demands that human resources be upskilled and integrated with processes (Bag et al., 2020a, b; Skrinjaric and Domadenik, 2019). This concept, which represents industry trailblazers bringing about a revolution in the manufacturing sector, was first presented at the Hannover Fair (2011) and subsequently it was formally recognised as a strategic initiative by Germany (2013). The manufacturing industry has adopted automation on a large scale, and this encompasses enablers like the internet of things (IoT), cyber-physical systems (CPS), and cloud computing in its scope. (Lu, 2017; Bag et al., 2020). IoT, CPS, and machine-to-machine communication are three technologies that I4.0 tries to use to connect the physical and virtual

worlds. Information and communication technologies (ICT) are the basis for innovative sectors as a result of this revolution, which has led to the emergence of systems like smart factories. A novel technology framework integrating intra- and inter-organizational processes has recently been introduced by I4.0. This will meet the growing information needs of sectors and their exploration of the many advantages of digitising different organisational processes. (PWC, 2016). The Pew Research Center recently performed a survey on the effects of artificial intelligence (AI) on society across 20 global publics. As AI becomes more and more important in our lives, redesigning our workplaces and increasingly powering things, the survey looked at the effects of AI on society. It took place in 20 locations across the Asia-Pacific region, the United States, Europe, Canada, Russia, and Brazil between the close of 2019 and the beginning of 2020. In this poll, more than half (53%) of respondents claimed that the use of AI and computer systems has improved society, while 33% claimed the opposite. Most Asians have favourable opinions of AI. On the topic of robots automating human occupations, there were differing views. A large proportion, 48% said that job automation has been a positively inclined innovation, whereas 42% disagreed. Digital workspace has emerged as a new paradigm and enables employees to work both in physical and cyberspace. It facilitates increased employee productivity. This work format will help employees save on useless commuting, give them more flexibility, enable them to manage work and collaborate without any time and place constraints (Koslowsky et al., 1996; Colbert et al., 2016). Despite organizations incorporating IT for facilitating digital work, employees prefer daily office routines (Ratti and Claudel, 2016). Thus, the transition toward
digitization requires a psychological shift of work definition from 9 to 5 in office to a no time and space constraint view of work. The latter perspective has the objective of efficient completion of work (Monaghan and Ayoko, 2019). Organizations have benefitted in multifaceted ways, in terms of increased employee productivity and efficiency (Jonker-Hoffr en, 2020) by incorporating and implementing ICTs (Ruiz, 2020). There has however been a flip side to these benefits. Although productivity and efficiency have been enhanced, but the question to be asked over here is, at what cost? The
costs may not be explicit, but a no time no space constraint workplace has definitely taken its toll and has proved to be counterproductive. Excessive inroads of ICTs into our personal time and space may have unintended consequences, in terms of stress and social isolation (Nakro sien_e et al., 2019). A clinical psychologist Brod (1984) proposed the concept of technostress and explained it as a modern day ailment resulting from an individual's inability to handle ICTs in a healthy manner. Workplace stress leads to several health issues while having an impact on quality of life (Rabenu et al., 2017). A WHO report (WHO, 2005) propounds that employee work patterns have been altered by increased use of ICTs. Although organizations take cognizance of health hazards prevailing at the workplace, but not of the psychological health hazards. Certain training and other interventions are however required to take care of the mental health of the employees. Stress among employees may be caused due to digitization of office work using technological interventions like AI (Korunka and Vitouch, 1999; Bag et al., 2021a, b) or increased workload (Giovanis, 2018). It could also be a combination of both factors.

Technostress could result from an overwhelming feeling of urgency, heightened expectations from employees and organizations rewarding very hard-working employees, who remain connected and accountable at all points of time (Bellmann and Hubler, 2020). This stress can have several detrimental fallouts like mental exhaustion from work, commitment issues and turnover intentions (Moore, 2000). The importance of technostress has been further IJM highlighted by Tarafdar et al. (2007). They have posited that this technostress may result in reduced job satisfaction, lower commitment and productivity. There is however a need to develop an in-depth understanding both in the aspects of stress and ICT applications like deploying AI. Although there have been several studies on the adoption of AI and I4.0, there still remains
a lacuna in the existing literature. Prior research has explored the positive impact of AI adoption on human resources as well as the negative aspects in terms of the creation of technostress among employees (Moore, 2000; Tarafdar et al., 2007). However, there exists a perceptible gap in the in-depth practical understanding of positive and negative employee experiences due to AI adoption and the creation of technostress. Digitization has resulted in ubiquitous technostress in organizations, hence there is a need to design and develop organizational interventions to combat this menace and benefit from its beneficial aspects. As complex technological interventions continue to overwhelm organizational human resources, it is vital to develop a detailed understanding of negative
impacts like technostress along with the positive aspects. This will not only satiate theoretical lacunae but also address the practical managerial demands, helping them to develop preventive measures.

LITERATURE REVIEW

AI and big data have ushered in Industry 4.0 by bringing about a paradigm shift in the economic and social realms. (Bag et al., 2018, 2021c, d; Telukdarie et al., 2018). Conceptually, AI has been defined as a system's capacity to learn from and make sense of digital data (Elish and Boyd, 2018). According to researchers, AI can improve workers' intelligence by enabling them to better understand and handle challenging circumstances. It assists in the process of making decisions by offering a variety of alternative options. (Bader and Kaiser, 2019). While using machines for routine chores, the employees are empowered to use their creativity thanks to this assistance in making decisions. Therefore, multinational companies with skilled personnel anticipate that AI will offer a variety of business advantages. (Hsieh and Hsieh, 2003; Liu et al., 2020). Notable developments in AI, robotics, and automation have benefited many industries. These technological interventions have affected and had an impact on the hospitality and tourist industries, among other service sectors. (Syam and Sharma, 2018). These interventions have been used by the hospitality industry to complete crucial management duties and address ongoing operational issues. Numerous deployments of AI are being used to speed up procedures, concierge services, visitor registrations, bartending, virtual speech assistance, and other things. (Kuo et al., 2017; Makridakis, 2017). The automation of services in airport management systems, such as traveller information desks, has also been done effectively with AI. By handling a number of tedious duties, technical assistance frees up the employees of

service providers to engage in profoundly enriching client relationships. The performance of humans is aided and improved by AI in many areas of operations administration. AI, for instance, can empower workers while enhancing organisational efficiency, quality, customer satisfaction, and return on investment. Sun (2019) used audits that used visual identification to support his argument for using AI in product inspection. It can also be used for enterprise resource planning by guiding managers through the decision-making process for consumers, offering suggestions for improvements in product development and process management, and adjusting human resource allocation to changes in consumer requirements. (Wang et al., 2019). AI algorithms can speed up the analysis of customer reviews, give designers deep insight, and assist managers in product positioning and product development based on design components. (Singh and Tucker, 2017). Customer orientation and customization are made possible by recommendations given by AI algorithms. This in turn aids businesses in maximising economic advantages and improving customer experiences. (Grover et al., 2020). Effective supply chain management, which has been identified as a critical growth input for organizations, is a further crucial application. In terms of supply chain management, AI facilitates information sharing and collaboration. (Gupta et al., 2020; Bag et al., 2021c, d). The satisfaction of customer requirements is the goal of effective supply chain operations (Muggy and Stamm, 2020). These algorithms are typically used to reduce budgeted expenses like procurement fees and efficient resource use. In the downstream supply chain, launching new products by analysing consumer requirements and preferences is another significant use of AI algorithms. (Grover et al., 2020). The underlying premise is that a symbiotic relationship between employees and AI algorithms is needed for its effective deployment, despite the fact that numerous uses of AI have been proposed. Big data analytics and AI have been extensively used in operations management (of different sectors). For instance, in the field of healthcare, a variety of web apps have improved the effectiveness of clinical procedures like scheduling surgeries and analysing images for the purpose of disease diagnosis and prognosis. (Panch et al., 2018). Big data and machine learning have enabled the digitization and automation of production processes, which has resulted in ground-breaking manufacturing facilities like self-learning plants. (Dogru and Keskin, 2020). The use of AI in retail processes is another. Online shopping equips e-retailers with a large quantum of data-related browsing patterns and shopping habits of consumers. This in turn allows them to design future promotions and product offerings while enabling them to manage their inventory efficiently (Dogru and Keskin, 2020). AI as a technological intervention is considered relatively superior. Recent literature
indicates that AI not only enhances creative thinking but also supports context awareness, reasoning ability, communication ability and self-organization ability (Eriksson et al., 2020). It
is the combination of AI, big data and robotics that has initiated the fourth edition of the industrial revolution (Grover et al., 2020). The premise behind these technological interventions is not to replace human resources, but to function as a complementary facilitator to augment human intelligence and knowledge (Jarrahi, 2018). There can exist a symbiotic relationship between employees and AI deployment by providing mutual benefits. Thus this study aims to explore an important research question, how can the adoption of AI in I4.0 create

positive employee experiences? The ubiquitous presence of ICTs has increased the efficiency of organizations by access to real-time data for informed decisions. However, the all-pervasive nature of ICTs has increased IJM the employee workload, created a constant need for adaptation to new technological interventions and excessive dependence on them. All this has resulted in technostress among employees (Wang et al., 2008; Tarafdar et al., 2007, 2010, 2011). Several researchers have posited a plethora of antecedents as well consequences for technostress. Some important causative factors are information overload and excessive work overload which lead to frustrated and demotivated employees and poor work performance (Rabenu et al., 2017; Tarafdar et al., 2007, 2010, 2011). Individual personality traits are also known to play a role in the way people experience organizational stress and their coping mechanisms (Garg and Dhar, 2017).

Modern-day organizations' quest to stay relevant with times has resulted in over- dependence on technological interventions and their burning need to incorporate these in their organizational processes. This has consequentially resulted in employees constantly striving to adapt to these new technologies (Ragu-Nathan et al., 2008). This omnipresent and all-pervasive incorporation of technology in all workflows has left the employees feeling overwhelmed with the mental and psychological effort required for coping with all this (Tarafdar et al., 2011). This cognitive response comprising of feelings of demotivation and depression has been referred to as technostress (Ragu-Nathan et al., 2008). The term "technostress" however was first coined by clinical psychologist Brod (1984). He described it as a modern-day malady resulting in poor health due to the use of ICTs. This concept was further extended by being described as stress that is caused by an employees' inability to handle organizational demands of computer usage (Tarafdar et al., 2007, 2010).

There may be multifarious reasons for this stress like constant connectivity, a variety of new applications (difficult to comprehend), multitasking, information overload, high level of uncertainty, job insecurities and technical problems (Chala et al., 2018; Coupe, 2019; Tarafdar et al., 2010, 2011). These causal factors could be related to the organization like an individual's job-related demands and job control. Besides job-related factors, excessive use of technology could also cause stress (technostress). Tarafdar et al. (2007) conducted a detailed study on technostress and identified five factors that lead to technostress: techno-invasion, techno-overload, techno-complexity, techno-uncertainty and techno-insecurity. Technostress has assumed great importance in this technological era; hence, there has been widespread research on the causal factors as well as their consequences. For instance, Shu et al. (2011) have investigated how cognitive factors like technology dependence and belief in self-efficiency might result in stress; while Ayyagari et al. (2011) posited that technology attributes might lead to stress. Tarafdar et al. (2007, 2014) have explored the impact of all five factors creating technostress on employee performance. They have further emphasized that the negative effects of technological interventions like AI can accentuate some dysfunctional arenas of role overload and role conflict. These findings validate that technostress and productivity of employees are inversely related. Tu et al. (2005) and Wang et al. (2008) posited that the techno-overload factor had a positive impact on productivity (due to cultural differences) and centralization and innovation had an impact on levels of technostress among employees. Yan et al. (2013) on the other hand have used the person fit theory and posited stress evaluating a model for technology users in the field of telemedicine and found a moderating effect of personal innovativeness. Thus, another area of exploration that opens up for an in-depth understanding is how does AI applications in I4.0 create technostress among employees? Further, can the adoption of AI in I4.0 create unintended consequences and adverse impacts?

RESEARCH TECHNIQUES

(i) Construction of a Data Collection- The decision to use patent portfolios of companies as an indicator of the stock of previous knowledge for the creation of new knowledge is based on a number of factors. R&D spending has been used as a proxy for companies' innovation efforts in many earlier studies (e.g. Hall and Mairesse 1995; Hall et al. 2012; Belderbos et al. 2015; Ortega-Argilés et al. 2015; Castellani et al. 2019). However, since R&D expenditures are usually aggregated measures retrieved from firms' balance sheets, they serve no purpose in studies intended to concentrate on particular types of knowledge inputs, as this research for AI does. Despite being historically regarded as a gauge of innovation production (Griliches 1990; Ernst 1995). The current research makes the case that a company's patent portfolio, which roughly captures its prior innovative efforts, does a good job of measuring its current knowledge that is usable for production. This is even more true for machine learning, which has been referred to as a "invention method," and general-purpose technologies like AI. (Cockburn et al. 2019). According to our understanding, only one other paper has looked at the effects of AI on businesses using this methodology. (Alderucci et al. 2020).
(ii) Data Gathering- The research employs a qualitative methodology to analyse the information gathered from 32 active professionals who have worked on I4.0 projects for multinational corporations. To get a more complete picture of the study questions, these professionals were chosen using purposive sampling from a variety of academic and professional backgrounds, as shown in Table 1. Twenty-five of the responses were men and seven were women out of the total of 32. The years of job experience have a standard deviation of four years, with an average of 7.6 years. The respondent has a maximum of 18 years of professional expertise. Up until potential saturation, interviews were conducted. The typical data saturation occurs at 30 according to Marshall et al. (2013) and Malterud et al. (2015) in a qualitative research. Semi-structured interviews were performed, and the respondents were questioned about the potential unintended consequences, negative effects, positive employee experiences, technological changes, and technostress among workers that the adoption of AI in I4.0 may have.

Academic background		Industry		Seniority in organization	
Bachelors in technology	21	Consulting	2	Senior management	6
Masters (General)	4	Mechanical	4	Middle management	13
MBA	3	Electrical	5	Business analyst	3
Graduate (General)	2	Computer Science/IT	6	Research	2
Bachelors in architecture	1	Industrial	4	CXO	2
Masters in technology	1	Construction/Mining	2	Engineering services	1
		Electronics	3	Technical analyst	5
		Financial services	4		
		Agro-based industry	2		

Note(s): $n = 32$

Table 1- Profile of the respondents

(iii) Sample and Variables- The finished dataset includes information on 5257 companies that filed AI patents between 2000 and 2016. It comprises businesses from the manufacturing and service sectors and has a global reach. It offers details on companies' patenting endeavours in areas related to AI and those unrelated to AI, accounting data (including turnover, employment, and capital formation), country location, and industrial activity. (NACE sector at 2-digit level). Since only companies involved in AI patenting are included, the sample may suffer from a "cherry-picking" effect because it is, by definition, more technologically oriented. In the case of SMEs, there may be champions chosen rather than the bulk of smaller businesses. The natural logarithm of company labour productivity is our dependent variable. In order to model the effects of cutting-edge AI technologies on firm performance, we employ a knowledge-augmented production function framework, which informs our choice of dependent variable.
(iv) Data Evaluation- The gathered statistics were examined using the next procedure. (Figure 1). By compiling the answers into a single response sheet for each research question individually, the responses from the interviews were first coded into text and turned into the transcript. The transcript was cleaned up in the following stage to get rid of special characters, numbers, and spaces. For these folders, cases were uniformed. The definition of stop phrases came next. Finally, NVivo was used to import these transcripts for analysis. While creating the codebook for associating answers with the themes that emerged from the interviews, intercoder reliability was established. Additionally, face validity was proven using a consensus-based approach in a group. Four researchers with doctorates in management and previous research backgrounds made up the team for determining reliability and validity. A word cloud was created, and the primary content of the analysis was extracted using it. Thematic and sentiment analysis were then performed using the autocode feature. The data gathered from the interview transcripts was combined with text mining and qualitative content analysis to reveal theme convergence.

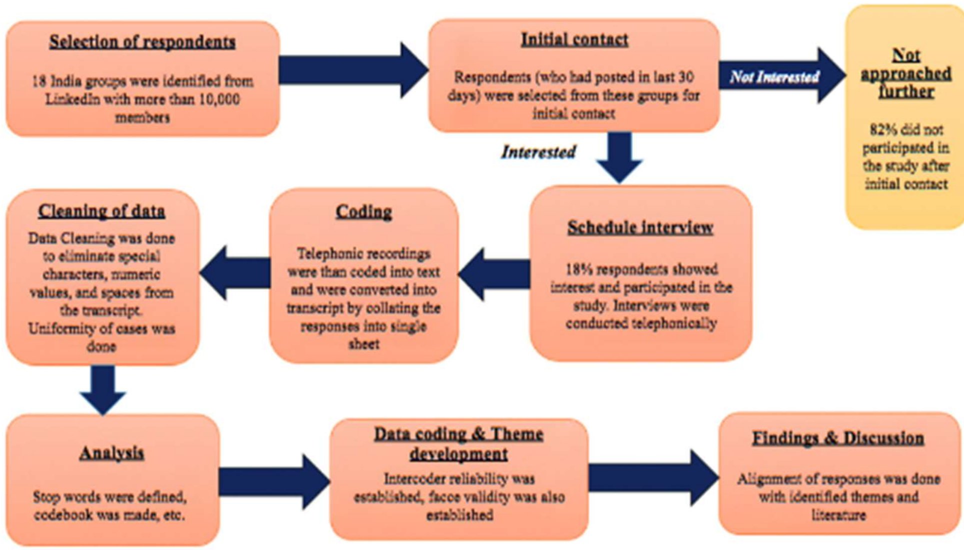

Figure 1- Data collection and analysis process

CONCLUSION

The study's results ultimately offer crucial developmental information. for human resource managers who are struggling with problems related to digitization. It requires multifaceted organisational assistance through the acquisition of soft skills like Clarity in conversation is aided by good communication and problem-solving abilities. take initiative and find answers that work), teamwork and building relationships (helps Learning abilities (helps in always having a learning mindset), job definitions, and collaborative work
attitude), analytical thinking abilities (which aid in knowledge evaluation and sound decision-making), conflict mediation abilities (helps in resolving conflicts in a peaceful circumstances), time management abilities (helps to increase efficacy and efficiency), and creative reasoning abilities (helps in devising new ways and means to complete tasks), Interpersonal and leadership skills are helpful in interacting with others and inspiring others to work towards a shared goal. All of these soft skills are crucial life preservers in a technologically advanced world and assist workers in coping with technological stress and preserving their physical and mental wellbeing. By using a special database of 5257 AI patenting firms to assess the immediate impact of AI technologies on firm labour output, we hope to close this gap in the literature. Using a sample of international businesses with at least one AI-related patent filed between 2000 and 2016, we test for this potential effect. Our findings show that AI patent applications have a positive and significant effect on labour productivity, even after controlling for businesses' patenting activities in unrelated areas. This effect is concentrated in the SME and service sectors, indicating that the effect of AI patenting is (possibly still) indistinguishable from the larger effect of non-AI patenting in the biggest and most innovative manufacturing sectors.

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