AI-Augmented HRM: Antecedents, Assimilation and Multilevel Consequences

Abstract

The current literature on the use of disruptive innovative technologies, such as artificial intelligence (AI) for human resource management (HRM) function, lacks a theoretical basis for understanding. Further, the adoption and implementation of AI-augmented HRM, which holds promise for delivering several operational, relational and transformational benefits, is at best patchy and incomplete. Integrating the technology, organisation and people (TOP) framework with core elements of the theory of innovation assimilation and its impact on a range of AI-Augmented HRM outcomes, or what we refer to as (HRM$^{(AI)}$), this paper develops a coherent and integrated theoretical framework of HRM$^{(AI)}$ assimilation. Such a framework is timely as several post-adoption challenges, such as the dark side of processual factors in innovation assimilation and system-level factors, which, if unattended, can lead to the opacity of AI applications, thereby affecting the success of any HRM$^{(AI)}$. Our model proposes several testable future research propositions for advancing scholarship in this area. We conclude with implications for theory and practice.

Keywords: Technology-driven HRM, AI-adoption in HRM, AI-augmented HRM, Processual Factors.

1.0 Introduction

Scholarly research on the application of information technology (IT) in HRM is rapidly increasing, and different scholars have coined several concepts linking HRM and IT (Bondarouk, Parry & Furtmueller, 2017a; Strohmeier, 2018). These efforts include examples, such as 'web-based HRM' (Ruel, Bondarouk & Looise, 2004), 'e-HRM' (Strohmeier & Kabst, 2009), 'HRIS' (Kundu & Kadian, 2012), 'HRM cloud computing' (Wang, Wang, Bi, Li & Xu, 2016a), 'HR analytics' (Vihari & Rao, 2013), 'Online HRM', 'Digital HRM', 'Smart HRM' (Bondarouk et al., 2017a; Strohmeier, 2018) and ad-hoc and strategic use of artificial intelligence (AI) enabled HRM applications (Malik, Budhwar, Patel & Srikanth, 2020; Malik, Srikanth & Budhwar, 2020a). Access to and generation of structured and unstructured HR-specific databases and an increasing reliance on the use of advanced digitalized HRM and AI applications for generating insights, solving problems and engaging in predictive decision-making for HR functions is on the rise (Saukkonen, Kreus, Obermayer, Ruiz & Haaranen, 2019; Malik et al., 2020b; Strohmeier & Piazza, 2015; Tambe, Cappelli & Yakubovich). The proliferation and use of AI-enabled innovative database management is evident in the real world with emerging AI-HR applications and solutions, such as CloudHR, SAP SuccessFactors, BambooHR, GustoHR, OnPay, CakeHR, Trakstar, Deputy, ZohoPeople and so on. Technology giants also developed such applications, such as Google, Microsoft, IBM, and LinkedIn. With increased digitalization and data usage by AI-enabled applications for HRM processes, the role of HR professionals is also being redefined and transformed (Hmoud & Laszlo, 2019; Papageorgiou, 2018). Recent research notes that contemporary AI applications have augmentation and automation functionalities, and in some cases, replaced HRM decision-making that humans typically undertook (Malik et al., 2020a, b; Vrontis, Christofi, Pereira, Tarba, Makrides & Trichina, 2021).

In general, AI can be referred to as the capacity of machines to make predictions or solve problems using large amounts of data for complex, structured and unstructured environments (Agrawal, Gans, & Goldfarb 2018). AI uses various techniques and applications, such as neural networks, speech/pattern recognition, genetic algorithms and deep learning (i.e., NLP- Neuro-linguistic Programming, machine learning and machine vision) (Jarrahi, 2018). The three components of AI: high-speed computation, use of big data and advanced algorithms, help AI differentiate from existing legacy IT applications (Cheng & Hackett, 2020; Guenole & Feinzig, 2018) for routine and non-routine decision-making and problem-solving processes (McGovern, Pandey, Gill, Aldrich, Myers, Desai, & Gera, 2018). The ability of AI applications to process large amounts of data fast assists HR managers in saving time and arrive at accurate HRM decisions (Lindebaum et al., 2020; Vrontis et al., 2021). There has been a rapid progression from a 'descriptive and diagnostic' to a 'prescriptive and predictive' approach to AI (Di Claudio, 2019, HRPA, 2017).

A critical review of current HRM literature suggests that AI-enabled HRM applications are becoming part of strategic HRM discussions (Upadhyay and Khandewal, 2018; Kwan et al., 2019) in almost all sub-functional HRM domains, such as recruitment and selection (Van Esch, Black & Ferolie, 2019), training and development (Maity, 2019), performance management (Leicht-Deobald et al., 2019), talent management (Malik, De Silva, Budhwar & Srikant, 2021), employee turnover (Li, Bonn & Ye, 2019), reward management (Escolar-Jimenez, 2019), job design (Huang et al., 2019), employee satisfaction (Nguyen & Malik, 2021) and employee engagement (Burnett and Lisk, 2019). Inherent in the use of AI applications in HRM are algorithms that augment HR practitioners' experience and HR decision-making and problem-solving processes. Despite the high adoption rate of various AI techniques (such as algorithms) in distinct functions of HRM, there is a limited understanding of an integrated and processual framework for the adoption of AI in HRM.

The existing conceptual frameworks and theoretical models around the use of AI in HRM reflect a comparatively cautious and conservative outlook (Cheng & Hackett, 2020; Tambe et al., 2019). Perhaps, Strohmeier and Piazza (2015) were the first to develop a conceptual base for identifying a range of areas for using AI-augmented applications for HRM, followed by Jia et al. (2018), who highlighted several strategic and operational aspects of HRM AI applications that could assist in these activities. However, although both of these studies offered a nuanced approach for using AI applications for different HRM functions, these studies lack an explanation of the theoretical basis for AI assimilation in HRM. Moreover, prior literature concerning technology-driven HRM (i.e., HRIS, e-HRM) considers adoption as a single point event (see, e.g., Bondarouk et al., 2017a; Burbach & Royle, 2014; Troshani, Jerram & Hill, 2014), yet adoption is only a part of the assimilation process. The migration from initial adoption to the diffusion of technological innovation is complex and involves additional steps of diffusion, routinization and extension of assimilation (Chatterjee, Grewal & Sambamurthy, 2002; Zhu, Kraemer & Xu, 2006). Such an approach is evident in technological innovations from different businesses, as noted in Hossain, Quaddus and Islam's (2014) four-stage process model explaining adoption, diffusion, routinization, extension for RFID- Radio Frequency Identification (RFID) technology assimilation. Similarly, Basole and Nowak (2016) and Nam, Lee and Lee (2019) used a three-stage process for supply chain adoption to examine drivers for each stage of business analytics adoption. Therefore, a processual conceptual framework comprising a stage-based process to understand the assimilation of AI in HRM is much warranted.

Thus, observing these limitations and subsequent call for comprehensive AI-HRM adoption framework incorporating interdisciplinary collaboration between HRM and other functional areas (Kiron & Schrage, 2019; Fountaine, McCarthy, & Saleh, 2019), this research proposes a new term 'AI-Augmented HRM' (HRM $^{(AI)}$), and a processual HRM$^{(AI)}$ assimilation framework comprising its antecedents and outcomes. Augmentation in the context of HRM$^{(AI)}$ implies a mindset of symbiotic enhancement (Davenport & Kirby, 2016) to develop AI-enabled HRM interactive systems, using a collaborative partnership between humans and machines to deliver productivity improvements, process efficiency, and human interactions at the interface of AI-human exchanges that augments human-machine cognition (Wilson & Daugherty, 2018).

Thus based on these observations, this research aims first to develop comprehensive and contemporary definitions of HRM$^{(AI)}$ (AI-augmented HRM) and HRM$^{(AI)}$ assimilation to highlight and explain the use of AI techniques in the context of HRM. These fine-grained definitions will help to distinguish HRM$^{(AI)}$ from these similar-sounding concepts (i.e. web-based HRM, e-HRM, HRIS, HRM cloud computing, HR analytics, Online HRM, Digital HRM and Smart HRM), and at the same time will allow several research questions – at multiple levels – to be generated and extended in future HRM$^{(AI)}$ research. Secondly, given the observation that migration of AI adoption for HRM to diffusion might involve different stages (Chatterjee, Grewal & Sambamurthy, 2002; Zhu, Kraemer & Xu, 2006), we propose a four stage process-view approach for HRM$^{(AI)}$ assimilation based on theory of assimilation innovation. Thirdly, while considering HRM$^{(AI)}$ assimilation as a full life-cycle that includes not only an organizations' initial evaluation of AI and its adoption but its full-scale deployment (i.e., stages of HRM$^{(AI)}$ process), this research aims to identify antecedents and consequences of HRM$^{(AI)}$ assimilation and provide future research propositions based on identified antecedents and consequences.

The essence of this research can be captured in three main contributions to the existing literature in the domain of adoption of AI in HRM. First, this research introduces the concept of HRM$^{(AI)}$ to differentiate use of AI in HRM from similar technology-enabled HRM terms. Second, this research proposes an HRM$^{(AI)}$ assimilation mechanism based on a four-stage process comprising the stages of initiation, adoption, routinization and extension in line with the theory of assimilation innovation. Last but not least, despite the current trend in an increased evaluation of research regarding the use of AI for a range of HRM activities and benefits linked to the adoption of AI technology in HRM (Charlier & Kloppenburg, 2017; DiClaudio, 2019; Gulliford & Dixon, 2019; Hmoud & Laszlo, 2019; HRPA, 2017; Marr, 2018; McGovern et al., 2018; Robinson & Sparrow, 2007; Rodney, Valaskova & Durana, 2019; Samarasinghe &

Medis, 2020; Saukkonen et al., 2019; Tambe et al., 2019), the extant efforts are limited in terms of development of a comprehensive framework that provides an understanding of antecedents and potential consequences of AI adoption in HRM. In order to conceptualise an integrated processual HRM$^{(AI)}$ assimilation framework, we identify antecedents for HRM$^{(AI)}$ assimilation based on Technology-Organisation-People (TOP) framework (Brandt & Hartman, 1999), and then further use operational, relational and transformational consequences framework (Bissola, 2014; Lepak & Snell,1998; Obeidat, 2016; Parry & Tyson, 2011; Ruel et al., 2004; Strohmeier, 2007) for proposing multilevel consequences of HRM$^{(AI)}$ assimilation.

The paper first offers a theoretical background informing the study, followed by definitions of the newly conceptualised terms HRM$^{(AI)}$ and HRM$^{(AI)}$ assimilation. Next, a detailed theoretical model and future research propositions for the antecedents and consequences of HRM$^{(AI)}$ assimilation. Finally, the paper highlights the critical theoretical and practical contributions, limitations, and future research possibilities.

2.0 Theoretical background

2.1 Theory of Assimilation Innovation

The theory of assimilation innovation suggests several stage-based processual models for the adoption-diffusion process of technological innovations (Zhu et al., 2006). For example, a three-stage (Basole & Nowak, 2018; Zhu et al., 2006) and a four-stage adoption-diffusion process (Hossain et al., 2016). While Basole & Nowak (2018) and Zhu et al. (2006) categorised this process into stages of initiation, adoption and routinisation, on the other hand, Hossain et al. (2016) extended the framework further by proposing the fourth stage of 'extension' in this adoption-diffusion process. The rationale being that routinisation does not ensure the full potential of the IS/IT application, and the extension stage needs to be considered for further value addition to the organisation. Due to the extension stage, the organisation might not need to go through the adoption stage again (Hossain et al., 2016). This theory has been used extensively in extant literature concerning assimilation of cloud computing (Liang, Ki, Zhang & Li, 2019; Maqueira et al., 2019), ERP assimilation (Shao, Feng & Hu, 2017), tracking technology (Basole & Nowak, 2018), RFID technology (Hossain et al., 2016, Wei, Lowry & Seedorf, 2015) in different management disciplines.

As noted earlier, initiation and adoption are only part of the assimilation process (Chatterjee et al., 2002; Zhu et al., 2006) and distinct from deployment or routinisation, wherein the antecedents and mechanisms of technology deployed for HRM may differ from the drivers of innovation adoption (Wei et al., 2015). In technologies with high implementation complexity, such as AI, little or no actual implementation occurs after technology adoption, thus creating an assimilation gap (Fichman & Kemerer, 1999). Further, considering HRM$^{(AI)}$ as a technological innovation that might have a far-reaching impact on the functioning of HR and its implications for organisation and employees as a whole, it is essential to consider all four stages of the assimilation processes (i.e. initiation→adoption→routinisation → extension) for developing a complete understanding of HRM$^{(AI)}$ assimilation. These four stages are considered distinct variables in the assimilation literature (see, e.g., Basole & Nowak, 2018; Hossain et al., 2016; Maqueira et al., 2019; Nam et al., 2019).

*2.2 **Technology-Organisation-People (TOP) Framework***

TOP framework stems from a socio-technical system approach, and it consists of three closely interconnected sub-systems: people, organisation, and technology (Brandt & Hartman, 1999; Stevens, 1989). Stevens (1989) noted that organisations need to focus on technological, organisational, and people dimensions to integrate the latest technologies fully. A careful review of the information system research suggests that the technology, organisation and environment (TOE) resource framework has been widely used in IT/IS adoption (Zhu et al., 2006). The TOE framework (Tornatzky & Fleischer, 1990) posits that various contextual factors influencing the organisational process of adoption and implementation of a technological innovation stem from technological, organisational, and environmental facets, although the factors identified and used within these three contexts vary across studies (Cao, Jones & Sheng, 2014; Chen, Preston & Swink, 2015). Despite the acceptance of this framework, recent research has called for the inclusion of people factors for the successful adoption of technology (Gupta, Meissonier & Roubaud, 2020).

The inclusion of people factors has attracted attention (Bondarouk et al., 2017a) and concluded that new technology adoption factors involve either technological, organisational or people (TOP) requirements. These factors vary in their influence on the adoption and implementation of technological innovations across different studies (Bondarouk et al., 2017a; Gupta et al., 2020). Prior literature focusing on technology-driven HRM (i.e., e-HRM, HRIS) has considered TOP factors for understanding adoption (see, e.g., Bondarouk et al., 2017a; Burbach & Royle, 2014; Strohmeier & Kabst, 2009; Troshani et al., 2014), which reinforces the importance of TOP framework in identifying the antecedents of HRM$^{(AI)}$ assimilation in an organisation.

2.3 ***Operational, relational and transformational consequences***

Previous research has conceptualised macro-level consequences of technology-driven HRM into operational, relational and transformational consequences (Bissola & Imperatori, 2014; Lepak & Snell, 1998; Obeidat, 2016; Parry & Tyson, 2011; Ruel et al., 2004; Strohmeier, 2007). While operational consequences refer to efficiency and effectiveness outcomes of a technology-driven HRM (Lengnick-Hall & Moritz, 2003), such as reducing costs and alleviating administrative burdens, relational consequences emphasise the interactions and networking of different actors in sustaining the relationships with an employee by improving HR services and empowering employees (Parry & Tyson, 2011; Ruel et al., 2004). Finally, technology-driven HRM impacts transformational outcomes (Lepak & Snell, 1998), such as improving strategic orientation towards HRM (Bissola & Imperatori, 2014; Shrivastava &

Shaw, 2003). Thus, the HRM$^{(AI)}$ framework captures the consequences of this disruptive technological innovation in our HRM$^{(AI)}$ assimilation framework.

3.0 Definitions of HRM$^{(AI)}$ and HRM$^{(AI)}$ Assimilation

3.1 Defining HRM$^{(AI)}$

Most literature emphasises the importance, benefits, key considerations and challenges in establishing AI-augmented HRM practices in organisations (Charlier & Kloppenburg, 2017; DiClaudio, 2019; Guenole & Feinzig, 2018; HRPA, 2017; McGovern et al., 2018). Since Lawler and Elliot's (1996) initial investigation of an expert system within the HRM context, several academic studies have evaluated the current position and utilisation of recruitment and selection for incorporating AI techniques (see Hmoud & Laszlo, 2019; Jantan, Hamdan & Othman, 2010; Rodney et al., 2019; Strohmeier & Piazza, 2015). Others have shed light on views held by the HRM community on the impact of AI technologies (Saukkonen et al., 2019). Despite the above literature on AI-enabled HRM applications, there exists a limited understanding of what constitutes AI-augmented HRM.

We define HRM$^{(AI)}$, keeping in mind two key points. First, the success of any AI-enabled model requires a deeper integration of AI techniques into business intelligence (BI) systems and processes to simplify the deployment of intelligent applications (Sirosh, 2017). Second, developing and implementing AI techniques de novo and outside an existing BI system can be a resource-intensive exercise (Alvarado, 2017; Sirosh, 2017). Thus, configuring a successful HRM$^{(AI)}$ framework within an organisation requires a precursor condition of an established BI system so that new HRM$^{(AI)}$ technologies can be embedded and integrated effectively into that system. A BI system is an 'umbrella' term to describe the processes, concepts and methods that aid decision-making using fact-based decision support systems (Trieu, 2017).

Tambe et al. (2019) highlighted the gap between what AI applications can and cannot deliver in the domain of HRM. They argue that the HRM-AI life cycle comprising stages of operations, data generation, machine learning and decision-making follows the core flow of a typical BI system, but incidentally, the apparent reference of using BI systems as a base for developing the HRM-AI life cycle is missing in their work. This research overcomes this shortcoming by suggesting an HRM$^{(AI)}$ framework is grounded in BI systems theory (Ariyachandra & Watson, 2006; Baars & Kemper, 2008; Mazón & Trujillo, 2008; Wirtz & Müller, 2019) and further suggests comprehensive mechanisms depicting the flow of data and use of AI techniques and leading to a range of consequences.

Thus, in line with the above discussed, this research defines HRM$^{(AI)}$ as the capacity of the HRM function to integrate with existing BI system and utilise the latest AI technologies to ingest, process and analyse data to aid problem-solving and decision-making for positive domain-specific operational, relational and transformational consequences. It must be noted, though, that HRM$^{(AI)}$ relies on the application of aggregation using different AI technologies, such as Artificial Neuro Networks (ANN) for workforce planning, Neuro-linguistic Programming (NLP) for recruitment, blockchain technology for HR analytics, delivering positive domain-specific operational, relational and transformational impacts. We posit HRM$^{(AI)}$ as a composite term that goes hand-in-hand with other functions of management (i.e. marketing, finance, supply chain and so on), and all data about these functions are centrally accumulated, which can be further used for effective decision-making. The above conceptualisation does not undervalue prior research focusing on e-HRM, HRIS, as this technology-driven HRM approach further facilitates organisations' HRM$^{(AI)}$ assimilation process. Thus, an organisation's robust e-HRM or HRIS system makes it easier to implement the HRM$^{(AI)}$ framework, as it further contributes effectively to HRM$^{(AI)}$ assimilation. Extant literature indicates that e-HRM and HRIS have been elaborated and discussed mainly in the HR domain, without any apparent reference to other management functions. Table 1 distinguishes HRM$^{(AI)}$ from e-HRM and HRIS – the most frequently used technology-driven HRM concepts.

-------------Insert Table 1 about here-------------

3.2 HRM$^{(AI)}$ Assimilation

As noted earlier, the theory of innovation assimilation posits a stage-based HRM$^{(AI)}$ assimilation process (Basole & Nowak, 2018; Zhu et al., 2006). In line with this theory, we consider HRM$^{(AI)}$ assimilation as a four-staged process comprising initiation→adoption→routinisation → extension.

The first stage initiation can be explained as the awareness and evaluation stage of the potential benefits of an HRM$^{(AI)}$ application/s to improve organisational performance. This stage implies evaluating the success potential of an AI technique for a particular HR function and comparing the intended application for checking the effectiveness (improved results) than the already established HR technique (Strohmeier & Piazza, 2015). In contrast, the adoption stage explores organisation needs, the capabilities of the technology, and the accessibility of the resources required for the adoption (Hossain et al., 2016; Nam et al., 2019). In addition, the intended exploration may encompass the investigation of technological functionalities related to a particular activity of HR, task characteristics, and the potential fit of both - task-technique combinations - and the resulting consequences (Strohmeier & Piazza, 2015).

Adoption of HRM$^{(AI)}$ application/s would be further followed by the adjustment and reengineering of the business processes, and the adopters of HRM$^{(AI)}$ will evaluate their adoption decision (confirmation) (Hossain et al., 2016). Based on confirmation evaluation, the HRM$^{(AI)}$ adopters may decide to diffuse the innovation or eliminate it (Bhattacherjee, 2001).

The conscious decision of diffusion of HRM$^{(AI)}$ techniques takes the form of routinisation, and the organisation will use the HRM$^{(AI)}$ techniques in such a manner that it becomes an integral part of the business operations (Hossain et al., 2016). Routinisation stage also encompasses a robust 'user training' and 'technical user support' mechanism that further helps HR personnel with the necessary procedural knowledge and support mechanism to operate the focal HRM$^{(AI)}$ applications (Ahearne, Jelinek & Rapp, 2005; Schillewaert, Ahearne, Frambach & Moenaert, 2005). These activities reduce the opacity of the AI applications and hence can reduce the adverse and dark-side impacts (i.e. of AI data privacy, security, ethical/moral judgement) on the longer-term outcomes.

In the extension stage, the organisation would tend to derive incremental use of HRM$^{(AI)}$ techniques, which is very much feasible and plausible – given that the HRM$^{(AI)}$ adopters have routinised its use and are much confident to experiment incremental adjustments through iterations to reach the total HRM$^{(AI)}$ deployment potential (Hossain et al., 2016). Moreover, HR personnel who get used to frequently carry out particular tasks with HRM$^{(AI)}$ applications can use their extra cognitive and time resources to generate and implement new and valuable ideas that help in trying new HRM$^{(AI)}$ applications (Bos-Nehles, Renkema & Janssen, 2017). In this study, we thus define HRM$^{(AI)}$ assimilation as a series of stages from a firm's initial evaluation of AI technologies at the pre-adoption stage to its formal adoption, to its regular use in the HR activities, and finally to its exploration of newer AI techniques.

4.0 Towards a Theoretical Framework of HRM$^{(AI)}$ assimilation

We develop a theoretically informed research model underpinning research propositions to guide future empirical research to understand the HRM$^{(AI)}$ assimilation process. The proposed model comprises the three TOP factors, four distinct phases of assimilation and a resultant group of three significant consequences: operational, relational and transformational outcomes, as shown in Fig.1.

-------------------**Insert Figure 1 about here**------------------

4.1 Antecedents of HRM$^{(AI)}$ assimilation

Based on our earlier discussion, this research posits HRM$^{(AI)}$ initiation, adoption, routinization, and extension as dependent variables of the following three TOP factors.

4.1.1 Technological factors

The existing technological infrastructure of an organisation plays a vital role in the successful integration of technology within its HR function (Broderick & Boudreau, 1992, cited in Bondarauk et al., 2017a). The extent of technological advancement and the techno-HR alliance is becoming increasingly important as it provides support to a diverse set of actors in HRM to undertake their tasks effectively (Jeyaraj, Rottman & Lacity, 2006; Strohmeier, 2007; Thite, Kavanagh & Johnson, 2012). Based on an extensive review of two streams of literature (i.e., information system and HR), this research posits the 1) Extent of IT adoption, 2) Task-Technology-Fit, and 3) Current e-HRM Configuration as technological antecedents of HRM$^{(AI)}$ assimilation.

Information systems research suggests that the extent of IT adoption can facilitate adopting new technologies in contemporary business organisations (Bruque-Cámara et al., 2004). The extent of IT adoption refers to the number of computers, robotics and telecom technologies, and software applications dedicated to IT functions in the organization. Previous research has used these measures to predict the degree to which innovative applications have been adopted (Teo et al., 2007). Furthermore, four types of organisational characteristics affect the extent of IT adoption: age, size, employee's AI knowledge and information intensity (Bruque-Cámara, Vargas-Sánchez & Hernández-Ortiz, 2004; Thong et al., 1999). In addition, previous research has observed that the extent of IT adoption within an organisation influences its interest in introducing new technologies (Bruque-Cámara et al., 2004; Thong, 1999; Teo & Pian, 2003; Teo et al., 2007).

Further, given that AI techniques are dynamic and evolve rapidly, the organisations may need to establish and extend the IT systems (such as new generation BI systems) to update the innovations in AI techniques (Hazen, Overstreet & Cegielski, 2012). This practice of updating the extent of IT systems becomes integral to the organisation and thus also contributes to the routinisation of the latest HRM$^{(AI)}$ techniques (Pluye, Potvin, Denis, Pelletier & Mannoni, 2005). Similarly, IT adoption helps the organisation using AI techniques for different HR activities (Hossain et al., 2016). For example, while gaining confidence in successfully using NLP for recruitment and selection, the HR department may impress the top management to provide the necessary IT equipment to use NLP in contract management. Thus, we propose that:

Research Proposition 1 (a-d): *The extent of IT adoption within an organization is positively related with HRM(AI) (a)initiation, (b)adoption, (c)routinization, and (d)extension*

Task-Technology-Fit (TTF) theorises that a fit among the task, technology, and users positively influences utilisation and performance (Goodhue & Thompson, 1995). In other words, TTF theory posits that successful adoption of new innovative technology depends on the fit between technology characteristics and the task where the technology has to be implemented (Zhou, Lu, & Wang, 2010). For example, adoption in talent acquisition by IT organisations (Pillai & Sivathanu, 2020), shopper-facing technologies under the current social distancing rules (Wang et al., 2021), cloud-based ERP (Cheng, 2020), gamification for training (Vanduhe et al., 2020) and learning management systems (McGill & Klobas, 2009).

Thus, we assume that any organisation will initiate a new HRM$^{(AI)}$ technology if, and only if, the functions of HRM$^{(AI)}$ technology support the user needs (Dishaw & Strong, 1999), a view that is consistent with Nguyen and Malik's (2021) finding of AI satisfaction with AI quality. Further, a positively perceived TTF environment leads to a belief that new technology is valuable and superior for performing various tasks, leading to its effective adoption

(Jarupathirun & Zahedi, 2007; Strohmeier & Piazza, 2015). Adopting a particular HRM$^{(AI)}$, technique may lead to a positive TTF environment, thus contributing to positive perceptions of HR professionals towards new AI applications, which may result in the routinisation of certain HR tasks such as training and performance management. At the routinisation stage, the organisation may analyse a new AI technique's task-technology-fit and resultant business value for a specific HR activity relative to accrued value from existing technology applications (Curtin, Kauffman & Riggins, 2007). A better AI application gives confidence to the top management of an optimal fit between the requisite tasks, new AI application and the users, thus motivating them to extend the use of AI techniques to other HR activities. The higher the fit, the better assimilation HRM$^{(AI)}$ is likely. Thus, the following proposition:

Research Proposition 2 (a-d): *A positive task-technology-fit (TTF) environment within an organization is positively related with HRM$^{(AI)}$ (a)initiation, (b)adoption, (c)routinization, and (d)extension.*

The concept of 'e-HRM Configuration' (Galanaki, Lazazzara & Parry 2019; Strohmeier & Kabst, 2014) focuses on the combination of technological presence and technologies used to enable HRM activities (Galanaki et al., 2019). As the technological focus is on the physical presence of information technologies to facilitate HR activities (Galanaki et al., 2019), existing e-HRM configuration must therefore be explored in developing an understanding of the HRM$^{(AI)}$ assimilation process. Strohmeier and Kabst (2014) categorised e-HRM configurations along three dimensions: ' Non-users', 'Operational users', and 'Power-users'. The assessment of these configurations and their contextual characteristics may affect the ability of an organisation to assimilate with different stages of HRM$^{(AI)}$.

A non-user configuration of HRM is characterised by a small number and weak institutionalization of HRM practices, leading to a lack of specialisation and professionalisation, rendering e-HR systems irrelevant (Galanaki et al., 2019; Strohmeier & Kabst, 2014). Thus, non-user e-HRM configuration may have adverse impacts on all the

HRM(AI) assimilation stages. On the other hand, an operational user e-HRM configuration helps e-HRM to reduce the administrative burden, though it has a weak strategic HR orientation (Galanaki et al., 2019). This may amount to a positive impact on the HRM(AI) initiation stage, but due to the non- strategic orientation, it may not lead to a fuller adoption of new HRM(AI) techniques, this adversely affecting the routinisation and extension stages.

The final category of power-users e-HRM configuration fully exploit the operational, relational and transformational benefits of e-HRM (Strohmeier & Kabst, 2014). Furthermore, this e-HRM configuration is marked by the broad support for technology usage in HR activities and is often backed by an organisation's strategy. Therefore, it is 'fitting' to assume that power-users e-HRM configuration will have higher initiation and adoption rates of AI techniques. Thus, we propose that:

Research Proposition 3 (a-d): *Power-users e-HRM configuration will have a positive influence on HRM(AI)* ***(a)*** *initiation,(b) adoption, (c) routinization, and (d) extension.*

4.1.2 Organisational factors

Organisational characteristics have been noted to affect IT/significantly IS applications (Bondarouk et al., 2017a; Gupta et al., 2020; Hossain et al., 2016; Zhu et al., 2006). Therefore, in the context of the HRM(AI) assimilation process, our framework focuses on three factors: 1) Organisational readiness, 2) Top management support, and 3) Dynamic organisational information technology capability (DITC).

Organisational readiness is the state of preparedness and the availability of the needed organisational resources to adopt technology (Helfrich et al., 2011). It is unlikely that HRM(AI) transformation can be realized if an organisation is not ready for it (Halpern et al., 2021). Several studies have found organisational readiness as a strong predictor of artificial intelligence adoption (Abuzaid et al., 2020; Alsheibani et al., 2018; Wong et al., 2019). Iacovou et al. (1995) identified two dimensions in their organisation readiness framework: technological and financial readiness. Hossain et al. (2016) further extended this by adding technical human resources to influence organisational readiness in IT adoption. Technological readiness refers to the level of technical sophistication, whereas financial readiness refers to an organisation's readiness and sufficiency to invest in new technologies (Hossain et al., 2016; Iacovou et al., 1995). Technical human resources refer to the availability of technical professionals within an organisation who possesses critical knowledge and expertise to implement and maintain technical innovations in software applications (Zhu & Kraemer 2005). Thus, through these three dimensions, organisation readiness can impact all the HRM$^{(AI)}$ assimilation stages. This leads to the following proposition:

Research Proposition 4a-d: *Organizational readiness is positively related with HRM$^{(AI)}$ (a) initiation,(b) adoption,(c) routinization, and (d) extension.*

Top management support has been noted as a significant factor in successful adoption, implementation, and use in complex information systems (Clohessy & Acton, 2019; Shao et al., 2017; Wang & Zander, 2018). In our theorization, a high level of top management support indicates top managers cognition of the benefits of new AI techniques and demonstrate their commitment and political support. Furthermore, top management support can inspire, motivate, resolve conflict, rebalance power, and reward desirable behaviour at different phases of the technology assimilation lifecycle (Liang, Saraf, Hu & Xue, 2007; Shao et al., 2017). Typically, in the context of technology-driven HRM, scholars (such as Teo et al., 2007; Alsheibani et al., 2018; Chen, Li & Chen, 2021; Zefass et al., 2021) found that top management support helps identify business opportunities for exploitation by information systems in HRM, and their active involvement provides a strategic impetus for the adoption and implementation of these technologies. In line with these observations, we expect top management support to affect all HRM(AI) assimilation stages positively. Therefore, we propose that:

Research Proposition 5 a-d: *Top management support is positively related to HRM$^{(AI)}$ a) initiation, b) adoption, c) routinisation, and d)extension.*

Dynamic organisational information technology capability (DITC) is rooted in the dynamic capabilities view and comprises dynamic capabilities that extend, modify or create existing IT capabilities to derive appropriate value from such digital technologies (Li & Chan, 2019; Lim, Stratopoulos & Wirjanto, 2011). As more and more AI applications and technologies are increasingly associated with business value creation, the DITC framework is gaining attention (Li & Chen, 2019; Mikalef & Pateli, 2017). The constituent components of DITC include dynamic digital platform capability, dynamic IT management capability, and dynamic IT knowledge management capability (Li & Chan, 2019). Li and Chan (2019), while adopting the DITC framework introduced by Winter (2003) and typology of IT capability developed by Bharadwaj (2000), proposed that a high-level DITC framework is an antecedent for HRM$^{(AI)}$ assimilation. The DITC perspective is different from the 'extent of IT adoption' (discussed above), as it is more dynamic in and examines the capacity of the organisation to extend or build upon IT-related existing and ordinary capabilities.

In the context of HRM$^{(AI)}$, the dynamic digital platform capability of an organisation facilitates HRM$^{(AI)}$ initiation by planning and fulfils changes to ordinary capabilities that relate to the functioning of particular HRM$^{(AI)}$ techniques. Effective organisation-wide integration may also influence adoption, routinisation and extension of HRM$^{(AI)}$ application/s (Tan, Pan, Lu & Huang, 2015). Furthermore, the dynamic IT management capability of an organisation has the potential to be actively involved in the design and execution of strategic IT plans as well as the identification of solutions to address unpredictable and novel developments while implementing HRM$^{(AI)}$ in the HR department (Daniel, Ward & Franken, 2014; Pavlou & El Sawy, 2010). Last but not least, an organisation's dynamic IT knowledge management capability can help initiate, adopt, and routinise HRM$^{(AI)}$ applications by sharing valuable IT knowledge with HR personnel and the line managers across the organisation (Karimi, Somers & Bhattacherjee, 2007). The DITC framework may also facilitate relationships, communication and knowledge sharing within the HR department that helps in further extension of AI techniques in HRM. There is emerging research that points to such multilevel influences of knowledge sharing in online tools and platforms (Nguyen, Siri & Malik, 2021), requiring a combination of cognitive and motivational approaches to encourage the key actors in a system to share knowledge (Nguyen & Malik, 2020, 2021). Thus, the following proposition is proposed:

Research Proposition 6 (a-d): *Dynamic organisational information technology capability (DITC) is positively related with HRM$^{(AI)}$ a) initiation, b) adoption, c) routinisation, and d) extension.*

4.1.3 People factors

People factors, such as IT skills, people dynamics, values, personal disposition, traits and experience affect information systems adoption and technology usage (Bondarouak et al., 2017a; Bruque-Camara et al., 2004; Devaraj, Krajewski & Wei, 2008; Galanaki et al., 2019;) and enables successful technology adoption and its implementation (Mehrtens, Cragg & Mills, 2001; Stratman & Roth, 2002). This analysis proposes factors of HR staff's ICT skills, Supervisor Support, and Personal innovativeness in technology adoption (PIIT) as instrumental influences on HRM$^{(AI)}$ assimilation. While ICT skills of HR employees refer to the skills possessed by HR professionals for using the latest AI techniques, supervisor support enables and inspires them to use such AI techniques actively. Finally, PIIT signifies an extension of HR professionals' values, personal disposition and traits.

Previous research has observed that the ICT skills of employees have significantly influenced IT adoption. Their ICT skills, knowledge, and understanding of ICT practices are essential determinants of new applications' adoption (Shiels, McIvor & O'Reilly, 2003; Wainwright, Green, Mitchell & Yarrow, 2005). The World Economic Forum (2020) confirmed the skills required to keep up with significant technological development as a crucial future workforce challenge. Employees' ICT skills are commonly rated as a significant challenge (Alsheibani et al., 2018; Lambert et al., 2019). Given that HRM$^{(AI)}$ assimilation is a foray into a high-level technical and professional domain, the HR employees' ICT skills to design, operate and maintain different HRM$^{(AI)}$ functions is crucial for its effective assimilation. These skills are primarily reliant on digital literacy and tech-savviness HR staff in AI-enabled HR applications (Malik et al., 2020, 2021), as is their learning and attitudes for using state of the art HRM$^{(AI)}$ techniques (Bruque-Camara et al., 2004; Yang, Tong & Teo, 2015).

Further, a lack thereof of skills inhibits the routinisation and extension of technically complex applications given the technical nature of such applications (Lefebvre, Lefebvre & Harvey, 1996). HR staff who have good ICT skills are more knowledgeable about IT and are more likely to adopt the latest AI techniques in HR (see Thong, 1996). Similarly, the level of HR staff's digital literacy and tech-savviness of AI applications will further influence the routinisation and extension of HRM$^{(AI)}$ assimilation, a view also confirmed by other scholars (Fink, 1998; Sarosa & Zowghi, 2003; Shiels et al., 2003; Wainwright et al., 2005). Therefore, it is proposed that:

Research Proposition 7 (a-d): *HR staff's ICT skills will be positively related to HRM$^{(AI)}$ a) initiation, b) adoption, c) routinisation and d) extension.*

Supervisor support is another factor instrumental in HRM$^{(AI)}$ assimilation stages. Several information systems studies support supervisor's impact on adoption through their usage and persuasive communication (Igbaria, Parasuraman & Baroudi, 1996; Karahanna & Straub, 1999; Leonard-Barton & Deschamps, 1988; Schillewaert et al., 2005). Furthermore, previous research has highlighted the 'symbiotic relationship between supervisors and HR practices' and noted that most of the HR practices experienced by employees are those enacted by supervisors (McCarthy, Cleveland, Hunter, Darcy & Grady, 2013; Purcell & Hutchinson, 2007; Stripe, Bonache & Trullen, 2015). As a result, HR staff who receive active support from their supervisors gain a sense of ownership and familiarity with HRM$^{(AI)}$ systems (Bendoly et al., 2006; Kolbjørnsrud et al., 2017). Thus, supervisors' actions constitute essential cues to help HR personnel make sense of the latest HRM$^{(AI)}$ techniques and subsequently encourage employees to initiate and adopt HRM$^{(AI)}$ (McCarthy et al., 2013; Tierney & Farmer, 2004). Moreover, HR supervisors can positively influence HR personnel by interpreting the new AI technologies in

HRM and help contextualise these technologies in different HR activities (Townsend, Wilkinson, Allan & Bamber, 2012). This further lays down a reliable platform for routinisation and extension of HRM$^{(AI)}$ techniques. Therefore, it is proposed that:

Research Proposition 8(a-d): *Supervisor support will be positively related to HRM$^{(AI)}$, (a) initiation, (b) adoption, (c) routinisation, and (d) extension.*

Personal innovativeness in technology adoption (PIIT) illustrates the consequences of individual perceptions about new information technology (Agarwal and Prasad,1998). PIIT is an important concept used in information system research to examine the acceptance of information technology innovations (Lin & Nguyen, 2011; Lu, Yao & Sheng-Yu, 2005) and has been explored in context-specific AI-based applications, such as Fan et al. (2020) in healthcare and Huang and Yang, (2020) for mobile applications. PIIT tend to control new technology and usually feel comfortable with AI applications and tools (Fan et al., 2020).

In HRM$^{(AI)}$ assimilation context, PIIT refers to the willingness of HR professionals to try out any new HRM$^{(AI)}$ techniques that may further help in the initiation of HRM$^{(AI)}$ techniques (Lin & Nguyen, 2011). People with highly innovative attitudes are active information seekers and are willing to cope with a high level of uncertainty (Gronhaug, 1972), a view confirmed in recent research from an IT MNE (Malik et al., 2020). Moreover, the greater the level of personal innovativeness, the greater the likelihood that this attitude would lead to routinisation and higher intention to search and extend intentions to try new AI techniques (Lee, Qu & Kim, 2007). Therefore, we propose that HR professionals with higher levels of PIIT are expected to develop a positive perception of HRM$^{(AI)}$. Thus, we propose:

Research Proposition 9 (a-d): Higher levels of *Personal innovativeness in technology adoption will be positively related to* HRM$^{(AI)}$ *a) initiation, b) adoption, c) routinisation, and d) extension.*

4.2 HRM$^{(AI)}$ assimilation consequences

In our proposed framework of HRM$^{(AI)}$ assimilation, we focus on operational, relational and transformational consequences (Bissola, 2014; Lepak & Snell,1998; Obeidat, 2016; Parry

& Tyson, 2011; Ruel et al., 2004; Strohmeier, 2007). For conceptualising the consequences of HRM$^{(AI)}$ assimilation, this analysis considers a full lifecycle that includes an initial evaluation of AI and its adoption to full-scale deployment, as full lifecycle HRM$^{(AI)}$ assimilation incorporates the success and value creation of HRM$^{(AI)}$ that can only be fully realized through full-scale assimilation (Liang et al., 2019). This line of thinking is also noted in previous empirical research on the full-scale assimilation of technological innovations (Maqueira et al., 2019; Wei et al., 2015). The following section elaborates operational, relational and transformation consequences of HRM$^{(AI)}$ assimilation.

4.2.1 Operational consequences

Operational consequences refer to efficiency and effectiveness outcomes of HRM$^{(AI)}$ assimilation, including time and cost savings and related macro-level consequences (i.e., reduction of HR staff, faster-processes, cost reduction, and a release from administrative burdens) (Bondarouk et al., 2017a; Panayotopoulou, Vakola & Galanaki, 2007; Strohmeier, 2007). Rule and Kapp (2012) observed that technology-driven HRM renew ways of implementing HR policies and practices, resulting in improved efficiency and effectiveness. The authors concluded that most outcome variables for technology-assisted HRM could be categorised into three groups: efficiency, effectiveness, and HRM service quality, as key-value creation drivers. This research further deconstructs HRM value creation along with three levels (see Guest and Peccei, 1994) – HR philosophy, policy and practice and proposes policy and practice level factors, HRM system strength and HR efficiency as operational consequences of HRM$^{(AI)}$ assimilation, in addition to – HRM service quality.

HRM system strength refers to an employee's perceptions of the organisation's meta-features that helps HRM systems to create a robust organisational climate, in which unambiguous messages on the appropriate behaviour are communicated to employees (Jia, Yan, Jahanshahi, Lin & Bhattacharjee, 2020; Ostroff & Bowen, 2016). HRM system strength is mainly built on signalling and attribution perspectives and addresses how HRM system is designed and administered to send signals to employees that enable them to create shared meanings of 'the desired and appropriate responses and form a collective sense of what is expected' (Bowen & Ostroff, 2004, p. 204). Thus, an HRM system is considered vital, provided the employees agree that it is highly distinctive, consistent, and based on a broader consensus (Bondarouk et al., 2017b; Ostroff & Bowen, 2016).

Since HRM system strength is based on social influence theory, scholars in information system research have also investigated technology adoption behaviours through a social influence theory perspective (Vannoy & Palvia, 2010). Thus, it becomes imperative to discuss the impact of HRM$^{(AI)}$ assimilation on HRM system strength. Furthermore, given that previous studies have observed a positive influence of technology perspective of HRM on HRM system strength (Bondarouk, Harms & Lepak, 2017b; Obeidiat, 2016; Ruel et al., 2007), we posit that HRM$^{(AI)}$ assimilation will also strengthen the HRM system through visibility, consistency of HR messages, and building agreement among employees. Hence, we propose:

Research Proposition 10: *HRM$^{(AI)}$ assimilation will positively influence HRM system strength*

HR efficiency comprises efficient HR processes such as effective personnel data handling (Rule & Kapp, 2012), timeliness and within allocated budgets to deliver high levels of HR efficiency (Guest & Peccei, 1994; Ulrich & Grochowski, 2018). Previous research has observed that technology-driven HRM significantly contributes to HR efficiency by reducing the costs and increasing the speed of a process (Bissola & Imperatori, 2014; Martin, 2008; Parry, 2011; Ruel & Kaap, 2012). More recently, Guliyeva et al. (2020) observed that HR analytics also positively affects the efficiency of HR professionals. The utilization of the latest AI applications and tools in HRM functions can bring faster turnaround time, immediacy in feedback to staff and help the managers make informed decisions, thus resulting in enhanced HR efficiency (Ukundu et al., 2014). In addition, HRM$^{(AI)}$ assimilation of sophisticated techniques offers managers, and employees access to deep expertise to improve and perform everyday administrative tasks with enhanced credibility and reliability (Parry, 2011; Ulrich & Grochowski, 2018). Thus, we propose that:

Research Proposition 11: *HRM $^{(AI)}$ assimilation will positively influence HR efficiency.*

HR service quality can be defined as the quality of HR professionals' service to line managers and employees and comprises of three aspects of input, process, and output qualities of HR service (Uen, Wang & Chen., 2005). While HR input service quality is competence-based on necessary professional knowledge and skills for providing the requisite information to solve internal customers' problems, HR process service quality is the capacity of HR professionals to provide reliable and responsive services for internal customers in an interactive manner (Uen, Ahlstrom, Chen & Tseng, 2012). Finally, HR output service quality is the HR service relationship built around the notions of innovativeness, comprehensiveness, and customisation of HR services with other departments (Uen et al., 2012). HR service quality in an organisation allows employees to carry out HR-related activities more comfortably (Heikkilä et al., 2017; Obeidat, 2016; Ruel & Kaap, 2012). Bondarouk and Ruël (2009) also noted that e-HRM results in a decrease in information errors, improvement in tracking and subsequently, HR control produces higher levels of HR service quality.

We propose that HRM$^{(AI)}$ assimilation can be seen as implementing HRM strategies, policies, and practices in organizations through conscious and directed support of AI applications and tools. Assimilation of AI applications in different HRM functions can create value for an organisation by improving the way the HRM services are delivered to its employees (Wahyudi & Park, 2014). For example, HRM$^{(AI)}$ assimilation can improve HR input service quality through enhancing necessary professional knowledge and skills of HR personnel through an AI application to support their services (Uen et al., 2005). Furthermore, HRM$^{(AI)}$ assimilation can also impact the HR process service quality by increasing the responsiveness and reliability of the AI's service quality (Nguyen & Malik, 2021). Moreover, the use of the latest HRM$^{(AI)}$ techniques ensures that HR professionals provide services with innovativeness, comprehensiveness, and customisation to positively influence HR output service quality, thereby resulting in satisfaction of internal customers' needs and demands. Accordingly, it is proposed that:

Research Proposition 12: *HRM $^{(AI)}$ assimilation will positively influence HR service quality.*

4.2.2 Relational consequences

Relational consequences in the context of this research can be referred to as specific applications of certain technologies specifically designed and implemented to manage sustenance of stakeholder (i.e., line manager and employee) relationships for improving HR services and directly empowering employees (Parry & Tyson, 2011; Ruël et al., 2004; Strohmeier & Kabst, 2014). Our review suggests that HR empowerment, trust in the HR department and an internal relational social capital are the essential relational consequences sought through strong HRM$^{(AI)}$ assimilation.

HR empowerment refers to an adaptive HR solution for helping line managers improve working flow and support employees within an organisation. HRM is too important a function to be solely in the hands of the HR manager (Guest, 2001). Therefore, certain HR activities, such as recruitment, discipline and absence control, must be devolved to employees, line managers and senior management (Cunningham, Hyman & Baldry 1996). The empowerment of HR activities to the line managers and the internal stakeholders has been acknowledged in several studies (Budhwar, 2000; Isari, Bissola & Imperatori, 2019). Kim, Su and Wright (2018) further suggested a bundle of HRM practices designed to improve the relationship between HR and line managers and termed it as 'HR–line-connecting HRM system (HRLCS)'. Thus, *HR empowerment* can be defined as the empowerment of line managers with a bundle of adaptive HRM practices that help to improve the relationship between HR and line managers and result in increasing employee's and line managers' empowerment and positive HR outcomes. HRM$^{(AI)}$ assimilation within an organisation can help organisations develop and adopt HRLCS through remote access to HR databases and information through the latest HRM$^{(AI)}$ techniques. This will empower individual employees, line managers and senior managers to perform HR tasks themselves, thus reducing response time and improving service levels (Parry, 2011; Parry & Tyson, 2011). Therefore, it is proposed that:

Research Proposition 13: *HRM$^{(AI)}$assimilation will positively influence HR empowerment.*

Another factor identified in the extant literature is trust in the HR department (Bissola & Imperatori, 2014; Burbach & Royle, 2014). Trust as a relational factor has been noted as an antecedent for the success and effectiveness of technology-driven HR (Björkman & Lervik, 2007; Burbach & Royle, 2014). It has also been highlighted as a coordinating mechanism between employees and the HR department (Graham & Tarbell, 2006). Bissola and Imperatori (2014) observed that relational technology-driven HR practices could help employees perceive activities and criteria underlining HR policies that enhance their trust in the HR department, thus legitimating their role and credibility (Graham & Tarbell, 2006).

Further, it has been noted that digitisation of HRM can make HR policies transparent, accessible, unambiguous and relevant to employees, thereby enhancing employee's trust in the organisation (Bondarouk et al., 2017). Thus, HRM$^{(AI)}$ assimilation may influence trust in HRM as it affects both employees and managers and further improves their relationships with each other and the HRM department (Iqbal et al., 2019; Imperatori et al., 2019). Furthermore, HRM$^{(AI)}$ assimilation offers the opportunity to connect employees with HR functions and participate and interact with HR activities through an AI- meditated social exchange, thus strengthening the links between the HR department and employees (Gara et al., 2020). This results in building relationships across organisations through collaboration, transparency and eventually trust between employees and the HR department (Imperatori, 2017). Thus, we propose that:

Research Proposition 14: *HRM$^{(AI)}$ assimilation will positively influence trust towards the HR department.*

This framework also proposes it improved internal relational social capital in line with social capital theory's (Nahapiet & Ghoshal, 1998) internal relational social capital dimension, which describes the affective relationships among employees requiring high levels of trust, shared norms, perceived obligations, and a sense of mutual identification (Bolino, Turnley & Bloodgood 2002). We posit that HRM$^{(AI)}$ assimilation can play a crucial role in facilitating, accumulating, and utilising relational social capital within an organisation (Chuang et al., 2013). Advanced AI technologies' acknowledged potential to change HR functions' fundamental nature from a 'descriptive and diagnostic' to 'prescriptive and predictive' nature (Di Claudio, 2019) can help strengthen relational coordination among employees and enhance relational social capital.

Moreover, the complexity of the HRM$^{(AI)}$ assimilation process can increase dependence among organisation members within the same group or unit in various ways, which can increase trust, cooperation, shared understanding and strengthen relationships (Park, 2014, cited in Ahmed, 2018). Similarly, task heterogeneity and task complexity related to HRM$^{(AI)}$ assimilation may require effective communications and brainstorming sessions, sharing of useful and reliable information that might contribute to form a strong relationship among participating members, thus enhancing internal relational social capital (Lee, Park & Lee, 2011; Sheriff, Hoffman & Thomas 2006). Thus, we propose that:

Research Proposition 15: *HRM$^{(AI)}$ assimilation will positively influence internal relational social capital.*

4.2.3 Transformational consequences

Transformational consequences of HRM$^{(AI)}$ assimilation refer to improvements in the business support and strategic orientation of HRM via AI assimilation, thus transforming HRM into a more strategic function (Bissola & Imperatori, 2014; Strohmeier, 2007). Our framework proposes factors of Enhanced human resource analytics capability (Enhanced HRAC), HR strategic involvement and HR global orientation as transformational consequences of HRM(AI) assimilation.

Human Resource Analytics (HRA) provide managers with the information and knowledge of HRM processes to connect it to employee attitudes and behaviours and ultimately to organisational outcomes (Marler & Boudreau, 2017). HRA is deep-seated around the notions of innovation adoption in previous literature (Marler & Boudreau, 2017; Vargas et al., 2018). Artificial intelligence is considered as one of the 'exponential technology' to generate discontinuities (Deloitte, 2018), and as Margherita (2021) observed, exponential technologies such as AI can support HR analytics in diverse HRM functions (i.e. talent management, coaching, onboarding and performance management) using real-time analysis and AI techniques. We extend the HRA concept by focusing on 'Enhanced human resource analytics capability (HRAC)' as the transformational outcome of HRM(AI) assimilation. This seems appropriate, as, through HRM(AI) assimilation, an organisation can enhance their 'Big data analytical capabilities' (Wang et al. 2016b) - an all-encompassing term for techniques destined to handle big data characterised in terms of 5Vs: high volume, velocity, variety, veracity and value (Arunachalam et al., 2018). Thus, HRM(AI) assimilation serving as capacity building framework may enhance HRAC by absorbing large amounts of the data (volume), maintaining structural heterogeneity (variety), enhancing the speed of data generation (velocity), ensuring data quality (veracity), and reaping economic benefits (value) of big data (Arunachalam et al., 2018). Therefore, we propose the following:

Research Proposition 16: *HRM(AI) assimilation will result in enhanced HR analytical capabilities.*

Strategic HR involvement is defined as HR professionals' involvement in HRM strategy and policy development (Marler & Parry, 2016) and can be viewed as an HRM system to support the long-term strategy by transforming HR into a strategic partner role (Olivas-Lujan, Ramirez & Zapata-Cantu, 2007; Parry, 2011; Ruel et al., 2004). However, other scholars have contradicted this observation and note that a technology-driven HRM has not yet realised its potential to facilitate a strategic role for the HR function (Bondarouk & Ruel, 2013; Marler & Fisher, 2013; Ruel, Bondarouk & Van der Velde, 2007). Thus, it remains unclear if technology-driven HRM can make the HR function strategic. Nevertheless, extant research has observed that HR professionals' strategic involvement and primarily administrative functions may create conflict. Therefore, elevating the status of HR professionals to a more strategic role, there is a need to re-design HRM roles (Legge, 2005; Ulrich, 1997). HRM$^{(AI)}$ assimilation in an organisation can relieve HR professionals from essential administrative functions and empower them with portraying a stellar role in the strategic matters of organisations. Moreover, given that previous research scholars in this domain have urged for more research that provides an understanding as to how this technology can contribute to HR's strategic contribution and organisational performance (Marler & Fisher, 2013; Strohmeier, 2007) accordingly this research proposes further inquisition into impact of HRM$^{(AI)}$ assimilation on HR strategic involvement and proposes the following:

Research Proposition 17: *HRM$^{(AI)}$ assimilation will have a positive effect on HR strategic involvement.*

HR global orientation refers to the standardisation of HR functions across units or departments within an organisation (Ruel et al., 2004 - Cited in Parry & Tyson, 2011). Ruel et al. (2004) suggested that technology-driven HRM can improve the global orientation of an organisation through standardisation of HR processes across units or departments. Standardised HR platforms such as HR cloud technology, SaaS, BPaaS, and HR SSPs force HR to become more standardised, requiring less centralised HR teams to maintain it, thus ensuring HR professionals' more strategic involvement (Parry, 2011), though there is emerging evidence that standardisation. This proposed standardisation across different units in an organisation can help managers use the shared HR services to be HR compliant and improve the management process, resulting in strategic contribution and competitive advantage (Parry, 2011; Ruel et al., 2004).

The strategic contributions arising due to HRM$^{(AI)}$ assimilation will thus result in HR global orientation. Thus, the following proposition:

Research Proposition 18: *HRM$^{(AI)}$ assimilation will positively impact the HR global orientation.*

5.0 Theoretical contributions

In terms of knowledge gaps within the existing literature, this research is the first to propose HRM$^{(AI)}$ assimilation framework following a processual approach. The development of our HRM$^{(AI)}$ framework, definition and a research model with testable future research propositions based on the relationship between antecedents of HRM$^{(AI)}$ assimilation and resulting consequences are five distinctive theoretical contributions this paper makes. First, we define the HRM$^{(AI)}$ concept using business intelligence systems, distinguishing it from new technology-driven HRM terms (see Table 1). This firmly lays down a platform for future research in the HRM$^{(AI)}$ domain. Second, by extending the notion of HRM$^{(AI)}$ adoption along the more predominant assimilation process, this review and analysis of the literature endorse the most recent research (Hossain et al., 2019), which advocates that technological innovation adoption should not be a single decision in a one-stop adoption step; instead, it is a continuous and iterative process comprising different stages. Third, though previous research on technology-driven HRM has discussed adoption in detail, it has not systematically presented the antecedents of adoption coherently into a framework. This research overcomes this limitation by suggesting various antecedents of the HRM$^{(AI)}$ assimilation process. Forth, the framework further extends it to significant factors (i.e. operational, relational and transformational) considering HRM$^{(AI)}$ assimilation at a full-scale deployment. Lastly, this research future research propositions based on the relationship between antecedents and HRM$^{(AI)}$ assimilation and between adoption and consequences for future empirical testing.

6.0 Practical implications

The findings of this study have implications for organisations considering or currently pursuing assimilation of AI technologies for HRM. Organisations with higher levels of technology integration supported by functional BI systems are poised to reap the benefits from such applications. Substantial prior investments in BI systems or specific technology-driven HRM practices (i.e., e-HRM, HRIS) can create a favourable setting for an organisation to assimilate HRM$^{(AI)}$ in their HR department. However, in the absence of precise data and research concerning BI systems and even lesser research on AI applications for HRM functions, it is quite challenging to develop an understanding of concrete outcomes of HRM$^{(AI)}$ assimilation. Furthermore, even most previous research efforts explore the usage and adoption of AI applications in distinct functions of HRM instead of a consolidated approach or their linkage with the BI systems. Based on this, we recommend further exploration of different practical issues and challenges for using various AI applications across different HRM functions and developing an understanding of their linkage with BI systems.

We opine that with the help of the proposed HRM$^{(AI)}$ framework, the HR professionals and managers can develop an understanding of antecedents and outcomes of HRM$^{(AI)}$ assimilation in an organisation, which will necessitate inquisition into the relevance of BI systems as the basis for inducting new AI technologies in their HR department. The HR departments have to establish new structures to align with BI systems in a valuable way for realising the potential of HRM$^{(AI)}$ assimilation. In order to understand AI applications and utilise their full potential in the context of HRM functions, HR departments need to understand the relevance of BI systems and at the same time integrate within the BI system to derive maximum benefits.

The suggested HRM$^{(AI)}$ framework serves as a starting point for assessment and evaluation of HRM$^{(AI)}$ status, where an organisation can evaluate where they are in terms of the HRM$^{(AI)}$ assimilation stage and plan accordingly to proceed to the next stage. The proposed

TOP factors can provide a clear picture of the availability or shortage of resources to help them transform their HRM department towards more advanced HRM$^{(AI)}$. Further, the proposed theoretical research model can help managers understand the relationships among TOP factors and HRM$^{(AI)}$ assimilation stages and that can help achieve the desired HRM$^{(AI)}$ consequences by assimilating the latest AI techniques in the HRM department. Moreover, the proposed HRM$^{(AI)}$ assimilation framework and understanding the relationship among different variables can bring agility in HR operations, and resultant domain-specific consequences can contribute to organisational performance.

7.0 Limitations and future research

This research examines HRM$^{(AI)}$ assimilation as a group of AI technologies. While this assumption might be appropriate, given that this research advocates a BI ecosystem of platforms for effective assimilation of suggested AI technologies for HR activities, it can be argued that AI can be divided into sub-segments (Saukkonen et al., 2019). Thus, future research can always examine sub-segments of AI for different HR activities and pinpoint a particular AI technology for a specific HR activity.

Although we have conceptually introduced and described HRM$^{(AI)}$ assimilation framework, detailed measures are needed to assess the construct practically. We recommend that scholars develop and validate several sets of measures – for the four assimilation stages and components of antecedents and consequences of HRM$^{(AI)}$ assimilation. Though the authors have taken much caution to include variables for antecedents and consequences of HRM$^{(AI)}$ assimilation based on the availability of validated empirical scales used in technology-driven HRM so as facilitate adaption in the context of HRM$^{(AI)}$, a few of variables relating to relational and transformational consequences, require validated instruments to measure them. Though previous research has used terms such as - 'HR empowerment', 'Enhanced HRAC', 'HRM global orientation'- in the context of technology-driven HRM, the researchers need to develop empirical scales further to measure them. We encourage scholars to develop a comprehensive HRM$^{(AI)}$ assimilation measurement instrument using the extant literature. The validation and use of appropriate HRM$^{(AI)}$ assimilation instruments may be challenging because of the volume of items likely to be needed.

Further, the proposed theoretical model assumes HRM$^{(AI)}$ assimilation as a full-scale deployment, in which HRM$^{(AI)}$ becomes an integral part of the HRM department, and HRM$^{(AI)}$ consequences are based on this assumption. This analysis has not discussed the consequences of HRM$^{(AI)}$ assimilation during the distinctive stages. Given that previous research has identified an 'assimilation gap' where complete assimilation into the organisation typically lags behind initial adoption rates (Chatfield & Reddick, 2018; Wei et al., 2015), empirical or qualitative research based on the distinct stage of assimilation has the potential to inform the organisations at different stages of HRM$^{(AI)}$ assimilation, about the influence HRM$^{(AI)}$ assimilation at a particular stage and associated consequences. Last but most importantly, this research only provides a conceptual framework and a qualitative theoretical model comprising testable propositions, thus more empirical work, such as exploring the viability of given propositions for antecedents and consequences, can help validate the proposed theoretical model.

8.0 Conclusion

Based on extensive information systems and technology-driven HRM literature, this research proposes an HRM$^{(AI)}$ framework and theoretical model with propositions to guide future empirical research. The proposed framework is an initial integrative framework that lays a foundation for highlighting the antecedents for successful assimilation for embedding and integrating AI applications in HRM effectively and contemplating propositions for assumed benefits of such assimilation. To the best of our knowledge, this integrated HRM$^{(AI)}$ framework and a theoretical model is the first approach to systematically propose and offer an extensive theoretical model conceptualising the HRM$^{(AI)}$ assimilation process based on TOP antecedents and also to discuss consequences of consolidated HRM$^{(AI)}$ assimilation. We further invite researchers to build on the HRM$^{(AI)}$ definition and expand the understanding of the HRM$^{(AI)}$ assimilation process.

References

Abuzaid, M. M., Elshami, W., Tekin, H., & Issa, B. (2020). Assessment of the willingness of radiologists and radiographers to accept the integration of artificial intelligence into radiology practice. *Academic Radiology*. Online ahead of print: DOI: 10.1016/j.acra.2020.09.014

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research*, 9(2), 204-215.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Ahearne, M., Jelinek, R., & Rapp, A. (2005). Moving beyond the direct effect of SFA adoption on salesperson performance: Training and support as key moderating factors. *Industrial Marketing Management*, 34(4), 379-388.

Ahmed, Z. (2018). Explaining the unpredictability: a social capital perspective on ICT intervention. *International Journal of Information Management*, 38(1),175-186.

Alvarado, P. (2017). "Building the Machine Learning Infrastructure." Teradata Operation, Inc. Accessed 15 April 2020. http://blogs.teradata.com/data-points/building-machine-learning-infrastructure-2/

Ariyachandra, T., & Watson, H.J. (2006). Which data warehouse architecture is most successful?. *Business Intelligence Journal*, 11(1), 4.

Arunachalam, D., Kumar, N. & Kawalek, J.P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transportation Research Part E: Logistics and Transportation Review*, 114, 416-436.

Alsheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. In *PACIS* (p. 37).

Baars, H., & Kemper, H.G. (2008). Management support with structured and unstructured data—an integrated business intelligence framework. *Information Systems Management*, *25*(2),132-148.

Basole, R.C., & Nowak, M. (2018). Assimilation of tracking technology in the supply chain. *Transportation Research Part E: Logistics and Transportation Review*, 114, 350-370.

Beckers, A. M., & Bsat, M. Z. (2002). A DSS classification model for research in human resource information systems. *Information Systems Management*, *19*(3), 41-50.

Bendoly, E., Bachrach, D. G., Wang, H., & Zhang, S. (2006). ERP in the minds of supervisors: joint roles of task interdependence and cultural norms. *International Journal of Operations & Production Management*, 26 (5), 558-578.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS Quarterly*, 169-196.

Bhattacherjee, A., Perols, J., & Sanford, C. (2008). Information technology continuance: A theoretic extension and empirical test. *Journal of Computer Information Systems*, 49(1), 17-26.

Bissola, R., & Imperatori, B. (2014). The unexpected side of relational e-HRM: Developing trust in the HR department. *Employee Relations*, 36(4), 376-397.

Bissola, R., & Imperatori, B. (Eds.). (2020). *HRM 4.0 for Human-centered Organisations*. Emerald Publishing.

Björkman, I., & Lervik, J.E. (2007). Transferring HR practices within multinational corporations. *Human Resource Management Journal*, 17(4), 320-335.

Bolino, M. C., Turnley, W. H., & Bloodgood, J. M. (2002). Citizenship behavior and the creation of social capital in organisations. *Academy of Management Review*, 27(4), 505-522.

Bondarouk, T., & Ruël, H. (2013). The strategic value of e-HRM: results from an exploratory study in a governmental organisation. *The International Journal of Human Resource Management*, 24(2), 391-414.

Bondarouk, T., Parry, E., & Furtmueller, E. (2017a). Electronic HRM: four decades of research on adoption and consequences. *The International Journal of Human Resource Management*, 28(1), 98-131.

Bondarouk, T., Harms, R., & Lepak, D. (2017b). Does e-HRM lead to better HRM service?. *The International Journal of Human Resource Management*, 28(9), 1332-1362.

Bos-Nehles, A., Renkema, M., & Janssen, M. (2017). HRM and innovative work behaviour: A systematic literature review. *Personnel Review*, 46(7), 1228-1253.

Bowen, D.E., & Ostroff, C. (2004). Understanding HRM–firm performance linkages: The role of the "strength" of the HRM system. *Academy of Management Review*, 29(2), 203-221.

Brandt, D., & Hartmann, E. (1999). Research topics and strategies in socio-technical systems. *Human Factors and Ergonomics in Manufacturing & Service Industries*, 9(3), 241-243.

Broderick, R., & Boudreau, J.W. (1992). Human resource management, information technology, and the competitive edge. *Academy of Management Perspectives*, 6(2), 7-17.

Bruque-Cámara, S., Vargas-Sánchez, A., & Hernández-Ortiz, M.J. (2004). Organisational determinants of IT adoption in the pharmaceutical distribution sector. *European Journal of Information Systems*, 13(2), 133-146.

Budhwar, P.S. (2000). Evaluating levels of strategic integration and devolvement of human resource management in the UK. *Personnel Review*, 29(2), 141-157.

Burbach, R., & Royle, T. (2014). Institutional determinants of e-HRM diffusion success. *Employee Relations*, 36(4), 354-375.

Burnett, J.R. & Lisk, T.C. (2019). The future of employee engagement: Real-time monitoring and digital tools for engaging a workforce. *International Studies of Management & Organization*, 49, pp.108-119.

Cao, Q., Jones, D.R., & Sheng, H. (2014). Contained nomadic information environments: Technology, organisation, and environmental influences on the adoption of hospital RFID patient tracking. *Information & Management*, 51(2), 225-239.

Charlier, R., & Kloppenburg, S. (2017). Artificial intelligence in HR: A no brainer. Price Waterhouse Cooper report. https://www.pwc.nl/nl/assets/documents/artificial-intelligence-in-hr-a-no-brainer.pdf.Accessed 21 Jan 2020.

Chatfield, A.T., & Reddick, C.G. (2018). Customer agility and responsiveness through big data analytics for public value creation: A case study of Houston 311 on-demand services. *Government Information Quarterly*, 35(2), 336-347.

Chatterjee, D., Grewal, R., & Sambamurthy, V. (2002). Shaping up for e-commerce: institutional enablers of the organisational assimilation of web technologies. *MIS quarterly*, 26(2), 65-89.

Chen, D.Q., Preston, D.S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems*, 32(4), 4-39.

Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics*, 8(1), 36-68.

Cheng, M. M., & Hackett, R. D. (2019). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review*, DOI: 10.1016/j.hrmr.2019.100698

Cheng, Y.-M. (2020). Understanding cloud ERP continuance intention and individual performance: a TTF-driven perspective. *Benchmarking: An International Journal*, Vol. 27 No. 4, pp. 1591-1614.

Cheng, Y., & Zou, Y. (2021). Whether and when e-HRM improves organizational performance: A meta-analysis. In *Academy of Management Proceedings* (Vol. 2021, No. 1, p. 13990). Briarcliff Manor, NY 10510: *Academy of Management.*

Chuang, C. H., Chen, S. J., & Chuang, C. W. (2013). Human resource management practices and organizational social capital: The role of industrial characteristics. *Journal of Business Research*, *66*(5), 678-687.

Clohessy, T., & Acton, T. (2019). Investigating the influence of organisational factors on blockchain adoption. *Industrial Management & Data Systems*, 119(7), 1457-1491.

Cunningham, I., Hyman, J., & Baldry, C. (1996). Empowerment: the power to do what?. *Industrial Relations Journal*, 27(2), 143-154.

Curtin, J., Kauffman, R. J., & Riggins, F. J. (2007). Making the 'MOST' out of RFID technology: a research agenda for the study of the adoption, usage and impact of RFID. *Information Technology and Management*, 8 (2), 87-110.

Daniel, E.M., Ward, J.M. & Franken, A. (2014). A dynamic capabilities perspective of IS project portfolio management. *The Journal of Strategic Information Systems*, 23(2), 95-111.

Deloitte. (2018). Exponential Technologies in Manufacturing. Transforming the Future of Manufacturing Through Technology, Talent, and the Innovation Ecosystem. *Deloitte Development LLC*.

Devaraj, S., L. Krajewski, & J. C. Wei. (2007). Impact of e-Business Technologies on Operational Performance: The Role of Production Information Integration in the Supply Chain. *Journal of Operations Management*, 25(6): 1199–1216.

DiClaudio, M. (2019). People analytics and the rise of HR: how data, analytics and emerging technology can transform human resources (HR) into a profit centre. *Strategic HR Review*, 18(2), 42-46.

Dishaw, M.T., & Strong, DM (1999). Extending the technology acceptance model with the task–technology fit constructs. *Information & Management*, 36(1), 9-21.

Dixon. J. (2019) "Pentaho Hadoop and Data Lakes. URL: http://jamesdixon.wordpress.com/2010/10/14/pentaho-hadoop-and-data-lakes Accessed 20 April 2020.

Dulebohn, J.H., & Johnson, R.D. (2013). Human resource metrics and decision support: A classification framework. *Human Resource Management Review*, 23(1), 71-83.

Escolar-Jimenez, C.C., Matsuzaki, K., Okada, K. and Gustilo, R.C. (2019). Data-Driven Decisions in Employee Compensation utilising a Neuro-Fuzzy Inference System. *International Journal of Emerging Trends in Engineering Research*, ***7***, pp.163-169**.**

Fan, W., Liu, J., Zhu, S., & Pardalos, P. M. (2020). Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). *Annals of Operations Research*, *294*(1), 567-592.

Festing, M., & Eidems, J. (2011). A process perspective on transnational HRM systems—A dynamic capability-based analysis. *Human Resource Management Review*, 21(3), 162-173.

Fichman, R.G. and Kemerer, C.F., (1999). The illusory diffusion of innovation: An examination of assimilation gaps. *Information Systems Research*, 10(3), pp.255-275.

Fink, D. (1998). Guidelines for the successful adoption of information technology in small and medium enterprises. *International Journal of Information Management*, 18(4), 243-253.

Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization technology isn't the biggest challenge, culture is. *Harvard Business Review*, 97(4), 62–73.

Furneaux, B. (2012). Task-technology fit theory: A survey and synopsis of the literature. In *Information systems theory* (pp. 87-106). Springer, New York, NY.

Galanaki, E., Lazazzara, A., & Parry, E. (2019). A cross-national analysis of e-HRM configurations: integrating the information technology and HRM perspectives. In *Organising for digital innovation* (pp. 261-276). Springer, Cham.

Gara, G. L., & La Porte, J. M. (2020). Processes of building trust in organizations: internal communication, management, and recruiting. *Church, Communication and Culture*, *5*(3), 298-319.

Goodhue, D.L., & Thompson, R.L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213-236.

Graham, M.E., & Tarbell, L.M. (2006). The importance of the employee perspective in the competency development of human resource professionals. *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management*, 45(3), 337-355.

Grønhaug, K. (1972). Risk indicators, perceived risk and consumer's choice of information sources. *The Swedish Journal of Economics*, 74(2), 246-262.

Guest, D.E., & Peccei, R. (1994). The nature and causes of effective human resource management. *British Journal of Industrial Relations*, 32(2), 219-242.

Guest, DE (2001). Human resource management: when research confronts theory. *International Journal of Human Resource Management*, 12(7), 1092-1106.

Guenole, N., & Feinzig, S. (2018). *Evaluating Assessments in the Age of Big Data and AI*. BM Smarter Workforce Institute, IBM Corporation.

Guliyeva, A., Rzayeva, U., & Abdulova, A. (2020). Impact of Information Technologies on HR Effectiveness: A Case of Azerbaijan. *International Journal of Advanced Computer Science and Applications*, *11*(2), 81-89.

Gupta, S., Meissonier, R., Drave, VA, & Roubaud, D. (2020). Examining the impact of Cloud ERP on sustainable performance: A dynamic capability view. *International Journal of Information Management*, 51, 102028.

Halpern, N., Mwesiumo, D., Suau-Sanchez, P., Budd, T., & Bråthen, S. (2021). Ready for digital transformation? The effect of organisational readiness, innovation, airport size and ownership on digital change at airports. *Journal of Air Transport Management*, 90, 101949.

Heikkilä, J. P., Rentto, O., & Feng, Y. (2017). Aiming for Strategic e-HRM: Motives and Consequences of e-HRM Implementation in an MNC. In *Electronic HRM in the Smart Era*. Emerald Publishing Limited.

Helfrich, C.D., Blevins, D., Smith, J.L., Kelly, P.A., Hogan, T.P., Hagedorn, H., Dubbert, P.M. and Sales, A.E., 2011. Predicting implementation from organizational readiness for change: a study protocol. *Implementation Science*, 6(1), pp.1-12.

Hazen, B. T., Overstreet, R. E., & Cegielski, C. G. (2012). Supply chain innovation diffusion: going beyond adoption. *The international journal of logistics management*, 23(1), 119-134.

Hmoud, B., & Laszlo, V. (2019). Will Artificial Intelligence Take Over Human resources Recruitment And Selection?. *Network Intelligence Studies*, *7*(13), 21-30.

Hossain, M.A., Quaddus, M., & Islam, N. (2016). Developing and validating a model explaining the assimilation process of RFID: An empirical study. *Information Systems Frontiers*, 18(4), 645-663.

HRPA. (2017). *A new age of opportunities: what does artificial intelligence mean for HR professionals?*. https://www.hrpa.ca/Documents/Public/Thought-Leadership/HRPA-Report-Artificial-Intelligence-20171031.PDF (April 03, 2020).

Huang, M.H., Rust, R. & Maksimovic, V. (2019). The feeling economy: managing in the next generation of artificial intelligence (AI). *California Management Review*, 61, pp.43-65.

Huang, C. Y., & Yang, M. C. (2020). Empirical investigation of factors influencing consumer intention to use an artificial intelligence-powered mobile application for weight loss and health management. *Telemedicine and e-Health*, *26*(10), 1240-1251.

Hussain, Z., Wallace, J., & Cornelius, N. E. (2007). The use and impact of human resource information systems on human resource management professionals. *Information & Management*, *44*(1), 74-89.

Iacovou, C.L., Benbasat, I., & Dexter, A.S. (1995). Electronic data interchange and small organisations: Adoption and impact of technology. *MIS Quarterly*, 19(4),465-485.

Iqbal, N., Ahmad, M., & Allen, M. M. (2019). Unveiling the relationship between e-HRM, impersonal trust and employee productivity. *Management Research Review*, 42(7), 879-899.

Imperatori, B. (2017). *Engagement and disengagement at work: Drivers and organizational practices to sustain employee passion and performance*. Springer.

Imperatori, B., Bissola, R., Bodega, D., & Butera, F. (2019). Work and HRM in the 4.0 era: insights and research directions. *Work and HRM in the 4.0 era: insights and research directions*, 9-26.

Isari, D., Bissola, R., & Imperatori, B. (2019). HR Devolution in the Digital Era: What Should We Expect?. In *HRM 4.0 For Human-Centered Organisations*. Emerald Publishing Limited.

Jantan, H., Hamdan, A.R., & Othman, Z.A. (2010). Intelligent techniques for a decision support system in human resource management. *Decision Support Systems*, 261-276.

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

Jarupathirun, S., & Zahedi, F. M. (2007). Exploring the influence of perceptual factors in the success of web-based spatial DSS. *Decision Support Systems*, 43(3), 933-951.

Jeyaraj, A., Rottman, J.W., & Lacity, M.C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology*, 21(1), 1-23.

Jia, J., Yan, J., Jahanshahi, A.A., Lin, W., & Bhattacharjee, A. (2020). What makes employees more proactive? Roles of job embeddedness, the perceived strength of the HRM system and empowering leadership. *Asia Pacific Journal of Human Resources*, 58(1), 107-127.

Karahanna, E., Straub, D.W., & Chervany, N.L. (1999). Information Technology Adoption Across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs, *MIS Quarterly*, 23(2),183-213.

Karimi, J., Somers, T.M., & Bhattacherjee, A. (2007). The role of information systems resources in ERP capability building and business process outcomes. *Journal of Management Information Systems*, 24(2), 221-260.

Kim, S., Su, Z.X., & Wright, P.M. (2018). The "HR–line-connecting HRM system" and its effects on employee turnover. *Human Resource Management*, 57(5), 1219-1231.

Kiron, D., & Schrage, M. (2019). Strategy for and with AI. *MIT Sloan Management Review*, 60(4), 30–35.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: how organizations can win over sceptical managers. *Strategy & Leadership*.

Kitchenham, B., 2004. Procedures for performing systematic reviews. *Keele, UK, Keele University*, 33(2004),1-26.

Kundu, SC, & Kadian, R. (2012). Applications of HRIS in human resource management in India: A study. *European Journal of Business and Management*, 4(21), 34-41.

Lamberti, M. J., Wilkinson, M., Donzanti, B. A., Wohlhieter, G. E., Parikh, S., Wilkins, R. G., & Getz, K. (2019). A study on the application and use of artificial intelligence to support drug development. *Clinical Therapeutics*, *41*(8), 1414-1426.

Lawler, J.J., & Elliot, R. (1996). Artificial intelligence in HRM: an experimental study of an expert system. *Journal of Management*, 22(1), 85-111.

Lee, H. Y., Qu, H., & Kim, Y. S. (2007). A study of the impact of personal innovativeness on online travel shopping behavior—A case study of Korean travellers. *Tourism Management*, 28(3), 886-897.

Lee, H.J., Park, J.G., & Lee, J.W. (2011). Leadership competencies of IT project managers: from team social capital perspective. *Journal of Information Technology Services*, 10(4), 133-147.

Lefebvre, L. A., Lefebvre, E., & Harvey, J. (1996). Intangible assets as determinants of advanced manufacturing technology adoption in SME's: toward an evolutionary model. *IEEE Transactions on Engineering management*, 43(3), 307-322.

Legge, K. (2005). *Human resource management: Rhetorics and realities*. Macmillan Education UK.

Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I. and Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. *Journal of Business Ethics*, 160**,** pp.377-392.

Lengnick-Hall, M. L., & Moritz, S. (2003). The impact of e-HR on the human resource management function. *Journal of Labor Research*, 24(3), 365-379.

Lepak, D. P., & Snell, S. A. (1998). Virtual HR: Strategic human resource management in the 21st century. *Human Resource Management Review*, 8(3), 215-234.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management. *MIS quarterly*, 31(1),59-87.

Liang, Y., Qi, G., Zhang, X., & Li, G. (2019). The effects of e-Government cloud assimilation on public value creation: An empirical study of China. *Government Information Quarterly*, 36(4), 101397.

Li, TC, & Chan, Y.E. (2019). Dynamic information technology capability: Concept definition and framework development. *The Journal of Strategic Information Systems*, 28(4), 101575.

Lin, C., & Nguyen, C. (2011). Exploring e-payment adoption in Vietnam and Taiwan. *Journal of Computer Information Systems*, 51(4), 41-52.

Lim, J.H., Stratopoulos, T.C., & Wirjanto, T.S. (2011). Path dependence of dynamic information technology capability: An empirical investigation. *Journal of Management Information Systems*, 28(3), 45-84.

Li, J.J, Bonn, M.A. and Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organisational support and competitive psychological climate. *Tourism Management*, 73, pp.172-181.

Lindebaum, D., Vesa, M., & Den Hond, F. (2020). Insights from "the machine stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations. *Academy of Management Review*, *45*(1), 247-263.

Lu, J., Yao, J.E., & Yu, CS (2005). Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *The Journal of Strategic Information Systems*, 14(3), 245-268.

Maity, S. (2019). Identifying opportunities for artificial intelligence in the evolution of training and development practices. *Journal of Management Development*, **38,** pp. 651-663.

Malik, A., Budhwar, P., Patel, C., & Srikanth, N. R. (2020). May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE. *The International Journal of Human Resource Management*, 1-31.

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

Malik, A., Srikanth, N. R., & Budhwar, P. (2020b). Digitisation, Artificial Intelligence (AI) and HRM. In J Crawshaw, P. Budhwar and A Davis (eds) *Human Resource Management: Strategic and International Perspectives*, 88-11, London: Sage.

Malik, A., De Silva, M. T., Budhwar, P., & Srikanth, N. R. (2021). Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: Evidence from an IT-multinational enterprise. *Journal of International Management*, *27*(4), 100871.

Manuel Maqueira, J., Moyano-Fuentes, J., & Bruque, S. (2019). Drivers and consequences of innovative technology assimilation in the supply chain: cloud computing and supply chain integration. *International Journal of Production Research*, 57(7), 2083-2103.

Margherita, A. (2021). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, https://doi.org/10.1016/j.hrmr.2020.100795

Marler, J.H., & Fisher, S.L. (2013). An evidence-based review of e-HRM and strategic human resource management. *Human Resource Management Review*, 23(1), 18-36.

Marler, J.H., & Parry, E. (2016). Human resource management, strategic involvement and e-HRM technology. *The International Journal of Human Resource Management*, 27(19), 2233-2253.

Marler, J.H., & Boudreau, J.W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, 28(1), 3-26.

Marr, B. (2018). The Amazing Ways How Unilever Uses Artificial Intelligence to Recruit and Train Thousands of Employees. *Forbes*. 14 December 2018. https://www.forbes.com/sites/bernardmarr/2018/12/14/the-amazing-ways-how-unilever-uses-artificial-intelligence-to-recruit-train-thousands-of-employees/#7b812e16274d .Accessed 4 Feb 2020.

Mazón, J.N., & Trujillo, J. (2008). An MDA approach for the development of data warehouses. *Decision Support Systems*, 45(1), 41-58.

Martin, G. (2008). *Technology, outsourcing & transforming HR*. Oxford, UK: Butterworth-Heinemann.

McCarthy, A., Cleveland, J. N., Hunter, S., Darcy, C., & Grady, G. (2013). Employee work–life balance outcomes in Ireland: a multilevel investigation of supervisory support and perceived organisational support. *The International Journal of Human Resource Management*, 24(6), 1257-1276

McGill, T.J. and Klobas, J.E. (2009), A task-technology fit view of learning management system impact, *Computers and Education*, 52(2), 496-508.

McGovern, S.L., Pandey, V., Gill, S., Aldrich, T., Myers, C., Desai, C., & Gera, M. (2018). The new age: artificial intelligence for human resource opportunities and functions. Ernst & Young LLP. All 010978-18Gbl ED.

Mehrtens, J., Cragg, P.B., & Mills, A.M. (2001). A model of Internet adoption by SMEs. *Information & Management*, 39(3), 165-176.

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

Myllymäki, D. (2021). Beyond the 'e-'in e-HRM: integrating a sociomaterial perspective. *The International Journal of Human Resource Management*, 1-29

Nam, D., Lee, J., & Lee, H. (2019). Business analytics adoption process: An innovation diffusion perspective. *International Journal of Information Management*, 49, 411-423.

Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organisational advantage. *Academy of Management Review*, 23(2), 242-266.

Ngai, E. W. T., & Wat, F. K. T. (2006). Human resource information systems: a review and empirical analysis. *Personnel review*, 35(3), 297-314.

Nguyen, M., & Malik, A. (2020) Cognitive processes, rewards and online knowledge sharing behaviour: The moderating effect of organisational innovation, *Journal of Knowledge Management*, 24(6), 1241-1261

Nguyen, T. M., & Malik, A. (2021). A Two-Wave Cross-Lagged Study on AI Service Quality: The Moderating Effects of the Job Level and Job Role. *British Journal of Management*, https://doi.org/10.1111/1467-8551.12540

Nguyen, M., Malik, A., & Sharma, P. (2021) How to motivate employees to engage in online knowledge sharing: Differences between posters and lurkers? *Journal of Knowledge Management, 25(7)*, 1811-1831

Nguyen, M., Siri, N.G., & Malik, A. (2021, in press). Multi-level influences on knowledge sharing behaviour: Moderating effect of knowledge sharing opportunity and collectivism. *Journal of Knowledge Management.* Vol. ahead-of-print. https://doi.org/10.1108/JKM-01-2021-0009

Obeidat, S.M. (2016). The link between e-HRM use and HRM effectiveness: An empirical study. *Personnel Review*, 45(6), 1281-1301.

Olivas-Lujan, M.R., Ramirez, J., & Zapata-Cantu, L. (2007). e-HRM in Mexico: adapting innovations for global competitiveness. *International Journal of Manpower,* 28(5), 418-434.

Ostroff, C., & Bowen, D.E. (2016). Reflections on the 2014 decade award: Is there strength in the construct of HR system strength? *Academy of Management Review*, 41(2), 196-214.

Panayotopoulou, L., Vakola, M., & Galanaki, E. (2007). E-HR adoption and the role of HRM: evidence from Greece. *Personnel Review*, 36(2), 277-294.

Papageorgiou, D. (2018). Transforming the HR function through robotic process automation. *Benefits Quarterly*, 34(2), 27-30.

Pan, Y. (2016). Heading toward artificial intelligence 2.0. *Engineering*, 2(4), 409-413.

Park, R.E. (1915). The city: Suggestions for the investigation of human behaviour in the city environment. *American Journal of Sociology*, 20(5), 577-612.

Parry, E. (2011). An examination of e-HRM as a means to increase the value of the HR function. *The International Journal of Human Resource Management*, 22(05), 1146-1162.

Parry, E. & Tyson, S. (2011). Desired goals and actual outcomes of e-HRM. *Human Resource Management Journal*, 21(3), 335-354.

Pavlou, P.A., & El Sawy, O.A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, 21(3), 443-471.

Pluye, P., Potvin, L., Denis, J. L., Pelletier, J., & Mannoni, C. (2005). Program sustainability begins with the first events. *Evaluation and Program Planning*, 28(2), 123-137.

Purcell, J., & Kinnie, N. (2007). HRM and business performance. *Oxford Handbook of Human Resource Management, The*, 533.

Rodney, H., Valaskova, K., & Durana, P. (2019). The Artificial Intelligence Recruitment Process: How Technological Advancements Have Reshaped Job Application and Selection Practices. *Psychosociological Issues in Human Resource Management*, 7(1), 42-47.

Rousseau, D.M., Manning, J. & Denyer, D. (2008). 11 Evidence in management and organisational science: assembling the field's full weight of scientific knowledge through syntheses. *Academy of Management Annals*, 2(1), 475-515.

Ruël, H., Bondarouk, T. & Looise, J.K. (2004). E-HRM: Innovation or irritation. An explorative empirical study in five large companies on web-based HRM. *Management Revue*, 15(3), 364-380.

Ruel, H.J., Bondarouk, T.V. & Van der Velde, M. (2007). The contribution of e-HRM to HRM effectiveness. *Employee Relations*, 29(3), 280-291.

Ruël, H., & Van der Kaap, H. (2012). E-HRM usage and value creation. Does a facilitating context matter? *German Journal of Human Resource Management*, 26(3), 260-281.

Sarosa, S., & Zowghi, D. (2003). Strategy for adopting information technology for SMEs: Experience in adopting email within an Indonesian furniture company. *Electronic Journal of Information Systems Evaluation (EJISE)*.

Saukkonen, J., Kreus, P., Obermayer, N., Ruiz, Ó.R. & Haaranen, M. (2019), October. AI, RPA, ML and Other Emerging Technologies: Anticipating Adoption in the HRM Field. In *ECIAIR 2019 European Conference on the Impact of Artificial Intelligence and Robotics* (p. 287). Academic Conferences and publishing limited.

Schillewaert, N., Ahearne, M.J., Frambach, R.T. & Moenaert, R.K. (2005). The adoption of information technology in the sales force. *Industrial Marketing Management*, 34(4), 323-336.

Shao, Z., Feng, Y., & Hu, Q. (2017). Impact of top management leadership styles on ERP assimilation and the role of organisational learning. *Information & Management*, 54(7), 902-919.

Sherif, K., Hoffman, J., & Thomas, B. (2006). Can technology build organisational social capital? The case of a global IT consulting firm. *Information & Management*, 43(7), 795-804.

Shiels, H., McIvor, R., & O'Reilly, D. (2003). Understanding the implications of ICT adoption: insights from SMEs. *Logistics Information Management*, 16(5), 312−326.

Shrivastava, S., & Shaw, J. B. (2003). Liberating HR through technology. *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management*, 42(3), 201-222.

Sirosh, J. (2017). "Delivering AI with Data: The Next Generation of the Microsoft Data Platform." Microsoft Corporation Data Group. Accessed 15 April 2020. https://blogs.technet.microsoft.com/dataplatforminsider/2017/04/19/delivering-ai-with-data-the-next-generation-of-microsoftsdata-platform/

Stevens, G. C. (1989). Integrating the supply chain. *International Journal of Physical Distribution & Materials Management*.

Stratman, J.K., & Roth, A.V. (2002). Enterprise resource planning (ERP) competence constructs: two-stage multi-item scale development and validation. *Decision Sciences*, 33(4), 601-628.

Stirpe, L., Bonache, J., & Trullen, J. (2015). The acceptance of newly introduced HR practices. *International Journal of Manpower*, 36(3), 334-353.

Strohmeier, S. (2007). Research in e-HRM: Review and implications. *Human Resource Management Review*, 17(1), 19-37.

Strohmeier, S., & Kabst, R. (2009). Organisational adoption of e-HRM in Europe: An empirical exploration of major adoption factors. *Journal of Managerial Psychology*, 24(6), 482-501.

Strohmeier, S., & Kabst, R. (2014). Configurations of e-HRM-an empirical exploration. *Employee Relations*, *36*(4), 333-353.

Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management—a conceptual exploration. In *Intelligent techniques in engineering management* (pp. 149-172). Springer, Cham.

Strohmeier, S. (2018). Smart HRM–a Delphi study on the application and consequences of the Internet of Things in Human Resource Management. *The International Journal of Human Resource Management*, 1-30.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: challenges and a path forward. *California Management Review*, 61(4), 15-42.

Tan, B., Pan, S.L., Lu, X., & Huang, L. (2015). The role of IS capabilities in the development of multi-sided platforms: the digital ecosystem strategy of Alibaba.com. *Journal of the Association for Information Systems*, 16(4), 2.

Teece, DJ (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Academy of Management Perspectives*, 28(4), 328-352.

Teo, T.S., & Pian, Y. (2003). A contingency perspective on Internet adoption and competitive advantage. *European Journal of Information Systems*, 12(2), 78-92.

Teo, T. S., Lim, G. S., & Fedric, S. A. (2007). The adoption and diffusion of human resources information systems in Singapore. *Asia Pacific Journal of Human Resources*, 45(1), 44-62.

Thite, M., Kavanagh, M. J., & Johnson, R. D. (2012). Evolution of human resource management and human resource information systems. *Introduction to HRM*, 2-34.

Thong, J.Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems*, 15(4), 187-214.

Tierney, P., & Farmer, S. M. (2004). The Pygmalion process and employee creativity. *Journal of Management*, 30(3), 413-432.

Tornatzky, L., & Fleischer, M. (1990). *The process of technology innovation*. Lexington, MA: Lexington Books, 165.

Townsend, K., Wilkinson, A., Allan, C., & Bamber, G. (2012). Mixed signals in HRM: the HRM role of hospital line managers 1. *Human Resource Management Journal*, *22*(3), 267-282.

Trieu, V.H. (2017). Getting value from Business Intelligence systems: A review and research agenda. *Decision Support Systems*, *93*, 111-124.

Troshani, I., Jerram, C., & Hill, SR (2011). Exploring the public sector adoption of HRIS. *Industrial Management & Data Systems*, 111(3), 470-488.

Uen, J., Wang, B.J., & Chen, W.F. (2005). Internal service quality factors of the human resource department and their relationships with organisational performance: Top and middle managers' viewpoints. *Taiwan Journal of Human Resource Management*, 5(2), 39-66.

Uen, J.F., Ahlstrom, D., Chen, S.Y., & Tseng, P.W. (2012). Increasing HR's strategic participation: The effect of HR service quality and contribution expectations. *Human Resource Management*, 51(1), 3-23.

Ukandu, N. E., Iwu, C. G., & Allen-lle, C. O. (2014). Influence of E-HRM in decision making in selected tertiary institutions in South Africa. *Problems and Perspectives in Management*, 12(4), 397-405.

Ulrich, D. (1997). *Human Resource Champions.* Boston, Mass: Harvard Business School Press

Ulrich, D., & Grochowski, J. (2018). Building a world class HR department. *Strategic HR Review*.

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

Vanduhe, V.Z., Nat, M. & Hasan, H.F. (2020).Continuance intentions to use gamification for training in higher education: integrating the technology acceptance model (TAM), social motivation, and task technology fit (TTF), *IEEE Access*, 8, pp. 21473-21484.

Vannoy, S. A., & Palvia, P. (2010). The social influence model of technology adoption. *Communications of the ACM*, 53(6), 149-153.

Vargas, R., Yurova, Y.V., Ruppel, C.P., Tworoger, L.C., & Greenwood, R. (2018). Individual adoption of HR analytics: a fine-grained view of the early stages leading to adoption. *The International Journal of Human Resource Management*, 29(22), 3046-3067.

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

Wahyudi, E., & Park, S.M. (2014). Unveiling the value creation process of electronic, human resource management: An Indonesian case. *Public Personnel Management*, 43(1), 83-117.

Wainwright, D., Green, G., Mitchell, E., & Yarrow, D. (2005). Toward a framework for benchmarking ICT practice, competence and performance in small firms, performance management. *The International Journal for Library and Information Services*, 6(1), 39−52.

Wang, X.L., Wang, L., Bi, Z., Li, YY, & Xu, Y. (2016a). Cloud computing in human resource management (HRM) system for small and medium enterprises (SMEs). *The International Journal of Advanced Manufacturing Technology*, 84(1-4), 485-496

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016b). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, 176, 98-110.

Wang, X., & Zander, S. (2018). Extending the model of internet standards adoption: a cross-country comparison of IPv6 adoption. *Information & Management*, 55(4), 450-460.

Wang, X., Wong, Y.D., Chen, T. & Yuen, K.F., 2021. Adoption of shopper-facing technologies under social distancing: A conceptualisation and an interplay between task-technology fit and technology trust. *Computers in Human Behaviour*, p.106900.

Wei, J., Lowry, P.B., & Seedorf, S. (2015). The assimilation of RFID technology by Chinese companies: A technology diffusion perspective. *Information & Management*, *52*(6), 628-642.
Wilson, H. J., & Daugherty, P. R. (2018). *Human+ machine: Reimagining work in the age of AI*. Harvard Business Review Press.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, 24(10), 991-995.

Wirtz, B.W., & Müller, W.M. (2019). An integrated artificial intelligence framework for public management. *Public Management Review*, 21(7), 1076-1100.

Wong, S. H., Al-Hasani, H., Alam, Z., & Alam, A. (2019). Artificial intelligence in radiology: how will we be affected?. *European Radiology*, 29(1), 141-143.

World Economic Forum. (2020). The Future of Jobs Report 2020. Geneva: World Economic Forum. Available at : http://www3.weforum.org/docs/WEF_Future_of_Jobs_2018.pdf. Accessed 5th Aug, 2021.

Yang, X., Tong, Y., & Teo, H.H. (2015). Fostering fast-response spontaneous virtual team: Effects of member skill awareness and shared governance on team cohesion and outcomes. *Journal of the Association for Information Systems*, 16(11), 2.

Zerfass, A., Hagelstein, J., & Tench, R. (2020). Artificial intelligence in communication management: a cross-national study on adoption and knowledge, impact, challenges and risks. *Journal of Communication Management.* 24 (4), 377-389.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760-767

Zhu, K., Kraemer, K.L., & Xu, S. (2006). The process of innovation assimilation by firms in different countries: a technology diffusion perspective on e-business. *Management Science*, 52(10), 1557-1576.

Table 1: Distinction between e-HRM, HRIS and HRM$^{(AI)}$

	e-HRM	Human Resource Information Systems (HRIS)	HRM$^{(AI)}$
1.Goals/objectives	Following are the goals of e-HRM: • the strategic orientation of HRM • Cost reduction/efficiency gains • Client service improvement/facilitating management and employees (Ruel et al., 2004)	HRIS's primary goals are: • to facilitate the provision of quality information to HR managers and organisation • to provide significant competitive advantage through human resource functions to help HR professionals perform their job roles more effectively(Hussain et al., 2007)	To ingest and process data for data-driven analytics that aid decision-making and further results in positive HR domain-specific operational, relational and transformational consequences
2.Nature and focus	e-HRM can play a significant role in operational, relational and transformational HR services as following: • *Operational e-HRM:* The choice to employees to keep and update their data on a website • *Relational e-HRM:* Supporting different functions(i.e. recruitment, selection, contract management) through web-based applications • *Transformational e-HRM:* Using an integrated set of web-based tools to align the workforce with an organisations' strategic choices (Parry & Tyson, 2011; Ruel et al., 2004)	HRIS is more focused on systems and technology underlying the design and acquisition of information systems supporting HR activities.	HRM$^{(AI)}$ is the latest concept that uses state-of-art technologies (i.e. Internet of things) and AI software for extracting and streaming descriptive, diagnostic, predictive and prescriptive information for operational, relational and transformational consequences.
3.Technological base	e-HRM concept largely is built around technology and its implementation for HR function and HRM practices. Though which technologies exactly make up e-HRM configuration, studies on e-HRM rarely discuss the distinction among different technologies encompassed in e-HRM (Myllymaki, 2021).	HRIS includes databases, computer applications, and hardware and software necessary to collect/record, store, manage, deliver, present, and manipulate data for human resources (Ngai & Wat, 2007).	A robust HRM$^{(AI)}$ framework is based on the latest business intelligence systems comprising cloud data lakes, warehouse and HR domain-specific analytical data mart.
4.Impact	e-HRM is known to create value across organisational boundaries by controlling and coordinating data capture, information communication and information creation (Cheng & Zou, 2021)	HRIS has been observed for the following administrative and strategic advantages: • increase the competitiveness of HR operations • production of a variety of HR-related reports • shift the transaction focus of HR to strategic HRM • reengineering HR functions (Beckers & Bsat, 2002)	HRM$^{(AI)}$ can extract and process data from multiples resources and further analyse the refined data with the latest AI technologies to impact HRM system strength, HR efficiency and HR service quality

Figure 1 - A proposed theoretical model