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

Abstract

Artificial Intelligence (AI) is increasingly adopted within HRM and other business domains as it has the potential to create value for the both the 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 Human Resource management (HRM) have looked at the applications of AI, anticipated benefits, and impact at both organizational and employee levels. Our aim is to systematically review multi-disciplinary literature stemming from International Business, Information Management, Operations Management, General Management and HRM to provide a comprehensive and holistic understanding of organisational resources required for organisations to develop AI capability. Our findings show that organisations need to think beyond technical resources, and focus on developing non-technical ones such as human skills and competencies, leadership, team co-ordination, organisational culture and innovation mindset, governance strategy, and most importantly AI-employee integration strategy. Based on these findings, we contribute five research positions to advance AI scholarship in HRM. Theoretically, we unearth, why complementary organisational resources and not just technical infrastructure are essential to achieve organisationally valued outcomes. Furthermore, our proposed framework offers a systematic way for the managers to self-assess organisational readiness to adopt and implement AI-enabled solutions 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 (Davenport and Ronanki, 2018). 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 \$85.3 billion in 2021 to more than \$204 billion in 2025, making the compound annual growth rate 2021-2025 to be 24.5%. AI has featured in Gartner research's top 10 technology trends both in 2019 and 2020, and according to the recent economic analysis published by PwC, IBM, Deloitte and Gartner Research, adoption of AI will increase the global GDP by 15% in 2030 (additional \$15.7 trillion dollar). Furthermore, World Economic Forum has predicted that the adoption of AI will make 75 million jobs redundant and create 133 million new ones worldwide by 2022 (WEF, 2018).

AI has become the key source of business model innovation, process transformation, disruption and competitive advantage in organisations embracing data-centric and digital culture (Ransbotham et al., 2020). 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; Schroeder et al., 2019). 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 (Dubey et al., 2019), 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 and business analytics, human like behaviour, i.e., replicating human cognitive processes and emulating human learning mechanisms. We define, *AI as the ability of a manmade system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from 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 (manufactured by human) system comprising of algorithms (drawn from computing and mathematics literature), which are translated into software programs. While calling AI as manmade may be debatable (Steels and Brooks, 2018), however 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 process big data and efficiently identify patterns between multiple streams of data to generate insights and simultaneously learn from it (Malik et al., 2020). Finally, the tasks and goals are predetermined, i.e., algorithms employed in each AI-enabled solution have a specific purpose to achieve (Kaplan and Haenlein, 2019). For e.g., the algorithms used for analysing sentiments from textual data differ from the ones used for analysing emotions from 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 – it is manufactured (artificial), and it has some form of intelligence (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
Dwivedi et al., 2019	The increasing capability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general
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	Artificial Intelligence: 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	Artificial Intelligence: The endeavour to mimic cognitive and human capabilities on computers
Wamba-Taguimdje et al., 2020	Artificial Intelligence: defined as 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

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; Faliagka et al., 2014). 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; Jantan et al., 2010) and employee engagement (Bankins & Formosa, 2020). In this context, recent reviews have outlined the role of AI to facilitate HR analytics (Margherita, 2021), and impact of AI-based technologies on HRM process and practices (Vrontis et al., 2021).

Despite the above interest and claims regarding the applications, benefits, and impact of AI in HRM practices, processes and decision-making, the existing literature has found that many companies have failed to experience anticipated organisationally valued outcomes (Canhoto and Clear, 2020; Fountaine et al., 2019). A recent survey (by Boston Consulting Group and MIT) which was conducted with executives 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). In this context, research has found that organisations often find it difficult to integrate AI within their business processes and systems, which often inhibits AI adoption (Davenport and Ronanki, 2018; Mikalef., et al., 2019). On one hand the reports from early adopters indicate that investment in AI is failing to incur business value, while existing literature has also discussed the business value generated by adopting AI in business operations (Ransbotham et al., 2017; Wilson et al., 2018). The popular press and technology vendors have overinflated expectations about benefits and drivers to AI adoption and implementation, and the existing research in HRM outlining and objectively understanding the organisational resources required to effectively leverage AI-enabled technologies and enhance business productivity and competitiveness is sparse (Vrontis et al., 2021; Margherita, 2021). 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 employment conditions, and 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; Loebbecke & Picot, 2015; Markus, 2015). 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 theoretical framework, consolidating all the technical and non-technical organisational resources that will help to capture the potential value from AI-enabled solutions (Mikalef and Gupta, 2021). This framework provides a holistic understanding of how to adopt AI within HRM processes and use it in the organisations. Second, the framework helps to unearth, why complementary organisational resources and not just technical infrastructure are essential to benefit from 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 narrative of AI-employee integration, and the role of HRM in this context. Finally, the framework stemming from the systematic review of literature also unearths new sets of barriers and challenges to create a research agenda shaping the direction of future research.

In terms of implications for HRM managers, the proposed capability framework will offer a systematic way to self-assess the organisational resources and then help to determine the organisational readiness to adopt and implement AI-enabled solutions. In this context, the self-assessment will also help HRM managers and senior leadership to develop AI strategies, i.e., purpose of using AI, the fit between the desired purpose and AI adoption, anticipated outcomes to measure the benefits of implementation. This will lead the way to develop concrete business cases aligned to solving a specific HRM problem, enhancing HR processes, and thus create a blueprint for other players in the industry. Our review also provides useful insights in the form of strategies that will help to develop a collaborative, conducive, creative, and innovative culture within the organisation, to embrace collective intelligence. This is both a challenging and unknown territory, equally for researchers and business practitioners. In this context, we provide several recommendations to create, share and develop AI knowledge within the organisation to enhance understanding, trust, confidence, and satisfaction of employees with regards to effective AI-employee integration.

The rest of this paper is organised as follows: Section 2 will present the review methodology. Section 3 will present the findings from the systematic review of literature classified into five different themes. Section 4 will present the AI capability framework summarising the findings of the review and linking the different themes discussed in Section 3. The research propositions, theoretical and practical implications stemming from the review are presented in Section 5. Finally, we present the conclusions, limitations of the review and further directions to extend this review in Section 6.

2. Review Methodology

We conducted a systematic review of literature following the protocol suggested in the existing literature (Tranfield et al., 2003; Denyer and Tranfield, 2009; Wolfswinkel et al., 2013; Hopp et al., 2018) to ensure that the review process is transparent, easily reproducible, and critically analyses and systematises research themes (stemming from the review).

Selection of Articles

We have used a list of 59 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 also included Operations Management (OM) journals in our review. We have selected journals from multiple disciplines because role of AI in HRM has received significant attention in GM, IB, IM, OM literature and developing linkages between the works published in these disciplines will help to make this review comprehensive and add rigor (Loebbecke & Picot, 2015; Newell & Marabelli, 2015). We have also included more venues such as California Management Review, Harvard Business Review, MIT Sloan Management Review, and Journal of Business Research, owing to recent publications on impact of AI adoption on organisational strategies and developing collaborative intelligence in these journals. Therefore, the final list comprised of 98 journals. The final list focused on journals ranked 3, 4 and 4* in the on the Association of Business Schools (ABS) Journal Guide 2020. As the review focussed on HRM, therefore we included research works which overlapped with HRM practices, processes, issues related to AI adoption.

Search Strategy

To establish the search strings, we have identified trends in keywords usage (AI in HRM) by performing an initial scoping search of relevant articles, which was followed by examining the keywords used in the recent review articles (for e.g. Vrontis et al., 2021; Margherita et al., 2021; Enholm et al., 2021), and both empirical and conceptual studies (e.g. Jaiswal et al., 2021; Malik et al., 2021; Giudice et al., 2021; Makarius et al., 2020; Mikalef and Gupta, 2021; Cao et al., 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 the journal was not covered in the database or the abstract was missing in the final list of articles (for e.g., in case of California

Management Review, Harvard Business Review), or the search results either did not show the articles from these journals. To ensure that the information extraction following the search string is meaningful and aligned with the core objective of this manuscript, we used a filtering mechanism. The filtering mechanism used the following inclusion criteria: (1) all types of articles (journals, conference papers, book chapter) to ensure rigor; (2) articles published in English only; (3) the search string should appear either in abstract, title or the keywords listed by the authors themselves; (4) subject areas 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; time duration was not restricted to get as many relevant articles as possible (last search date: Jun 2021).

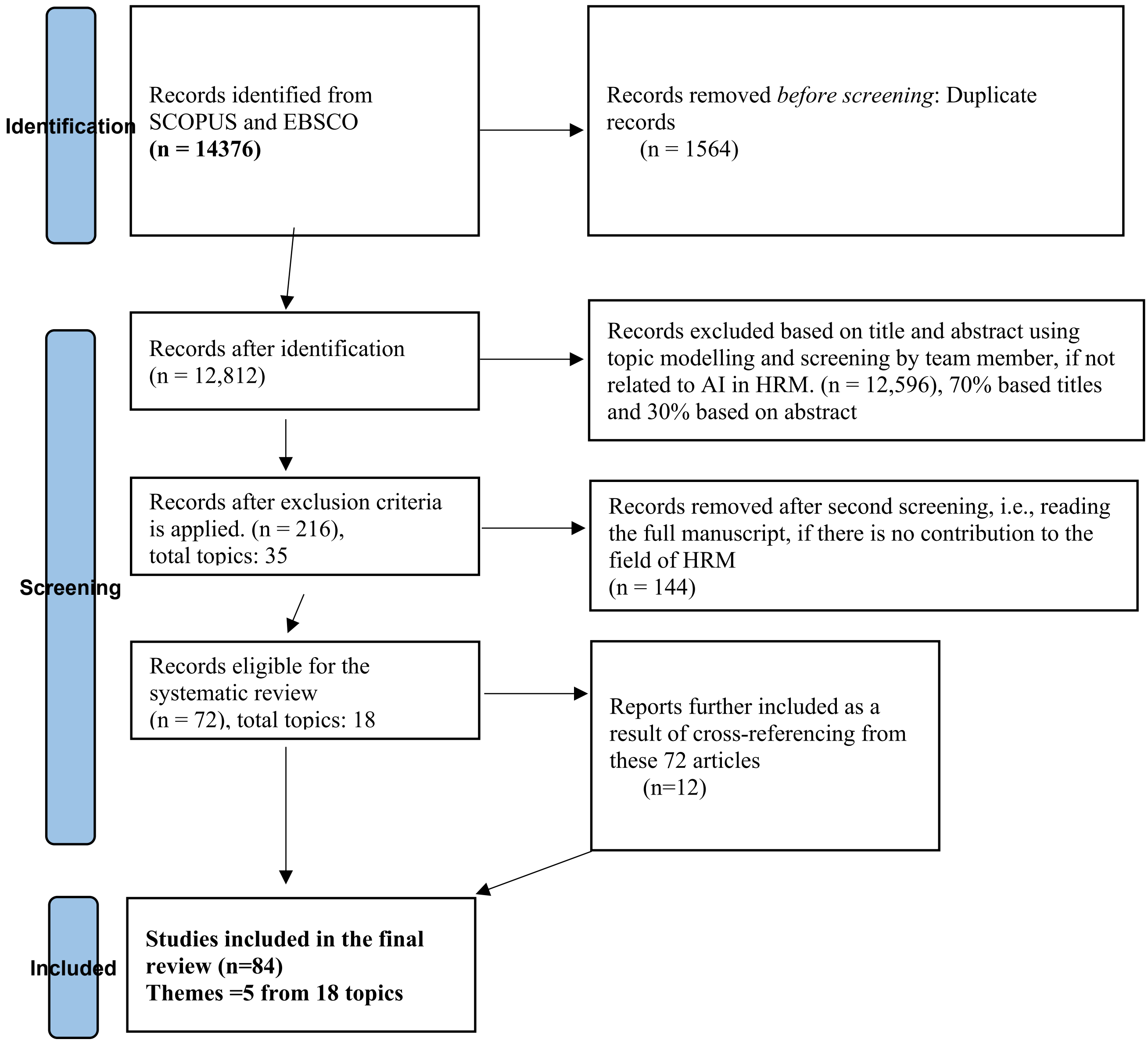
Article Screening (See Figure 1)

After collecting the metadata of all the articles meeting the search criteria from the SCOPUS database and Business Source Ultimate (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 in the target databases. After capturing all the metadata for each article, we created a database capturing the title and abstract of each article. This database was next used to run topic modelling algorithm. Given notable advances in natural language processing techniques, we employed topic modelling, which is a machine learning technique to analyse the text corpus (abstract and titles). The output of the topic modelling is a cluster of similar keywords, which are grouped together, and each group of keywords represents a topic. This process is 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. For this study, we employed Latent Dirichlet Allocation (LDA) technique developed by Blei et al., 2003, where each topic is represented by a set of keywords and each article is characterized by a particular topic probability distribution (defined as the probability of an article being associated to a topic).

First 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 provides 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), and then we employed another algorithm (integrating variant of topic modelling and text mining) to identify manuscripts that were related to these 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 (Andresen & Bergdolt, 2017). D1 captured the following information for each article: (1) citation; (2) title and abstract; keywords used by the authors; type of article (review, conceptual, empirical); key contributions of the article; key results and corresponding findings; key limitations and future direction; commentary on relevance to the theme; relevance to other themes. Following the recommendations in Tranfield et al. 2003, this process ensured that the procedure is transparent, reproducible, and devoid of human errors.

Based on the extracted information from each article, we created the following tables in 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 column in Table 1 – limitations and future direction). Next, all these documents 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 documents were integrated to propose a list of resources required to successfully adopt AI within the organisations, which led to 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 article (primarily using the column – research topic), and then categorize them into research themes, which would enable us to answer our research question (Bailey et al., 2017). This was initially done individually by each researcher and then consensus was reached through a group discussion to finalize the key themes emerging from the study.

Figure 1: Selection process for the review



3. Findings

We used topic modelling and coding (by the research team) to find common features (topics) between the articles, and then cluster similar features to form research themes, which would: (1) enable us to answer the research questions; (2) identify the trending research areas; (3) find the knowledge gaps, i.e., (4) propose research priorities. The key research themes stemming from our review and analysis 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 discuss the key findings related to each theme, rather than providing an exhaustive analysis of each article, similar to the approach followed in other systematic reviews (Vrontis et al., 2021; Christofi et al., 2019; Leonidou et al., 2020).

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; Davenport and Bean, 2017): 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) are 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; (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, rather than a more generic strategic focus. 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 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, Saling and Do, 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, increase the time devoted for non-trivial tasks, heighten creativity, 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 (and beyond the theoretical narratives), if employees (human workers) understand, trust, and adopt AI. The use of

AI was originally seen as benefiting the workforce by providing tools to enhance day to day working activities/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, teamwork assistants to cyber-machine peers and even AI managers who can evaluate and coordinate the work of others (Malone, 2018). Seeber et al (2020) went further and suggested that effective AI teammates required 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, choosing among options, making plans, taking actions, learning from past interactions, and participating in after-action reviews' (Seeber et al, 2020). However, the use of AI socialization faces several questions and challenges often centred around human perceptions of the AI teammates (Zhang et al 2021), such as teammate aesthetic, the division of labour and accountability.

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). Two streams of research have emerged in this context: (1) concerns about the negative impact of AI such as bad decision-making, discrimination, bias, inaccurate recommendations (Davenport et al., 2020); (2) fear and skepticism among human workers because of potential job losses (Rampersad, 2020). 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 building on the tenets of socio-technical systems theory and organisational socialisation framework by Makarius et al., 2020 integrating AI with employee within the business organisations has discussed the role of AI as a collaborator (new employee), where AI-employee collaboration can help the organisations to achieve competitive advantage. 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

HR practitioners need to have certain AI skills and knowledge to effectively use the technology to its capacity. We have identified AI skills as realization (adoption), utilization (using it) and maintenance (managing, governance and evolution). AI realization refers to the identification of tasks and suitable applications in the business operations (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 embody competence in data visualization and analytics, which will involve interpreting AI responses and recommendations (Dubey et al., 2019), i.e., technical skills to deal with the implementation of the AI system and its subsequent use. 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 management of these competencies, skills and knowledge is considered an asset for organisations that can be supported using AI (Younis and Adel, 2020). For example, Liebowitz (2001), reported how AI enhanced knowledge management by facilitating effective knowledge sharing. Abubakar et al (2019) showed how AI could be used to highlight knowledge hiding. Tsui et al., 2000 put forward how AI can be used for knowledge engineering that can aid knowledge searching and knowledge processes.

Developing AI skills and expertise among the human workers will minimize the friction and potential forces of inertia, which could delay the adoption of AI, and impede business value. Therefore, these skills will be strategic intangible resource that will be difficult to imitate by other firms, which will provide 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 (Bharadwaj, 2000; Ravichandran et al., 2005). These skills 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). 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).

Bughin (2018) has discussed how the use of AI within business 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, labour market and expert commentators have discussed the machine dominance and job redundancies, they have failed to point out, how AI will create new jobs, i.e., the skills required for the job will change. The growth of digitized sharing and gig economy innovating existing business models has led to the emergence of 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, considering existing work design theories which have focussed on the impact of work attributes on work outcomes, work design on job enrichment and employee motivation, perceptions of collaborative work environment and empowerment. The aim was 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, Gaur and Riaz, 2019). AI can provide more flexibility and work-related autonomy, promote creativity and innovation, and allow to streamline organizational processes (Malik et al., 2021). This is achieved by automating trivial manual repetitive processes that require considerable time and human capital. 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 (Belhadi et al., 2021), and identifying traits and skills of potential candidates to facilitate adaptation and enhance performance (Wilson and Gosiewska, 2014). Although it can also reduce bias when screening candidates (Belhadi et al., 2021, 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 the overall situation of 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), and also analyzing financial data for payment and motivating personnel based on compensation (Kulkov, 2021) .

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), enhance creative process within organisations by freeing up employees' time to concentrate on non-trivial and complex procedures, resulting in performance gains (Deb at al., 2018; Mishra and Pani, 2020; 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 adapt/re-engineer business operations and processes, 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 enhance business productivity.

The concept of resilience has received significant academic attention in recent years. Organizational resilience involves the capacity to absorb, respond and transform to capitalize on disruptions that threaten the organization (Lengnick-Hall et al., 2011). Organizational resilience is valuable to help businesses plan, prepare, strategize operations, and respond to unpredictable disruptions and efficiently recover from such disruptions (Scholten et al., 2019, Macdonald et al., 2018, Bag et al., 2021b). Studies have also highlighted the was organizational leadership, strategy, resource capacity and human resource capability can facilitate restructuring business operations to deal with unprecedented events (Ambulkar et al., 2015). Resilient organisations often rely on changes on the corporate culture and re-design of processes (Bag et al., 2021a). Hence, the company must promote the development of skills that can use by employees to support the capacity of the organization to withstand disruptions through the introduction of HR management able to ensure human resources are managed effectively and that they can be employed at the right time and in the right conditions to help the company manage different circumstances (Slusarczyk, 2018). An example is given by Mortazavi et al. (2020), who suggest the implementation of AI using information about employees to predict the most vulnerable people to make adjustments with the aim to increase the capability of the company to withstand the disruptions caused by the COVID-19 pandemic. This has the potential of increasing the safety of the workforce and the sustainability of jobs in the long term

seventeen Sustainable Development Goals (UNSDGs) to promote the design of solutions for the key problematics affecting development for the future (UN, 2015). Despite the recent investment on social responsibility programs, the general consensus is that companies are failing to tackle the SDGs because of limited visibility, flexibility and resilience (Bag et al., 2021a). Looking at the 2030 Agenda for Sustainable Development, the field of HRM is closely related to SDG8, which aims to “Promote sustained, inclusive, and sustainable economic growth, full and productive employment and decent work for all” because it considers the importance of labor market conditions, the existence of decent work, and the value of employment creation and work opportunities (UN, 2015). This has led to the development of sustainable human resource management, which aims at accomplishing organizational sustainability supported by the design of HR policies, strategies and practices simultaneously underpinning social, environmental, and economic aspects (Wesley Ricardo de Souza et al., 2011). This stream of research includes studies focused on capability reproduction, fostering environmental and social health, and contributions looking into examining the interrelationships between managerial practices and environmental and social outcomes (Macke and Genari, 2019). Considering the importance of leveraging technology to increase the productivity of human resources to support sustainable development (Reddy et al., 2019), technology has been related to sustainable human resource management. For instance, examining the use of green data processing centers to improve recruitment and training of employees (Zhou, 2021).

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 (Little, 2018; Chesney and Citron, 2019), lack of understanding, intrusion, inequality (Buolamwini and Gebwu, 2018) and labour displacement (Autor, 2015) may 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. The IEEE 7010 (2020) considers the impact of AI on well-being and a well-being indicator dashboard. The framework also offers guidance and steps on how best to achieve the well-being indicator dashboard: user and stakeholder assessment and engagement, appropriate indicators and their development and refinement, data collection and plan for continuation, well-being analysis and any improvements needed (e.g., to the AI or intervention) and the iteration of this process.

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; Kiron and Schrage, 2019); 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 (Pigni et al., 2016; Ransbotham, et al., 2020; Haenlein and Kaplan, 2020); developing a data-centric culture within the organisation, so that everyone is onboard with the implementation and usage (Pigni et al., 2016; ; Tarafdar et al., 2019; Bieda, 2020); technology turbulence, i.e. pace at which technology is changing and disrupting business models and processes (Silverman, 2020; Correani et al., 2020; Morse, 2020).

The impact of these barriers in practice can be significant. AI algorithms designed for human resource planning require well-structured decision objectives to provide good solutions (Meechang et al., 2020). For recruitment and hiring, this means that the core components of the organizational culture must be clearly delimited to obtain useful results. Another barrier is related to transparency in the decision-making process. 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). 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. There are several reasons why transparency is particularly necessary in a HR context (Chowdhury et al., 2020; Silvernam, 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.

Certain groups have been found to be disproportionality disadvantaged in AI algorithms, e.g., black faces associated as gorillas (Dougherty, 2015) and Asian people categorised as blinking (Wade, 2010). If a proportion of society is consistently marginalised 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; Shin and Park, 2019). 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).

Use of AI powered by the algorithms provides HR recruitment with efficient tools to both market jobs to an increasingly digitally based candidate and perform the rudimentary initial checks before candidates can be interviewed. Particularly 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, society is has 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 to some precision individual attributes and characteristics, doesn't it also limit 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. That also requires operators to be constantly revising and updating the parameters incorporated in the AI algorithm to account for organizational changes such as shifts in priorities and inclusion of relevant criteria for external stakeholders, which supports the claim that successful AI implementation can only be fully achieved when there is an acceptance from decision-makers for its use (Cao et al., 2021).

4. Framework Development

The review has identified trending research themes and under-researched research themes with regards to AI adoption in HRM. While each theme identified in the review have been discussed in isolation, we propose the AI capability framework (Figure 2) linking the themes outlined in the review. The objective is to answer the research question by proposing the AI capability framework identifying resources required to utilize AI to transform HRM processes and practices. We also show the impact of these transformations on the business organisations, derived from the literature in this area. The framework is developed by integrating the tenets of resource-based view (RBV), Knowledge based view (KBV) and knowledge management strategies.

RBV is one of the most widely applied theoretical perspectives to explain how resources within an organisation can help 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 (Bromiley and Du, 2016; Mikalef and Gupta, 2021). Knowledge based view (KBV) theory draws from classical management theories such as theory of the firm, the organizational theory, and the resource-based view (RBV) of the firm. It 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 are co-created within the organisation (Grant, 1996). However, KBV does not specify mechanisms to share knowledge that will promote and satisfy individual-level outcomes (and in this case related to AI). Drawing from the knowledge management literature, knowledge sharing has been identified by Hansen et al. (1999) as a key practice to create business value that will enhance economic performance of business organisations. In this context, codification strategy involves storing the knowledge in a database, which facilitates identification of good practices and their re-use by employees over time, whereas personalization involves communication of knowledge between individuals and teams through dialogue (person-person). These theoretical perspective helps to holistically 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

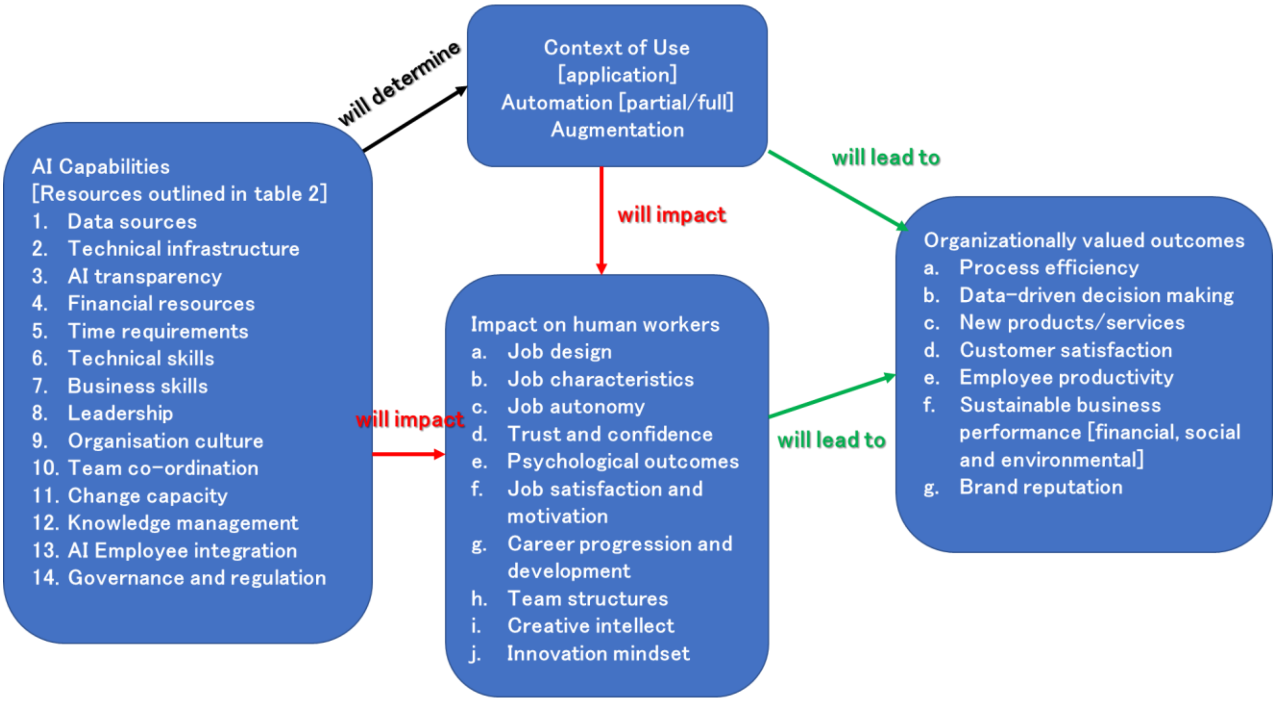
Resource Type	Resources	Description	Reference
Technical Resources	Data resources	Internal data from internal operations. External data from stakeholders, suppliers and market environment. Data collected using sensor-based technology, existing HRIS and ERP, enterprise social media and public facing social media	Zhao et al., 2014; Colson (2019); Afiouni, 2019; Keding, 2020. Pumplun et al., 2019; Schmidt et al., 2020; The Economist (2017); Bean, 2017.
	Technology infrastructure	Data storage, data management, data cleaning and aggregation, processing power (parallel computing), network bandwidth, cloud-based solution, algorithms and software programs	Bayless et al., 2020; Chui and Malhotra, 2018; 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; Choudhury et al., 2020; Satell and Sutton, 2019; Ribiero et al., 2016; Zhang et al., 2019; Silvernam, 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 facilitate career development	Chui and Malohtra, 2018; Fleming, 2018; Mikalef and Gupta, 2021.

	Time requirements	Time to experiment, achieve maturity in the sense of moving beyond proof-of-concept solutions, yield value from adoption gradually over a period	Schryen, 2013; Chui and Malohtra, 2018; Fleming, 2018; 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.	Kolbjørnsrud et al., 2016; 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, develop good working relationships with employees and teams, follow clear communication mechanisms	Chui and Malhotra, 2018; Davenport and Ronanki, 2018; Alsheibani et al., 2020; Lee et al., 2019; Kiron, 2017
	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; Pumplun et al., 2019; Lee et al., 2019; Fountaine et al., 2019; Ransbotham, et al., 2018; Ransbotham et al., 2019
	Co-ordination between teams	Common understanding and shard vision between the employees working in different team impact or not impacted by AI adoption, to develop mutual goals and collaborative behaviour.	Benitez et al., 2018; Fountaine et al., 2019; Ransbotham et al., 2018 and 2019
	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 (and will depend on leadership, culture, co-ordination between teams, employees' skills and knowledge)	Grover et al., 1995; Besson and Rowe, 2012; Zheng et al., 2017; Pumplun et al., 2019; Ransbotham et al., 2019
	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	Jôhnk et al., 2021; Pillai and Sivathanu, 2020; Mikalef et al., 2020, Makarius et al., 2020; Mikalef et al., 2019; Ransbotham et al., 2018
	AI-employee integration	Develop collective intelligence capability within organisations through AI socialisation, informing employees about adoption strategy, seek their views, clarify job roles, responsibilities and expectations, job autonomy and job characteristics, provide a clear path for career progression to enhance employee psychological outcomes and productivity [will depend on knowledge management and AI	Bieda et al., 2020; Barro and Davenport, 2019; Makarius et al., 2020; Amabile, 2020; Ciechanowski et al., 2020; Brougham & Haar, 2018; Tambe et al., 2019, Tarafdar et al., 2019; Keding, 2020

		adoption strategy, and impacted by leadership, culture and co-ordination between teams].	
	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)	Baier et al., 2019; Coombs et al., 2020; 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. The framework further integrates the themes (AI applications, collective intelligence, and AI employment) linking them to organisational resources. The organisational resources will determine 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 context of use will depend on the business problem and priority. We envisage the context will 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 collective intelligence. The impact on employees will depend on the type of AI, which processes will be transformed, AI strategy of the organisation, knowledge creation, sharing and management mechanisms 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. Both codification and personalization strategies have been used to build expertise and facilitate skills development in the context of platform ecosystems (Tiwana, 2013) and IT sectors (Garavelli et al., 2002). Therefore, 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 will help to explain how knowledge can be shared within organisations, which will enhance the AI-employee integration (a unique and hard to imitate capability), which in turn will lead to performance gains. All of these will lead to developing a 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, type of AI, context of use, and psychological investment of human employees will lead to several benefits enhancing both organisational and employee productivity. Organisational productivity will take the form of: (1) process efficiency, which will let employees 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 and costs in terms of inventory management through optimising resource utilization (Wamba-Taguimdje et al., 2020; Alsheibani 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 and employee appraisal, and improving employee experience and working conditions by analysing enterprise social media anonymous 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 knowledge management strategies and 6 listed above, and ability to dynamically adapt innovation and re-engineer processes, having minimal friction from employees (Makarius et al., 2020); (8) developing successful business cases related to AI implementation which will enhance reputation among the business stakeholders, competitors, policy makers and consumers (Davenport and Ronanki, 2018).

5. Discussion

5.1 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 developing favourable conditions 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 HRM applications.

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 hard-to-imitate AI capabilities. Our review showed 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 outlook 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 (applications identified in the review). While we have integrated RBV, KBV and knowledge management strategies to objectively develop the framework considering both technical and non-technical resources, the impact of the proposed capabilities on organisational creativity, innovation, dynamic capability, and business productivity, warrants empirical investigation. Such studies will help to objectively understand the relationship between the resources and the outcome variables (creativity, innovation, dynamic capability, and productivity) using mathematical models. Based on this discussion, we propose the following research questions.

- *A1: What is the relationship between 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 we prioritize organisational resources required to adopt AI objectively considering the context of utilization, organisational priorities, and business goals*

AI transparency and explainability

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 explainability?*
- *A4: How will enhancing transparency of AI algorithms impact the decision-making strategy and perception of both employees and HR managers in business organisations?*

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 (Amabile, 2020; Ciechanowski et al., 2020; 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 progression and 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 and our limited understanding exists in the HRM literature on the factors that will influence AI-employee collaboration, and the potential business impact of this collaboration. 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; Grant, 1996). However, the impact of knowledge management strategies and practices on AI-employee collaboration needs further empirical investigation. 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 antecedents to AI-employee collaboration and how the antecedents and AI-employee collaboration will impact organisationally valued outcomes such as sustainable business performance, organisational creativity, and capability to innovate?*
- *A6: How knowledge management strategies can 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?*

AI Skills Development

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 should become more analytical to understand and create business insights, an understanding of research design skills and data capture process, and communicating the business requirements to developers. Furthermore, 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; WambaTaguimdje 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? 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 context of use?*

Extremely less researched themes

We found that recent reports published by the European Commission have emphasised on ethical and moral aspects surrounding AI, which has led to responsible 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 does country-specific factors 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?*

5.2 Theoretical Implications

From a theoretical perspective, firstly, we contribute to shaping the narrative of the current debate on AI adoption in HRM from the impact on human jobs in organisations which are likely to be disrupted by AI to how organisations can strategize the AI-employee collaboration (where both AI and human intelligence will co-exist). This will facilitate developing 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 (Makarius et al., 2020; Fleming, 2019). 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 (Fleming, 2019, Makarius et al., 2020), which has emerged as a new research theme in the literature (Murray et al., 2020). Research on this theme is less developed in the management literature, except Makarius et al, 2020 reporting an AI socialisation theoretical framework. The importance of collaboration, cooperation, and coordination, to understand the capabilities and limitations of AI in the organisational settings has been discussed in (Malone, 2018; 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 has discussed the role of leadership and senior management to enhance the innovation capability of organisations for achieving competitive advantage (Lei et al., 2021). In this context, previous studies have also shown the decisive role of leadership to developing and shaping a positive culture within the organisations, which is conducive to introducing, implementing, and managing innovation within the organisations (Le and Lei, 2019; Le, 2020). Such environment helps to create a supportive culture within the organisations that will enhance motivation and commitment of the employees to embrace innovative ideas, processes and strategies, helping the organisations to dynamically adapt and evolve (Lei et al., 2020; Al-Husseini et al., 2019). Leadership plays an important role to intellectually stimulate employees' ability to perform their tasks and embrace change, through career development programmes (Nguyen and Mohamed, 2011). It also helps to develop appropriate conditions, strategies, and resources within the organisation, which will allow the employees to harness new skills building on existing knowledge, facilitate access to relevant knowledge and expertise base, and finally encourage on sharing this knowledge with peers (Alsheibani et al., 2020; Demlehner & Laumer, 2020). Adoption of AI-enabled solutions within HRM will change the organisation's business model, processes, and practices, which we have identified throughout the review. AI-HI collaboration will inherently change organisational structure, roles and responsibilities and teams. Therefore, AI can be considered as an innovative technology and organisational leadership will play a critical role to develop facilitating conditions to deploy, manage and evolve AI (Alsheibani et al., 2020).

Thirdly, we also find that with advances in technological and algorithmic innovations, the problem has shifted from collecting huge volumes of data, turning data into knowledge and conclusions (Kersting and Meyer, 2018), to understanding how AI algorithms generate these conclusions (Gulliford and Dixon, 2019). This will facilitate building trust among the managers and turn these conclusions into actionable insights. However, these techniques currently lack transparency and explainability, which makes it difficult for managers to trust the output of AI (Agarrwal et al., 2020; Bieda et al., 2020). strategies (Shin and Park, 2019; Makarius et al., 2020). The primary goal of embedding transparency within AI-based ML models is to help the decision-making authorities understand what the AI system is doing, how it is generating the output responses and why a particular response is generated (Choudhury et al., 2020). This will help these business users to confidently assess the accuracy of the responses based on their own tacit domain expertise, which will increase trust in these systems (Cowgill and Tucker, 2020). The ability to get explanations for the output responses will also reduce biases in business processes, operations, and decision-making, thus enhancing fairness (Satell and Sutton, 2019). For example, gender discrimination in hiring employees and setting up credit card borrowing limits stemming from AI systems has led to mistrust among both businesses and their consumers, demonstrating the need for AI transparency (BBC, 2019). Furthermore, AI transparency can also aid in identifying and resolving flaws within ML models stemming from improper training datasets (input issues), wrong settings, configurations and hyperparameters (algorithmic issues), and overfitting or underfitting models, which will enhance the value offered by these AI-based systems (Chowdhury et al., 2020; Satell and Sutton, 2019). The human-AI interaction within the work environment is a less understood phenomenon considering the cognitive (AI context of use), relational (factors impacting AI-employee integration) and structural complexities (organisational strategy and innovation ecosystem) related to AI replacing human tasks (Makarius et al., 2020; Kaplan and Haenlein, 2020; Syam and Sharma, 2018). Therefore, developing employee-AI trust by embedding transparency in AI algorithms will facilitate better understanding and confidence in AI system. This will be the pathway to augmenting human intelligence, rather than replacing it entirely within HRM decision-making processes.

Finally, we propose a theoretical 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), knowledge management codification and personalisation strategies, 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, and including IM (Budhwar & Malik, 2020a, 2020b; Vrontis et al., 2021). While, IM has primarily focussed on technical resources and infrastructure, and wider BAM research has focussed on non-technical resources, our capability framework objectively brings these two rather fragmented pieces of literature together (Loebbecke & Picot, 2015; Markus, 2015). Therefore, the framework provides a holistic understanding of all resources necessary to make organisations 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; Phan and Wright, 2018), 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. While this may be viewed as antithesis to what has been reported in some media outlets regarding AI, and how benefits offered through AI adoption is inconclusive from the academic literature (and often inflated).

5.3 Practical Implications

The extant business and management literature on AI have highlighted how the adoption will shape nature of work and job design within business organisations, and its positive impact on business productivity, whereas negatively for employees' emotional state and job performance (Fleming, 2019). In this context, existing research has identified the importance of collective intelligence, i.e., symbiotic partnership between AI and HI, and how this will also increase the capability of human workers, which will lead to higher employee productivity, better psychological outcomes, low turn-over and improved quality of outputs (Glikson and Wooley, 2020; Murray et al., 2020; von Krogh, 2018). Our review has several implications for managers, which are discussed below.

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 should 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, managers must create mechanisms within the organisations that will facilitate knowledge sharing among the employees about AI processes, systems, and contexts of use within the HRM business activities. The knowledge sharing mechanism should also involve appropriate interventions to store information, which can be accessed by employees conveniently (Aleksander, 2017). This will require creating a hybrid knowledge strategy, i.e., combining both codification and personalisation, investing in the technical resources necessary to store and disseminate information among the employees. This should help to share knowledge which will also create new knowledge through the process of restructuring, merging, and synthesising, and evolving this knowledge in a systematic, incremental, and iterative manner. This is critical as AI systems will extend beyond the current capabilities, therefore albeit knowledge co-creation and sharing, evolving it is equally important to remain updated and competitive in the highly turbulent AI technology environment.

Thirdly, managers must provide information with regards to job design, i.e., how the nature of work, employees' roles and responsibilities and relevance of human intelligence in AI-employee collaboration networking environment (Makarius et al., 2020). This will require communicating the strategic business goals and priorities of the company, how AI will be used and the rationale for its adoption. The communication should be not only documented but involve face-face meetings with employees to foster a two-way communication that will also facilitate answering queries from employee and alleviate their concerns (which is widely reported in media outlets, often leading to a very negative perception among humans). This will lead to a better understanding of AI adoption context, and enhance trust and confidence in the management initiatives and strategy (Mahidhar and Davenport, 2018). Such communication mechanisms and strategy dissemination initiatives will require commitment from organisations' senior management (leadership) to enhance employee development, job satisfaction and workforce performance (Alsheibani et al., 2020). The dedication and engagement of managers as well as top-level management will be a strong contributor towards AI adoption (Davnport and Ronanki, 2018). This will also require developing 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 (Kolbjørnsrud et al., 2016; Alsheibani et al., 2020; Pumplun et al., 2019).

Fourthly, AI-employee collaboration is likely to be facilitated by tacit experience (Leonard and Sensiper, 1998) within the organisations, i.e., implicit knowledge sharing which is communicated by employees having prior understanding of AI and experience working with AI systems. Therefore, managers must develop a process to identify tacit AI experience within the organisation, which according to KBV is a critical resource to enhance organisational dynamic capability and employees' trust, skills, and job clarity (according to Makarius et al., 2020). Evaluating the internal expertise will help to identify employees having knowledge (technical and/or non-technical) to use AI, understand business processes and functions which can benefit, and how the benefits will serve both employees' and organisational goals/priorities (Mikalef and Gupta, 2021). For example, HR managers can either disseminate a questionnaire through the existing employee management system that will help to gather information about the existing AI skills and knowledge possessed by the employees or put an open proposal inviting individuals or teams interested to form AI-employee workforce committee (where members have prior experience with AI systems). Such initiatives will help managers to recognise hidden talent within the organisation and enhance the visibility of such skills across the organisation, which will be instrumental in improving employees' commitment and contribution to AI-human collaborative working environment.

Finally, to adopt AI within HRM, organisations must develop a 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 (Brock and Von Wangenheim, 2019).

6. Conclusion and Future Direction

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 62 top-tier HRM, GM, IB and IM journals, and based on the inclusion criteria as well the research question 69 articles were found to be relevant. 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 primarily has focussed on the applications of AI in HRM, anticipated benefits, impact of AI on jobs, and AI-driven decision-making augmenting human intelligence. However, collective intelligence is nascent and emerging within academic research. While, many studies have reported the drivers and barriers related to adoption and implementation of AI, we consolidate these to propose AI capability theoretical framework. The capability framework will help organisations assess their readiness to leverage AI-based systems. Based on the systematic review, we also propose four 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; (2) impact of AI transparency and trust; (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 has few limitations, which can be adequately acknowledged in future research. 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.

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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), Agarwal et al. (2021),
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. 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)