World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Strategic framework for ai-driven human resource management architecture

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World Journal of Advanced Research and Reviews, 2024, 24(03), 202–213

Publication history: Received on 22 October 2024; revised on 30 November 2024; accepted on 02 December 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.24.3.3672

Abstract

Academic literature is currently lacking on the topic of how to acquire, deploy, integrate, and reconfigure AI technologies to achieve HRM goals. This void is filled largely from the viewpoint of technology-driven human resource management. This research fills that knowledge vacuum by proposing a new standard for the architectural framework of human resource management strategies that make use of artificial intelligence. This paper presents an all-encompassing operational architectural framework for AI-powered HRM, drawing on theory of management and AI integration literature. It addresses the following areas: corporate setting, HRM(AI) architecture's inner workings, its connection to HRM domain-specific outcomes, organizational level conclusions, and subsequent performance. Additional exploration into the suggested AI framework for linked strategic architecture might be facilitated by a plethora of viable research ideas.

Keywords: AI-augmented HRM; HRM; Human Resource Management; architectural framework; strategic framework

1. Introduction

In order to handle data processing and information sharing for particular HR functions, organizations are turning to advanced tools and techniques like artificial intelligence expert systems (Saukkonen and others, 2019; Strohmeier and Piazza, 2015; Tambe et al., 2019). This is because modern HR practices incorporate both structured and unstructured data. Human resource experts may revolutionize HR strategy management and get a competitive edge by learning more about the digital renaissance powered by AI (Hamoud and Laszlo, the year 2019; Papageorgiou, 2018). Human resources tasks may soon become more "prescriptive and predictive" because of AI advancements, shifting their focus from "descriptive and diagnostic" (Di Claudio, 2019). The ability of computers to reason and act in complicated, unstructured settings by analyzing vast quantities of data is known as artificial intelligence (AI) (Agrawal et al., 2018). Newer studies have shown that AI's impact on human resource management can increase substantial organizational advantages (Guenole; Feinzig, 2018). AI-powered intelligent database administration for different tiers of the human resources department (e.g., "CloudHR" for almost all HR tasks, "SAP SuccessFactors" transforming standalone self-services into comprehensive intelligent services), '*BambooHR*' for recruitment and employee administration, '*GustoHR*' for compensation and smart benefits scheme, '*OnPay*' for payroll management, '*CakeHR*' for HR processes, '*Trakstar*' for employee appraisal, '*Deputy*' for scheduling and time-management, '*Zoho People*' for reward management) smoothens various HR functions such as recruitment and selection, ongoing monitoring, training and development, designing compensation, competency management, talent acquisition and performance appraisals (Marr, 2018; McGovern et al., 2018). Despite increasing research on AI and HRM (e.g. Kshetri, 2021; Malik, Srikanth, and Budhwar, 2020; Meijerink et al., 2021) and conceptualization of a new structural-functionalist theoretical model for AI-Augmented HRM ($HRM^{(AI)}$) (Charlwood and Guenole, 2022; Prikshat, Malik and Budhwar, 2021), there is still a lack of integrated framework for $HRM^{(AI)}$ that explains the business intelligence (BI) architectural process involved, and its linkage with HRM(domain-specific), organizational level outcomes and its impact on organizational performance. Moreover, there is lack of understanding of organizational antecedents that may serve as a basis for integrating AI into HRM, and how these

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antecedents may further impact upon domain specific (HRM), organizational level outcomes and resultant organizational performance. BI architecture in this context is used as a term that describes methodological process involved in deployment of AI into the HRM department of an organization. Extant literature in information systems research has extensively conceptualized and recommended BI system architectures for deep integration of AI into different management disciplines (Dignan, 2018; Moorhead, 2018; Moreno et al., 2019; Wells, 2019). The need for such an integrated framework comprising detailed BI architectural process and its linkage with HRM and organizational level outcomes based on exploration of organizational antecedents arises due to the three main facts. First, in the absence of a guiding architectural process that explains how AI can be integrated into HRM, the key stakeholders (i.e. top management, HR managers and executives) are not clear of the mechanism involved in implementing AI techniques in different functions of HRM. Second, even if AI is sparingly used in some distinct functions of HRM following an indigenous approach, there is no precise understanding of the organizational antecedents that are the basis for developing a robust BI architecture for integrating AI into HRM. Thirdly, there is absence of any robust theoretical framework in the domain of AI and HRM that explains the intricate process involved in integrating AI into HRM and how a particular framework may contribute to strategic goals of HRM as well as organization and resultant organizational performance. Though, previous research in HRM domain has highlighted the use of AI in HRM functions, but seldom has this research presented a consolidated theoretical framework that explains the organizational antecedents for integrating AI into HRM, detailed architectural process, and how it can contribute to domain-specific and organizational level objectives and its further impact on organizational performance.

Thus, in line with the observations of increasing inclusion of more sophisticated and advanced AI technologies for performing specific HR functions, and the noticed gap observed in the extant literature concerning an architectural process for incorporating AI in HRM and its apt linkage with HRM and organizational level outcomes, this research configures an integrated strategic architectural framework for HRM$^{(AI)}$ exploring organizational antecedents, the processual mechanism of HRM$^{(AI)}$ architecture, its linkage with HRM, organizational level outcomes and resultant organizational performance. The core of this comprehensive HRM$^{(AI)}$ framework is situated in *Data Hub Architecture'*. The data hub architecture is the latest AI-based BI system that has been advocated by AI tech companies (i.e., Cloudera, SAP, Informatics, MarkLogic, Pure Storage) to ensure the applicability of AI techniques in BI system (Alvarado, 2017; Sirosh, 2017; Wells, 2019). Moreover, the proposed HRM$^{(AI)}$ framework uses 30 validated HRM data items based on six major functions in HRM process map (i.e. HR insight, employee journey, employee relations, time management , rewards and organization change) (See Pape, 2016 for more details). The proposed model has the potential to inform the key stakeholders to develop an understanding of basic mechanism of inducting AI into HRM and also to realize the value in terms of achieving domain level (HRM) and organizational level strategic objectives for enhancing organizational performance.

The rest of the paper is organized in the following manner. In section 2, we first define HRM$^{(AI)}$, followed by section 3 that discusses organizational antecedents for integrating HRM$^{(AI)}$ into an organization. Section 4 is about configuring HRM$^{(AI)}$ discuss the basic operational enablers for transforming the exiting HRM operations in the organization towards HRM$^{(AI)}$. Section 5 presents the detailed HRM $^{(AI)}$ architectural framework and section 6 discusses and presents the integrated strategic HRM$^{(AI)}$ framework that blends HRM$^{(AI)}$ architectural framework with the HRM domain level outcomes of HRM$^{(AI)}$ and organizational level outcomes and resultant organizational performance. Section 7 and 8 discuss theoretical and practical implications, and limitations and future research directions followed by last section of conclusion.

2. HRM$^{(AI)}$ definition

Since Lawler and Elliot's (1996) initial investigation of an expert framework in an HRM setting, numerous works have examined the present state and application of AI approaches in recruitment and selection, including Hamoud and Laszlo is, 2019; Jantan et al., 2010; a lot Rodney et al., 2019; Strohmeier and the Square, 2013. Saukkonen et al. (2019) provide insight into how human resource management experts see the effects of AI. The disparity between AI's potential and actual efficacy in human resource management has just been explored in depth by Tambe et al. (2019). They provide the framework for further research by suggesting a typical HRM-AI life cycle. They propose a more thorough HRM-AI life cycle that adheres to the standard operating procedure of any decent BI system. Data generation, operations, machine learning, and taking decisions are the four phases that make up the process. By the way, none of them have of these professors provided an explanation of HRM(AI) that adequately portrayed the core of incorporating cutting-edge AI methods into HRM procedures. According to Prikshat, Malik, and Budhwar's (2021) revised definition of HRM(AI), the field is concerned with employing data-driven analytics to make sound functioning, relational, and transformational choices within a given domain. It is important to mention that according to this definition, HRM(AI) depends on integrating various AI technologies to carry out core HRM tasks. When these technologies are used together, they might make a significant difference. Also, what we know about HRM(AI) now is in line with what we know about similar tech-driven concepts (e.g., e-HRM, HRIS): as pointed out by Prikshat et al. (2021), tech-driven HRM mechanisms like electronic HRM, HR systems of information, HR cloud computing, along with HR analytics make it easier to incorporate HRM(AI).

3. Organizational antecedents for HRM$^{(AI)}$

It is not solely up to the HR department's judgment to decide to use AI approaches in HRM. For the job of human resources management to reach its full potential, it is essential to integrate AI-assisted HRM with the organization's strategic goals. An AI-oriented culture and technology enablers are necessary complements to an HRM(AI) goal that is tightly linked to the organization's strategic objective. Organizational facilitators, "AI-oriented culture," and "AI-HRM strategy" are the three domains that make up this level. We propose two kinds of integration between HRM(AI) strategy and the overall strategy of enterprises at the AI-HRM strategic level as a result (Henderson and Venkatraman, 1999). The first, known as alignment of strategy, is the connection between HRM(AI) and corporate strategies, which explains how HRM(AI) affects and bolsters business strategies. The second one, operational integration, has to be able to describe the connection between HRM(AI) infrastructure (e.g., HRM data marts or hubs) and the organization's business intelligence infrastructure (e.g., cloud data lake or warehouse). The second organizational component that may strongly influence the adoption of AI is the AI-oriented culture. This culture encompasses the attitudes of workers, managers, and leaders towards the use of AI methods. Twati and Gammack (2006) cite prior studies that found that company culture has a significant role in whether or not new information system approaches are accepted and implemented. Therefore, a more thorough examination of the present organizational culture and its potential for improvement or transformation onto a AI-oriented culture is required to comprehend the dynamics of HRM(AI). In addition, studies in information systems that concentrate on the topic of technology adoption have shown that facilitators inside companies have a significant impact on how individuals embrace new ideas and technology. To ensure a seamless rollout of new technologies, these enablers are often supplied by upper-level management in the form of a variety of policies and activities. Some of the organizational level factors that require thorough study in the context of HRM(AI) include the current state of technological infrastructure, workforce with technological skills, technologies that enable (such as user training and technical user support), project management system, and the human-technology relationship.

4. HRM$^{(AI)}$ configuration

Using a business intelligence (BI) architecture methodology, HRM (AI) configuration is recommended for a deeper understanding of the fundamental operational enablers for HRM(AI) transformation of the organization's current HRM operations. In the context of building a strong business intelligence architectural framework in an organization, it is important to analyze the "AI method" for enhancing various HRM activities, the "AI assimilation" process in HRM functions, and the "ethical principles." At the HRM reconfiguration level, finding AI solutions that can be applied to different HRM functions is the goal.

Several HRM tasks have been shown to benefit from the use of AI approaches in earlier studies. Artificial intelligence (AI) methods like data mining, algorithms, and AI-enabled biometrics are becoming more popular in the HRM domains of recruitment and selection (Chien and Chen, 2008; Danieli et al., 2016, and in Strohmeier and Piazza, 2013, Van Esch and Black, 2019). Training and development is the second most important HRM function where AI approaches are gaining a lot of attention. According to Maity (2019) and Davenport (2019), the training and development function heavily depends on artificial intelligence (AI) methods such as simulation-based training, HRM algorithms, and HR Analytics to support workers' ongoing learning and development requirements. Data mining techniques have been utilized in performance management to design fair performance appraisal systems that boost employee performance. In contrast, talent analytics/HR analytics and fuzzy logic techniques are widely used in talent management (Karatop et al., 2015; Shivathanu and Pillai, 2019). Firms have shown success in predicting and reducing employee turnover via the application of AI-based statistical analysis, data mining, or machine learning in the function of employee turnover (Fan et al., 2012; Sajjadini et al., 2019; Wang et al., 2011). Burnett and Lisk (2019), Chien and Chen (2008), Escolar- Jimenez (2019), and Huang et al. (2019) are among the first to mention the use and advantages of AI approaches in human resource management (HRM) tasks such as job design, engagement of staff members, retention and reward management. Therefore, in order to build an HRM(AI) architecture, it is necessary to examine the potential of different AI approaches for specific HRM activities in a comprehensive and diversified manner. Instead of relying on a single AI approach or a single HRM function, it is recommended to use a combination of AI techniques that may be applied across various HRM functions for a successful BI based HRM(AI) architecture.

Further steps of diffusion, routinization, and extension of assimilation may be required for the migration from initial usage to the continued diffusion from AI techniques (Prikshat et al., 2021), thus it is warranted for additional growth of

HRM(AI) to understand the processual assimilation mechanisms that comprises these stages. In order to inculcate AI approaches in different HRM functions, it is necessary to understand such a system, which will guarantee greater acceptance of AI techniques. Finally, it is important to critically analyze the ethical implications of the new role demands, professional challenges, as well as leadership expectations that organizations and HRM professionals may face as a result of identifying AI techniques for specific HRM functions and integrating them into the prescribed HRM(AI) architecture (Prikshat, Patel, Varma and Ishizaka, 2022). Problems with data privacy, security, ethical/moral decision-making, AI-human goal alignment, AI-related agency and justice, and other similar concerns may arise in the future of human resource management with AI (Du and Xie, 2021). All of these problems and dangers, which are very real, show how important it is to have well-defined ethical standards that address the problem of artificial intelligence (AI) in HRM and its many applications, as well as the roles and duties of those involved in the decision-making process.

5. HRM$^{(AI)}$ architectural framework

Two facts may help you understand the difficulties of creating a solid HRM(AI) framework. To begin, according to Sirosh (2017), AI approaches must be integrated into BI systems for any AI-aided model to be effective. This integration will make intelligent application deployment easier. Keep in mind that engineers may be occupied with AI technologies that aren't integrated into your company's business intelligence system (Alvarado, 2017; in addition, Sirosh, 2017). For new HRM(AI) approaches to be successfully integrated into an existing system, a firm needs a proven BI architecture. This will allow for a successful HRM(AI) infrastructure inside the company. Decisions may be supported by additional facts if one uses a business intelligence system, which is a "umbrella" word for several connected procedures, ideas, and methods (Trieu, 2017).

The three main parts of a BI architecture are data lakes, warehouses, and marts. Over the years, several research have put forward different ideas for business intelligence systems. Some of them are Inmon et al. (2010), Kimball et Ross (2013), Fang (2015), and Fernandez et al. (2019). Data lakes are notable because they pique the interest of several business domains. A data lake is a repository for all cleansed data, similar to a data warehouse or information mall (Khine and Wang, 2018). It has become clear that data lakes have limitations due to the proliferation of cloud computing and AI techniques, as well as the growing amount and variety of data formats (structured, semi-structured, and unstructured) and the fact that they tend to store data in separate silos and cannot integrate AI techniques (Dignan, 2018; Wells, 2019). There has been a demand for new ways to corporate intelligence that can tackle these challenges (Moorhead, 2018; Moreno the authors, 2019). Following the natural progression of the "Data Warehouse" and a "Data Lake" into the third-generation data structures known as the "Data Hub," companies may now have access to their data (Wells, 2019). Our goal is to rethink data hub storage by combining various aspects of parallel computing with storage. With the flexibility to adjust and divide these features individually, many clients may access particular to an application performance parameter, such as throughput, latency, and the quantity of I/O operations per second (Moorhead, 2018). Like MarkLogic, Cloudera, SAP, information technology PureStorage, and many more have created data hub architecture in its early stages (Wells, 2019). In light of recent findings on data hubs and recommendations from earlier studies on business intelligence architecture, this research presents a new formal HRM(AI) framework (Fig.1a) (Ariyachandra and Watson, 2006; Baars alongside Kemper, 2008, at which point Mazón and Trujillo, 2008; Schmidt et al., 2014; Wirtz along with Müller, 2019). Following is a detailed description of the components that make up the proposed framework.

5.1. HRM$^{(AI)}$ data source layer

The HRM (AI) data source layer is responsible for storing all HRM-related data, both structured and unstructured, for the benefit of management. Common HR functions are covered by the HR process map (Pape, 2016) and include things like HR insights, the employee journey, interactions with workers, time management, remuneration, and organizational change. To categorize HRM procedures, this framework consults this map. The choice to base this strategy on Pape (2016) HR procedure has two primary rationales. To get things off, the HR process map that has been prescribed is based on the suggestions of the HR analysts as well as the predictive HR analyses that have been identified in academic and professional literature. Furthermore, it prioritizes thirty pieces of validated HRM data for BI system storage in preparation for future analytics. This layer's job is to pull HRM-related data from all over the place, whether it's organized or unstructured, and from different systems both within and outside the company. It is possible that other HR information systems, such as enterprise resource planning (ERP), have access to the structured data kept internally in HRIS. Because earlier studies have shown that the next generation of computers would not be limited to desktop computers alone, the HRM(AI) data source layer utilizes the Internet of Things (IoT) (Gubbi et al., 2013).

5.2. HRM$^{(AI)}$ingestion layer

The HRM $^{(AI)}$ ingestion layer comprises the extraction (E) and loading (L) of data into cloud data lake as well as cloud data hub. Still, data is not transformed (T) until the data are required and called by the application for query in HRM$^{(AI)}$

data hub layer. The transform (T) operations are only performed when data is needed and is more flexible and agile, giving the developers, data scientists, managers and HR professionals the ability to easily configure the models, queries, and apps on-the-fly (Khine and Wang, 2018). The proposed ELT process is different from a typical ETL process. In a traditional data warehouse setting, the ETL process periodically refreshes the data warehouse during idle or low-load, periods of its operation and has a specific time-window to complete, thus making it challenging to answer out-of-box questions of decision-makers or questions that need to extract transactions data combined with unstructured data (Khine and Wang, 2018; Vassiliadis and Simitsis, 2009). Once intended users use the data, the data is stored in the enterprise data warehouse and further distributed in functional cloud data marts (i.e., HRM data mart). The proposed HRM$^{(AI)}$ ingestion layer also suggests the latest AI techniques for extracting (E) and loading (L) the data into HRM$^{(AI)}$ data hub layer based on works of Wirtz and Muller (2019).

5.3. HRM$^{(AI)}$ data hub layer

HRM$^{(AI)}$ data hub layer comprises the most recent cloud-based configuration approach instead of the traditional data warehouse or data lake layer (Dignan, 2018, Moorhead, 2018; Wells, 2019). The data lake and data warehouse in addition to data marts are still the integral part of the data hub layer, but with current trends of cloud-based computing, these are proposed to be cloud-based. Data hub can be defined as a complete cloud-based software system that has real-time processing, on-demand infrastructure and virtualization capabilities that support unification and delivering of data and can be accessed by multiple applications at the same time with full data integrity. Data hubs are a necessary response to the challenge of cloud computing, data silos and the increasing demands of data science use cases (Wells, 2019). In line with the recent observations (Dignan, 2018, Moorhead, 2018; Wells, 2019), streaming analytics and latest AI techniques can be utilized to transform (T) the data as per the queries of developers, data scientists, managers and HR professionals and to process data for cloud data warehouse and data marts. Following are the main components and process of HRM$^{(AI)}$ data hub layer:

5.3.1. Cloud data lake

A cloud data lake is a centralized massive data repository that allows organizations to collect a larger volume and variety of data. Cloud data lake stores all structured, semi-structured and unstructured data at any scale without the rigidity and overhead of traditional data warehouse architectures (Dixon, 2019 cited in Moreno et al., 2019). Intended users can retrieve data at any point of time (See a simplified view of a data lake in Figure 1, p-4 in Khine and Wang, 2018). A data lake can be further categorized into two main tiers, namely raw zone and curated zone.

While raw zone tier has the capacity of storing data as it is (i.e., without structuring), on the other hand, curated tier stores high-value data that has passed quality data checks and can be Used to ad-hoc dashboards and visualizations, real-time analytics, and machine learning to guide better decisions (Moreno et al., 2019). 5.3.2 Cloud data warehouse

The typical data warehouse still plays a fundamental role in HRM $^{(AI)}$ data hub layer, but in a big data analytics environment, it becomes a cloud data warehouse. Cloud data warehouse in the context of this research is enterprise collection of data from multiple sources (internal or external) as well as from cloud data lake that is scrubbed and integrated with the help of AI techniques and streaming analytics to provide a consolidated view of the enterprise client for optimized reporting and analysis (Rifaie et al., 2008). A cloud data lake and cloud data warehouse don't compete directly but complement each other, and a data warehouses can be fed by data lakes as shown in the Fig.1(a) (Fang, 2015; Moreno et al., 2019; Ngala, 2019).

5.3.2. HRM analytical data mart

Data marts usually contain a subset of the data warehouse or a limited volume of aggregated data for the specific analysis needs of a particular business unit, rather than the needs of the whole enterprise (Song, 2009). The proposed HRM analytical data mart is designed to allow selection of HR data from disparate HR activities to be integrated, enabling AI-augmented analytics, reporting and ad hoc analysis (Beznos et al., 2017). The HRM analytical data mart deals with the selection of data relating to HR activities that can provide business intelligence users, analysts and HR professionals ability to perform deeper analytics based on their subjective understanding of the application task specifics.

5.4. HRM$^{(AI)}$ applications layer

Pape (2016) lists many HRM functions (including HR insight, personnel journey, relationships with staff members, time management, reward, and organization transformation) that rely on AI-augmented HRM process analytics. These analytics mostly support this layer. See Figure 1(b) for an illustration of how this suggested layer incorporates all the AI methods and tools that are already transforming the HR industry. Fuzzy logic, models of artificial neural networks, various temporal aggregation/holistic, integrated forecasting, and the use of UltiPro or Cake HR software for workforce planning are all real-world examples. According to the research, a multidisciplinary the data scientist team will analyze the HRM(AI) applications layer. This team should retrieve relevant data from various sources, such as the cloud data lake, cloud data warehouse, HRM analytical data mart, or marts for other functional areas like production, marketing, or finance. The goal is to generate valuable insights that can be used for decision-making in various HRM functions.

5.5. HRM(AI)logic layer

Processing various types of data and doing suitable analysis to extract insights is the primary goal of integrating HRM(AI) into a company (Ward in et al 2014). The data collected in the preceding step may be used for analysis on the platform provided by the HRM(AI) logic layer. Holsapple et al. (2014) presented three dimensions—'domain, 'method,' and 'orientation'—to assist with logical reasoning and corporate data analytics. Analytics are used in a variety of contexts; one is the domain, which in this case is human resource management. The second is the method, which describes the specific ways data is analyzed; in this case, it's artificial intelligence techniques. Lastly, there's the orientation, which is more general and not specific to any a specific company domain (Holsapple et al., 2014). The most popular taxonomy of analytics approaches, with the final dimension orientation, has been expanded to four levels: descriptive, diagnostic, predictive, and regulatory (Delen and Zolbanin, 2018). Therefore, HR professionals are able to make educated, fact-based decisions that support their organizations' strategic and tactical goals through the application of AI techniques, which provide them with descriptive, diagnostic, predictive, and restricting data analytic capabilities (Delen and Zolbanin, 2018). Diagnostic analytics seeks to explain "why did it happen?" by analyzing data or content, in contrast to descriptive analytics, which aims to investigate HR data content to address "what happened?" or "what is happening?" (Delen and Zolbanin, 2018). Additionally, algorithm models with an emphasis on producing empirical rather than predictions based on theory are the backbone of predictive analysis (Shmueli al Koppius, 2011). Lastly, prescriptive analytics may enhance HR process systems by determining the appropriate action given a complicated collection of goals, criteria, and limitations; it follows descriptive and predictive analytics (Lustig et al., 2010).

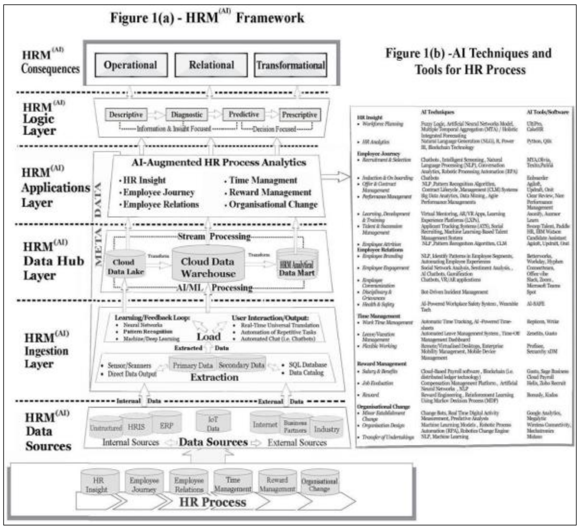

Figure 1 HRM(AI) architectural framework

5.6. HRM domain level consequences

Technique, orientation, and domain are the three dimensions that were created by Holsapple et al. (2014). This section is devoted to the HR-domain aspect. Many studies have examined the impact of information technology on HR using a three-pronged paradigm. These include Lepak and Snell (1998), Bissola and Imperatori (2014), Obeidat (2016), Parry and Tyson (2011), Sanders et al. (2014), Snell et al. (1995), and Strohmeier (2007). The research concludes that operational, relational, and transformational factors are all outputs of HRM(AI).

A strong HRM(AI) architecture, if integrated into HR department operations, may improve HR service quality, system resilience, and human resource effectiveness. Supporters of these HRM elements argue that HR services are improved, HR is more efficient, and HR is stronger overall when technology is used (Bondarouk et al., 2017; Bissola and Imperatori, 2020; Bondarouk and Ruël, 2009).

Human resource empowerment, trust, and internal relational social capital might be the outcomes of integrating AI design into HRM. An area where AI has the potential to improve HRM is in facilitating closer ties between HR and line management. This allows for better service and quicker answers from line managers, senior managers, and even individual employees by spreading out HR tasks (Parry and Tyson, 2011). Among AI's many possible applications is the improvement of interpersonal trust. By helping employees better grasp the norms and activities that support HR regulations, AI might boost HR's credibility and position (Bissola and Imperatori, 2014). Additionally, with the help of state-of-the-art AI technology, HRM might possibly transition from a "descriptive and diagnostic" approach to a "prescriptive and predictive" one (Di Claudio, 2019). This shift would likely lead to an increase in internal relational social capital as a consequence of better relational coordination.

According to Strohmeier and Piazza (2015), when AI approaches enhance HRM's strategic direction and business support, the function takes on a more strategic role and undergoes revolutionary changes. Revolutionary consequences of a strong HRM(AI) architecture in the HR department include a more global HR focus, more HR strategic involvement, and improved HR analytics capabilities (Enhanced HRAC). Arunachalam et al. (2018) argue that companies may improve their "Big data analytical abilities" by using state-of-the-art AI approaches into HRM programs. This capacity growth mechanism aids in data absorption, structural heterogeneity maintenance, data generation speed, data quality, and assurance, all of which are economically benefited by big data. You may find more details in the study of Wang et al. (2016). Human resource management that makes use of AI might also free up HR professionals from mundane administrative tasks, giving them more time to concentrate on the big picture and improving HR's input on organizational decisions. Finally, technology-driven

HRM has the potential to enhance an organization's global orientation by unifying HR operations across divisions or departments, according to studies. This is why HR global orientation, or the practice of standardizing HR processes inside a company, can have such a profound impact (Parry and Tyson, 2011). Supervisors might potentially influence the company's strategy by enhancing the management process and using AI approaches to standardize human resource management procedures among divisions (Parry and Tyson, 2011). As promised in our last meeting, I've included the blueprint for the HRM(AI) system. This five-tiered HRM(AI) architectural framework showcases the various AI methods and technologies used in HRM tasks.

This article presents a technique that connects the dots between domain-level AI HRM outcomes, organizational-level results, and overall organizational performance. Using metrics like perceived organizational support, organizational citizenship behavior, and collective job satisfaction, this paper builds upon the work of Jiang et al. (2012) on three key points: human capital, which is the sum of an organization's employees' skills, knowledge, and abilities; employee motivation, which is the proportion of employees who tend to stay for longer terms; and organizational support. Human capital, motivation, and opportunity to engage are the three components that make up Guest's (1997) HRM paradigm. This classification is mostly based on this model. We expect that operational performance—which encompasses innovation, service, quality, and overall operational performance—will be positively affected by an organization's integration of HRM(AI). Value proposition and competitive position are components of strategic performance. Total financial performance comprises ROA, ROE, market return, sales growth, and return on equity. We expect these outcomes to be visible at the operational, relational, and transformational levels. Research on the interplay between human capital, employee motivation, and retention may follow the implementation of HRM(AI) in companies. These factors are expected to have varying degrees of effect on the operational, strategic, and financial performance of the business. Figure 2 shows the strategic HRM(AI) framework, which includes the HRM(AI) logic layer as an architectural component.

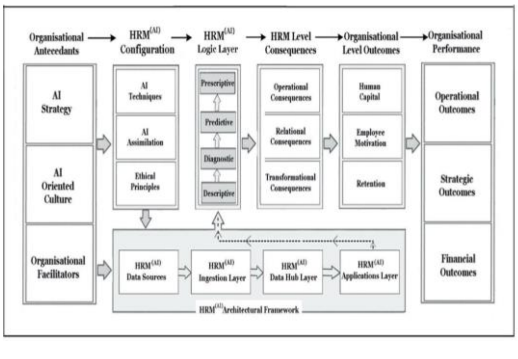

Figure 2 A Strategic Framework for AI-Driven Human Resource Management Architecture

6. Theoretical and practical implications

In terms of knowledge gaps within the existing literature, this research is the first to propose a strategic architectural framework HRM $^{(AI)}$ framework based on BI systems context. This paper shows the complementary perspective of BI systems for designing a robust HRM$^{(AI)}$ architectural framework. The study uses the latest industry-based 3rd generation data hub architecture as the core component of this framework, to ensure practical applicability of architectural framework in organizations. Following on 'HR Process Map'(Pape, 2016), the research provides hands-on approach to configure a practical HRM$^{(AI)}$ framework comprising 30 validated data items based on six HRM functions. Additionally, this research contribute to the theory by proposing a Strategic Framework for AI-Driven Human Resource Management Architecture that can be further explore through developing testable propositions and hypotheses for empirical research. The integrated strategic architectural framework first identifies organizational antecedents and HRM$^{(AI)}$ configurational factors that may help developing a HRM$^{(AI)}$ architectural framework in organization. The HRM$^{(AI)}$ architectural framework comprising six layers has the capacity to inform key stakeholders to build up a mechanism to integrate AI within the HRM department of the organization. Last but not least, this research connects the final logic layer of the proposed architectural framework with HRM domain level operational, relational and transformational consequences that can help understand how the investment on HRM$^{(AI)}$ architectural framework may help achieving the HRM level objectives and further enhance organization performance.

The findings of this study have important implications for organizations considering or currently pursuing assimilation of AI technologies in the HRM department. Indeed, organizations with higher levels of technology integration supported by already functional BI systems can more easily reap the benefits from the use of AI techniques in HRM. Substantial prior investments in BI systems or specific technology-driven HRM practices (i.e., e-HRM, HRIS, HR analytics, Cloud computing) would further create a favorable setting for an organization to assimilate HRM$^{(AI)}$ in their HR department. For the organizations, which haven't moved into this direction or are on the verge of implementing AI techniques in HRM, this study help them understand that for effective utilization of these AI techniques, they require a sophisticated nexus of BI systems. This study provides an operational blueprint for integrating HRM$^{(AI)}$ in organizations with components of HRM$^{(AI)}$ framework and associated strategic theoretical model for assessing the requisite antecedents and resultant consequences of the full- scale deployment of HRM$^{(AI)}$.

Moreover, the components of integrated strategic architectural framework for HRM$^{(AI)}$ can serve as a starting point for assessment and evaluation of HRM$^{(AI)}$ status, where an organization can evaluate where they are in terms of HRM$^{(AI)}$ integration and plan accordingly to proceed to the next stage. Moreover, the integration of proposed HRM$^{(AI)}$ framework and use of suggested mechanism and latest state-of-the-art data-hub and AI techniques for various activities of HR, has the potential to bring agility in HR operations and resultant domain-specific consequences can contribute to organizational performance.

7. Limitations and future research

The first main limitation of the study rests on the fact, that although the composition of HRM$^{(AI)}$ framework is presented simply in Fig. 1a, but it is acknowledged that the interrelationships among the HRM$^{(AI)}$ components, and among the BI systems, as well as how the suggested framework has to set within the central IT unit of an organization and its interoperability with other functions (i.e. finance, supply chain, marketing), are very complex. More detailed insights and studies are needed to explore these mechanisms.

Second, as mentioned previously 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. Third, to the best of author's knowledge, only Pape's (2016) HR process map has prioritized and validated the HR data items for business analytics. Thus, researchers can further examine or investigate the utility of these data items and can expand or refine the data items as per the dynamic needs of the HRM department. 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 different proposition based on proposed model and the viability and validity the proposed theoretical model can be tested empirically.

8. Conclusion

Infusion of latest HRM$^{(AI)}$ techniques pertaining to different HRM activities into robust BI systems can enable HRM professionals to prepare effectively, create, and deploy analytic models to leverage the high level of augmented data analytics (i.e., complex data flows based on multiple advanced algorithms and models) for high-level decision-making.

Organizations with sound BI systems will have the upper hand in integrating HRM (AI) techniques into their databases, data lakes and cloud database, on the other hand, the organizations without any BI system will have to start investing in BI systems and gradually prepare them for using latest HRM(AI) techniques most effectively. Based on extensive information systems and technology-driven HRM literature, this research proposed an integrated strategic architectural HRM(AI) framework that has the potential to be explored in the form of multiple testable research propositions for future research.

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