Unlocking the Value of Artificial Intelligence in Human Resource Management through AI Capability Framework

Abstract

Artificial Intelligence (AI) is increasingly adopted within Human Resource management (HRM) due to its potential to create value for consumers, employees, and organisations. However, recent studies have found that organisations are yet to experience the anticipated benefits from AI adoption, despite investing time, effort, and resources. The existing studies in HRM have examined the applications of AI, anticipated benefits, and its impact on human workforce and organisations. The aim of this paper is to systematically review the multi-disciplinary literature stemming from International Business, Information Management, Operations Management, General Management and HRM to provide a comprehensive and objective understanding of the organisational resources required to develop AI capability in HRM. Our findings show that organisations need to look beyond technical resources, and put their emphasis on developing non-technical ones such as human skills and competencies, leadership, team co-ordination, organisational culture and innovation mindset, governance strategy, and AI-employee integration strategies, to benefit from AI adoption. Based on these findings, we contribute five research propositions to advance AI scholarship in HRM. Theoretically, we identify the organisational resources necessary to achieve business benefits by proposing the AI capability framework, integrating resource-based view and knowledge-based view theories. From a practitioner's standpoint, our framework offers a systematic way for the managers to objectively self-assess organisational readiness and develop strategies to adopt and implement AI-enabled practices and processes in HRM.

1. Introduction

The availability of big data and emergence of Internet of Things in the past decade has made Artificial Intelligence (AI) enabled technologies top priority for business organisations. AI has become the key source of business model innovation, process transformation, disruption and achieving competitive advantage in organisations embracing data-centric and digital culture (Ransbotham et al., 2020). In this context, existing literature has reported that the adoption of AI has increased by 70% in the last five years (Ghosh et al., 2019). International Data Corporation has predicted that the global spending in AI will increase from $85.3 billion in 2021 to more than $204 billion in 2025, making the compound annual growth rate 2021-2025 to be 24.5%. According to the predictions made by World Economic Forum adoption of AI will make 75 million jobs redundant and create 133 million new ones worldwide by 2022 (WEF, 2018).

The impact of AI in transforming both businesses and societies is comparable to that of the internet and world wide web, which led to the emergence of ecommerce, consume-centric practices, sharing economy and gig economy (Malik et al., 2020). The emergence of AI-based systems in the business organisations will significantly transform work force demographics, nature and meaningfulness of jobs, employer-employee relationship, relationship between people and technology, customer experience, and competitive advantage within dynamic market environment (Wilson et al., 2017; Connelly et al, 2020). A study conducted with 8,370 employees, managers and HR leaders across 10 countries that has been reported in Oracle and Future Workplace (2019) found that: (1) 50% of the human workforce are using some form of AI in their workplace in 2019, compared to 32% in 2018; (2) 76 percent of workers (and 81 percent of HR leaders) find it challenging to keep up with the pace of technological changes in the workplace; (3) 64% of people will trust a robot more than their manager. Workers want a simplified experience with AI at work, asking for a better user interface (34 percent), best practice training (30 percent) and an experience that is personalized to their behaviour (30 percent).

Even though AI has been a focal topic for several decades, there is currently no single universally accepted definition throughout the literature, which leads to a fundamental problem of coherent understanding of AI (Mikalef and Gupta, 2021). We have identified and selected eight definitions of AI from multiple disciplines to enable a more comprehensive understanding of AI in the HRM context (see Table 1). These definitions capture the overlap between AI, business analytics, mimicking human like behaviour, i.e., replicating human cognitive processes and emulating human learning mechanisms. Considering the AI conceptualisations presented in Table 1, we define, *AI as the ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from the data sources to achieve specific predetermined goals and tasks*. In line with this definition, our understanding of an AI application (in the HRM context) is that of any form of manmade system comprising of algorithms (derived from computing and mathematics literature), which are translated into software programs. While calling AI as manmade may be debatable (Steels and Brooks, 2018), we are yet to come across an AI system which is developed by AI itself in HRM. The software program has analytical capabilities and computational power to efficiently process big data, generate insights and simultaneously learn from it (Malik et al., 2020). Finally, the tasks and goals are predetermined, i.e., AI algorithms employed have a specific purpose and context to achieve desired outcomes (Kaplan and Haenlein, 2019). For e.g., the algorithms used for analysing sentiments from textual data differ from the ones used for analysing emotions in a static photograph and when compared to emotion detection in live videos. Therefore, the definition primarily covers the two core aspects of this emerging technology: (1) it is manufactured (artificial); (2) it has some form of intelligence (i.e., ability to learn from the data just like human beings learn from their experiences in life).

Table 1: AI Definitions

Citation	Definition
Kaplan and Haenlein, 2019	A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation
van Esch et al., 2019	Any intelligent agent (e.g., device) that distinguishes between different environments and can take a course of action(s) to increase the success of achieving predetermined objectives
Malik et al., 2020	AI, in business refers to the development of intelligent machines or computerised systems that can learn, react and perform activities like humans for a range of tasks
Makarius et al., 2020	A system's capability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaption
Schmidt et al., 2020	The endeavour to mimic cognitive and human capabilities on computers
Wamba-Taguimdje et al., 2020	A set of theories and techniques used to create machines capable of simulating intelligence. AI is a general term that involves the use of computer to model intelligent behaviour with minimal human intervention
Mikalef et al., 2021	AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals
Dwivedi et al., 2021	The increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general

The existing literature has claimed and outlined several benefits of AI adoption which includes, enhancing business productivity by optimising business operations and resources (Faulds and Raju, 2020), business model transformation/re-engineering (Duan et al., 2019), decision-making through predictive intelligence (Paschen et al., 2020), reducing employee costs and enhancing employee experience, job satisfaction and customer service (Bughin et al., 2017). This has led to increasing uptake of AI-enabled solutions in HRM sub-functional domains such as talent acquisition, video interviews, employee training and development (Maity, 2019), performance evaluation, talent prediction (Upadhyay & Khandelwal, 2018) and employee engagement (Bankins & Formosa, 2020). In this context, recent reviews have outlined the role of AI to facilitate HR analytics (Margherita, 2021), and its potential impact on HRM processes and practices (Vrontis et al., 2021).

Despite the above interest and claims regarding the applications, benefits, and impact of AI in HRM, the existing literature has found that many companies have failed to experience anticipated benefits (Fountaine et al., 2019). A recent survey conducted by Boston Consulting Group and MIT found that the seven out of ten AI projects generated limited impact (business value), and therefore AI implementation plans had dropped from 20% in 2019 to 4% in 2020 (The Economist, 2020; Deloitte, 2017). Research has also found that organisations often find it difficult to integrate AI within their business processes and systems, which inhibits AI adoption (Davenport and Ronanki, 2018; Mikalef., et al., 2019). On one hand the reports from early adopters have indicated that investment in AI is failing to incur business value, while existing literature has outlined the potential of AI to generate business (Ransbotham et al., 2017). While the recent academic reviews in the HRM literature (Vrontis et al., 2021; Margherita, 2021), have focussed on the impact of intelligent automation on firm performance, and facilitating human resource analytics, our study builds on and further extends them by answering the following research question.

What are the key organisational resources required to successfully adopt and implement AI in HRM (i.e., develop AI capability), which will lead to creating business value?

The primary objective of this article is to systematize the academic inputs through a comprehensive and systematic review of literature drawn from multiple disciplines, which includes HRM, international

Business (IB), operations management (OM), information management (IM), general management (GM), addressing the recent calls and reviews on AI in HRM (Budhwar and Malik 2020a and 2020b; Vrontis et al., 2021). Therefore, we are able to go beyond the boundary of HRM to synthesize and consolidate the current state of knowledge in the context of AI applications and adoption in HRM. In doing so, we theoretically contribute to AI scholarship in HRM, by developing the AI capability framework, consolidating all the technical and non-technical organisational resources that will help to capture the potential value from AI implementation (Mikalef and Gupta, 2021). This framework provides a holistic understanding of resources and strategies necessary to adopt AI within HRM. Second, the framework helps to unearth the importance of complementary organisational resources and not just technical infrastructure to adopt AI and achieve organisationally valued outcomes (e.g., business and employee productivity). Third, our review sheds light on the importance of developing collective intelligence within the organisations, i.e., a collaborative working environment where AI and human intelligence (HI) can co-exist, therefore introducing the new research stream, AI-employee integration, and the role of HRM in this context. Finally, the framework consolidates the multi-disciplinary literature to create a research agenda shaping the direction of future AI research in HRM.

In terms of implications for HRM managers, the proposed capability framework will offer an objective tool to self-assess the organisational resources, which will help to determine the organisational readiness to adopt and implement AI-enabled solutions. The self-assessment will help HRM managers and senior leadership to develop AI strategies clearly focussing on the purpose of using AI, the fit between the desired purpose and AI adoption, anticipated outcomes, and key performance indicators to measure the benefits of AI implementation. This will facilitate developing concrete business cases of AI implementation aligned to solving HRM problems, enhancing HR processes, and therefore serve as a blueprint for other players in the industry. Our review also provides useful insights that will help managers to strategize AI-HI integration within the organisation, to develop collective intelligence capabilities. While this is an unknown territory for HRM practitioners, our initial recommendations will help organisations to enhance understanding, trust, confidence, and satisfaction of employees with regards to AI adoption for developing symbiotic partnership between AI and human workforce,

The rest of this paper is organised as follows: Section 2 will present the review methodology. Section 3 will discuss the findings from the systematic review of literature, which is classified into five different themes. Section 4 will present the AI capability framework summarising the findings of the review and developing linkages between the five discussed in Section 3. The research propositions stemming from the review are presented in Section 5. Finally, we conclude with the research implications and limitations of the review in Section 6.

2. Review Methodology

We have conducted a systematic review of literature following the protocol suggested in the existing literature (Tranfield et al., 2003; Hopp et al., 2018) to ensure that the review process is transparent, easily reproducible, and systematises research themes critically.

Selection of Articles

We have used a list of 56 journals in HRM, General Management (GM), International Business (IB), Information Management (IM), which was also adopted by Vrontis at al., 2021 and Cooke et al., 2017. We have also included Operations Management (OM) journals in our review. We have selected journals from multiple disciplines because the role of AI in HRM has received significant attention these disciplines. We aim to develop links between the works published in these disciplines to make this review comprehensive and add rigor. The final list comprised of 82 journals (ranked 3, 4 and 4* in the on the Association of Business Schools Journal Guide 2020). As the review focussed on AI in HRM, therefore we have included research works overlapping with HRM practices, processes, issues related to AI adoption.

Search Strategy

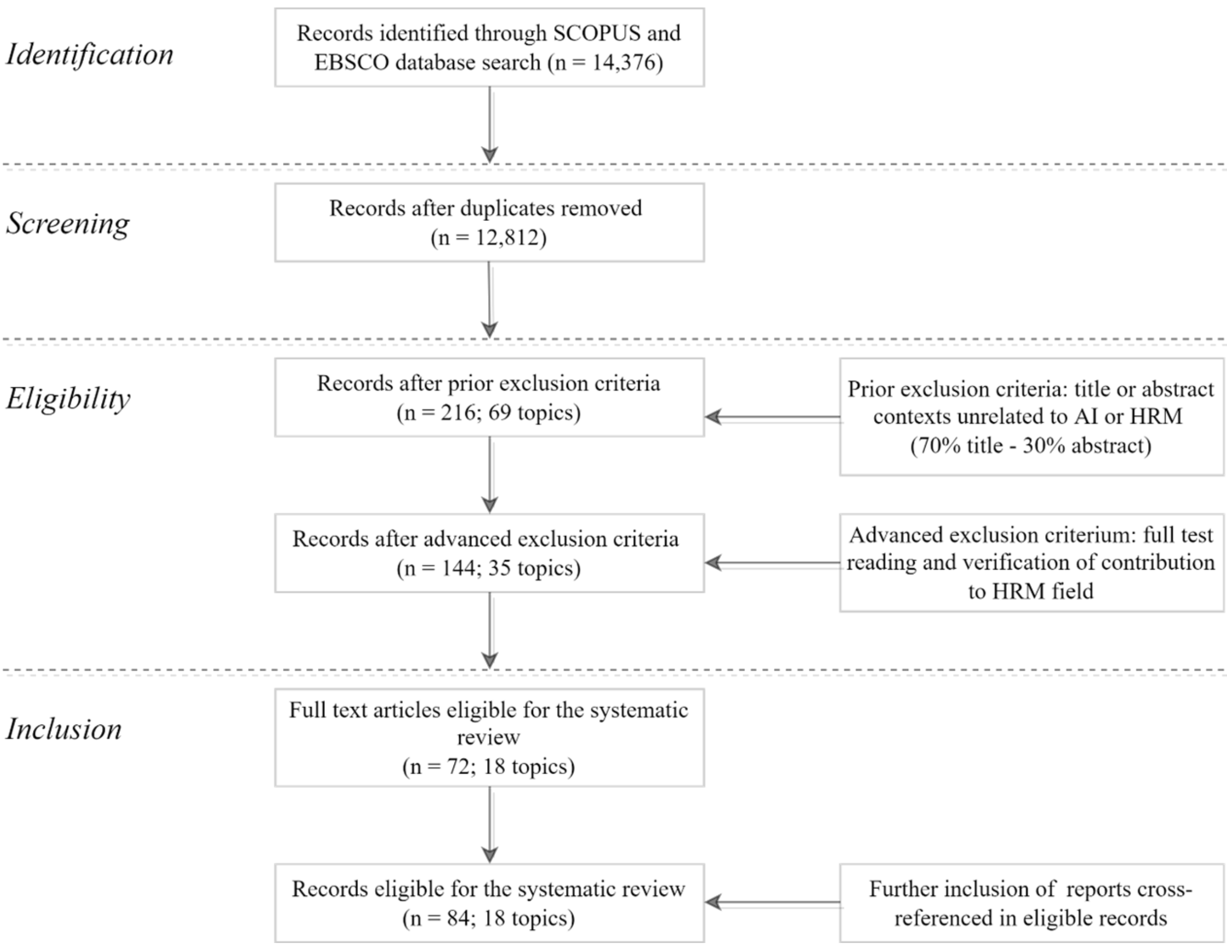
To establish the search strings, we have identified trends in the keywords usage (AI in HRM) by performing an initial scoping search of relevant articles in two research databases - SCOPUS database and Business Source Ultimate (EBSCO). The search was followed by examining the keywords used in the recent review articles (for e.g., Vrontis et al., 2021; Margherita et al., 2021), and both empirical and conceptual studies (for e.g., Malik et al., 2021; Makarius et al., 2020; Mikalef and Gupta, 2021). For specialised HRM Journals, the search string used was: ("intelligent automation" OR "artificial intelligence" OR "AI" OR "conversational agent" OR "chatbot" OR "bot "OR "machine" OR "machine intelligence" OR "automated intelligence" OR "collective intelligence" OR "collaborative intelligence"). For non-HRM journals, given the diversity of articles and topics covered in the context of AI, we used HRM-related keywords to exclude studies which did not cover HRM issues. The search string used was as follows: ("intelligent automation" OR "artificial intelligence" OR "AI" OR "conversational agent" OR "chatbot" OR "bot "OR "machine" OR "machine intelligence" OR "automated intelligence" OR "collective intelligence" OR "collaborative intelligence") AND ("HR" OR "HRM" OR "human resource management" OR "human resource" OR "IHR" OR "IHRM" OR "international HRM" OR "employ* relation*" OR "human resource development" OR "human resource performance system" OR "human resource analytics" OR "people analytics" OR "talent analytics" OR "workforce analytics" OR "HR analytics" OR "human capital analytics" OR "human collaboration" OR "employee integration" OR "socialisation" OR "teammate"). These keywords were derived from the recent reviews concerning AI in HRM (Vrontis et al., 2021 and Margherita et al., 2021) and prior systematic reviews within the area of HRM (Cooke et al., 2017; De Kock et al., 2020).

The search was also conducted in individual journal websites, where a journal was not included in the database or the abstract was missing in the final list of articles (for e.g., California Management Review and Harvard Business Review), or the search results did not show the articles from the selected journal list. A filtering mechanism was employed in the research databases to ensure that the metadata extracted is meaningful and aligned to the core research question being investigated. The filtering mechanism used the following inclusion criteria: (1) all types of peer-reviewed journal articles to ensure scientific rigor; (2) articles published in English only (to facilitate natural language text analytics processing); (3) the search string should appear either in the abstract, title or the author listed keywords of the articles; (4) subject areas chosen were business, management, decision sciences, and social sciences; (5) additional keywords which were absent in the search string and related to HRM recommended by the search interface were included (iteratively); (6) time duration was not restricted to obtain maximum number of relevant articles (last search date: Jun 2021).

Article Screening (See Figure 1)

After collecting the metadata from all the articles conforming with the search criteria from the SCOPUS database and EBSCO, we used a script written in R open-source programming language to eliminate all the duplicates. Our initial sample of potentially relevant studies was 14,376 articles. After capturing all the metadata for each article, we created a data repository capturing the title and abstract of each article. Given notable advances in natural language processing techniques, we employed a topic modelling, which is a machine learning technique to analyse the text corpus. For this study, we employed a topic modelling algorithm known as Latent Dirichlet Allocation (LDA, Blei et al., 2003) technique on the repository. The output of the algorithm is set of keywords representing a topic, and each article is characterized by a particular topic probability distribution (defined as the probability of an article being associated to a topic). This process employs an unsupervised machine learning technique, meaning that it does not require prior categorization (of topics) by the researcher, but rather relies on statistical procedures to identify topics.

Figure 1: Selection process for the review



The execution of topic modelling on 12,812 articles (after removing duplicates) resulted in 69 topics, and each topic was represented by a set of keywords. Only 35 topics were found relevant to the study, therefore articles belonging to other topics were manually screened and removed, to deal with misclassification errors of the algorithm. Next, we employed a coding process, where each member of the research team gave a meaningful identifier/name for each topic considering the keywords listed under that topic (for 35 topics represented by 216 articles). After the individual coding process, all authors came together to finalise the topics corresponding to each cluster of keywords, and then went on identifying the topics which are relevant to our research question. Based on the above exercise, we found 18 topics relevant to the study (72 articles + 12 from cross-referencing). This was followed by executing another algorithm in R (integrating topic modelling and text mining) to identify manuscripts that were related to these 18 topics. The output was a heatmap and a probability distribution, showing the relevance of the articles to each topic. We found 84 articles relevant to the study matching these 18 topics. Each article was reviewed by the authors to extract meaningful information and store this information in a document extraction table D1 capturing the following data for each article: (1) citation; (2) title and abstract; (3) keywords used by the authors; (4) type of article (review, conceptual, empirical); (5) key contributions of the article; (6) key results and corresponding findings; (7) key limitations and future direction; (8) commentary on the relevance to the topic; (9) relevance to other topics. This process followed the recommendations outlined in (Tranfield et al., 2003) to ensure that the procedure is transparent, reproducible, and devoid of human errors

Based on the document extraction table D1, we created the following tables in an Excel spreadsheet: (1) list of applications of AI in HRM reported in the literature; (2) list of drivers (for AI adoption in HRM) outlined in the existing research; (3) list of AI adoption barriers discussed in these articles; (4) under-researched themes (formulated from the last columns 7, 8 and 9 in D1). Next, all the tables were verified by each team member to ensure that the information is consistent with the literature and covered all relevant information (e.g., study protocol, or strategic implications relevant to our research question). Next, all the tables were integrated to propose a list of resources required to successfully adopt AI within the organisations, which facilitated the development of the AI capability framework for HRM applications. Finally, our research team used the knowledge extraction document (D1) to find common streams of research between the articles (primarily using column 8 - research topic), and then categorized them into research themes (merged multiple similar topics to form a single theme), which will enable us to answer our research question. This was initially done individually by each researcher and then consensus was reached through a group discussion to finalize the key themes.

3. Findings

We have used topic modelling algorithms and coding conducted by the research team members to find common topics between the articles, and then clustered similar topics together to form research themes, which will: (1) enable us to answer the research question; (2) identify the trending research areas; (3) find the knowledge gaps and inconsistencies; (4) propose research priorities. The key research themes stemming from our review analysis and topic clustering are: (1) Applications of AI in HRM; (2) Collective Intelligence (i.e., AI-human collaboration); (3) AI and employment; (4) Drivers to AI adoption; (5) Barriers to AI adoption. We will discuss the key findings related to each theme, rather than providing an exhaustive analysis of each article, similar to the approach followed in other AI-related systematic reviews in HRM (Vrontis et al., 2021; Margherita, 2021).

3.1 AI Applications

The existing literature has reported different types of AI systems within business organisations (Haenlein and Kaplan, 2019; Daugherty et al., 2019: 1) automated intelligence, which involves automating routine and manual tasks, so that human workers can spend more time in non-trivial complex tasks. For example, digital assistants (chatbots) developed using machine learning (ML) algorithms, to understand user's needs (through questions), and providing a personalised and conversational experience; (2) assisted intelligence, where AI systems can facilitate human decision-making by generating insights from big data (i.e. recommendation systems); (3) augmented intelligence, where AI systems augment human decision-making and continuously learn from the interaction with the human and environment (example – speech recognition systems); (4) autonomous intelligence, where AI systems can adapt themselves and act autonomously without any human involvement in the process (example, self-driving autonomous vehicles and drone applications).

In the field of HRM, AI is seductive as it alludes to an ability to reliably understand and predict human behaviour within an organisation, which in turn, has great appeal for managing productivity. HR analytics is described as a 'must have' capability for the HR profession, serves as a tool for creating value from people and a pathway to broadening the strategic influence of the HR functions (CIPD, 2013). Organisations are investing in AI-enabled HR software packages to collate and make sense of the employee data available for achieving strategic organisational goals. Case in point, data stored in cloud platforms like HRIS (HR Information Systems) are composed of information on employee's demographic information (employment history, skills and competencies, formal educational qualifications and demographic information) alongside softer performance data that might be collected at appraisals and performance reviews (Angrave *et al.*, 2016). In this context, AI-driven HR analytics has emerged as a popular research area within HRM (Baakeel, 2020), leveraging datasets stored in HRIS. It allows to redefine the way companies will manage their workforce (Giermindl et al., 2021), particularly to have a proficient workforce (i.e., suitable skills, expertise and experience) required to succeed in the organizations (Singh and Malhotra, 2020; Sivathanu and Pillai, 2018). The purpose is to leverage the power and potential of state-of-the-art AI-enabled systems to guide decisions. This will allow organisations to develop the capability of workforce, improve teamwork, support flexible working and improve performance measurement (Chornous and Gura, 2020). Recently a review reported by Margherita, 2021 has presented several applications of HR analytics, and offered insights that will help to design AI-based HR analytics projects within the organisations.

AI is valuable in HR decision-making (case in point employees) because of the potential to avoid subjectivity, with more objective decisions guided by the information extracted through employee data mining (Chornous and Gura, 2020). Initially, the role of AI was linked to the development of expert systems for job evaluation (Margherita, 2021), but it can be now linked to activities in the whole HR life cycle. Employee monitoring tools can help identify issues, share insights, guide decisions and encourage stakeholders to act, whereas organizational research helps examine aspects that are relevant for the organization and an evidence-based culture encourages decisions being made based on analytics and data (Peeters et al., 2020). Sparrow et al. (2015) cite the example of Tesco analytics tools to understand its customers to better understand its workforce and similarly how McDonalds was able to identify staff demographics, management behaviours and employee attitudes to optimise employee performance. The above examples demonstrate that there needs to be strategic insight among senior HR professionals to direct the use of AI-driven HR analytics within firms. Sparrow, et.al. (2015) argue that this strategic focus needs to be contextualised within the organisation. The use of technology to support HR has significant potential to support the business strategy (Kakkar and Kaushik, 2019).

AI can be used for various aspects of recruitment. Based on the model proposed by Mehrabad and Brojeny (2007), it can be used to select applicants from a pool of submitted applications (selection), make a decision based on the interview and organisational need (appointment) and propose a suitable salary and benefits based on their qualifications. This is even more so during times of crisis when organisations need to be resilient. AI recruitment has become increasingly more efficient at finding and hiring high quality staff than wholly human centred recruitment (Black and Van Esch, 2020). AI recruitment decreases the time taken to recruit individuals, enables organisations to respond to events more quickly and ultimately improve their competitive advantage through intangible assets of better recruited people. Tambe et al. (2019) show that the use of AI allows several prediction tasks for recruitment, selection, on-boarding, training, performance management, advancement, retention, and employee benefits. In particular, Baakeel (2020) examined the use of AI in recruitment, and found the potential for fast resume scanning, quickly and automatically responding candidate's queries, and virtual recruitment activities.

AI has a significant potential to support organizational research because of the capacity to analyze multiple streams of big data and support decision-making. AI can be useful to describe job requirements to attract the best suited candidates (Saling and Do, 2020), to undertake sentiment analysis for monitoring new employees joining the company (Kakkar and Kaushik, 2019) and employee motivation

(Saling and Do, 2020), to support hiring decisions through screening and matching profiles with job roles (Peeters et al., 2020), to identify personality traits from potential candidates and match them to the predominant traits found in the culture of the company (Lee and Ahn, 2020), to access a larger pool of candidates and reduce bias eliminating subjective criteria (Kshetri, 2020), to forecast absenteeism (Araujo et al., 2019), to improve retention through predictions at the individual level (Saling and Do, 2020, Kshetri, 2020), and to support decision-making for team formation (La Torre et al., 2021). Kot et al. (2021) argue that the appropriate implementation of AI to support recruitment and retention can be essential to enhance employer brand and reputation as well. A list of HRM practices where AI has been used is presented in Appendix 1.

3.2 Collective Intelligence

Jarrahi (2018) has suggested that the computational power and analytical capabilities of AI can be leveraged to deal with the complexity in decision-making process, with the intention to augmenting human intelligence (HI) and decision-making tasks, rather than replacing human from the process. Such augmentation in any job context will boost the decision-making abilities of employees and therefore enhance both employee and business productivity (Wilson and Daugherty, 2019). However, potential benefits of such AI-employee collaboration established through a symbiotic partnership can be fully realised in practice, if employees understand, trust, and adopt AI (Chowdhury et al., 2022). The use of AI was originally seen as benefiting the workforce by providing tools to enhance day to day working tasks. However, this view of AI is now being extended to encompass more than tools to support organisational performance and productivity, but for AI to become more like a peer and fellow teammate. The idea was first discussed by Malone (2018), who considered the intelligence of humans and that of machines as the intertwining of 'collective' intelligence. The machine-human collective intelligence can create, decide, remember, and learn, in a number of different roles ranging from AI tools to support team working, and even AI managers who can help evaluate and coordinate the work of others (Malone, 2018). Seeber et al (2020) went further and suggested that effective AI teammates are more than social robots and digital assistants. AI teammates 'would be involved in complex problem solving: defining a problem, identifying root causes, proposing, and evaluating solutions, selecting suitable options, making plans, taking actions, learning from past interactions, and participating in after-action reviews' (Seeber et al, 2020). However, the concept of AI socialization faces several questions and challenges often centred around human perceptions on AI as teammates (Zhang et al 2021). These challenges include, teammate aesthetic, the division of labour and accountability, team dynamics and interpersonal communication among teammates.

AI-enabled systems will both automate and augment HRM decision-making in organisations, which has been a subject of both attention and fear among the corporate leaders (Janssen et al, 2019). The existing literature has outlined concerns about the negative impact of AI such as bad decision-making, discrimination, bias, inaccurate recommendations (Davenport et al., 2020). Fear, negative perception, limited trust on AI systems and skepticism among human workers because of potential job losses has been also reported in the literature (Rampersad, 2020), and often debatable. There is limited consensus on the new jobs that will created due to AI adoption, meaningfulness of these jobs, how roles and responsibilities of human workers will be redesigned, nature of AI-employee collaboration, and strategies to manage this change. Fear of job losses and obscurity about AI-human responsibilities in a collaborative working environment will prevent organizations to concretize AI Adoption (Bughin, 2018). Furthermore, clarification about the limits and advantages of AI will help organizations to successfully integrate AI in human working environment (Malone, 2018). Knowledge sharing strategies and efforts will decrease skepticism among human employees by promoting awareness and better understanding of AI systems, and AI-human role articulations (Klein and Polin, 2012). Wilson et al., (2017) and Malone (2018) have discussed the impact of AI on the workforce and how it will re-define the jobs, tasks and roles in a business organisation adopting AI technology to strengthen their analytical capabilities. Wilson et al., (2017) have proposed three new categories of jobs as a result of AI adoption within the business organisations, which will complement the capabilities of AI: trainers will help to train AI systems, which will enhance the performance and efficacy of machine and deep learning algorithms; explainers will help to increase the interpret the outputs processed by AI systems, which will make these opaque and black-box systems transparent, that will enable building trust among the stakeholders and decision makers; sustainers will work towards AI governance, i.e. purposeful and effective use of AI, to alleviate reputational risks for the organisations posed by unintended consequences.

The IM literature has reported that humans often reject and ignore a new technology, if they feel threatened by it (i.e., affects their financial and psychological wellbeing), irrespective of their interest and enthusiasm in it (Elkins et al., 2013). Barro and Davenport, 2019 have argued that although organisations have acknowledged the potential benefits offered by AI adoption, they are yet to augment human intelligence or replace employees with AI expert systems. This can be attributed to limited knowledge, skills and understanding among the workforce (both employees and managers) about AI capabilities, limitations, strategic initiatives, and integration with the existing business processes. The recent theoretical framework by Makarius et al., 2020 has discussed the role of AI as a collaborator (new employee), where AI-employee collaboration can help the organisations to achieve competitive advantage and business productivity. This can be achieved through AI socialisation among the human workers. Makarius et al., 2020 have defined AI socialisation as the process to introduce AI systems within the organisations by providing employees with AI knowledge, skills, and expectations pertaining to job roles and tasks involved in these roles. These will enhance ability of employees to trust, use and adopt AI, productivity, and career satisfaction.

3.3 AI and Employment

Based on the review, we have identified realization (adoption), utilization (using it) and maintenance (managing, governance and evolution) as key skills required for successful AI adoption. AI realization refers to the understand and ability to identify suitable tasks and applications in the business operations to adopt AI that will lead to business process transformation or re-engineering. (Jôhnk et al., 2021; Pillai and Sivathanu, 2020), and creating AI processes (Mikalef et al., 2020; Dubey et al., 2019), i.e., understanding how and why AI should be used. AI utilization skills require knowledge and competency in data visualization and analytics, to interpret AI responses and recommendations, i.e., technical skills requited to implement and use AI systems for decision-making (augmenting human intelligence). AI maintenance is associated with knowledge to sustain the necessary infrastructure, manage, and evolve it (Mikalef et al., 2020, Makarius et al., 2020), i.e., domain specific expertise to understand the positive and negative consequences of using AI, and strategic initiatives to roll-out these systems within the firm. The development and management of these competencies, skills and knowledge will be an asset to adopt, implement and maintain AI systems within the organisations (Younis and Adel, 2020).

Companies need to develop AI skills and expertise among their workforce to support the digital transformation (Trenerry et al., 2021). This will help to minimize the friction from the human workers, which could delay the adoption of AI, and subsequently impede business value. The skills and expertise provide the organisations with capability to innovate, re-engineer and optimise both business processes and resources, efficiently, and dynamically adapt and remain responsive (Mikalef et al., 2020). Therefore, these skills are strategic intangible resources that will be difficult to imitate by other firms, providing competitive advantage (Barney, 1991). The technical and business skills necessary for each of the roles outlined above are two crucial components to drive AI adoption in organisations. These skills are crucial to bridge the gap between application of AI in a specific business context (how and why it should be used) and managing the implementation (clarity about how business processes, and human tasks will change) (Wilson et al., 2017).

Bughin (2018) has discussed how AI adoption within organisations is likely to increase the number of employees, rather than job losses, because the early adopters of AI are positioning themselves for growth which will stimulate employment. Although the labour market and expert commentators have argued against the possibility of machine dominance and job redundancies, they have failed to point out how AI will create new jobs and the skills required for the job will change. The growth of digitized sharing and the gig economy innovating existing business models has led to the emergence of a digital workforce using digital technologies to accomplish their work role and responsibilities. This will significantly impact the organisational processes, nature and meaning of work, work design structure within organisations, competencies and skills required in specific roles within the digital workforce, technology exposure, employer and employee expectations, work practices within the organisation and human resource strategy to bridge the skills gap to increase employee motivation and productivity, which will lead to business productivity (Schroeder et al., 2019; Wilson et al., 2017) . In this context, Connelly et al. (2020), have proposed a work design model to understand how increasing reliance on digital technologies, automation, and AI is shaping organisational workforce structure and environment, and its impact on employee's experience, collaborative and relational practices, work arrangement models and contracts.

3.4 Drivers to AI adoption

Major drivers identified in the literature for the adoption of AI-enabled systems include the potential to be more objective, less likely to make mistakes, and the ability to predict future behavior through the identification of patterns in the historical datasets (Giermindl et al., 2021). AI can provide more flexibility and work-related autonomy, promote creativity and innovation, and allow to streamline organizational processes (Malik et al., 2021). For recruiting, AI can help writing job profiles, screening resumes, using enhanced video analysis to identify behavioral patterns of potential candidates, comparing them with the criteria required for the position, and identifying traits and skills of potential candidates to facilitate adaptation and enhance performance (Wilson and Gosiewska, 2014). Although it can reduce bias when screening candidates (Gaur and Riaz, 2019), there is a discussion in the literature stemming from the example of the recruitment tool of Amazon showing bias against women (Meechang et al., 2020).

Additionally, AI can be useful for monitoring, performance measurement and tracking employee morale (Gaur and Riaz, 2019). AI algorithms can be combined with techniques such as data envelopment analysis to identify underperforming employees, their impact on the efficiency and effectiveness of the company, and the overall performance of the organization (Panteia, 2020), AI can be combined with agent-based simulation to predict human resource development over time in a company to identify potential changes in recruitment strategies, the effect of promotion and development conditions, and the proportion of leavers under the conditions defined for the company (Pashkevich et al., 2019). The use of AI for monitoring can also boost employee retention by analyzing social media data to identify employees interested on leaving and introducing interventions to prevent them from leaving the company (Gaur and Riaz, 2019).

AI capabilities can improve and optimize business operations and resources through task automation and augmenting human intelligence, which will reduce operational costs, lead production time, improve output/delivery response time (throughput), resulting in performance gains (Wamba-Taguimdje et al., 2020). The existing research has also indicated that IT adoption (such AI-enabled systems) within organisations will enhance dynamic capabilities which drives market capitalization, increased flexibility to re-engineer business operations and processes, resource agility, and responsiveness to address uncertain and evolving market demands and mitigate trade-offs within the organisation (Mikalef and Pateli, 2017). All these drivers will reduce bottlenecks and improve overall operational efficiency, which will result into superior business productivity.

Growing developments and usage of AI in everyday life and organisations has resulted in a need for HRM to consider the role and impact of AI on the well-being of employees. Issues such as bias (Chouldechova et al., 2018), misinformation (Chesney and Citron, 2019), lack of understanding, intrusion, inequality (Buolamwini and Gebwu, 2018) and labour displacement (Autor, 2015) may negatively impact on employees' well-being and their feelings of security, trust and privacy. This has led to a standard of recommended practice for assessing the impact of AI on well-being (IEEE, 2020), which aims to offer guidance for AI creators 'seeking to understand and measure direct, indirect, intended, and unintended impacts to human and societal well-being' (Schiff et al, 2020). If handled appropriately, AI can offer a number of well-being benefits. For example, building well-being awareness, measuring well-being and the impact of interventions and changes, managing any AI risk on well-being, supporting positive well-being initiatives and providing employers insight into employee work-life-balance (Schiff et al, 2020).

3.5 Barriers to AI adoption.

Tambe et al. (2019) argues that the adoption of AI for HRM faces four major challenges, namely the complexity of the HR phenomena, small data, ethical constraints, and the reaction of employees to the implementation of artificial intelligence. On top of that, Giermindl et al. (2021) and Malik et al. (2021) highlight the importance of privacy and data protection concerns, issues stemming from constant tracking, and the potential of bias in the algorithms themselves. Other barriers include, assessing the data quality to ensure the decisions and recommendations are precise, accurate and relevant (Ransbotham, et al., 2020); optimal training dataset to reduce bias and reputational risks (Chowdhury et al., 2020; Glikson and Woolley, 2020); integrating existing systems with the AI implementation, to streamline information processing and management (Haenlein and Kaplan, 2020); developing a data-centric culture within the organisation, so that everyone is onboard with the implementation and usage (Bieda, 2020); technology turbulence, i.e. pace at which technology is changing and disrupting business models and processes (Morse, 2020).

These barriers can have a significant impact in practice. There are several reasons why transparency is particularly necessary in a HR context (Chowdhury et al., 2020). An AI algorithm might identify a relevant criteria or relationship between criterion affecting the successful integration of employees into the company. However, that relationship may not be evident for decision-makers, which could question the reliability of the results (Meechang et al., 2020). For example, in the employee recruitment process, if the outcome of an AI algorithm is unfavorable for an applicant, the applicant and HR managers (unless they have been trained), have no mechanism for discovering why the applicant was unsuccessful, and consequently the applicant cannot knowingly improve his or her skillset. It is assumed in this argument that there is a way of controlling the input data and changing the outcome. This may not always be the case, as identified by Crain (2018), whereby transparency can be disconnected from power. This leads to the second area in which transparency is necessary, to address bias. In fact, several of the decisions made by humans are based on judgement and intuition (Meechang et al., 2020). Therefore, the interpretability of results from AI and the potential clash with the human perspective can hinder the successful implementation of AI. This is important because it highlights that the source of bias in AI is associated to the bias of the people implementing the AI.

Certain groups have been found to be disproportionality disadvantaged in AI algorithms, e.g., black faces associated as gorillas (Daugherty, 2015) and Asian people categorized as blinking (Wade, 2010). If a proportion of society is consistently marginalized in the job market or in a particular organisation, HR managers need to answer user and societal questions. If users or HR managers do not understand the algorithms' affordances and variants, this can result in an inability to use the algorithms effectively to recruit and retain the best possible staff and to be swayed by prejudice (Chowdhury et al., 2020). It should not be acceptable that 'blame' for such inappropriate outcomes such as prejudice fall upon a 'mathematical model'. Ownership of the AI algorithm and its results may be placed on HR managers, and as such they would need to know the rationale for the data input choices and results (Davenport and Ronanki, 2018).

For HR recruitment the decision-making process of targeting potential candidates and taking them through the rudimentary checks, is accelerated using AI. However, this raises significant questions about quality of the process itself, in particular an epistemological issue regarding the reliance on digital quantitative data from which the AI algorithms learn (Faraj et al., 2018). Case in point, the HR recruiters are relying on the meta-data available on social media outlets to target potential candidates for roles within organisations. The lowering of costs and easy access to the digital world, coupled with relative ease with which vast amounts of meta-data can be processed, has led society to become dominated with the logic of quantification (Espeland and Stevens, 2008). This quantification has become a substitute for an individual's social life, personality, abilities and choices, attributes upon which recruitment decisions are being made. While the algorithms can predict with some precision individual attributes and characteristics, it also limits the recruitment pool by choosing a particular set of characteristics to target. Further, learning algorithms are reductionist in nature as they use predictive modelling based solely on correlational analysis of measured dimensions, thus reducing the individual to only those measured criterion (Faraj et al., 2018). Thus, reducing individuals to a set of measured dimensions and avoiding dealing with a person's evolution and alternative explorations that may explain how one ends up in specific category (Ananny, 2015). This inevitably raises questions about overreliance on AI decisions regarding targeted recruitment and following recruitment processes.

Additionally, AI is assumed to have shortcomings in creative and social intelligence (Mak et al., 2020). For instance, AI has the potential to identify areas of lower performance based on the achievements of employees, but it would struggle to process the underpinning factors leading to low performance and therefore it could interpret a need for action in instances that may be temporary or affected by external variables. The effect of those external variables is in fact another key barrier for the use of AI. The predictive capacity of AI can be hindered by the challenges to accurately describe the complexity of human behavior (Pashkevich et al., 2019) and the effect of unknown external effects affecting the conditions of the environment and the company itself. The complexity of incorporating uncertainty in the environment (e.g., the COVID-19 contingency) and the inability to accurately predict human behavior represents a challenge for the predictive capabilities of AI. Therefore, the capability of AI needs to be combined with the capacity of humans to empathize and understand the results within the global, organizational, and personal context. In this way, humans become gatekeepers leveraging the potential from AI (Wang et al., 2021) to use the findings in the most appropriate way, thereby augmenting decision-making. This will also require human operators to constantly review, revise and update the parameters in the AI algorithm to account for organizational changes such as shifts in priorities and inclusion of relevant criteria for external stakeholders. Such initiatives will lead to successful AI implementation and acceptance from decision makers for its subsequent adoption (Cao et al., 2021).

4. Framework Development

The aim of this review is to coalesce both the popular and under-researched research themes exploring the links between AI and HRM. The framework put forward (Figure:2) seeks to illustrate the multiple resources required to build capability to integrate AI into HR processes and practices within the context of a firm. We demonstrate the impact of these transformations on the business organisations, derived from the literature in this area. The framework draws upon and integrates the theories of resource-based view (RBV) and Knowledge based view (KBV). This is particularly relevant as both RBV and KBV are important lens to study developing new capabilities in organisations (Grant, 1996; Bromiley and Du, 2016).

RBV is one of the most widely applied theoretical perspectives to explain how resources within an organisation can help to enhance business performance and competitiveness (Barney, 2001). The existing literature has also demonstrated appropriateness of RBV to be applied as a theoretical lens for developing distinctive and hard-to-imitate capabilities (such as AI implementation) in a turbulent and technology-driven business environment (Mikalef and Gupta, 2021). Knowledge based view (KBV) theory draws from classical management theories, is often considered as an extension of the RBV theory, and posits that knowledge created within the organisation is a critical asset which will help to produce sustainable competitive advantage in dynamic market environments because: (1) knowledge-based sources are socially complex to understand and embedded within the firm; (2) difficult to imitate by another organisation; (3) continuously evolve and often co-created within the organisation (Grant, 1996). Although, KBV does not specify mechanisms to share knowledge that will promote and satisfy individual-level outcomes, knowledge management literature (Hansen et al., 1999) has outlined strategies such as codification and personalisation to enhance knowledge sharing mechanisms, initiatives, and interventions to achieve organisationally valued benefits. Consolidating these theoretical perspectives will help to critically understand how internal resources (satisfying the valuable, rare, inimitable, non-substitutable, VRIN in short) within an organisation and not just technical resources can facilitate enhancing capabilities, competencies, and business competitiveness to adopt, implement, deploy, and evolve AI-based solutions

Table 2: Resources to develop AI Capability

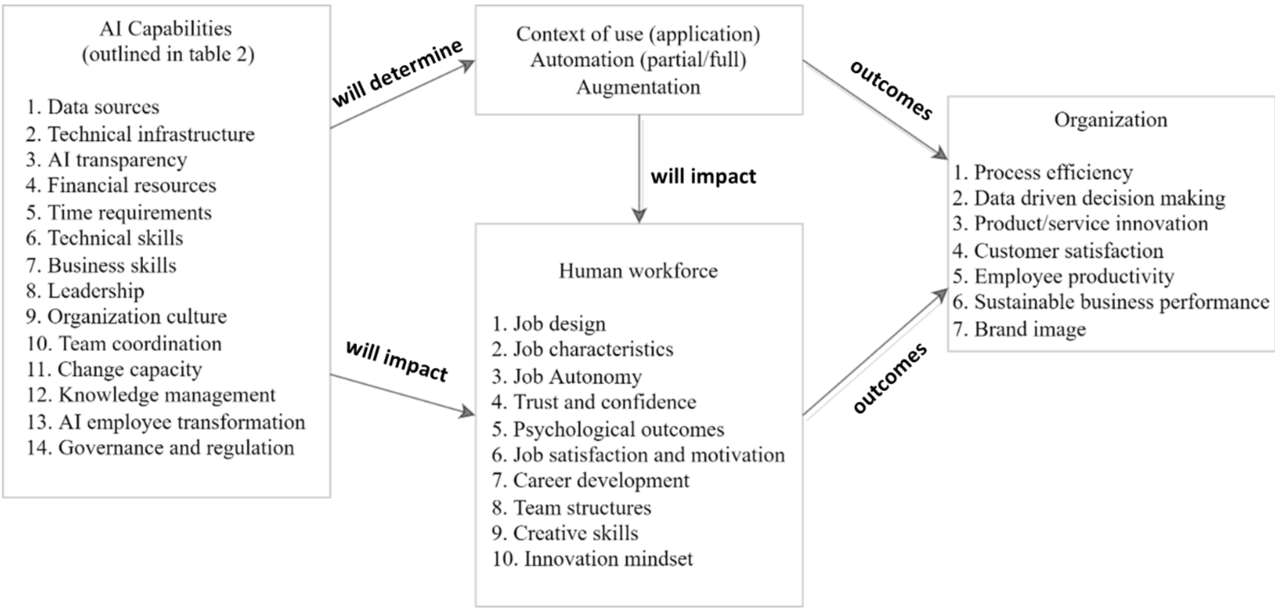
Resource Type	Resources	Description	Reference
Technical Resources	Data resources	Internal data from internal operations. External data from stakeholders, suppliers and market environment. Data collected using sensor-based technology, existing HRIS and ERP, enterprise social media and public facing social media	Colson (2019); Keding, 2020; Pumplun et al., 2019; Schmidt et al., 2020; The Economist (2017);
	Technology infrastructure	Data storage, data management, data cleaning and aggregation, processing power (parallel computing), network bandwidth, cloud-based solution, algorithms and software programs	Wamba-Taguimdje et al., 2020; Borges et al., 2020; Wang et al., 2019

	AI transparency	Learning algorithms, software such as Local Interpretable Model-Agnostic Explanations (LIME) AI design infrastructure,	Shin and Park, 2019; Chowdhury et al., 2020; Satell and Sutton, 2019; Silverman, 2020
Non-technical resources	Financial Resources	Access to capital, internal budgeting, financial resource allocation to experiment and validate AI solutions, before adoption. Budget allocation for employee skills development and facilitating career development	Fleming, 2019; Mikalef and Gupta, 2021.
	Time requirements	Periods for experimentation, achieving maturity in the sense of moving beyond proof-of-concept solutions, yielding value from adoption gradually over a period	Chui and Malohtra, 2018; Fleming, 2019; Mikalef and Gupta, 2021.
	Technical skills	Support implementation and development of AI solutions, primarily, statistical, programming, design thinking and data business analytics skills.	Wilson et al., 2017
	Business skills	How and where to apply AI, understanding capabilities and limitations of the technology, business process modelling, interpreting AI response, governance and management of AI solutions.	Ransbotham et al., 2019; Ransbotham et al., 2018; Fountaine et al., 2019.
	Leadership	Resource allocation, providing capital funds, understanding the needs of employees, business goals and priorities, strategic orientation, develop good working relationships with employees and teams, follow clear communication mechanisms	Chui and Malhotra, 2018; Davenport and Ronanki, 2018; Lee et al., 2019;
	Culture	Foster collaboration, conducive working environment, encourage creativity and innovation, risk-oriented approach meaning developing a culture which is agile, experimental and adaptable to the needs of the market and that of the human workers,	Mikalef & Gupta, 2021; Lee et al., 2019; Fountaine et al., 2019; Ransbotham, et al., 2018; Ransbotham et al., 2019
	Co-ordination between teams	Common understanding and shared vision between the employees working in different teams, whether impacted or not impacted by AI adoption, to develop mutual goals and collaborative behaviour.	Fountaine et al., 2019; Ransbotham et al., 2018 and 2019; Mikalef et al., 2021
	Organisation change	Ability to respond to change with minimal friction from employees which does not impede business growth, ability to plan, communicate, strategize and manage change to realise performance gains (it will depend on leadership, culture, co-ordination between teams, employees' skills and knowledge)	Pumplun et al., 2019; Ransbotham et al., 2020
	Knowledge management	Mechanisms and strategy to create, share, co-create, store, evolve, communicate, and apply knowledge individually by employees, and collaborating with other employees to enhance their understanding, capability, creative intelligence and innovation mindset	Chowdhury et al., 2022; Mikalef et al., 2020, Makarius et al., 2020; Mikalef et al., 2019;

	AI-employee integration	Develop collective intelligence capability within organisations through AI socialisation, informing employees about the adoption strategy, seeking their views, involving them in the implementation process, clarifying job roles, responsibilities and expectations, job autonomy and job characteristics, providing a clear path for career progression to enhance employee psychological outcomes and productivity (it will depend on knowledge management and AI adoption strategy, and impacted by leadership, culture and co-ordination between teams).	Bieda et al., 2020; Makarius et al., 2020; Amabile, 2020; Chowdhury et al., 2022
	Governance and regulation	Embed ethical and moral principles governing implementation, utilization, and evolution of AI-based solutions in the CSR strategy to address issues related to bias, inaccuracy, opacity, accountability, safety and security, societal and environmental well-being. Deciding when to use AI and when to rely on human judgement (also guided by the context of using AI). Defining protocols for the secure management of information managing data privacy and data protection.	Demlehner & Laumer, 2020; (European Commission, 2019a and 2019b; Arrieta et al., 2020

The organisational resources derived from the themes (AI drivers and barriers, and collective intelligence) are listed in Table 2. These unique resources represent the basis for defining the organisational readiness to utilize AI (i.e., resources that need financial investment and time to develop) and how it will be used (i.e., context which will lead to business process transformation). The framework further integrates these organisational resources with the themes identified in the review (AI applications, collective intelligence, and AI employment). The context of use will depend on the specific characteristics of the firm and the problems faced. We envisage the context will also determine type of AI (automation, augmentation and assisted). We have not included autonomous intelligence because we are yet to come across such an AI system in HRM, which can function without any human involvement. We argue that bots (chat systems) are based on rule-based systems, and often monitored by humans, given the risks associated with them (e.g., sexist, and racist remarks), which can negatively impact an organisation's reputation. This leads us to the next piece of the puzzle, i.e., impact on human workers and traditional HR structure within organisations, stemming from AI-Human collaboration (collective intelligence). The impact on employees is shaped by various factors such as: type of AI, particular process where it is used (e.g., recruitment, payroll), overarching AI strategy of the organisation, knowledge creation and dissemination related to AI and finally existing effort to develop skills, knowledge, and expertise of employees. The development of skills and expertise in-house will provide role clarity in a collaborative AI-HI working environment, develop trust and confidence among the human workers, which will enhance their emotional engagement with AI, and lead to superior business performance (Chowdhury et al., 2022). In the context of AI knowledge sharing, codification will facilitate scaling up the knowledge dissemination across the organisation and re-using the knowledge, and personalization will promote trust and cooperative attitude of employees towards AI, through networking and discussion. These strategies and initiatives will facilitate in developing an organisational culture which fosters creativity, innovation capability, collaboration between teams, less resistance to change and conducive to the needs of human workers (where their human attributes such as intuitive intelligence, empathy, negotiation, and communication skills are acknowledged).

Figure 2: Framework summarising the review findings



Finally, the evidence from the literature alludes to increased productivity benefits from acceptance of AI process within the workplace by employees. This takes the form of: (1) process efficiency, which will help the employees to focus on non-trivial tasks requiring their business expertise and creative intellect (Mikalef and Gupta, 2021); (2) generating hidden patterns and unlocking useful insights from big data facilitating data-driven decision-making efficiently ((Lichtenthaler, 2019); (3) introducing new products and services, improving the quality of existing ones positively impacting operational performance (Wamba-Taguimdje et al., 2020); (4) customer satisfaction by proactively understanding their needs, preferences and both positive and negative experiences (Davenport and Ronanki, 2018); (5) environmental performance by reducing energy consumption and greenhouse gas emissions, re-using resources (Borges et al., 2020); (6) social performance by reducing human subjective bias in HR processes such as recruitment, employee appraisal, and improving employee experience and working conditions by analysing enterprise anonymous social media data (Toniolo et al., 2020); (7) economic performance realised through business growth and revenue generation from 1-5 listed above, optimal employee turnover as a result of effective knowledge management strategies and 6 listed above, and ability to dynamically adapt AI innovation and re-engineer processes; (8) developing successful business cases related to AI implementation which will enhance reputation among the business stakeholders, competitors, policy makers and consumers.

5. Discussion and Research Propositions

Considering the systematic review of literature and the AI capability framework, we present five key research priorities and associated pathways that will help develop conducive organisational context and effective strategies to adopt AI in HRM. In doing so, we also identify emerging research areas considering the most recent developments and advances in the adoption and implementation of AI-enabled applications for human resource management.

5.1 AI Organisational Resources

While existing studies have focussed on applications of AI, potential benefits, and perception among the business users and consumers (Makarius et al., 2020), there is a gap in literature empirically examining the organisational resources that are required to develop firm-specific and unique AI capabilities. Our review illustrates the importance of understanding complementary organisational resources required to benefit from AI adoption in HRM, and exploring beyond the data and technological resources (Mikalef and Gupa, 2021). This underscores the need to adopt a holistic approach to develop AI capability in the organisations as investment on technology alone is unlikely to result in business gains. In this context, we have presented the AI capability framework outlining the resources required to utilize AI effectively within the core HRM operations. While we have integrated RBV and KBV to objectively develop the framework considering both technical and non-technical resources, potential impact of the proposed capabilities on organisational creativity, innovation, dynamic capability, and business productivity warrants empirical investigation. Given the interpretive nature of some of these outcomes, a mixed method approach to discern the role of organisational resources relevant for AI adoption and the outcome variables (creativity, innovation, dynamic capability, and productivity) is proposed (Bell, Bryman and Harley 2019). Based on this discussion, we propose the following research questions.

- *A1: What is the relationship between the organisational resources required to adopt AI in HRM processes and organisationally valued outcomes such as creativity, innovation dynamic capability and sustainable business performance?*
- *A2: How can organisational resources be prioritized in their impact on successful AI adoptions within an organisational context of utilization, priorities, and business goals*

5.2 'Behind the Algorithmic curtain': Issues of AI transparency and access

One of the core issues regarding the use of algorithms in making key organisational decisions is the inscrutability of the decision-making process that the algorithm engages with to arrive at the outcome (Faraj et al., 2018). For example, big tech companies like Facebook, Google and Amazon design algorithms that contributes to their success, however, these algorithms are closely guarded and protected as intellectual property (O'Neil, 2017). Further, even if the algorithm were designed by the firm for its own purpose, the learning capability of the algorithm eventually makes it impossible to discern the process of how the decision was reached. Even if auditing were to be applied to such algorithms, understanding them would be limited only to a select professional class of knowledge workers with highly specialized skills and technical training for comprehending code of immense size and logical complexity (Dourish, 2016). This inscrutability of the algorithm lends itself to an inherent lack of transparency in the use of AI within the organisational context. This lack of transparency is echoed by other scholars who argue that the inherent lack of transparency in the process of decision making by AI, makes organisational agents hesitant about using AI for important decisions (Schmidt et al., 2020). However, the organisational behaviour and psychology literature also suggests that individual's intention to use AI for decision making is dependent on perceptions and beliefs about technology (Ajzen, 1991), which would suggest that there would be a demographic divide in openness to AI. Equally, further expansion of models to delineate motivations and drivers for AI use have come back to the issue of trust and transparency of the AI systems. The findings from our review shows that research studies examining the domain of AI transparency and its impact on workplace trust is extremely limited in the HRM literature. In the context of data-driven decision-making, the issue with explainability is that business managers do not know how AI-based machine learning (ML) algorithms generate the outputs by processing the input data because the algorithm is either proprietary or that the mathematical computational models used in the algorithm are very complex to understand (Shin and Park, 2019). Limited transparency and explainability of output responses generated by the AI systems has emerged as a key barrier to experiencing anticipated benefits by confidently turning data-centric decisions into effective actionable strategies (Shin and Park, 2019; Makarius et al., 2020). We propose following streams of research that will help advance our knowledge in this area

- *A3: Which organisational resources (both technical and non-technical) are needed to enhance AI transparency and accessibility?*
- *A4: How will enhancing transparency of AI algorithms impact the decision-making strategy and perception of both employees and HR managers in business organisations?*

5.3 Knowledge Sharing: AI-Employee Collaboration

Despite the benefits offered by AI systems such as automation, process efficiency, augmenting human intelligence through their superior analytics capability, forecasting clinical demands during the ongoing pandemic (Islam et al., 2021), and decision support tools in HR processes (Daugherty et al., 2019; Davenport and Bean, 2017), majority of the organisations have failed to experience the anticipated value (The Economist, 2020 and Deloitte, 2017). This can be attributed to the fact that organisations often find it difficult to integrate AI systems with existing human workers, processes and business strategy (Deloitte, 2017), and there is a lack of both understanding as well as knowhow on the best practices to effectively develop collaborative intelligence capability (Chowdhury et al., 2022; Makarius et al., 2020). Our review found that the adoption of AI within HRM processes and wider organisation will impact employees in different ways, such as job substitution, training needs, and uncertainty regarding roles and responsibilities (Frey & Osborne, 2017), limited understanding about how and why AI will be used (Raisch & Krakowski, 2020), trust and confidence (Gunning, 2017), formation of project teams where AI and HI will co-exist as teammates (Parry et al., 2016), concerns about career development (Makarius et al., 2020). All of these are likely to result in negative perception, skepticism, and psychological detachment with regards to AI adoption and implementation (Makarius et al., 2020).

The knowledge gap is situated in this interpretive-objectivist nexus, how will the use of AI foster or impede employee collaboration and knowledge sharing. In this context, research has shown that knowledge management practices (sharing, creation, co-creation, storage etc.) in the organisations will lead to knowledge integration and evolution which will enhance organisational dynamic capability and business competitiveness (Kearns and Sabherwal, 2006; Nickerson and Zenger, 2004). However, the impact of knowledge management strategies and practices on AI-employee collaboration needs further empirical investigation, particularly in light of intangible employee attitudes of trust and psychological contracts. We propose following streams of research that will help advance our knowledge in this unknown and unchartered territory to facilitate organisations with evidence-based practices, strategies, and interventions to enhance AI-employee collaboration.

- *A5: What are the boundary conditions in terms of employee attitudes that are required to ensure employee collaboration following introduction and continued use of AI processes in the workplace?*
- *A6: How can knowledge management strategies enhance collaborative intelligence capability within the organisations? What are the external resources required to effectively develop knowledge within the organisations, for e.g., considering the institutional view of firms?*

5.4 Learning and Development for use of AI at work

HR practitioners need to have certain AI skills and knowledge to effectively use the technology to its capacity. Malik et al (2020) have suggested that HR practitioners need to develop analytical skills and an overall understanding of the business, further, an understanding of research design and data capture and processing, and identifying business needs for continued AI development and improvement. Moreover, the management of these competencies, skills and knowledge is considered an asset for organisations that can be supported using AI (Younis and Adel, 2020). The skills and expertise provide the organisations with capability to innovate, re-engineer and optimise both business processes and resources, efficiently, and therefore can their ability to dynamically adapt and remain responsive (Mikalef et al., 2020). Ideally, they should also help to govern and regulate AI, which will ensure that the business code of ethics is adhered. A recent study has reported that data analysis, digital, complex cognitive, decision-making, and continuous learning skills are necessary for AI adoption in multinational corporations in India (Jaiswal et al., 2021). Organizational structural issues will be influenced by AI systems in a variety of areas that are yet to be examined. Considering the new set of skills and capabilities needed for managers, employees, and AI to collaborate, there will be a necessity to redesign jobs, create new ones, transform business model and strategies (Toniolo et al., 2020; Wamba Taguimdje et al., 2020). Considering, the need to reskill and upskill human workforce, we propose the following research questions which will advance the capabilities of both human workers and organisations to benefit from AI adoption.

- *A8: What are the factors that will help to determine skills, competencies and knowledge required by employees and managers for successful engagement with AI processes within the workplace? In this context, how can organisations, higher education institutions and policy makers collaborate (i.e., what will be the role of each stakeholder) to either reskill or upskill workforce?*
- *A7: What will be the influence of reskilling and upskilling employees on AI adoption and creating an environment where human intelligence and AI will co-exist? In this context, what is the relationship between skills development and job design and AI adoption?*

5.5 Sparsely researched niche themes

We found that recent reports published by the European Commission have emphasised on ethical and moral aspects surrounding AI, which has led inclusion of these criterion in development and use of AI (European Commission 2019a and 2019b). The aim here is to minimize potential risks faced by organisations with regards to using AI and simultaneously protect the interests of business users (and/or whose data is collected) (Arrieta et al., 2020; Coombs et al., 2020). While research in this area is slowly emerging in fields other than HRM (Bhave et al., 2020), future studies must examine and explore strategies and principles that will help organisations to align AI utilization with their core ethos and values. In this context, we propose the following pathway.

- *A8: How CSR principles and strategies within organisations can help account for AI ethics, governance, and regulations? What will be the implications and challenges in deploying AI within HRM processes (for e.g., workforce analytics, also considering data protection principles, such as European Union General Data Protection Regulation) and in a regulated environment.*

Finally, most studies reported in the literature and including HRM focus on multinational large organisations. According to world bank, SMEs represent about 90% of businesses and more than 50% of employment worldwide, and therefore play a major role in job creation and global economic development (World Bank, 2020). They are also considered essential drivers of innovation in both developed and developing economies. In emerging markets, most formal jobs are generated by SMEs, which create 7 out of 10 jobs (World Bank, 2020). In this context, research studies are yet to examine adoption of AI within SMEs, and considering various constraints faced by these enterprises such as access to finance, human resource skills and flattened HR structure, resource constraints and limited knowledge management tools. Along similar lines, we believe that the adoption of AI within HRM will also vary according to geographical regions (developed and developing economies) and industry sectors (such as manufacturing, construction, services, education creative industry and tourism) (Vrontis et al., 2021). We are yet to find cross-country and cross-sector studies examining factors influencing AI adoption. For e.g., while many studies have examined perceptions of employees and managers, cross-country/cross-sector comparisons will bring new insights from International HRM perspective. Based on the above discussion, we propose the following research streams.

- *A9: How do country-specific institutional determinants such as culture, regulations, and market environment, impact the dynamics pertaining to adoption, implementation, and evolution of AI applications in HRM? In this context, what are the drivers and barriers to AI adoption from the perspective of different stakeholders (managers, employees, consumers, policy makers and technology providers)? A similar study can be conducted to compare business sectors.*
- *A10: Can SMEs benefit from AI adoption? What are the key drivers and barriers for SMEs organisations to utilize AI-enabled solutions within their business processes? What are the resources required by SMEs to overcome these barriers?*

6. Conclusion, Implications and Limitations

The aim of this paper was to conduct a systematic review of literature concerning the state of AI research in HRM. We reviewed potentially relevant studies in top-tier HRM, GM, IB and IM journals, and based on the inclusion criteria as well the research question. The review has identified five key themes in the literature: AI applications in HRM; collective intelligence; AI employment and skills; AI drivers and barriers to adoption. We found that the current literature has primarily focussed on the applications of AI in HRM, anticipated benefits, impact of AI on jobs, and AI-driven decision-making augmenting human intelligence. However, research on collective intelligence stemming from AI-employee collaboration, AI transparency and explainable analytics, and AI ethics and governance is nascent and emerging within the HRM literature. While, many studies have reported the drivers and barriers related to adoption and implementation of AI, we consolidate these multi-disciplinary perspectives, and integrate RBV and KBV theories to propose AI capability framework. The capability framework will help managers in the organisations assess their readiness to leverage AI-based systems. Based on the systematic review, we also propose research priorities for theoretical and empirical advancement of scholarship on AI in HRM. The research priorities identified are: (1) validation of the AI capability framework (resources and knowledge); (2) impact of AI transparency and trust on employee and business productivity; (3) antecedents to AI-employee collaboration and its impact on business performance; (4) knowledge management strategies to upskill and reskill workforce, and its impact on AI-employee collaboration. Our review findings show the need to undertake empirical studies to provide conclusive evidence showing the impact of AI adoption on employees, managers, HRM processes, and business productivity. These studies should be developed on the conceptual work reported in the existing literature by adopting multi-disciplinary and multi-theoretical perspectives to enhance impact of the findings and research rigor.

6.1 Theoretical Implications

From a theoretical perspective, firstly, we contribute to shaping the narrative of the current debate on AI adoption in HRM and its impact on human jobs in organisations which are likely to be disrupted by AI. Further, we put forward some areas of knowledge that can shape organisational strategies for AI-employee collaboration (where both AI and human intelligence will co-exist). This will facilitate development of strategies and capabilities within organisations to build hybrid workforce in the future, that has the potential to enhance business performance, and dynamically adapt to market uncertainty and volatility (Chowdhury et al, 2022). In this context, our review had identified that the anticipated benefits of AI in HRM processes and practices can be realised by developing collective intelligence capability within the business organisation. The existing research studies have indicated the importance of AI-human collaboration (Makarius et al., 2020, Chowdhury et al., 2022), which has emerged as a new research theme in the literature. Research on this theme is less developed in the management literature, except Makarius et al, 2020 reporting an AI socialisation theoretical framework, and Chowdhury. The importance of collaboration, cooperation, and coordination, to understand the capabilities and limitations of AI in the organisational settings has been discussed in (Caputo et al., 2019). The authors have concluded that effective collaboration between human intelligence and AI will help to unlock the real potential of digital technology to solve pressing business and societal challenges, and this will require careful crafting of a strategy to re-define and recategorize existing jobs, by considering the skills-gap.

Secondly, our review found that developing appropriate conditions, strategies, and resources within the organisation will allow the employees to harness AI skills, facilitate access to relevant knowledge and expertise base, and therefore will facilitate AI adoption and implementation within the business processes. According to Lei et al., 2020 have reported that the motivation and willingness of employees to embrace change, innovation, dynamically adapt and evolve is guided by a supportive and sharing culture within the organisations. In this context, organisational leadership will play a significant role in developing and shaping a positive culture and innovation mindset within the organisations, which is conducive to introducing, implementing, and managing innovation (such as AI) within the organisations (Le, 2020). Therefore, AI can be considered as an innovative technology and organisational strategies put forward by the managers will play a critical role to develop facilitating conditions to deploy, manage and evolve AI.

Thirdly, our review shows that explainable analytics, i.e., understanding how AI algorithms generate recommendations based on the inputs will facilitate building trust among the managers and turn these outcomes into meaningful and actionable insights (Cowgill and Tucker, 2020). The ability to understand the output responses will also reduce biases in business processes, operations, and decision-making, thus enhancing fairness (Satell and Sutton, 2019). The aim of transparent and explainable AI is for the business users to confidently assess the reliability and accuracy of the output responses based on their own tacit domain expertise, which will augment trust in these systems. Therefore, embedding transparency in AI algorithms will facilitate better understanding and confidence in AI system. This will lead to faster adoption of AI-based systems within the HRM processes and practices, and in true sense augmenting human intelligence (i.e., human will be able to trust these systems).

Finally, we propose the AI capability framework consolidating the drivers and barriers related to AI adoption in business organisations, derived from multidisciplinary literature. In this context, we have used a multidimensional theoretical approach consolidating knowledge-based view (KBV), and resource-based view theory (RBV) to objectively identify the technical, non-technical and human-centric resources required by organisations to adopt and implement AI. In doing so, we follow the calls and directions in the extant literature to examine the development of AI and implications in HRM, building on the research reported in multiple fields of business and management, including IM and OM (Budhwar & Malik, 2020a, 2020b; Vrontis et al., 2021). While, IM research has primarily focussed on technical resources and infrastructure required to adopt AI, and wider B&M studies have focussed on non-technical resources, our capability framework objectively brings these two rather fragmented pieces of literature together. Therefore, the framework provides a comprehensive understanding of all the organisational resources necessary to strategize AI adoption. The multidimensional theoretical approach also considers the cognitive, structural, and relational implications of AI-employee integration, which has been highlighted in the existing literature (Makarius et al., 2020), meaning that we do not view AI has a stand-alone technology which will solve all business problems. On the contrary, AI is a technology and its adoption, implementation, and impact within HRM will depend on other resources and organisational strategies operationalising and governing these resources. Although, our findings may be viewed as antithesis to overinflated benefits of AI reported in the media, our review shows that the business value and tangible benefits resulting from AI adoption in HRM is still inconclusive in the academic literature.

6.2 Practical Implications

Our review has several implications for managers. Firstly, the AI capability framework proposed in this article can be used by HRM practitioners to assess the readiness of the organisations to adopt and implement AI systems. In doing so the framework will help to objectively identify both technical and non-technical resources required to operationalise AI systems. Our review found that albeit the technical resources, managers need develop appropriate strategies, communication mechanisms and interventions that will foster co-ordination, mutual understanding, collaboration and cooperation between departments, project teams and employees (Mikalef and Gupta, 2021). This will facilitate mobilization and orchestration of AI within organisations.

Secondly, knowledge sharing mechanisms within organisations need to be strategized by the managers to facilitate development of skills, competencies, and knowledge among the human workforce in the context of adopting and utilising AI-based systems. These strategies must aim to develop an organisational culture that enables interdisciplinary collaboration, interdepartmental co-ordination, data-driven decision making, shared and common understanding between employees, experimental and adaptable mentality, risk-oriented approach (rather than risk-averse strategic orientation). According to Fountaine et al., 2019 and Davenport and Ronanki, 2018, organisations should develop their own innovation ecosystem (i.e., using the resources available and further developing capability within the organisation). This ecosystem can follow a hub and spoke model, where 'hub' is responsible for AI governance and regulations, determining AI-employee collaboration strategy and initiatives, and managerial responsibilities, while 'spokes', will handle responsibilities closer to the use of AI (i.e., interpreting AI outputs and training AI systems) (Fountaine et al., 2019). In this context, our review shows that innovative culture will stimulate employees to embrace AI, identify and seize new opportunities to use AI through their creative intellect, and dynamically respond to change resulting from HR business process and practice transformation, which will help to enhance business productivity and competitiveness. AI systems will extend beyond the current capabilities, therefore albeit knowledge creation, co-creation and sharing, evolving the knowledge is equally important to remain updated and competitive in the highly turbulent AI technology environment.

Thirdly, to alleviate negative perceptions and skepticism around AI adoption in human-centric business processes, managers need to establish clear and transparent communication strategies and dialogues with the employees. The aim should be to clearly outline the AI adoption and change management strategy, its impact on job design, roles and responsibilities of the employees, expectations from the employees, purpose of using AI, its capabilities and limitations. Our review has outlined that better understanding of AI adoption context, and enhance trust and confidence in the management initiatives and strategy (Mahidhar and Davenport, 2018). This will also require the managers to develop their own knowledge and understanding with regards to capabilities and limitations of AI, since AI-based solutions will be operationalised according to their organisational business process transformation strategies, contextual design directives and financial investment.

Finally, our review shows that understanding the capabilities, scope and limitations of AI to solve the business problems are critical elements for developing the AI digital strategy, which must be driven by potential impact that the AI implementation (Ransbotham et al., 2018). In this context, HR managers should consider the following dimensions to develop the AI digital strategy: (1) business case to adopt AI, i.e. problem scope to utilise AI; (2) business process analysis to identify the changes within the existing workflows resulting from AI adoption; (3) digital readiness assessment both in terms of digital infrastructure and competencies of the human workforce; (4) data management strategy, i.e. availability of existing data, requirement to collect/store new data, data governance and ownership; (5) decision to buy off-the-shelf AI system or develop the solution in-house; (6) multidisciplinary team having variety of skills, domain expertise, digital experience and providing complementary viewpoints, supporting the technology team involved in AI implementation; (7) strategy to develop data-centric culture within the organization, where technology is used as driver to augment human tasks and intelligence; (8) integrating design thinking and agile methods to make employees an integral part of the development/implementation team, which will help employees to understand the implications of AI adoption; (9) AI governance policy which will put emphasis on accountability; explainability of the automated decisions; fairness, data rights of the user, to have a clear understanding of how and why AI is being used; (10) periodic assessment of the AI systems (i.e. whether the existing strategy fulfils the KPIs and business goals), initiatives to maintain the systems, and customize, evolve and adapt according to the dynamic market and competitive environment.

6.3 Limitations

Our review has few limitations, which can be adequately addressed in future. Firstly, our review is restricted to studies published in top tier peer reviewed journals (ABS ranking – 3, 3*, 4 and 4*). We believe studies published in lower ranked journals, non-peer reviewed articles (e.g., The Conversation), and practitioners' literature (e.g., reports published by business consultants) can further enhance our understanding to make the knowledge synthesis more rigorous. Secondly, our search (using the selected keywords and Boolean operators) may not have identified all the articles relevant to the topic due to issues related to database unavailability or human error. We believe future research should also include other repositories such as Web of Science, DBLP, Social Science Research Network (SSRN) and SpringerLink, to extract new articles from multiple disciplines further advancing the AI scholarship. In this context, we believe that including databases publishing law journals can facilitate comprehensive review of the literature on the theme of AI governance, ethics and regulations in HRM. Finally, while, in this review we relied on the judgement of academic experts and the existing academic literature to select the trending themes of AI research in HRM, research propositions (i.e., under-researched and emerging areas in the field), and resources to develop AI capability within organisations. Future studies can build on these findings by capturing empirical evidence from HR business practitioners to further validate the trending themes and determine the importance of research propositions. The importance of research propositions can be determined through interviews or Delphi-study, and then analysing the quantitative data using AHP. Such an initiative will bridge the gap between academic findings and perception of HR practitioners, to develop research agenda aligned to the needs of both industry and society.

References

Ajzen, I. (1991). The theory of planned behavior. Orgnizational Behavior and Human Decision Processes, 50, 179–211. In.

Alsheibani, S. A., Cheung, D., & Messom, D. (2019). Factors inhibiting the adoption of artificial intelligence at organizational-level: A preliminary investigation.

Amabile, T. M. (2020). Creativity, artificial intelligence, and a world of surprises. Academy of Management Discoveries, 6(3), 351-354.

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & SOCIETY, 35(3), 611-623.

Araujo, V. S., Rezende, T. S., Guimarães, A. J., Araujo, V. J. S., & de Campos Souza, P. V. (2019). A hybrid approach of intelligent systems to help predict absenteeism at work in companies. SN Applied Sciences, 1(6), Article 536. https://doi.org/10.1007/s42452-019-0536-y

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., . . . Benjamins, R. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities, and challenges toward responsible AI. Information Fusion, 58, 82-115.

Arslan, A., Cooper, C., Khan, Z., Golgeci, I., & Ali, I. (2021). Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies. International Journal of Manpower.

Babic, B., Chen, D. L., Evgeniou, T., & Fayard, A.-L. (2021). Onboarding AI. Harvard Business Review, 98(4), 56-65.

Bankins, S., & Formosa, P. (2020). When AI meets PC: Exploring the implications of workplace social robots and a human-robot psychological contract. European Journal of Work and Organizational Psychology, 29(2), 215-229.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of management, 17(1), 99-120.

Barro, S., & Davenport, T. H. (2019). People and machines: Partners in innovation. MIT Sloan Management Review, 60(4), 22-28.

BBC. (2020). Apple's 'sexist' credit card investigated by US regulator. https://www.bbc.com/news/business-50365609

Bhave, D. P., Teo, L. H., & Dalal, R. S. (2020). Privacy at work: A review and a research agenda for a contested terrain. Journal of management, 46(1), 127-164.

Bieda, L. C. (2020). How Organizations Can Build Analytics Agility MIT Sloan Management Review.

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? Business Horizons, 63(2), 215-226.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. the Journal of machine Learning research, 3, 993-1022.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. International Journal of Information Management, 57, 102225.

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. Journal of Business Research, 131, 485-494.

Budhwar, P., & Malik, A. (2020a). Call for papers: Artificial intelligence challenges and opportunities for international HRM. The International Journal of Human Resource Management.

Budhwar, P., & Malik, A. (2020b). Special Issue: Leveraging Artificial and Human Intelligence through Human Resource Management. Call for papers, Human Resource Management Review.

Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2018). Skill shift: Automation and the future of the workforce. McKinsey Global Institute, 1, 3-84.

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. Conference on fairness, accountability, and transparency,

Burgess, A. (2017). The Executive Guide to Artificial Intelligence: How to identify and implement applications for AI in your organization. Springer.

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, 102312.

Caputo, F., Cillo, V., Candelo, E., & Liu, Y. (2019). Innovating through digital revolution: The role of soft skills and Big Data in increasing firm performance. Management Decision.

Chesney, R., & Citron, D. (2019). Deepfakes and the new disinformation war: The coming age of post-truth geopolitics. Foreign Aff., 98, 147.

Chornous, G. O., & Gura, V. L. (2020). Integration of information systems for predictive workforce analytics: Models, synergy, security of entrepreneurship. European Journal of Sustainable Development, 9(1), 83-98, Article 83. https://doi.org/10.14207/ejsd.2020.v9n1p83

Chouldechova, A., Benavides-Prado, D., Fialko, O., & Vaithianathan, R. (2018). A case study of algorithm-assisted decision making in child maltreatment hotline screening decisions. Conference on Fairness, Accountability and Transparency,

Chowdhury, R., Rakova, B., Cramer, H., & Yang, J. (2020). Putting Responsible AI Into Practice MIT Sloan Management Review.

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems, and organisational socialisation framework. Journal of Business Research, 144, 31-49.

CIPD. (2013). Talent analytics and big data–the challenge for HR. In: Chartered Institute for Personnel and Development London.

Connelly, C. E., Fieseler, C., Černe, M., Giessner, S. R., & Wong, S. I. (2021). Working in the digitized economy: HRM theory & practice. Human Resource Management Review, 31(1), 100762.

Cooke, F. L., Veen, A., & Wood, G. (2017). What do we know about cross-country comparative studies in HRM? A critical review of literature in the period of 2000-2014. The International Journal of Human Resource Management, 28(1), 196-233.

Correani, A., De Massis, A., Frattini, F., Petruzzelli, A. M., & Natalicchio, A. (2020). Implementing a digital strategy: Learning from the experience of three digital transformation projects. California management review, 62(4), 37-56.

Cowgill, B., & Tucker, C. E. (2020). Algorithmic fairness and economics. Columbia Business School Research Paper.

Cubric, M. (2020). Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study. Technology in Society, 62, 101257.

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. Eurasian Business Review, 11(1), 1-25.

Daugherty, P. R., Wilson, H. J., & Chowdhury, R. (2019). Using artificial intelligence to promote diversity. MIT Sloan Management Review, 60(2), 1.

Davenport, T., & Bean, R. (2017). How P&G and American Express are approaching AI. Harvard Business Review (blog).

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of marketing Science, 48(1), 24-42.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.

De Kock, F. S., Lievens, F., & Born, M. P. (2020). The profile of the 'Good Judge'in HRM: A systematic review and agenda for future research. Human Resource Management Review, 30(2), 100667.

Deloitte. (2017). The 2017 Deloitte state of cognitive survey. https://tinyurl.com/4kn2c35s

Demlehner, Q., & Laumer, S. (2020). Shall we use it or not? Explaining the adoption of artificial intelligence for car manufacturing purposes.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. Journal of Business Research, 121, 283-314.

Dougherty, C. (2015). Google photos mistakenly labels black people 'gorillas'. The New York Times, 1.

Dourish, P. (2016). Algorithms and their others: Algorithmic culture in context. Big Data & Society, 3(2), 2053951716665128.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International Journal of Information Management, 48, 63-71.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

Economist, T. (2020). Businesses are finding AI hard to adopt. https://www.economist.com/technology-quarterly/2020/06/11/businesses-are-finding-ai-hard-to-adopt

Elkins, A. C., Dunbar, N. E., Adame, B., & Nunamaker, J. F. (2013). Are users threatened by credibility assessment systems? Journal of management information systems, 29(4), 249-262.

European-Commission. (2019a). Ethics guidelines for trustworthy AI. https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=60419

European-Commission. (2019b). Proposal for a Regulation laying down harmonised rules on artificial intelligence. https://digital-strategy.ec.europa.eu/en/library/proposal-regulation-laying-down-harmonised-rules-artificial-intelligence

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. Information and Organization, 28(1), 62-70.

Faulds, D. J., & Raju, P. (2021). The work-from-home trend: An interview with Brian Kropp. Business Horizons, 64(1), 29.

Fleming, P. (2019). Robots and organization studies: Why robots might not want to steal your job. Organization Studies, 40(1), 23-38.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. Harvard Business Review, 97(4), 62-73.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254-280.

Gaur, B., & Riaz, S. (2019). A Two-Tier Solution to Converge People Analytics into HR Practices. 2019 4th International Conference on Information Systems and Computer Networks, ISCON 2019,

Ghosh, B., Daugherty, P. R., Wilson, H. J., Burden A. (2019). Taking a Systems Aproach to Adopting AI. Harvard Business Review. https://hbr.org/2019/05/taking-a-systems-approach-to-adopting-ai

Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2021). The dark sides of people analytics: reviewing the perils for organisations and employees. European Journal of Information Systems, 1-26. https://doi.org/10.1080/0960085x.2021.1927213

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627-660.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. Strategic management journal, 17(S2), 109-122.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review, 61(4), 5-14.

Hansen, M. T., Nohria, N., & Tierney, T. (1999). What's your strategy for managing knowledge. The knowledge management yearbook 2000–2001, 77(2), 106-116.

Hopp, C., Antons, D., Kaminski, J., & Salge, T. O. (2018). The topic landscape of disruption research—A call for consolidation, reconciliation, and generalization. In: Wiley Online Library.

Iansiti, M., & Lakhani, K. R. (2020). Competing in the age of AI: strategy and leadership when algorithms and networks run the world. Harvard Business Press.

Islam, M. N., Inan, T. T., Rafi, S., Akter, S. S., Sarker, I. H., & Islam, A. N. (2021). A Systematic Review on the Use of AI and ML for Fighting the COVID-19 Pandemic. IEEE Transactions on Artificial Intelligence.

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. Journal of Business Research, 70, 338-345.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586.

Johnson, R. D., Stone, D. L., & Lukaszewski, K. M. (2020). The benefits of eHRM and AI for talent acquisition. Journal of Tourism Futures.

Kakkar, H., & Kaushik, S. (2019). Technology driven human resource measurement–A strategic perspective . International Journal on Emerging Technologies, 10(1), 179-184.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons, 63(1), 37-50.

Kearns, G. S., & Sabherwal, R. (2006). Strategic alignment between business and information technology: a knowledge-based view of behaviors, outcome, and consequences. Journal of management information systems, 23(3), 129-162.

Keding, C. (2020). Understanding the interplay of artificial intelligence and strategic management: four decades of research in review. Management Review Quarterly, 71(1), 91-134.

Klein, H. J., & Polin, B. (2012). Are organizations on board with best practices onboarding. The Oxford handbook of organizational socialization, 54, 267-287.

Kot, S., Hussain, H. I., Bilan, S., Haseeb, M., & Mihardjo, L. W. W. (2021). The role of artificial intelligence recruitment and quality to explain the phenomenon of employer reputation . Journal of Business Economics and Management, 22(4), 867-883.

Krekel, C., Ward, G., & De Neve, J. E. (2019). Employee wellbeing, productivity, and firm performance. Saïd Business School WP, 4.

Kshetri, N. (2020). Evolving uses of artificial intelligence in human resource management in emerging economies in the global South: some preliminary evidence . Management Research Review, 44(7), 970-990. https://doi.org/10.1108/mrr-03-2020-0168

Kshetri, N. (2021). Evolving uses of artificial intelligence in human resource management in emerging economies in the global South: some preliminary evidence. Management Research Review.

La Torre, D., Colapinto, C., Durosini, I., & Triberti, S. (2021). Team Formation for Human-Artificial Intelligence Collaboration in the Workplace: A Goal Programming Model to Foster Organizational Change . IEEE Transactions on Engineering Management.

Lei, H., Gui, L., & Le, P. B. (2021). Linking transformational leadership and frugal innovation: the mediating role of tacit and explicit knowledge sharing. Journal of Knowledge Management.

Lichtenthaler, U. (2019). Extremes of acceptance: employee attitudes toward artificial intelligence. Journal of Business Strategy.

Macke, J., & Genari, D. (2019). Systematic literature review on sustainable human resource management. Journal of Cleaner Production, 208, 806-815. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.10.091

Maity, S. (2019). Identifying opportunities for artificial intelligence in the evolution of training and development practices. Journal of Management Development.

Mak, S. L., Li, C. H., Tang, W. F., Wu, M. Y., & Lai, C. W. (2020). Adoption of information technology in modern manufacturing operation. IEEE International Conference on Industrial Engineering and Engineering Management,

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. Journal of Business Research, 120, 262-273.

Malik, A., Budhwar, P., & Srikanth, N. (2020). Gig economy, 4IR and artificial intelligence: Rethinking strategic HRM. In Human & Technological Resource Management (HTRM): New Insights into Revolution 4.0. Emerald Publishing Limited.

Malik, N., Tripathi, S. N., Kar, A. K., & Gupta, S. (2021). Impact of artificial intelligence on employees working in industry 4.0 led organizations. International Journal of Manpower.

Malone, T. W. (2018). How human-computer 'Superminds' are redefining the future of work. MIT Sloan Management Review, 59(4), 34-41.

Margherita, A. (2021). Human resources analytics: A systematization of research topics and directions for future research. Human Resource Management Review, 100795.

Meechang, K., Leelawat, N., Tang, J., Kodaka, A., & Chintanapakdee, C. (2020). The acceptance of using information technology for disaster risk management: A systematic review [Review]. Engineering Journal, 24(4), 111-132. https://doi.org/10.4186/ej.2020.24.4.111

Mehrabad, M. S., & Brojeny, M. F. (2007). The development of an expert system for effective selection and appointment of the jobs applicants in human resource management. Computers & Industrial Engineering, 53(2), 306-312.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & management, 58(3), 103434.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & management, 57(2), 103169.

Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. Journal of Business Research, 70, 1-16.

Nickerson, J. A., & Zenger, T. R. (2004). A knowledge-based theory of the firm—The problem-solving perspective. Organization science, 15(6), 617-632.

O'neil, C. (2016). Weapons of math destruction: How big data increases inequality and threatens democracy. Crown.

Panteia. (2020). Cost Figures for Freight Transport – final report. https://www.kimnet.nl

Parry, K., Cohen, M., & Bhattacharya, S. (2016). Rise of the machines: A critical consideration of automated leadership decision making in organizations. Group & Organization Management, 41(5), 571-594.

Paschen, J., Wilson, M., & Ferreira, J. J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), 403-414.

Pashkevich, N., Haftor, D., Karlsson, M., & Chowdhury, S. (2019). Sustainability through the Digitalization of Industrial Machines: Complementary Factors of Fuel Consumption and Productivity for Forklifts with Sensors. Sustainability, 11(23), 6708

Peeters, T., Paauwe, J., & Van De Voorde, K. (2020). People analytics effectiveness: developing a framework. Journal of Organizational Effectiveness: People and Performance, 7(2), 203-219.

Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An International Journal.

Pumplun, L., Tauchert, C., & Heidt, M. (2019). A new organizational chassis for artificial intelligence-exploring organizational readiness factors.

Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192-210.

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. Journal of Business Research, 116, 68-74.

Ransbotham, S., Gerbert, P., Reeves, M., Kiron, D., & Spira, M. (2018). Artificial intelligence in business gets real. MIT Sloan Management Review, 60280.

Ransbotham, S., Khodabandeh, S., Kiron, D., Candelon, F., Chu, M., & LaFountain, B. (2020). Expanding AI's impact with organizational learning. MIT Sloan Management Review and Boston Consulting Group.

Rutkowska, M., & Sulich, A. (2020). Green Jobs on the background of Industry 4.0. Procedia Computer Science, 176, 1231-1240.

Sabbineni, N. (2020). Understanding Employee Attrition Using Explainable AI.

Saha, N., Gregar, A., & Sáha, P. (2017). Organizational agility and HRM strategy: Do they really enhance firms' competitiveness? International Journal of Organizational Leadership, 6, 323-334.

Saling, K. C., & Do, M. D. (2020). Leveraging people analytics for an adaptive complex talent management system. Procedia Computer Science,

Schiff, D., Ayesh, A., Musikanski, L., & Havens, J. C. (2020). IEEE 7010: A new standard for assessing the well-being implications of artificial intelligence. 2020 IEEE international conference on systems, man, and cybernetics (SMC),

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. Journal of Decision Systems, 29(4), 260-278.

Schroeder, A. N., Bricka, T. M., & Whitaker, J. H. (2021). Work design in a digitized gig economy. Human Resource Management Review.

Seeber, I., Bittner, E., Briggs, R. O., De Vreede, T., De Vreede, G.-J., Elkins, A., . . . Randrup, N. (2020). Machines as teammates: A research agenda on AI in team collaboration. Information & management, 57(2), 103174.

Shankar, R. S., Rajanikanth, J., Sivaramaraju, V., & Murthy, K. (2018). Prediction of employee attrition using datamining. 2018 ieee international conference on system, computation, automation and networking (icscan),

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. Computers in Human Behavior, 98, 277-284.

Silverman, K. (2020). Why Your Board Needs a Plan for AI Oversight. MIT Sloan Management Review, 62(1), 1-6.

Singh, T., & Malhotra, S. (2020). Workforce analytics: Increasing managerial efficiency in human resource . International Journal of Scientific and Technology Research, 9(1), 3260-3266.

Smith, C. (2019). An employee's best friend? How AI can boost employee engagement and performance. Strategic HR Review.

Sparrow, P., Cooper, C., & Hird, M. (2016). Do we need HR?: repositioning people management for success. Springer.

Steels, L., & Brooks, R. (2018). The artificial life route to artificial intelligence: Building embodied, situated agents. Routledge.

Tallon, P. P., Queiroz, M., Coltman, T., & Sharma, R. (2019). Information technology and the search for organizational agility: A systematic review with future research possibilities. The Journal of Strategic Information Systems, 28(2), 218-237.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. California Management Review, 61(4), 15-42. https://doi.org/10.1177/0008125619867910

Tariq, M. U., Poulin, M., & Abonamah, A. A. (2021). Achieving Operational Excellence Through Artificial Intelligence: Driving Forces and Barriers. Frontiers in Psychology, 12.

Toniolo, K., Masiero, E., Massaro, M., & Bagnoli, C. (2020). Sustainable business models and artificial intelligence: Opportunities and challenges. Knowledge, People, and Digital Transformation, 103-117.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207-222.

UN. (2015). Sustainable Development Goals. Retrieved 17th December 2019 from https://www.un.org/sustainabledevelopment/sustainable-development-goals/

Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: implications for recruitment. Strategic HR Review.

Van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. Business Horizons, 62(6), 729-739.

van Esch, P., Black, J. S., & Arli, D. (2021). Job candidates' reactions to AI-enabled job application processes. AI and Ethics, 1(2), 119-130.

Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, 215-222.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2021). Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. The International Journal of Human Resource Management, 1-30.

Wade, L (2010) HP software doesn't see black people. Sociological Images. Accessed on 5 January 2021. Available at: https://tinyurl.com/cwccd9dc

Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. Business Process Management Journal.

Wang, G., Zhang, L., & Guo, J. (2021). Analysis on application level based on ordinal logistic regression and best of advanced manufacturing technologies (AMT) selection based on fuzzy-TOPSIS integration approach . Journal of Intelligent and Fuzzy Systems, 40(4), 8427-8437.

Wang, H., Huang, J., & Zhang, Z. (2019). The Impact of Deep Learning on Organizational Agility. ICIS,

Wang, W., Chen, L., Xiong, M., & Wang, Y. (2021). Accelerating AI Adoption with Responsible AI Signals and Employee Engagement Mechanisms in Health Care. Information Systems Frontiers, 1-18.

WEF. (2018). Machines Will Do More Tasks Than Humans. Retrieved from https://tinyurl.com/2bwa5nsc

Wilson, H., Daugherty, P., & Bianzino, N. (2017). The jobs that artificial intelligence will create. MIT Sloan Management Review Summer.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: humans and AI are joining forces. Harvard Business Review, 96(4), 114-123.

Wilson, J. P., & Gosiewska, S. (2014). Multi-agency gold incident command training for civil emergencies . Disaster Prevention and Management, 23(5), 632-648. https://doi.org/10.1108/DPM-11-2013-0212

World-Bank. (2020). Small and Meidum Enterprises (SMEs) Finance. https://www.worldbank.org/en/topic/smefinance

Younis, R. A. A., & Adel, H. M. (2020). Artificial intelligence strategy, creativity-oriented HRM and knowledge-sharing quality: Empirical analysis of individual and organisational performance of AI-powered businesses. Proceedings of the Annual International Conference of The British Academy of Management (BAM),

Zehir, C., Karaboğa, T., & Başar, D. (2020). The transformation of human resource management and its impact on overall business performance: big data analytics and AI technologies in strategic HRM. In Digital business strategies in blockchain ecosystems (pp. 265-279). Springer.

Zhang, R., McNeese, N. J., Freeman, G., & Musick, G. (2021). " An Ideal Human" Expectations of AI Teammates in Human-AI Teaming. Proceedings of the ACM on Human-Computer Interaction, 4(CSCW3), 1-25.

Zhang, Y., Song, K., Sun, Y., Tan, S., & Udell, M. (2019). " Why Should You Trust My Explanation?" Understanding Uncertainty in LIME Explanations. arXiv preprint arXiv:1904.12991.

Appendix 1: AI Applications in HRM

Context	AI application	Selected References
1-Candidate Experience (job applications)	Digital virtual assistant (chatbots) can respond to candidate queries in real-time and quickly, thus eliminating the need to email HR, help them learn about the organisation and the job role, show employees working in similar job roles, automatically pre-screen candidates analyze job matching using candidate resume, and therefore attract and identify high quality candidates, providing feedback to candidates to demonstrate efficient and fair review process, therefore building trust among the applicants, and thus enhance their candidate experience	van Esch et al. (2021) Upadhyay and Khandelwal (2018)
2-Candidate Recruitment	Digital virtual assistant can pre-screen the candidate based on the resume and other information. Machine learning enabled AI application integrating video scanning technology can recommend questions to the recruitment panel during the interview and provide recommendations considering the resume and interview performance to the recruiters (summarizing the profile of each candidate and comparing the profiles of all candidates). Predict the likelihood of a candidate accepting an offer, project future performance of the candidate by learning from historical similar profiles and similarly predict the expected tenure (i.e., likelihood of candidate leaving the organisation after 'n' years)	Upadhyay and Khandelwal (2018), Van Esch et al. (2019)
3-Onboarding	Digital virtual assistant can quickly answer questions, guiding the new hire through the steps, making them aware of their role and tasks, helping them complete mandatory training, capture information about the employee skills and recommend job-related learning content based on employees in similar roles.	Babic et al. (2021)
4-Employee engagement	Personalized experience to the employees customized to their daily needs and routine tasks as well as schedules by automatically managing calendars, scheduling meetings, answering queries efficiently, just in time recommendations and alerts facilitating decision making, improve engagement within a team, effectively collaborating across teams (individuals working in similar roles, having similar profiles, career progression), assigning mentors.	Wang et al. (2021)
5-Career Development	Interact with the employees to understand their career aspirations (through Q and A), and recommend opportunities, skills and corresponding training within the organization to develop the skills, help understand how the tasks, roles and job descriptions have changed over the years, and will change. Personalized recommendation on career path, by mapping career aspirations to specific skills and corresponding training/learning content to harness those skills, showing a pre-training and post-training skills map, maximizing their potential to perform and feel motivated.	Braganza et al. (2021)

6-Employee Performance Appraisal	Predict the performance of the employee based on the information available and new information provided before the appraisal and gathering information from other sources. Compare the performance of the employee to the set objectives. Provide recommendations to the manager based on the prediction and comparison (e.g. skills gap, new skills acquired, opportunities within the team and across the organisation, performance bonuses, promotion). Provide similar recommendations to the employee. .	Krekel et al. (2019), Smith (2019)
7-Compensation packages	Consider several heuristics such as, demand of the skills and expertise in the market and the market rate, current and past performance of the employee, relevance and importance of the skills and expertise for the organization, its competitiveness, productivity and dynamism. Therefore, making data-driven smart pay compensation.	Zehir et al. (2020)
8-Employee Skills development	Recommend an automatic skills map for the employee, considering input from the employee, manager and considering job role, past learning history, business team. The map will bring together and organize training content for the employee, and show the value offered by the training. For HR managers/personnel, optimize administrative tasks related to capturing, processing and summarizing learning and training activities of the learners (engagement and interactions), to model employee engagement, learning needs and facilitate managers to make data-driven strategies.	Bughin et al. (2018), Jaiswal et al. (2021)
9-Employee attrition detection	Predict the probability of an employee leaving the organisation using the available data drawn from employee profile, activities and appraisal, and historic dataset of employees who have worked/currently working in the organisation. Leveraging the power of explainable machine learning models, the decision makers can identify factors contributing to employee turnover and manage employee expectation by developing suitable strategies to retain employees.	Sabbineni (2020), Shankar et al. (2018)
10-Workforce management Analytics	AI can collect information about employee behavior, team practices and that of the department, to automatically detect mental health, well-being and presenteeism issues within a department. Providing information about engagement of employees within a team by aggregating and analyzing internal social media posts, to help understand social cohesion within teams, across teams, and support strategic workforce planning, to help increase employee motivation and engagement.	Margherita et al., 2021
11-HR Budget and resource allocation	AI can process all the quantitative and qualitative information obtained from all the available sources (internal and external market demands, competitors), additionally take the business priorities of the organisation as input, to provide recommendations and explain them, in the context of budget allocation (for each priority and department), to help allocate, manage, track spending, without reducing employees and their services, in an efficient manner, and identify new priorities.	Ahmed (2018), Altmeyer, 2019.

Appendix 2: Topics in the review

Sr. No	Topics	Citations
T1	AI and workforce analytics	Margherita, 2021
T2	AI and value for employee	Lichtenthaler (2019), Wang et al. (2021),
T3	AI and value for organization	Burgess (2017), Fountaine et al. (2019)
T4	AI and achieving sustainability development goals	Di Vaio et al. (2020)
T5	AI and organizational resilience	Arslan et al. (2021)
T6	Drivers and barriers to AI adoption	Tariq et al. (2021), Alsheibani et al. (2019)
T7	AI Trust/transparency	Schmidt et al. (2020)
T8	AI employee wellbeing	Krekel et al. (2019)
T9	AI skills and knowledge [for workforce]	Bughin et al. (2018)
T10	AI socialization [teammate]	Seeber et al. (2020), Makarius et al., 2020
T11	AI new jobs+ green jobs	Rutkowska and Sulich (2020)
T12	AI and organizational agility	Saha et al. (2017), Tallon et al. (2019)
T13	AI and organizational change management	Pumplun et al., 2019 ; Ransbotham et al., 2019
T14	AI in organizational decision-making	Araujo et al. (2020)
T15	Different types of intelligences required in	Haenlein and Kaplan, 2019 ; Daugherty et al., 2019
T16	HRM jobs/processes HRM theory related to enhancing AI skills among employees within organizations	Jarrahi (2018), Kshetri (2021), Johnson et al., 2020; Malik et al. (2020)
T17	AI and employee performance + business productivity	Damioli et al. (2021), Krekel et al. (2019),
T18	AI and organizational leadership	Iansiti and Lakhani (2020), Saha et al. (2017)