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Research Article

A New Technological Dimension In The Hrm - Finding The Correlation Between Artificial Intelligence Applications And Green Human Resource Management

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Abstract

Aim: The aim of this research was to assess the moderating effect of technological dimensions in HRM among the relationship of artificial intelligence applications and green HRM.

Method: Quantitative research design was adopted wherein data was gathered from a survey questionnaire from 301 participants. The data was analysed through the SEM technique, in which path analysis and CFA analysis were carried out.

Findings: The findings revealed a significant correlation between AI applications and green HRM. It was also revealed that technological dimensions strongly impact or moderate the strength of the relationship between AI applications and green HRM. The moderation of the HRM system and e-recruitment was identified to be significant. Whereas, the moderation of integrated performance management system was determined to be insignificant among the relationship of AI applications and green HRM.

Conclusions: It can be concluded that contemporary HRM needs to adopt AI, be it as a tool, product, software, method or technique, to improve their performance from recruitment and selection to performance. This is to effectively survive and compete in the current complicated and highly competitive business environment to obtain a competitive advantage and enhanced image in the global business market.

Keywords: *technological dimension, HRM, correlation, artificial intelligence applications, green HRM, SEM technique.*

Introduction

The adoption of novel technologies has emerged in contemporary HRM (Human Resource Management) practices, including artificial intelligence (AI), virtual reality (VR), machine learning (ML), and deep learning (DL) (Vrontis et al., 2021). Due to this, the best HRM solutions evolve to make the best use of technological innovation to improve and manage every construct of the HRM experience. Bondarouk and Brewster (2016) postulated that the technological dimension in HRM has shifted, impacting internal procedures, relevant practices, core competencies and organisational structure. It has provided significant activities for including innovation in the business processes that helps in incorporating advancement for future growth. Among the latest technologies implemented, AI has assisted in acquisition and recruitment, matching candidate experience with role needs, and screening applications in HRM (Garg, Srivastava and Gupta, 2018). Ertel (2018) explicated that AI is a simulation of human intelligence in machines, which are programmed to solve problems via learning like humans and impersonating their actions.

AI applications in HRM have prevented unconscious bias in interviewing, shortlisting and selection and matching the same criteria in precisely fair manners to each candidate. The applications have improved the process via matching features of previously skilled hires with the same capabilities and qualities in future applicants. Just as AI is a new notion in the field of information technology (IT), likewise, the concept of green HRM has evolved to preserve and protect environmental resources to ensure environmental sustainability while at the same time establishing and enhancing productivity (Garg, Srivastava and Gupta, 2018). Jyoti (2019) described that green HRM denotes utilising HR policies to inform effective use of green resources in business premises and address the sustainability of environment that assists businesses in cooperating sustainable business frameworks, giving a boost to all HR functions from recruitment to performance management.

Therefore, the core rationale of conducting this research is to determine the relationship between AI and practices of Green HRM via assessing the moderating impact of technological dimension in HRM. Limited studies can be found regarding the application and impact of AI on green HRM practices, such as the studies of Garg, Srivastava and Gupta (2018); Rao and Goli (2020). However, not many studies have assessed the relationship between the variables, and even less research is available on the moderating impact of technological dimension between both variables. Both inferences present a huge gap in the current literature and a lack of actual implementation of AI for Green HRM. As stated by Hmoud (2021), contemporary HRM experiences challenges; nonetheless, huge gaps in the adoption of AI to solve them alongside availing opportunities for applying green HRM practices are present. Despite being apparent that AI, machine learning and big data can determine patterns, trends and insights concerning green HRM, today’s enterprises are deficient in applying the novel technology for enhancing business competitiveness in the international market. Thus, this research looks into the phenomenon to contribute to the existing literature and add value to the practical application of AI via drawing implications.

This research aims to assess the moderating effect of technological dimensions in HRM between artificial intelligence applications and green HRM.

Literature Review

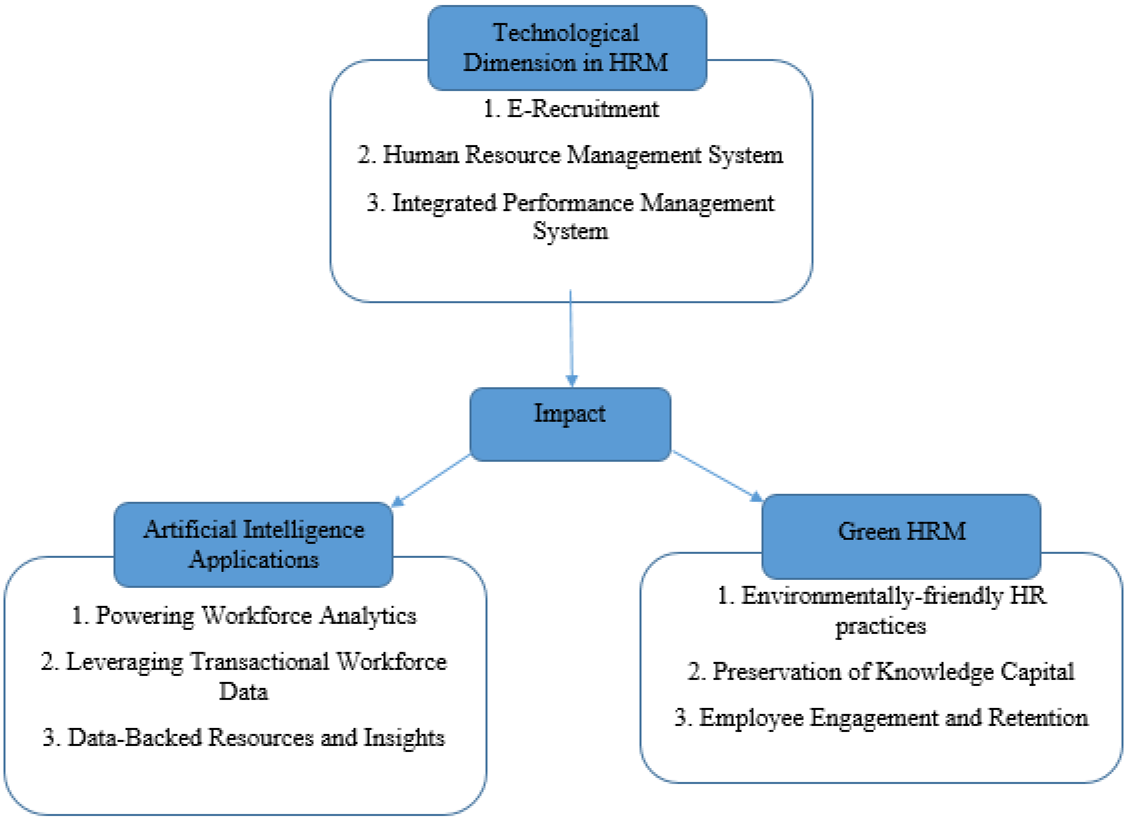
The existing technological dimensions, including HR, recruitment and performance management systems, deliver the opportunity to embrace technologies such as AI as it allows for redesigning HR practices and processes, which is the core success factor to an organisations’ objectives and mission (Silva & Lima, 2018). Technological dimensions have already transformed how HR manages, stores, collects, uses and disseminates information concerning resources, cost and budget. The addition of AI-based systems is a plus to enhance the chances of competitive advantage. Similarly, Stone et al. (2015) asserted that current technological aspects in HRM provide with incorporating most feasible technological solutions that can lead to creating an eHR firm. This can assist in focusing on interconnecting individuals and business procedures to accomplish quick adaption to shifting requirements common to businesses and people. Without overtly saying, it is clear that technological dimensions deliver benefits of including breakthrough technologies to enhance the business HRM progression and competitive advantage.

AI applications play a vital role in transforming HRM processes, improving effectiveness in candidate assessment, compliance, workplace learning, and relationship with employees with decreasing human bias (Tiwari et al., 2021). This is because AI technology automates procedures, examines corporate compliance, workforce, and reduces redundant and repetitive administrative tasks. However, Tambe, Cappelli and Yakubovich (2019) argued that despite AI is already being applied in various fields, including IT and corporate businesses, HR professionals are resistant to adopt the revolutionary technology. This is for the purpose that many HR professionals consider the costs of delivering training and education to the employees increase along with improving own learning, which is a time, effort, cost and resources consuming task. Many organisations are tight on budget that compels them to implement technologies that are less costly and easy to use. Nonetheless, Szedlak et al. (2020) highlighted that AI applications are not different from existing software or technologies when using them in HRM; however, certain aspects of their use might require training and awareness. From the prior arguments, it can be instituted that applications of AI are beneficial for improving practices of HRM; nevertheless, current businesses are reluctant towards its adoption due to fear of increased resources, costs and budget allocation.

On the other hand, sustainability methods are emerging broadly within business practices worldwide to fight the catastrophes and challenges of climate change, for which private and public sectors, both, are adopting green HRM (Rani & Mishra, 2014). Jyoti (2019) implied that green HRM has now become important as it can help in minimising expenses via smart use of electricity, manufactured goods, rare and expensive resources and water at the workplace, leading to enhanced well-being of employees with increased job dedication and satisfaction. The prior notions present that green HRM allows accomplishing lower costs with greater effectiveness in organisations with decreasing ecological waste and renovating HR tools and products. This incorporates a sense of environmental consciousness within daily work routines. Nevertheless, a plethora of information is available on green HRM associated skills, practices and findings, as well as AI and machine learning alone. However, gaps exist in the literature regarding promoting the concept that AI needs to be addressed in applying green HRM to balance the relationship between technology and society to work towards sustainability and a green environment (Garg, Srivastav & Gupta, 2018). Therefore, there is a need to adopt new management pedagogy that emphasises adopting a sociotechnical view to ensure green HRM with the implementation of AI applications.

Conceptual Framework

The below framework shows the moderating role of technological dimensions in HRM in the relationship between artificial intelligence applications and green HRM.



Hypothesis

H0: There is no direct and significant relationship between artificial intelligence and green HRM.

H1: There is a direct and significant relationship between artificial intelligence and green HRM.

H2: Technological dimension in HRM moderates the relationship between artificial intelligence and green HRM.

Methodology

Data Collection and Population

The primary method of data collection was adopted in this research as it allowed to include first-hand, updated and latest evidence regarding the phenomenon under discussion. The primary method of survey questionnaire was utilised to include a set of questions, as well as interpret, analyse and gather data (Roopa & Rani, 2012). Since the study was grounded on assessing the relationship between artificial intelligence and green HRM, the targeted population was restricted to surveying HR professionals and managers only. The sample size was also kept limited to only include a feasible amount of research participants that represent the entire category of population sufficiently. In this regard, the estimation of appropriate sample size was determined from the equation provided in the study of Fugard (2015) with regards to the targeted population. The equation for calculating sample size is given below:

$$n = \frac{z^2 \times p \times q}{e^2}$$

In the above-presented equation, ‘n’ signifies the number of population or sample size. Symbol ‘z’ denotes a z-score estimated at 1.96; meanwhile, CI (Confidence Interval) was calculated to be 95%. Symbol ‘p’ is taken as variability proportion calculated to be 50%, whereas ‘q’ is the population portion that was not considered in this research. Lastly, ‘e’ indicates the error that was 5%.

$$n = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.05)^2} = 384$$

After putting values in the equation, the appropriate sample is size was determined to be 384. Thus, 384 questionnaires were distributed among the targeted population, in which 301 responses were received. The response rate was estimated to be 78.38%.

Sampling Technique

Since it is discussed previously that inclusion of whole targeted population in the research was not possible, for which suitable sample size was determined that represented the entire populations. Based on this, non-probability sampling was followed, wherein the purposive sampling technique was chosen. Etikan, Musa and Alkassim (2016) explicated that purposive sampling is where the researcher chooses samples based on subjective judgment instead of random selection. It allowed to present results even with a limited number of research respondents and assisted in collecting data on the grounds of the purpose of the study (Bloor & Wood, 2016). Therefore, the selection of purposive sampling was also the best for this research as it is one of the most time and cost-effective sampling techniques available.

Research Instrument

Survey questionnaire instrument was used for data collection in this study to investigate the relationship between independent variable of artificial intelligence applications and dependent variable of green HRM. This allowed to set questions and receive responses from the targeted population as per the exact purpose and intended contribution of the research. Taherdoost (2016) mentioned that survey questionnaires are an effective method as they are economical in gathering feedback and responses with accurate interpretation of comprehensive data and ease of application. The survey questionnaire was self-administered that took an estimated time of 10 to 15 minutes for answering all questions.

Data Analysis Method

For analysing gathered data, the technique of SEM (Structural Equation Modelling) was chosen. SME technique allowed to conduct an explicit assessment of measurement error, perform model testing where a structure can be examined to fit the data, and calculate variables through observed variables (Jenatabadi & Ismail, 2014). Martínez-López, Gázquez-Abad and Sousa (2013) inferred that the SEM technique is used for survey response analysis that forms the grounds for carrying out CFA (Confirmatory Factor Analysis) and path analysis for the aim of estimating the model. CFA falls in the calculation part of SEM that depicts the relationship between underlying variables and their predictors (Brown & Moore, 2012). It allowed validating the network of variables by testing hypotheses via exploring the association between latent variables and observed variables exists. Whereas path analysis displays how variables of interest are associated with examining correlation within the structure or network (Garson, 2013). It assisted in studying the causal association between independent and dependent variables. The software of SmartPLS was used for testing the hypotheses. Ringle, Da Silva and Bido (2015) concurred that SmartPLS is software with GUI (Graphical User Interface) for variance grounded SEM that utilises PLS (Partial Least Squares) path modelling method. The software enabled to determine associations between variables, indicator variables and latent variables with easier testing of moderating variables that supported explaining the use of AI applications in green HRM.

Results and Discussion

Confirmatory Factor Analysis

As per the above discussion, CFA is regarded as the crucial dimension of SEM technique which assists in comprehending the structure of latent constructs by considerate examination among latent variables and constructs. The study conducted by Brown (2012) argued that factor assessment with the help of CFA ensured comprehending the association among latent variables and constructs through which the degree of latent variables explaining the constructs is determined. In contrast to this, the study conducted by Geldhof (2014) argued that several measures assist the CFA in terms of determining the reliability and validity of the constructs. In this manner, the validation of constructs is identified through discriminant validity, Cronbach's alpha, convergent validity, composite reliability and outer loadings.

The study of Garson (2012) stated that measure of factor loading is used for the purpose of determining the variance extracted by factor from the variable. According to Shau (2017), the threshold of outer loadings is 0.6 and the items must possess value greater than 0.6. Therefore, it can be determined with the help of Table 1 that factor loadings of all the items is above 0.6 as the lowest value is determined to be 0.626. Another aspect of the CFA is related to the test of reliability which has been determined with the help of composite reliability and Cronbach's Alpha. The study conducted by Ahmad, Zulkurnain & Khairushalimi (2016) argued that 0.6 is the threshold for composite reliability and Cronbach's alpha. Based on the below table 1, it can be determined that lowest value of Cronbach's alpha is obtained to be 0.665 which is above 0.6. On the other hand, the lowest value for composite reliability is determined to be 0.813 which is also above 0.6. Therefore, the constructs are considered as reliable as they fulfil the criteria of both Cronbach's alpha and composite reliability.

The other significant feature of CFA is validity of the latent constructs which is considered as the convergent validity. This type of validity is measured with the help of average variance extracted (AVE). As per the study conducted by Afthanorhan (2013), AVE is considered as the measure for identifying the convergent validity among constructs and has the threshold of 0.5. It can be determined from the below Table 1 that the lowest value of average variance extracted is 0.592 which is well above the criteria of 0.5. Therefore, it can be stated that the constructs are reliable and valid and are eligible for further analysis.

Table 1 Convergent Validity, Composite Reliability and Cronbach's Alpha

Constructs	**Indicators**	**Factor Loadings**	**Cronbach's Alpha**	**Composite Reliability**	**Average Variance Extracted (AVE)**

Data Backed Resources and Insights	DBRI1	0.854	0.856	0.912	0.776
	DBRI2	0.905			
	DBRI3	0.884			
Employee Engagement and Retention	EER1	0.925	0.926	0.953	0.871
	EER2	0.928			
	EER3	0.946			
Environmentally-Friendly HR Practices	EFHP1	0.875	0.825	0.896	0.741
	EFHP2	0.807			
	EFHP3	0.897			
E-Recruitment	ER1	0.782	0.653	0.813	0.592
	ER2	0.825			
	ER3	0.696			
Human Resource Management System	HRMS1	0.842	0.778	0.871	0.693
	HRMS2	0.787			
	HRMS3	0.866			
Integrated Performance Management System	IPMS1	0.917	0.912	0.944	0.849
	IPMS2	0.926			
	IPMS3	0.922			
Leveraging Transactional Workforce Data	LTWD1	0.900	0.684	0.826	0.624
	LTWD2	0.885			
	LTWD3	0.626			
Preservation of Knowledge Capital	PKC1	0.900	0.763	0.867	0.687
	PKC2	0.879			
	PKC3	0.690			
Powering Workforce Analytics	PWA1	0.644	0.665	0.820	0.606
	PWA2	0.844			
	PWA3	0.830			

Discriminant validity has been presented in the Table 2 below which has been measured with the help of Heterotrait-Monotrait (HTMT) ratio. The study conducted by Franke (2019) argued that 0.9 is the threshold of HTMT and the values must not be greater than the defined threshold. Therefore, it can be determined from the below Table 2 that none of the value exceed the threshold of 0.9. In this manner, it can be stated that constructs possess discriminant validity.

Table 2 Discriminant Validity

	DBRI	EER	EFHP	ER	HRMS	IPMS	LTWD	PKC
DBRI								
EER	0.259							
EFHP	0.311	0.439						
ER	0.959	0.319	0.448					
HRMS	0.614	0.248	0.354	0.868				
IPMS	0.055	0.116	0.131	0.125	0.135			
LTWD	0.349	0.587	0.831	0.649	0.564	0.158		
PKC	0.522	0.298	0.515	0.836	0.769	0.044	0.705	
PWA	0.519	0.837	0.473	0.775	0.746	0.074	0.788	0.596

Path Analysis

The below table shows the path analysis of the model which has been tested in this study. Therefore, it can be determined from the below Table 3 that there is significant effect of Data Backed Resources and Insights over the Artificial Intelligence Applications as B= 0.197, p= 0.000< 0.01. On the other hand, the effect of employee engagement and retention is also significant over the Green HRM as B= 0.475, p= 0.000< 0.01. In addition to this, the effect of Environmentally-Friendly HR Practices was also significant over the Green HRM as B= 0.438, p= 0.000< 0.01. Moreover, the effect of E-Recruitment is also significant over the technological dimension as B= 0.650, p= 0.000< 0.01. Additionally, the effect of human resource management system was also significant over the technological dimension as B= 0.406, p= 0.000< 0.01. Lastly, the effect of integrated performance management system was insignificant over the technological dimension as B= 0.120, p= 0.179> 0.1.

On the other hand, the effect of Leveraging Transactional Workforce Data was also significant over the Artificial intelligence applications as B= 0.637, p= 0.000< 0.01. Similarly, the effect of Presentation of Knowledge Capital was also significant over the Artificial intelligence applications as B= 0.416, p= 0.000< 0.01. Lastly, the effect of Powering Workforce Analytics was also significant over the Artificial intelligence applications as B= 0.390, p= 0.000< 0.01.

Table 3 Path Coefficients

	Original Sample (O)	**T Statistics (|O/STDEV|)**	**P Values**
DBRI -> AIA	0.197***	3.711	0.000
EER -> GHRM	0.475***	40.505	0.000
EFHP -> GHRM	0.438***	37.366	0.000
ER -> TDHRM	0.650***	6.050	0.000
HRMS -> TDHRM	0.406***	3.796	0.000
IPMS -> TDHRM	0.120	1.345	0.179
LTWD -> AIA	0.637***	8.723	0.000
PKC -> GHRM	0.416***	32.275	0.000

PWA -> AIA	0.390***	4.499	0.000
*Significant at 10%; **Significant at 5%; ***Significant at 1%			

Discussion

The research investigated the correlation between AI applications and green HRM via determining the role of technological dimensions to identify the strength of their relationship. The findings revealed that there exists a significant relationship between AI applications and green HRM. Similarly, the study of Garg, Srivastava and Gupta (2018) identified that using AI applications can play a significant role in catering to challenges of cost, budget and resources while implementing green HRM. It is because AI delivers insinuations with the potential to determine trends and analysis to improve business and workforce practices to enhance business competitiveness in the international market. Further, it was uncovered that technological dimensions strongly impact or moderate the strength of the relationship between AI applications and green HRM. Similarly, the research of Stone et al. (2015) highlighted that technological constructs deliver a range of prospects to manage the use and dissemination of information in HRM. These dimensions allow to include best resolutions that can lead a firm towards technological innovation.

The concept of green human resource management encompasses all the practices the approaches which lead towards environmental and social sustainability. The field has become incredibly pertinent in developing businesses on ecologically friendly lines, which is specially related to organisations that work in this dimension (Muster, 2011). Since modern corporate organisations have increasingly integrated with international markets to prevent globalisation, strong emphasis is being exerted on minimising their adverse environmental and social sustainability (Muster, 2011). This is because environmentally damaging practices of a firm could seriously thwart the entire supply and product chain, negatively impacting related industries and markets (Alzgool et al., 2021). In this regard, it is the responsibility of the human resource department to identify those factors which may create problems in the sustainable management of the firm concerning its human resource and formulate strategies to ameliorate those factors (Sharma and Gupta, 2015). However, it was identified during the literature search that green HRM is not a singular concept. Instead, Alzgool (2019) stated that it is an amalgam of various concepts of HRM which do not necessarily address the sustainability issue by themselves. These include lean human resources and transformational management etc.

The role of digital technology has been significant in organisational management since internet emergence. Whereas, the internal culture of organisations with regards to technology was identified as one of the most primitive variables determining the extent of adoption of technology (Mehta and Chugan, 2015). With social sustainability being identified as a prerequisite for attaining environmental sustainability, organisations have to synthesise their corporate social responsibility precisely in line with sustainability issues of the local populace. Artificial intelligence is also shown to facilitate this avenue through a cross-sectional analysis of societal issues and deciphering their relationship the interrelationship of society with that certain organisation (Garg et al., 2018). After accurate identification, the firm could strategies to develop its human resource, which would work towards attaining more social sustainability.

Artificial intelligence coupled with day-to-day other digital technologies within the organisation could also help improve normal management. Through automation of repetitive administration related tasks, HR managers find it easier to focus on matters which are more human-centric (Sinniah et al., 2020). Although, Yawalkar (2019) propounded that workforce management still continues to remain a task requiring human intervention. In this respect, the utilisation of AI in human resource management could be deemed as a tool to help HR in strategising for litigation, synthesis of new policies, monitoring and processing of data, managing payrolls, and investigate compliance with industrial codes etc. (Yawalkar, 2019). Since green practices in HRM mandate precision and easy availability of wide-ranging data related to human resources, some theorists like Bag et al. (2021) asserted that true green HRM is not possible without the facilitation of artificial intelligence and big data implementation.

The findings also unveiled that moderation of HRM system and e-recruitment was identified to be significant. Whereas moderation of integrated performance management system was determined to be insignificant between the relationship of AI applications and green HRM. However, Silva and Lima (2018) asserted that technological aspects of HR, recruitment and performance management systems open chances of including breakthrough technologies such as AI, machine learning, deep learning and virtual reality to remodel growth and increase opportunities for future success with regards to organisations' vision, purpose and mission. Therefore, it can be deduced that technological dimensions are essential to consider while aiming to opt for using AI applications in the process of achieving sustainable HRM practices.

Conclusion

The highly competitive business market has compelled firms to be more technologically innovative than ever for the aim of maintaining a competitive advantage in the sector. Additionally, increasing the adoption of green and sustainable practices for avoiding hazards of climate change between businesses has provided firms with the thinking to improve their HRM processes via adopting environmentally friendly practices. Nonetheless, the use of advanced technologies such as AI is delivering the opportunity to smaller and larger firms to automate their procedures and save a significant amount of time, cost, and resources. The adoption of quantitative research allowed to gather data via survey questionnaire to analyse the phenomenon through the SEM technique. The findings unfolded that there is a significant correlation between AI applications and green HRM. It was also revealed that technological dimensions strongly moderate the strength of the relationship between AI applications and green HRM. Conclusively, there is a need to adopt AI to improve sustainable practices from recruitment to performance management.

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