Effective Organisational Behavioural Dimensions of AI HRM

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Abstract

In this conceptual paper an analysis of the effective organizational behavioral dimensions of the successful adoption and practice of AIHRM is undertaken. AIHRM adoption presents major challenges to the organization in the same way that any change programme encounters. Implementation of AI HRM in organizations brings about substantial outcomes to the organization provided the moderators are identified and controlled. The moderators identified include organizational behavioral process variables of structure, culture, leadership, change readiness, sense-making in organizations, technology acceptance, AI ecosystem and technology-organization-environment fit. Key theories like the technology acceptance model, theory of planned behavior, unified theory of acceptance and use of technology, and human-organization-technology fit are discussed to put forward the importance of technology acceptance. The moderators moderate the relation between AI HRM technology and effective HRM outcomes. However good the AI HRM technology appears to be, unless and until the moderator variables are attended to, the effectiveness of the same may be diminished as the context of the implementation cannot be overlooked.

Keywords: Artificial Intelligence, AI HRM, Organisational behaviour, Organisational Effectiveness

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Introduction

AI is the talk of this age as it has captured the imagination of the professionals and the non-professionals in all walks of life. The applications of AI have permeated everywhere, and all information and communication technology operations are mediated by this magic of algorithms that take on human functions accomplishing the objectives on its own for which it is set. There is hardly any field that does not depend on the applications of AI in some way and the fields include medicine/healthcare, entertainment, service industry like HRM, marketing, finance, e-commerce, agriculture and accounting, education, sports, manufacturing industry, space research, governance and the list goes on (Titareva, 2021). The explosion of AI applications being recent, it is also evident that a major segment of the workforce is still grappling with its complexities and the industry personnel is no exception to this (Tornatzky, Fleischer and Chakrabarti,1990). The problem that is confronted with the implementation of AI centres on the organizational behavior variables that either facilitate or inhibit the introduction, adoption and practice of AI HRM in business organizations (Kurup & Gupta, 2022). Ineffective organizational and human factors can result in "…underuse, resistance, workarounds and overrides, sabotage, and even abandonment…" of AI technology (Holden & Karsh, 2010, p.1). The objective of the paper is to delineate the same variables that can either facilitate or inhibit the implementation, adoption and practice of AI in human resource management functions in the context of the extant literature.

Conceptual Background Literature

Even when AI applications are ubiquitous it is found that there is no single definition that is accepted in the literature which is due to its varied nature and applications (Chowdhury, Dey, Joel-Edgar, et al., 2023). For Mikalef, Krogstie, Pappas et al., (as cited by Chowdhury, et al., 2023, p.2) "AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals". A second definition of AI as given by Yao, Jia, and Zhou, (2018) focuses on machines using algorithms to make human-like decisions. AI is also viewed as a computing technology that functions like human intelligence which is not technical but cognitive, emotional and sensitive to other realities of human life in a limited way and not in the fully developed way as of now (Pereira, Hadjielias, Christofi, et al. 2023; Vrontisa, Christofia, Pereira, et al., 2021). A definition that appears to be comprehensive and explanatory is that of Chowdhury, et al., (2023) who define "AI as the ability of a man-made system comprising of algorithms and software programs, to identify, interpret, generate insights, and learn from data sources to achieve specific predetermined goals and tasks"(p.1). The two key aspects of this definition are that it is artificial (man-made), and it has the form of intelligence, that is learning from the past, the current and the projected future data in the same way human beings learn from their experiences (Chowdhury, et al., 2023). It can be inferred from this definition that the nature and the applications of AI are evolving as newer developments are taking place.

AI, the industrial revolution 4.0 can be characterized by big data, machine learning, deep learning, generic algorithms, neural networks, smart robots, virtual and augmented reality applications mobile technology, the Internet of Things, geo-tagging, virtual reality, speech recognition, bio-metrics among others have changed the way business is run and managed and there is the launch of AI HRM in business organizations to hand over the human resource activities to machine intelligence (Budhwar, Malik, De Silva, et al., 2022; Vrontisa, et al., 2021; Pereira, et al. 2023). These technologies are classified into weak and strong AI wherein the former function "as if they are intelligent" and strong AI is identical to human intelligence (Pereira, et al. 2023, p.2).

AI HRM produces countless benefits in theory but in actual practice, any technology adoption or for that matter AI, presents serious impediments to its fruition that emerge from the organizational participants, the organizational structure and the organizational context which are largely non-technological in nature but behavioral and socio-psychological (Fakhr Hosseini, Chan, Lee, et al., 2024; Budhwar, et al., 2022). The need to analyze the socio-psychological-organizational processes that either mediate or moderate the relationship between AI HRM technology and AI HRM outcomes is underlined by researchers (for e.g. Budhwar, et al., 2022; Fakhr Hosseini et al., 2024; Chowdhury, et al., 2023). Human-AI configuration demands reorganizing, restructuring and renewing organizational behavioral processes in the context of AI, without which the intended AI HRM outcomes would be machine-centric and devoid of employee satisfaction and optimum performance of organizations as there are several organizational behavioral factors that prevent the successful adoption of AI (Hamm & Klesel, 2021; Budhwar, et al., 2022). It is this gap in literature, the significance of moderators in the adoption and practice of AI HRM and effective organizational outcomes that becomes the focus of this study.

To study the adoption of innovative technology in organizations one finds significant models that explain the process of adoption (Taherdoost, 2018). Roger's model of innovation, referred to as the diffusion of innovation, which is nothing but the adoption of technology that comprises hardware and software in organizations identifies it as "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation" (Rogers, 2003 p. 172). The five steps of the innovation-decision process are (1) knowledge, (2) persuasion, (3) decision, (4) implementation, and (5) confirmation (Rogers, 2003). The technology acceptance model (TAM) states that the acceptance of the new technology is determined by the favourable attitude and the behavioral intention, equivalent to its acceptance, which is formed by the perceived ease of use and the perceived usefulness of the technology (Holden & Karsh, 2010). The technology acceptance model 2 (TAM 2) is an improved version of TAM wherein two groups of factors, social influence (image, subjective norms and voluntariness) and cognitive (results in demonstrability, job relevance and output quality) are added (Holden & Karsh, 2010; Taherdoost, 2018). An integrated model of technology acceptance was suggested by Venkatesh, Morris, Davis, et al., (2003) labelled Unified Theory of Acceptance and Use of Technology (UTAUT) in which effort expectancy, performance expectancy, social influence and facilitating conditions lead to the development of behavioral intention in the adoption of technology. Besides these models, there are other explanations like the social cognitive theory, motivational theory, perceived characteristics of innovation theory and the like that focus on similar variables drawn from the person, environment (organizational conditions and processes), behavior and the nature of the technology in the adoption of technology (Taherdoost, 2018; Rana & Dwivedi, 2015). In the light of these models, a general model of the adoption of AI HRM in organizations that incorporates these variables is put forward.

A General Model of AI HRM

AI-mediated HRM practices are the golden tool in the hands of the HR department provided its adoption and practice cater to the content and contextual variables of AI HRM technology. The content variables refer to the quality of AI tools whereas the contextual variables are the structural and behavioral variables that moderate the relationship between AI HRM and HR outcomes (Budhwar, et al., 2022; Fakhr Hosseini et al., 2024). AI HRM applications include recruitment and selection (AI takes over the function of screening and identifying the potential candidates and even making an intelligent decision), training and development functions (AI HRM does the training need identification at the individual, task and organizational levels and develops the training content including the role of an AI trainer, if the situation demands so), performance management (AI software conduct the performance analysis of employees on a reliable and valid basis which can be in the pattern of a 360 degree evaluation, devoid of human bias and errors), human resource planning (supply and demand forecasting of personnel is undertaken by AI HRM), compensation management (functions like compensation determination based on objective criteria, distribution of incentives, development of new incentives, promotional decisions, transfer decisions and much more can be transformed into AI operations) (Jia, Guo, Li, et al.,2018; Alsaif & Aksoya, 2023; Pereira, et al. 2023; Tewari & Pant, 2020). These stand-alone AI HR tools/functions are moderated by the organizational behavioral processes that finally underlines the AI HRM effectiveness.

Figure 1 depicts the model that specifies the relationship between AI tools, AI HRM activities and the moderating variables influencing HR effectiveness.

Successful adoption and practice of AI technology in organizations are to be accompanied by changes in the organizational, behavioral processes, and task-related processes that in many instances become either a mediator or a moderator of critical significance (Napier, Amborski and Pesek, 2017). The moderating variables discussed include task-related variables, organizational structure, organizational culture, leadership, behavioral processes of change readiness, sense-making in organizations, technology acceptance, AI ecosystem and the technology-organization-environment fit.

Task-related variables

In the Hackman and Oldham model (1976), the job characteristics of skill variety, task significance, task identity, autonomy and feedback determine employee psychological states and individual organizational outcomes (Hackman & Oldham, 1976). Skill variety is that aspect of work that involves the use of different skills in performing various activities which is contrary to skill homogeneity of applying the same skills in the performance of same-level jobs. Task identity is defined as the completion of a whole identifiable piece of work. Task significance connotes the extent of impact the work is going to have on the immediate environment of the work setting and the remote environment outside the organization. Autonomy in the work provides the worker with independence, discretion and freedom to operate without taking direct orders from higher-ups and without frequent consultation. Another task-related variable suggested in the job characteristics model is that of feedback, the knowledge of results that the employee gets following his performance. The job characteristics model holds good with respect to employee responses and the relationship between job characteristics of skill variety, task identity, task significance, autonomy, feedback and behavioral outcomes are meaningful beyond criticism (Fried & Ferris, 1987). Job characteristics are found to be influencing the internal work motivation of employees (Batchelor, Abston, Lawlor, et al., 2014). What is inferred from the job characteristics model is that when going for AI, the identified job characteristics are to be incorporated into the job to avoid monotony and job dissatisfaction. Based on the extant literature the following postulates can be developed:

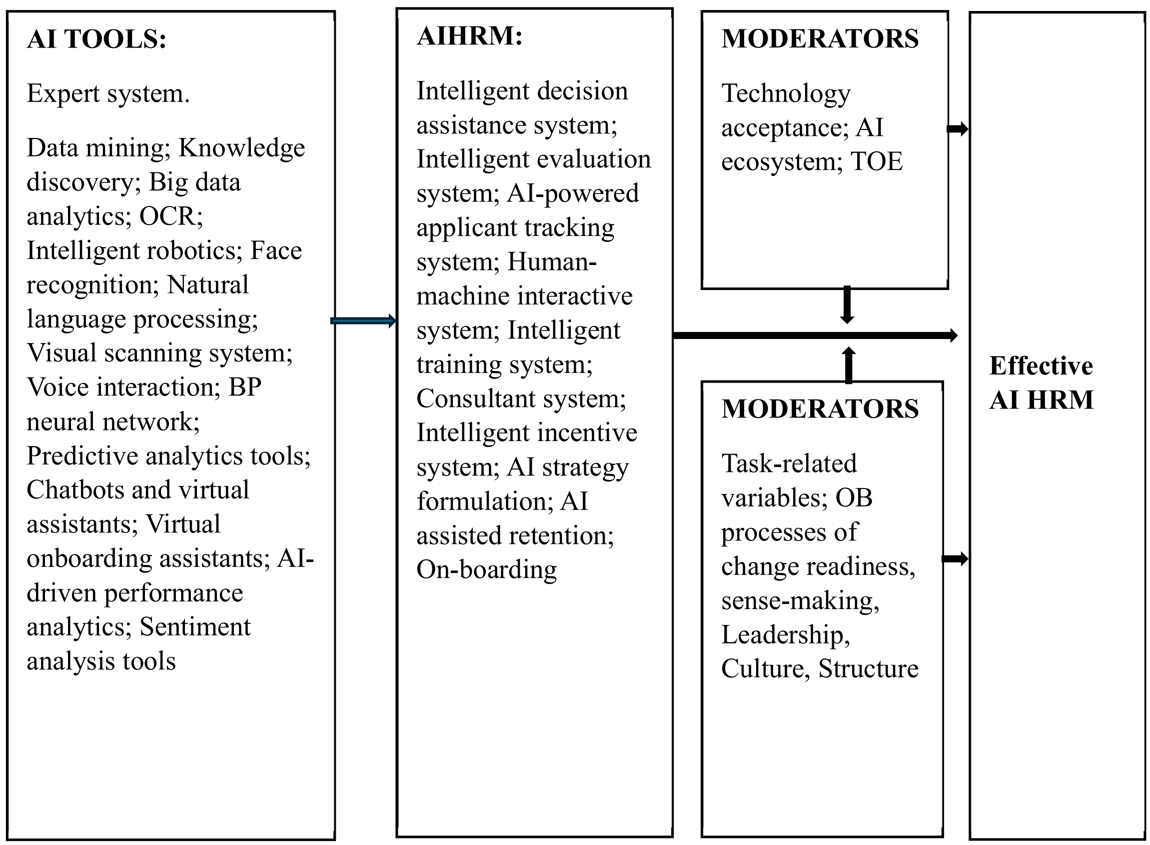
Postulate 01: Skill variety is significant in the adoption of AI HRM in organizations

Postulate 02: Task significance exercises an influence on the adoption of AI HRM tools

Postulate 03: Task identity plays an important role in the adoption of AI HRM tools

Postulate 04: Autonomy granted to the organizational participants acts as a facilitative variable.

Postulate 05: The practice of giving constructive feedback is important in technology adoption



Adapted from Jia, Guo, Li, et al., (2018)

Fig. 1. An Effective AI HRM Model

Organizational structure

The organizational structure is defined as "a system that determines how tasks are formally structured and coordinated within a group that is intentionally organized to accomplish a common goal" wherein the structure can be small or large, the nature of which can influence easy or difficult adoption of AI (Nene & Pillay, 2019, p.11; Hamm & Klesel, 2021). Along with the size of the organization, the mechanistic or the organic way the tasks are coordinated and integrated with the personnel in the organization that shapes and patterns the structure of the organization can influence the success rate of adoption. Mechanistic structures are patterned in accordance with the principles of specialized differentiation between jobs, well-defined expectations as to employee performance, cultivation of impersonal relations and a rigid hierarchical structure (Jewczyn, 2010). Organic structures are denoted by shared relations and diffusion of knowledge that does not always depend upon the strict system of rules and regulations, that does not depend upon a rigid bureaucratic structure of impersonality (Jewczyn, 2010; England, Stewart & Walker, 2000). Centralisation, which is a characteristic of bureaucratic structures, goes against the letter and spirit of innovation adoption in accordance with the diffusion theory of innovation (Rogers, 1995). Rigidity and bureaucratic processes do not encourage innovation adoption in organizations (England, et al., 2000). Another significant facet of organizational structure that promotes the easy adoption of technology as pointed out by Rogers (1995) is the organizational interconnectedness, the rate of which is indicative of the rate of adoption of innovation, which means that highly interconnected organizations are more likely to embrace innovations like AI.

It is also found that the autonomy and empowerment of employees are contingent upon the way the organization is structured wherein organic structures promote empowerment and transformational changes in the organization. In contrast, mechanistic structures constrain employee performance bringing in organizational inefficiency (Dust, Resick, & Mawritz, 2014). Less formalized and flexible organizational structures of an organic nature enhance employee and organizational performance. In the theory of diffusion, Rogers (1995) states that high formalization is a barrier to innovation adoption. Organizations are to reframe and restructure the existing patterns of organizations to embrace new technological innovations like AI. Organizational restructuring in organic mode becomes the fundamental way of introducing and maintaining the new technology on the path to transforming it into a core competency (Rizzoni, 1994). In relation to the nature of a facilitative organization structure for new technology adoption, the following postulate may be formulated:

Postulate 06: Organic structure facilitates easy AI adoption for HRM practices.

Organizational culture

The system of values, norms, beliefs, attitudes and assumptions that shape the behavior of the people in the organization is its culture (Sokro, 2016). The behavioral practices of employees, the interpersonal interactions, the employer-employee relations, the decision-making process, the leadership patterns and the communication styles besides the motivational strategies adopted by the organization are influenced by the culture reflected in the values, meanings, interpretations, beliefs and assumptions of the people (Nene & Pillay, 2019; Sokro, 2016). High-performance organizational culture as advocated by Truskie (1999) includes the four key elements of cooperation, consistency, achievement and inspiration. The classification of culture into a quadrant based on the two dimensions of sociability and solidarity of Goffe and Jones (1996) provides insights into the type of culture that promotes high organizational effectiveness. The four cultures suggested are 'fragmented' (low sociability and low solidarity), 'mercenary' (high sociability and low solidarity), 'networked' (high solidarity and low sociability) and communal (high sociability and high solidarity). The Truskie (1999) elements of cooperation, inspiration, consistency and achievement resonate well with these quadrants of organizational culture. Organizational culture goes a long way furthering the performance of individuals, groups and the organization. Understanding the causal link between the organizational culture and employee performance and the effectiveness of organization is the first step in the cultivation of an appropriate culture that suits the employees as well as the organizational functioning from the point of view of the adoption of A I technology (Malagas, Gritzalis, Nikitakos, et al., 2017). The significance of understanding and shaping the corporate culture in the adoption of AI tools is stated in the postulate:

Postulate 07: Communal organizational culture of high sociability and high solidarity is conducive to AI HRM

Behavioral processes of change readiness

Readiness for change is a process that is to be seriously considered in any radical/fundamental change programmes like the introduction of AI in HRM as the adoption of new technology rests with the initiative and drive of the organization, small as well as big ones (Nair, Chellasamy, & Singh,2019). Introducing change programmes without assessing the change readiness at the individual, group and organizational level is doomed to fail and poorly managed change efforts drive the organization to the depths of crises (Rafferty, Jimmieson & Armenakis, 2013). Change readiness may be defined as "a demonstrable need for change, a sense of one's ability to successfully accomplish change (self-efficacy) and an opportunity to participate in the change process" (Cunningham, Woodward, Shannon, et al., 2002, p.377). Yet another noteworthy definition is that of Holt, Armenakis, Feild, et al., (2007) who define it as "the extent to which an individual or individuals are cognitively and emotionally inclined to accept, embrace, and adopt a particular plan to purposefully alter the status quo". Rafferty, et al., (2013) refer to the facets of cognitive and affective components of individual-level change readiness. In the cognitive realm, the two systems of beliefs that ready the individual to change are that change is unavoidable and essential to compete and the belief that the individual and organization have the capacity, the resources and the know-how to bring about change (Rafferty, et al., 2013). The affective dimension of change is to be assessed at the levels of discrete emotions like delight, love, surprise, etc. (Rafferty, et al., 2013). It is to be emphasized that change readiness is to be assessed not only with respect to individual-level change readiness but also organization-level change readiness, both of which are significant in the introduction of great technologies that can bring about sweeping changes in the functioning of the organizations (Napier, et al., 2017). The discussion on change readiness leads to the following postulate:

Postulate 08: Organizations are to be change-ready for the adoption of innovations like AI technology.

Sense-making in organizations

It is the process of individuals and groups "seek(ing) plausibly to understand ambiguous, equivocal or confusing issues or events…" (Brown, Colville, & Pye, 2015, p.266). Lessening ambiguity involves finding an answer to the question "…what is going on…" and equivocality is the process of clarifying the actions by attending to it and in the process, what is going on is shaped giving meaning and interpretations to the organizational participants (Brown, et al., 2015, p.266). The definition given by Cornelissen (2012) is that "sense-making refers to processes of meaning construction whereby people interpret events and issues within and outside of their organizations that are somehow surprising, complex, or confusing to them (p.118). The definition given by Maitlis and Christianson (2014) is that it is "a process, prompted by violated expectations, that involves attending to and bracketing cues in the environment, creating inter-subjective meaning through cycles of interpretation and action, and thereby enacting a more ordered environment from which further cues can be drawn" (p.67). The meaning that runs through these definitions focuses on deriving a meaning and creating interpretations of the environment that might be contradictory to the initial ones as the process of meaning development is an inter-subjective process that involves interaction, sharing and discourse (Brown, et al., 2015). It can be inferred from this that the two dimensions of sense-making are sense-giving and collective (individual/group) sense-making (Mesgari & Okoli, 2019). Individuals and groups are always involved in the process of sense-giving and sense-making "sequentially, simultaneously and interactively" (Mesgari & Okoli, 2019, p.9).

In discussing the different forms of sense-making, Maitlis and Christianson (2014) refer to environmental sense-making, interpersonal sense-making, resourceful sense-making, and prospective sense-making and to this technology-related sense-making may be added in the context of AI HRM (Mesgari & Okoli, 2019). AI technology can be understood … "in very different ways by various people in diverse contexts, and this makes it necessary for individuals and collectives to make sense of technology before acting on it (Mesgari & Okoli, 2019, p.14). Sense-making of AI technology enables individuals and groups to make sense of it in terms of coordinated actions, varying applications and the accomplishment of organizational objectives. Adapting to AI technology demands sense-giving and sensemaking in individual and group interactions. The literature on sense-making brings up the following postulate:

Postulate 09: Sense-giving and sense-making are important moderators of the adoption of AI HRM in organizations.

Leadership in the context of AI

AI has unsettled the working of traditional organizations, and it continues to impact and challenge some of the classical principles of leadership that necessitate restructuring and renewing of the existing structure and the process of leading in the organizations as digital manager/leader effectiveness becomes instrumental in the path towards making AI HRM successful in organizations (Hamm & Klesel, 2021; Peifer, Jeske, & Hille, 2022). The leadership that is envisaged in AI-powered organizations is a "suitable leadership approach within an age of digital disruption… (and one that involves) calculated use of a company's digital assets in order to achieve business goals" (Breuer and Szillat, as cited by Titareva, 2021, p.7). Digital or AI leader as against the classical leader is to be leading in a digital way/path that focuses on AI-human interaction. This requires the redrawing of the leadership functions in terms of realignment of the task that involves human-AI interaction. This is a challenging role that a leader must assume as there are follower sentiments that cannot be ignored. In accordance with the findings of Peifer, et al., (2022) it is the responsibility of the leader to design the AI-human interaction based on the principles of protection of the individual, trustworthiness, sharing of resources and work-related outcomes, favourable work conditions of physical, interpersonal and social nature. Westerman, Bonnet, and McAfee (2014) suggest that leaders of high-tech digital organizations become successful in the event of creating a transformative digital vision, energises employee engagement, focuses on digital governance, sustaining and building a technological leadership that is responsive to the needs of the techno-environment.

Titareva (2021) identifies three different perspectives investigating the impact of leaders and leadership in the era of AI. The enhancement perspective emphasizes that "AI will enhance organizational leadership by taking care of the tasks that currently require time and energy of managers/leaders of modern organizations, as well as help top leadership of organizations with huge amounts of data and ready-made analysis of it" (Titareva,2021, p.9). Leaders in their leadership process and AI technologies are to come together to create cooperative models of efficiency. AI to its maximum extent can only assist the leaders and the leadership functions and not replace leadership.

The second perspective is the replacement perspective (Titareva, 2021) that in future there is no need for human leaders with flesh and blood who will be reactive, proactive and interactive with the followers following their needs, emotions and motivations. Robotic leaders are to be a reality in the near future. To top it all, not only leaders but followers too will cease to exist in the organization as organizations become robotic. The third perspective is the skeptical one that considers AI as an exaggerated fully blown balloon that may burst out sooner rather than later, forcing organizations to reduce their dependence on artificial intelligence as it is clearly artificial and not natural. AI is "an oversold idea" that will soon evidence its limitations in the human sphere of living killing the beauty of human life in the perspective (Titareva, 2021, p.17).

The three different perspectives, however, do not deny the reality of AI taking over some of the traditional functions of leaders and managers in organizations to increase the efficiency of leadership. Human leadership will thrive in a different manner that hopefully will ease the task of leading and impart a humane touch to the followers. The complete uprooting of human leaders/managers and leadership is a distant possibility that cannot be forecasted as of now. Drawing upon the different perspectives of AI leadership in organizations, the following postulate can be derived:

Postulate 10: Leadership can enhance the effective implementation of AI HRM tools in organizations

Technology acceptance

Another key variable that determines the effectiveness of AI adoption in the realm of HRM practices is the extent of technology acceptance in the organization. Of the many different interpretations of the adoption process, four significant approaches are considered here. The first model is known as the technology acceptance model (TAM). Originally proposed by Davis, Bagozzi & Warshaw (1989), TAM posits that perceived usefulness and perceived ease of use, a cognitive response to the adoption of technology become the precursor to the development of an affective response to technology in the form of a favourable attitude (intention to use) that leads to the actual use of technology. Perceived usefulness means "the degree to which an individual believes that using a particular system would enhance his or her job performance" (Davis, et al.,1989, p.25). Perceived ease of use is defined as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, et al.,1989, p.25). Attitude "refers to the degree of evaluative affect … that an individual associates with using the target system in his or her job" (Davis, et al.,1989, p.25).

A revised version of TAM was published known as TAM 2 in which the antecedents of perceived usefulness were specified as subjective norm, image, job relevance, output quality, and results demonstrability (Holden & Karsh, 2010). Subjective norm refers to the opinions of important individuals, associated with the individual, as to the person's use of the system, which is also a social influence process. Perceived usefulness and perceived ease of use together determine an individual's intention to use the system which is equivalent to the actual use of the technology (Holden & Karsh, 2010).

The second model considered is the unified theory of acceptance and use of technology (UTAUT) advocated by Venkatesh, Morris, Davis, et al., (2003). The core variables of the model include performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC) wherein PE is the gain that the individual is likely to obtain from the use of the technology, EE is the ease of use of the technology, SI is the demand placed by others on the individual to use the system and FC connotes the technical and infrastructure support available in the use of the technology. These are the antecedent variables that generate the behavioral to use the technology and theory is so called because it incorporates the variables suggested in other models of technology adoption including TAM, theory of reasoned action, theory of planned behavior and innovation diffusion theory Venkatesh, et al., 2003).

The third model discussed is the human (H)-organization(O)-technology(T) fit wherein the three dimensions "mutually interact with and influence each other through their bi-party relationships, i.e., the HO fit, HT fit, and OT fit, and finally impact the overall HOT fit" (p.5). The overall fit/congruence between/among the variables is derived from the bi-party relationships. The greater the bi-party and tripartite fit between/ among the variables, the greater the chances of technology adoption that will not compromise on human/technology/organizational factors (Xu, Lu & Papadonikolak, 2022).

The fourth model is known as the concerns-based adoption model (CBAM). Proposed by Hall, George, and Rutherford (1973) this model specifies how individuals experience change, and it provides a framework for assessing the implementation of technology. The seven Stages of Concern are unconcerned, informational, personal, management, consequences, collaboration, and refocusing.

These models imply that AI adoption is not a straightforward pattern of behavior as resistance to change is natural (Bovey & Hede, 2001). Individuals and groups show resistance to technology adoption at behavioral, social, political and economic levels. At the behavioral level the six sources of change resistance identified are (a) unwillingness to lose control, (b) cognitive rigidity, (c) poor psychological resilience, (d) intolerance and impatience with the adjustment/cooling period involved in change, (e) preference for low levels of stimulation and novelty, and (f) adherence to old habits (Oreg, 2003). Successful adoption of technology entails that the barriers are properly identified and dealt with before the actual introduction of AI technology. The process of embracing AI can go through four phases of initial denial, resistance, gradual exploration, and eventual commitment (Bovey & Hede, 2001). The models of technology acceptance give the following inference:

Postulate 11: Behavioral intention constitutive of cognitive, affective and motivational domains acts as an antecedent to technology adoption by individuals and groups in organizations.

AI ecosystem

Oxford English Dictionary defines an ecosystem as "a biological system composed of all the organisms found in a particular physical environment, interacting with it and with each other. Also in extended use: a complex system resembling this". The ecosystem concept is widely used in the business and management context wherein it can have features like "…the existence of numerous role players, inter-dependence of its components, cooperative evolution, dynamism and flexibility, simultaneous existence of competition and cooperation, shared fate, contribution to making innovations and achieving business successes" (Tafti, Kordnaeij, Hoseini, et al, p.201). The concepts of business ecosystems, industrial ecosystems, entrepreneurial ecosystems, knowledge ecosystems, brand ecosystems, organizational ecosystems and related ones are explored in the organizational and management research (Grumadaitė & Jucevičius, 2022). In the same vein, an AI ecosystem concept implies human and the non-human agents inside and outside the organization who are in a system of networked dynamic organization powering HRM intelligence.

The five essential principles of the ecosystem as drawn by Tsujimoto, Kajikawa, Tomita, et al., (2018) hold good when applied to an AI ecosystem. The first principle is that organic networks that function without a central hierarchical structure of control, and it can involve positive and negative aspects like ecosystem-level competition, predation, parasitism, and destruction of the whole system (Tsujimoto, et al., 2018). The second principle is that decisions taken by each participant are rational and are influenced by individual attributes, distinctive decision-making principles and purposes which may produce unintended consequences in the system. The third principle is that the ecosystem is beyond the geographical boundaries whereas it is defined by the service/product system. The fourth principle spells out the need to have the dynamic evolution of the product/service system studied longitudinally. The fifth principle refers to the emerging decision-making and behavioral chains that strongly affect the very future of the ecosystem (Tsujimoto, et al., 2018). To be sustainable, innovative, flexible and responsive, the AI ecosystem is to be governed by these principles as enshrined by Tsujimoto, et al., (2018). The postulates derived are:

Postulate 12: Effective organic networks facilitate positive aspects and inhibit negative trends.

Postulate 13: Decision-making influenced by individual attributes plays an important role in the implementation of AI tools in HRM.

Postulate 14: Non-business actors outside the formal boundary hold a significant influence on the effectiveness of AI HRM.

Postulate 15: Integration of all the sub-systems in the AI ecosystem promotes effectiveness

Technology-organization-environment fit

Technology-organization integration is a hallmark of effective organizations, and technology-organization compatibility ensures that there are only reconcilable differences between them in the event of incompatibility (West, 2001; Jere & Ngidi,2020). The technology-organization-environment (TOE) framework, a broader version of the AI ecosystem, advocated by Tornatzky, Fleischer and Chakrabarti (1990) enlists the interacting variables in technology adoption. The technology context of the TOE framework implies the variables of relative advantage, complexity and compatibility, the organizational context revolves around firm size, technology knowledge, financial resources and top management support and the environmental context pertains to government support, external support and competitive pressure (Tornatzky, et al., 1990). The relative advantage of AI technology in comparison to other technologies must be proved and that it provides superior advantages to the firm in many levels of operation. Compatibility is the seamless interaction between the organizational functioning and the technology processes. The complexity is the ease of use of technology and whether it presents cognitive, emotional and motivational challenges to the user. The size of the firm is a matter of concern as small and medium-sized firms are more flexible in following advanced technologies unless and until large firms do not take note of extra effort to be expended in implementing it (Jere & Ngidi, 2020). Government support, competitive pressure and external support also influence the effective functioning of AI HRM in an indirect way. TOE framework yields the following postulates:

Postulate 16: Relative advantages, complexity and compatibility of technology make the adoption smoother.

Postulate 17: Firm size, technology knowledge, top management support and financial resources determine the successful adoption of technology.

Postulate 18: External support can be vital in making the adoption successful

Postulate 19: Competitive pressure can exert an influence on the adoption process

Postulate 20: The interaction between technology, organization and environment can determine the nature of adoption.

The postulates derived from the model are primarily organizational behavioral variables except for a few that are technology related. The empirical verification of these postulates can prove the application of this model in the adoption of AI technology for HRM practices.

Conclusions

AI endows the organization with a superior competitive advantage besides ensuring the continued functioning of its operations with greater returns. In the same way, that every technology hurts its man-machine interaction, AI also suffers from it without exception. The challenge before the management is to minimize its negative effects by a scientific approach that makes use of the organizational behavioral principles of effective functioning that ensure employee satisfaction and organizational productivity.

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