Artificial Intelligence–HRM Interactions and Outcomes: A Systematic Review and Causal Configurational Explanation

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ABSTRACT

Artificial intelligence (AI) systems and applications based on them are fast pervading the various functions of an organization. While AI systems enhance organizational performance, thereby catching the attention of the decision makers, they nonetheless pose threats of job losses for human resources. This in turn pose challenges to human resource managers, tasked with governing the AI adoption processes. However, these challenges afford opportunities to critically examine the various facets of AI systems as they interface with human resources. To that end, we systematically review the literature at the intersection of AI and human resource management (HRM). Using the configurational approach, we identify the evolution of different theme based causal configurations in conceptual and empirical research and the outcomes of AI-HRM interaction. We observe incremental mutations in thematic causal configurations as the literature evolves and also provide thematic configuration based explanations to beneficial and reactionary outcomes in the AI-HRM interaction process.

Keywords:

Artificial intelligence, HRM, Systematic review, Thematic causal configurations, Fuzzy set qualitative comparative analysis

1. Introduction

Artificial Intelligence (AI) systems, and applications based on them, have started pervading personal, social, and organizational spaces (Haenlein and Kaplan, 2019; Tarafdar, Beath and Ross, 2019). Personal assistants (e.g. Cortana), home assistants (e.g. Alexa), and organizational interfacing assistants like chatbots, are promising and delivering enhanced efficiency and user convenience. Organizations too have started realizing the efficiency-based advantages (Tambe, Cappelli, & Yakubovich, 2019) obtained by leveraging AI systems in a variety of applications as well as higher-order decision making functions (Evans and Kitchin, 2018; Merendino, Dibb, Meadows, Quinn, Wilson, Simkin, & Canhoto, 2018). However, the expected surge in AI adoption by organizations has been anything but smooth (Brock & von Wangenheim, 2019). For one, given the organizational legacy, finding the optimal system has been a corporate resources, are known to oppose its adoption (Choudhury, Starr, & Agarwal, 2020). More importantly, the exponentially expanding AI capabilities into analytical and thinking tasks are speculated to restrict human workers into the ever-narrowing niche of interpersonal and empathic tasks.

Thus, on the one end of the spectrum, AI has the *potential* to herald a technological long wave which may impact human resources within the organization in different ways (Abrahamson, 1997; Ayres, 1990a; Ayres, 1990b). While it may create new job roles, AI may also rationalize existing roles (Miroshnichenko, 2018) causing livelihood uncertainties for employees who are otherwise unable to adapt to it. Such lack of adaptation may trigger organization-wide unrest, compromising the gains from AI adoption and increasing governance cost. On the other end of the spectrum, it is equally possible that AI may just be another management jargon (Braga & Logan, 2017), that caught the fancy of academia and practice as a *novel but transient bargaining opportunity to govern industrial relations,* but destined for a natural demise. Or it can be anything in between (Braga & Logan, 2019) or above the plane of human cognition like a *singularity* (Last, 2018; Potapov, 2018; Yampolskiy, 2018) and whose effects likewise on the organization and its human resources are beyond comprehension. We join the conversation and focus on how o*rganizations* in general *adopt* and *human resources* in particular *progressively adapt* to AI as the latter transgresses into the HRM domain. To that end we repose on three theoretical pillars, namely *evolutionary theory* (Nelson, 1985), *organizational adaptation* (Hrebiniak & Joyce, 1985; Miller & Friesen, 1980) *and uncertainty governance* (Carson, Madhok, & Wu, 2006; Folta, 1998; Weber & Mayer, 2014; Williamson, 1981) to guide our investigation. We commit ourselves to an epistemological search by raising *three* specific research questions namely:

(i) What are the emergent themes and subthemes at the interface of AI-HRM literature?

(ii) What are the causal configurations amongst those themes and subthemes that may provide us with a sense of *evolutionary direction* of the AI-HRM literature?

(iii) Are there any evolutionary *variances in the theme based causal configurations* between *conceptual* and *empirical* research at the interface of AI-HRM literature?

Nested within the *first question*, and drawing from adaptation and governance literature, we search for themes highlighting the nature of emotional/reactive and objective responses from the employees and the organization respectively and the antecedent themes/factors explaining those responses. We premise that any technological intervention including AI, will eventually become an *enabler* than *disruptor* as people adopt, *learn, and adapt* to the changes in their employment context. Thus, contingent on employment and the enabling governance contexts, AI may also receive objective responses from the organization as a whole. If, however, it consistently disrupts existing jobs, processes, and routines, empirical evidence will likely reveal reactionary responses from employees (Fountaine, Mccarthy and Saleh, 2019). Therefore, investigating the linkages amongst the contextual and governance themes, driving the adoption and adaption processes and the response outcomes, assumes importance. In continuation to the first question, the *second question* based on the *configurational approach and the evolutionary theory* helps us to determine the direction of evolution of the theme based configurations in AI-HRM literature. The second question is important for two reasons. First, it enables us to *causally* configure the identified themes/subthemes leading to specific response outcomes. Secondly, it helps us determine whether the initial interaction between HR and technological intervention (Abrahamson, 1997) exhibits *patterns of persistence or not.* For example, a persistence of reactionary response suggests a suboptimal adaptation and governance. While an *ex-ante* objective response, or its emergence *ex-post* to supersede the reactionary response, would suggest an evolution of configurations towards optimal adaptation and governance mechanisms that enable successful organizational adoption of AI (Kaplan and Haenlein, 2019). Building on the issue of persistence or subsequent change, the *third question* plots the variances in thematic configurations in the AI-HRM literature along methodological and temporal axes. Specifically, it attempts to identify configuration of themes/subthemes as conceptualized by some scholars vis-`a-vis as empirically reported by others, over an extended period of time. This is important as a convergence/similarity of causal configurations between theory and empirics will suggest enhanced managerial ability to device mechanism that mitigate uncertainties and increase organizational adaptation. However, *divergences along temporal axis* may suggest the persistence of high uncertainties (Pfeffer, 1990; Shapiro, 1957), and the need for a *continued search* for governance mechanisms and organizational adaptation. In short, a convergence will suggest an evolving sense of opportunity from AI and vice versa.

To answer our three research questions, we resort to a systematic literature review, coupled with stringent exclusion-inclusion criteria, to cull out a set of impactful articles from reputed journals that *jointly* refers to AI and HRM. We include all those subject words that capture those two concepts. Our search for the themes and nested/sub-themes follows a priori cause-effect framework to facilitate theorization. Further, with the abstracted themes/subthemes, we perform a *set theory* based qualitative comparative analysis (QCA) to identify the various causal configurations leading to specific (objective or emotional) outcomes. In line with our research questions, we analyze the causal configurations along *three dimensions*, namely *type* (conceptual vs empirical articles), *time* (early- vs late- stage), *and outcome* (objective vs reactive). Given the nascent and evolving stage of the AI-HRM literature, the empirical articles within the "type" dimension includes case studies as well. The "time" dimension is divided into early-stage research, and later-stage research. Finally, outcome is dichotomized as objective outcomes for the firm/organization and the reactionary outcome by people/ employees affected by AI.

Through this research, we intend to contribute to the AI-HRM literature in three distinct ways. First, we highlight the evolution of the dominant themes as investigated and reported by scholars over a temporal horizon in reputed journals. This content level identification of themes enables us to determine the evolutionary *response outcomes* to progressive levels of AI adoption in organizations and also to determine the combination of themes that leads in those outcomes. Secondly, at the process level, our research shows, via causal configuration, *how, why, and when* AI adoption may augur beneficial outcomes for the organization or disruptive outcomes due to employee reaction. Therefore, we provide evidence of the governance configuration themes that helps mitigate uncertainties (like adverse employee reaction) associated with AI adoption. Furthermore, our research exhibits temporal variances in the configurations and how the said changes impact the outcomes, as organizations and employees learn to adapt to uncertainties. Finally, we contribute *methodologically* by adopting the configurational approach to augur out the different sets of consistent and relevant themes and subthemes, and within them the set of factors that potentially affect and hence need to be governed in the context of organizational and human response to AI adoption and adaptation. Therefore, we contribute to theorization in a nascent but rapidly evolving discipline.

2. Literature review protocol – exclusion inclusion criteria

In reviewing the literature on leveraging AI through HRM, the primary challenge faced by scholarship is to define the scope of research, i.e., whether to study AI *and* HRM or AI *in* HRM. This jugglery of words, seemingly pedantic, is critical as one distinguishes between the *union* of two divergent sets of literature as opposed to their *intersection*. While union enhances the scope and breadth of review, an intersection sharpens the focus and depth. The current special issue solicits research at the *interface* of AI and HRM (Budhwar & Malik, 2020), implying an intersection. Consequently, we resorted to a *systematic review* (Denyer & Tranfield, 2009) due to its scientific nature, replicability, accuracy, and transparency in locating, evaluating, and incorporating previous literature (Booth et al., 2011; Fink, 2014). Systematic review is stringent and meticulous (Sageder, Mitter, & Feldbauer-Durstmüller, 2018), and needs reviewers to compile all available details of a phenomenon, comprehensively and in an impartial manner (Denyer & Tranfield, 2009). In the process of systematic review, we followed integrative literature search (Callahan, 2010, 2014) involving (i) database used, (ii) time of search, (iii) keyword combination, (iv) rationale for the inclusion of articles that showed up as a result of keyword-based search in the database, and (v) collation and categorization of the selected and retained articles.

We used the ISI Thomson Reuter/Clarivate Analytics Web of Science (WoS) database and defined Boolean query words, without restricting the date of publications. We considered articles only in English (Sageder et al., 2018) and ignored working papers and conference proceedings (Nolan & Garavan, 2016) in general, except one conference paper, which we found too compelling to exclude, given the scope of this research and the perceived importance of that proceedings amongst scholars. We conducted the literature search in June 2020 and repeated the same a month later (July 2020), to check for database updates and human errors. For our search algorithm, we created two comprehensive sets of keywords. The first set pertains to literature on human resource management and the second concerns studies in the domain of artificial intelligence. In the HRM domain we included all terms in the HRM literature as well as associated literature from behavioral science, labor economics, sociology, and strategy that relates to resource based economic value of labor like knowledge management and organizational capabilities. This search consisting of 47 keywords resulted in 4,429,362 articles. In the AI literature we included everything associated with artificial intelligence in the information systems literature, decision science literature as well as new product development and innovation literature. This search with 39 keywords yielded 2,007,207 articles. The entire list of keywords, including their *wildcard* (asterisk) syntax, is presented in Table 1.

Since our purpose is to review the literature at the intersection/interface of these two kinds of literature, we followed a two-step process. First, we combined the keywords of the two sets and repeated the search. Second, in line with the set-theoretic intersection function, we created a matrix consisting of the 47 keywords from HRM literature in the columns and 39 keywords from AI literature in the rows. This produced a combined list of 1833 keywords. We searched the literature once again with those 1833 words. Eliminating the duplicates from the two-step search, we were left with 252,124 articles. We refined the search once again using the Business and Management category, specified under the *category subheading* in the WoS database. This process of sieving produced a list of 3298 articles. As this list itself was huge, we applied our penultimate process of refinement using the source titles and specific fields of 'HRM,' 'General Management,' 'Strategy,' and 'Information Management,'. To ensure quality and reliability of scholarly output/ findings, we further imposed two quality database restrictions at the final stage. We retained only those articles that appeared in journals ranked as A/A* in the Australian Business Deans' Council (ABDC – 2019 list) as well as journals ranked "3 and above" in the Chartered Association of Business Schools (ABS - 2018 list). This further refined our list to 433 articles.

Of the 433 articles identified above, we performed the staged review process (Torraco, 2005) by first reading the abstract and keywords to determine whether the article investigates the association between AI and HRM. Secondly, we read through the content to determine whether the said association refers to an in-depth deliberation or a cursory reference suboptimal and unrelated to review purposes. Finally, we were left with a set of 100 articles forming the basis of this review. The selected articles and their summarized contents are provided in supplementary data.

Insert Table 1 about here
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3. Content analysis and thematic abstraction

In undertaking content analysis and thematic abstraction within the identified articles, we were guided by our research question and in conjunction with the theme of the Special Issue, '*how HRM leverage AI'*. We adopted a *cause effect* based a priori theoretical framework, clustering factors as '*antecedent → process → outcome*' of AI adoption in HRM. Our content analysis yielded a total of seven broad themes and one hundred and forty three subthemes nested within the themes. The seven broad themes are further aggregated according to the aforesaid framework into (a) antecedent elements consisting of the themes (i) context, (ii) stakeholders, (iii) drivers – environmental, organizational, and individual, (b) process based elements consisting of the themes (iv) types of AI – robotic and non-robotic, (v) AI application, (vi) AI adoption process, and (c) the outcome based elements consisting of theme (vii) outcomes broadly divided into – objective and reactive outcomes. We began by investigating the antecedent themes and progressed towards the outcome based themes in the AI-HRM linkages.

3.1. Antecedent themes in AI-HRM linkages

As revealed in the systematic review, we identified three broad antecedent themes that influence the AI-HRM linkages. They are (i) context, (ii) stakeholders, and (iii) drivers. *Context* refers to the broad setting or the environment in which the research is embedded. Context can be demographic, cultural, industry-specific, or even the phenomenon under investigation (Shah, Irani, & Sharif, 2017; Stavrou, Charalambous, & Spiliotis, 2007). For example, researchers investigated algorithmic management and the development of apps in the *context* of the gig economy (Duggan, Sherman, Carbery, & McDonnell, 2020). Likewise, researchers investigated the advances in information technology and collective leadership embedded in the *phenomenon* of e-leadership (Avolio, Sosik, Kahai, & Baker, 2014). Literature also provided an *amalgamation of contexts* like the emerging e-platforms and e-aggregating industry (e.g., Airbnb, Uber) and the decentralized, defused, and informal *demographic profile* of workers engaged in flexible employment (Bondarouk & Brewster, 2016), where the traditional HR practices and processes might not fully apply due to evolving IT processes and practices (Angrave, Charlwood, Kirkpatrick, Lawrence, & Stuart, 2016; Holtgrewe, 2014).

Complementing context were the *stakeholders*, whom we identified as *institutional entities, specific groups, or individuals* who influence AI processes and applications (Fleming, 2019; Jantan, Hamdan, & Othman, 2010). AI-based research appear to simultaneously affect and or be affected by multiple stakeholders (Anandarajan, 2002; Bennis, 2013) apart from the key players. For example, implementation of AI in service counters displaced and thus affected the frontline workers in call centers (Robinson et al., 2020), sales personnel (Darr, 2019), gig workers (Jabagi, Croteau, Audebrand, &

Marsan, 2019; Ravenelle, 2019), individual stakeholders like software developers (Ghobadi & Mathiassen, 2020), and even seemingly unrelated manufacturing industry personnel (Lloyd and Payne, 2019a). Probable reaction from extant and would-be affected stakeholders in further adoption of AI forms a core aspect of AI-HRM literature. Literature also explored the role of employers and management in an ecosystem that fostered decentralized decision making and capacity building in an increasingly digitalized world (Barro & Davenport, 2019). Finally, in AI-HRM literature, we also found individual stakeholders in the form of future employees and their career aspirations and anticipations (Skrbiˇs & Laughland- Booÿ, 2019) in the face of increasing automation.

Last but not the least, an essential antecedent theme in AI-HRM literature is the *drivers*. We conceptualized drivers as factors that encourage or inspire the application and adoption of AI processes within an organization (Fountaine, Mccarthy, & Saleh, 2019; Jia, Guo, Li, Li, & Chen, 2018). Drivers can be human related, such as technology savviness of the workforce, or personality characteristics, or leadership traits (Edwards and Ramirez, 2016). It can also be organization specific, such as firm strategy, or financial position, or the nature of task by a group/team, or managerial skills and competencies (Cˆorte-Real, Oliveira, & Ruivo, 2017; McAfee & Brynjolfsson, 2012; Park, 2018; Shujahat et al., 2019; Sousa & Rocha, 2019). Finally, there are environmental drivers such as industry characteristics, condition of economy, issues of labor, and other market factors (v. Alberti-Alhtaybat, Al-Htaybat, & Hutaibat, 2019; Wright, 2015). The literature provides evidence of leadership role (Tumbas, Berente, & vom Brocke, 2018) and leader's traits (Thor´en, Ågerfalk, & Rolandsson, 2018) driving the adoption and implementation of new technology (Bolden & O'Regan, 2016; Spisak, van der Laken, & Doornenbal, 2019). The literature also emphasizes on the importance of human elements in interfacing and driving AI, which comes from the former's ability to analyze and interpret (Braun, Kuljanin, & DeShon, 2018; Davis, 1989) complex data driven actual decision (Davenport, 2013; Merendino et al., 2018). An example of such human elements may be the data scientists (Davenport and Patil, 2012) who favor use of

AI systems as they can leverage their tacit knowledge and intelligence (Fowler, 2000) to facilitate AI-powered decision making (Kryscynski, Reeves, Stice-Lusvardi, Ulrich and Russell, 2018).

In contrast, drivers also subsume factors that oppose or discourage the adoption and implementation of AI-powered processes or may directly lead to resistance against such technologies. For example, the preference of top management towards digital transformation (Hall, 1999) may generate more internal stress and resistance (Edwards and Ramirez, 2016) as implemented technologyconflicts with existing skills, biases, and domain expertise of the employees (Chao & Kozlowski, 1986; Tambe et al., 2019), threatening job losses (Metcalf, Askay, & Rosenberg, 2019) and thereby necessitating a resolution mechanism (Choudhury et al., 2020). These inhibiting drivers form the basis of reactive outcomes, which we have described subsequently under the outcome-related themes.

3.2. Types and process related themes in AI-HRM linkages

A systematic review of the process part yielded two broad themes, namely, the types of AI under consideration and their application/adoption option process within the organization (Nunamaker, Derrick, Elkins, Burgoon, & Patton, 2011; Shrestha, Ben-Menahem, & von Krogh, 2019). In terms of types, AI can be categorized into three groups, namely a) *mechanical AI*, which performs repetitive tasks for consistent and reliable performance; b) *thinking AI*, which autonomously learns to adapt from data; and c) *feeling AI*, which can understand emotions and interact empathetically with people. Huang, Rust, and Maksimovic (2019) have argued that the capabilities of AI are "expanding beyond mechanical and repetitive to analytical and thinking" (p.43). New algorithms in machine learning are already capable of interpreting body language, facial gestures, emotional mix, and unstructured text to draw conclusions about the human capital from whom such data is gathered (Faraj, Pachidi, & Sayegh, 2018; Kobayashi, Mol, Berkers, Kismih´ok, & Den Hartog, 2018). Choudhury, Wang, Carlson, and Khanna (2019) studied body language and facial gestures of CEOs to predict their organizational strategies, while Campion, Campion, Campion, and Reider (2016) advocated the use of predictive modelling in interpreting an unstructured text document in employee selection procedures. These studies provide critical insight into the evolving nature of AI, the discretionary drivers that enable the evolution, and their possible impact on organizational performances, employment, and job roles of subjective evaluators and analysts (Faraj, Pachidi and Sayegh, 2018).

Literature also provides evidence of four types of AI applications, namely (a) *robotics and automation* in the office environment (Barro & Davenport, 2019; Beane & Orlikowski, 2015), digital chatbots for customer interfacing (Robinson et al., 2020), workplace social robots (Bankins & Formosa, 2020), industrial robots in manufacturing plants (Ballestar, Díaz-Chao, Sainz, & Torrent-Sellens, 2020) and robotics in healthcare (Compagni, Mele, & Ravasi, 2015; Mettler, Sprenger, & Winter, 2017) and social work (Lloyd and Payne, 2019a); (b) *machine learning* in the context of recruitment standards based on past performance, current performance, and career prospects (Cappelli, 2019; Kiron & Schrage, 2019; Upadhyay & Khandelwal, 2018; Skrbiˇs & Laughland-Booÿ, 2019), as well as in the context of Natural Language Processing and Neural Networks (Gal, Jensen, & Stein, 2020; Somers, 1999; Speer, 2020); (c) *algorithms* in the context of gig platform management (Jabagi et al., 2019; Ravenelle, 2019) as well as generic application of predictive algorithms in HR decision making (Leicht-Deobald et al., 2019); and (d) *big data and analytics* discussed in the context of promoting organizational innovation (Fayard, Gkeredakis, & Levina, 2016; Ghasemaghaei & Calic, 2019) and digital transformation (Kane, Phillips, Copulsky, & Andrus, 2019; Kappelman, Johnson, Torres, Maurer, & McLean, 2019). For this paper, we broadly divided AI into two types, namely *Robotic Types*, which has existing applications and established adoption processes, and *Non-Robotic Types*, consisting of machine learning, algorithms, and big data analytics, which has more of emerging applications.

The literature on *AI types* also focuses on its ability to invoke technological singularity (Upchurch, 2018), which opens up infinite possibilities from a single event. Such possibilities can take the shape of intelligent *applications* and their corresponding *adoption processes* within the organization. On the one end of the singularity-induced spectrum are applications like Artificial Swarm Intelligence (ASI), which can mimic the collective behavior of groups, by drawing on the group's collective knowledge (Metcalf et al., 2019). For HRM, this kind of technology can help the management to predict the coordinated response of employees for any proposed organizational changes. Unlike a typical AI environment, which relies on machine learning to analyze large data sets and deliver insights to decision-makers, ASI is capable of extrapolating explicit knowledge coded within machine algorithm and drawing on real-time response of networked individuals' explicit and implicit knowledge, to facilitate decisions (Kane, 2017; Merendino et al., 2018). However, this also throws up the managerial challenge of creating suitable adoption processes to harness its full potential (Angrave, Charlwood, Kirkpatrick, Lawrence and Stuart, 2016).

On the other end of the AI spectrum, within the context of HRM, we find applications involving simplistic IT services (Bardoel & Drago, 2016), big data based ERP systems (Evans & Kitchin, 2018), or automation of operations (Gekara & Thanh Nguyen, 2018) that require creation of suitable adoption processes. Such adoption processes become even more critical as HR functions evolve to seamlessly adopt newer technologies (Huang & Martin-Taylor, 2013) without stressing the organization (Ayyagari, Grover, & Purvis, 2011). A conceptual study on the adoption of interorganizational intelligent meeting scheduler (IIMS) that concurrently interacts with its organizational environment by learning from users, provides an example of AI application and adoption process (Glezer, 2003).

Adoption of AI-driven technology and processes in the organization receives its impetus from a variety of intra-organizational and environmental factors. Such factors include (a) *nature and suitability of task* that requires a high degree of personal and emotional exchange, risks, and other verbal and non-verbal cues (Robinson et al., 2020); (b) *characteristics of users* as in age or period of exposure to technology, which helps in early stage experimentation and adoption (Ghobadi & Mathiassen, 2020); (c) *nature of data*, especially in the context of big data, namely data velocity, data variety, and data veracity contributing to organizational learning and innovation competency and hence aiding in adoption (Braun, Kuljanin, & DeShon, 2018; Davenport, Barth, & Bean, 2012; Ghasemaghaei & Calic, 2019); (d) *management mindset* centered around confrontation or surveillance (Theory X) vs conformity or empowerment (Theory Y) influencing the algorithms that drive employee activities (Ravenelle, 2019); and finally (e) *incentives* that encourage the adoption of AI-based processes amongst workers (Darr, 2019).

While the literature provides guidelines on the conditions for successful adoption of AI, it also highlights the critical and recurrent theme of the difficulties in the adoption of AI in HRM (Stone, Deadrick, Lukaszewski, & Johnson, 2015). For instance, AI systems are seen as *impersonal and passive* and are designed for one-way communication, thereby inhibiting interpersonal interaction and emotional support (Chao & Kozlowski, 1986). Finally, understanding the interaction between AI and HR involves *exploring the process of adoption* of AI-driven technology in human encounters in organization, and the *dynamics of such exchange*. An instance of this is found in the conceptual work of Robinson et al. (2020). The authors propose that the dynamics of service encounter would differ depending on whether the two parties involved are humans or artificial entities, leading to three possible scenarios of AI involvement namely, (i) AI frontline executive interacting with human customer, (ii) Human frontline executive interacting with AI customer, and (iii) AI-driven frontline executive interacting with AI-driven customer representative.

3.3. *Outcome related themes in AI-HRM linkages*

Finally, the systematic review of AI-HRM literature revealed *outcome* related themes. These outcomes are broadly divided into two groups, namely (i) *objective outcomes,* related to some performance parameters of the organization, and (ii) *reactive outcomes*, related to employees' reactions to AI implementation that, inter alia, include threat to their livelihood (Kim, 2018; Krzywdzinski, 2017; Mesgari & Okoli, 2019; Petrakaki & Kornelakis, 2016). Early studies highlighted a range of objective outcomes. Such outcomes included benefits from the adoption of technology-based expert systems, such as enhanced quality of decisions by supplementing *cognitive limitations* (Lawler & Elliot, 1996; Yoon, Guimaraes, & Clevenson, 1996), enhanced *operational efficiencies*, increased *speed and accuracy*, and optimized *resource allocation* for employee training (Beane, 2019).

In the context of crowdsourcing platforms and gamification (Cardador, Northcraft and Whicker, 2017), by studying the model of distributed nodes, researchers have reported the benefits of unconstrained workspace and the opportunity to access resources anywhere in the globe (Lindsay et al., 2014). Another objective outcome of AI adoption is the *hyper-specialization* of jobs that enhances speed and quality by opening up the entire global labor market, while reducing the cost of operation (Malone, Laubacher, & Johns, 2011). However, the effect of the large distance (geographically diverse labor market) on relationships, team building, and skilling processes need further study (Colbert, Yee, & George, 2016; Holtgrewe, 2014).

One of the common apprehension associated with AI and technology adoption is the *loss of jobs due to automation* (Rampersad, 2020), although productivity and performance-related improvements are commonly observed (Ballester et al., 2020; Stavrou, Charalambous, & Spiliotis, 2007; Tarafdar, Beath, & Ross, 2019). In a different context, the literature suggests that increasing reliance on algorithms and data analytics for organizational decision making may be counterproductive as it leads to *pervasive surveillance of employee behavior and invasion of privacy* and *oversimplification* of a complex situation (Gal et al., 2020). That apart, AI systems are found to yield limited objective outcomes for some of the outlier but important organizational issue such as *dismissal, sexual harassment, bullying, and theft* by employees (Tambe et al., 2019). These incidences, by their very nature, are non-routine and outlier events which may not always get reported. Hence simulating and creating a robust data set, especially in the SME context, becomes a challenge. Consequently, decisions based on such small data sets are likely to be inaccurate, biased and counterproductive which may trigger adverse, dark sided responses from employees (Davenport, Barth, & Bean, 2012; Merendino et al., 2018).

Finally, AI application and adoption are also investigated in the context of employee wellbeing. Evidences suggest that increasing disruption to work-life balance (Bardoel & Drago, 2016; Bayo-Moriones, Billon, & Lera-L´opez, 2017) due to increasing demands on efficiency enhancement, result in increasing demoralization of the workforce. Thus, the outcome-related themes provide evidence on both sides of efficiency and effectiveness.

A theoretical framework highlighting the broad themes and the nested subthemes are provided in Fig. 1 below.

Insert Figure 1 about here

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4. Methodology

The three research questions in this review relate to *first*, identifying the emergent themes/subthemes at the interface of AI-HRM literature; *secondly* determining the causal configurations of the themes to obtain a sense of evolutionary direction, and *finally* investigating any thematic variances over time in the causal configurations between conceptual and empirical research. The first question is fulfilled by performing a systematic review of the AI-HRM literature along with stringent inclusion-exclusion criteria, and by abducting themes and the nested subthemes, which are summarized in Fig. 1. To seek an answer for our second question, we relied on our a priori inquiry framework of *antecedent* → *process* → *outcome*, specifically with the outcome being either *objective* or *reactive*. To determine the causal configurations, we dichotomized each of the nested subthemes by coding its presence in a particular article as (1, 0) and absence as (0, 1). We then analyzed the above dichotomized data using the fuzzy set qualitative comparative analysis (fsQCA). Our choice of fsQCA is guided by the following considerations. First, fsQCA follows the configurational approach as opposed to the contingency approach. Configurational approach is useful and appropriate at the nascent and evolving stage of a literature (e.g. AI-HRM) where inadequate number of reliable quantitative studies limits the choice of clearly identifiable contingency/moderating variables that enable variance estimation (Marx & Dusa, 2016; Marx, Rihoux, & Ragin, 2014). Secondly, and in continuation to the above, our research questions required the identification of specific configurations of causal themes/subthemes that led to either of the two outcomes. The set theory-based fsQCA is an appropriate tool for the said requirement. Third, an analytical tool (like fsQCA) developed using the configuration approach, provides a whole range of optimal combination of antecedent constructs/themes/variables, which explains a specific outcome. That apart, it also provides a guide with respect to the incompatible antecedent constructs/ variables which should *not be used together in a model* to explain an outcome. In the context of the present research, this means that by using fsQCA, our analysis is free from the confounding situation where the same set of antecedent themes lead to different outcomes (Basu, Munjal, Malik, & Verontis, 2021). Finally, fsQCA also provided us with the necessary consistency and coverage ratios (Roig-Tierno, Gonzalez-Cruz, & Llopis-Martinez, 2017). We thus focused on causal configuration-based fsQCA technique.

Through our third research question, we investigated any *divergence in the evolving configurations*, as organizations and employees endeavor to adopt and adapt AI. Assuming that conceptual research precedes empirical ones, we further segregated the data along two specific dimensions namely (i) type of research and (ii) time/stage of research, with the outcomes (objective and reactive) remaining as they were. In this paper, we have considered case studies as empirical research. With respect to time, we observe that AI and automation, as concepts, have been around for a while. But its intrusion into the HRM domain received significant traction after the creation of OpenAI®, the AI research and deployment company based out of California that scaled up and democratized AI based applications (Sudmann, 2018). OpenAI® brought together a critical mass of resources and capabilities, to fast track AI-based innovations and applications, from the end of 2015.[1] Assuming a lag of at least one year, between the initiation of research and its final publication in any reputed journal, we divided the time scale into end-2016 and beginning-2017 to capture the early-stage and later-stage research, respectively. These two dimensions serve as subgroups, enabling us to investigate deeper into the subtheme-based causal configurations and their respective outcomes. Given the 2 outcomes, we thus have a total of eight (2x2x2) subgroups namely (i) early stage-conceptual-objective (ECO), (ii) early stage-empirical-objective (EEO), (iii) later stage-conceptual-objective (LCO), (iv) later stage-empirical-objective (LEO), (v) early stage-conceptual-reactive (ECR), (vi) early stage-empirical-reactive (EER), (vii) later stage-conceptual-reactive (LCR), (viii) later stage-empirical-reactive (LER). Therefore, any *persistence* in evolution would ideally imply similarities in causal configurations along *type, time/stage, and outcome* and divergence otherwise.

5. Analysis and results

The results of the Descriptive Statistics and Pearson's Correlation Matrix are presented in Table 2. We performed the correlation test to understand the closeness of association amongst the themes in terms of frequency of occurrences, within the selected set of articles. Table 2 indicates the thematic focus of researchers in general. Contextual research dominates the spectrum (73.53%), closely followed by objective outcomes (69.61%). More researchers have focused on individual drivers (63.73%) rather than on organizational (48.04%) or environmental (10.78%) ones, which syncs well with nature of outcome. Further, authors have focused more on non-robotic types (55.88%) and adoption processes (67.65%) than on robotic types (41.18%) and applications (60.78%). The correlation matrix suggests that the robotic type and non-robotic types have significant negative correlations - 0.6608($p < 0.05$), meaning that researchers have distinguished between interventions through robotic-based applications/adoption and other forms of AI. Similarly, individual drivers have a significant positive correlation with reactive outcomes 0.5214 ($p < 0.05$), and a negative correlation with objective outcomes - 0.3655 ($p < 0.05$), which vindicates our choice of a priori framework. The scenario reverses for organizational drivers, where objective outcomes relate positively and significantly, and reactive outcomes relate otherwise. Objective and reactive outcomes are negatively and significantly correlated - 0.6872 ($p < 0.05$), suggesting that the researchers who have focused on objective outcomes have generally *stayed away* from investigating the reaction of employees. Finally, researchers have investigated the application of AI towards objective organizational outcomes, (correlation 0.2114, significant at $p < 0.05$). This is in sync with the general perception of automation enhancing organizational performance. There are significant gaps (correlation of - 0.3409, significant at $p < 0.05$) in literature on *application of AI and their adoption* *process within organizations*. This may be due to scholars assuming the above association to be obvious, and therefore not engaging in any meaningful research to investigate the same.

The results of the fuzzy set QCA, highlighting the dominant configurations (with highest consistency and maximum coverage) are presented in Tables 3A and B below.

In line with our second and third research question, we investigated the *dominant* causal configurations through the *prime implicants* with corresponding consistency, and unique coverage scores, respectively. This was done across the *two time periods* and according to the *type of* research, namely, *conceptual and empirical* and for *objective and reactive* outcomes. For objective outcomes and early-stage conceptual research, we found two dominant configurations (with consistency = 1.000 and coverage = 0.111) namely organizationally driven adoption process of non-robotic types and contextual research on application of robotic type AI. In contrast, the reactive outcome based configuration (with consistency = 1.000 and unique coverage = 0.200) suggests contextual research on the adoption process of robotic type AI via individual drivers. A higher coverage ratio (Ragin, 2006) for reactive organizational outcome suggests that the *early-stage* conceptual authors focused more on *employee reactions to the need to adopt to robotic AI* than on objective organizational performances. Early-stage empirical work for objective outcomes (with consistency = 1.000 and coverage = 0.1667), exhibits evidence of individual and organization driven contextual research focusing on both application and adoption of non-robotic AI. For reactive outcomes also, early stage empirical researchers predominantly (with consistency = 1.000 and coverage = 0.2143) focused on contextual application and adoption of non-robotic AI through individual drivers. It is important to note that both the outcomes focused on non-robotic AI and the narrative is much more cogent than that of early stage conceptual researchers.

Later-stage conceptual as well as empirical research, with *objective outcomes*, showed a continued emphasis on contextual research with individual drivers facilitating the adoption process of non-robotic AI. One of the empirical configurations also showed organizational interventions in the adoption process of non-robotic AI. On an average, the unique coverage is higher in later-stage research for objective outcomes, with consistency remaining at 100%. However, with respect to conceptual and empirical research that focus on reactive outcomes, we found evidence of contextual studies focusing on robotic type AI applications and adoption, driven predominantly by individuals but also by organizations. The focus on non-robotic AI application persists, but predominantly restricted to conceptual research. The consistency and coverage are same for both empirical and conceptual research and nearly similar to that of objective outcomes. It may be noted that in general, both the objective and reactive outcomes for later stage empirical research *show higher frequency of configurations,* but with lower unique coverage, suggesting pluriversal proliferation of research.

A *stylized and simplified* thematic trend of conceptual and empirical research for the two outcomes is presented in Table 4 below, to facilitate inferences with respect to our third research question.

Insert Table 2 about here

Insert Table 3A about here
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6. Discussion and Conclusion

We undertook this review to determine how organizations and their human resources adopt and adapt to AI as *perceived and reported* by theoretical and empirical scholarship. Specifically, we were driven by the need to investigate the possibility of AI *posing a sustained disruptive threat to existing jobs of human resources of the organization* (Fleming, 2019). Such a threat would trigger an adverse reaction from the employees, which in turn would have organization wide adverse ramifications. As modeled by us, a preponderance of reactive employee response to AI adoption over objective organizational response, would signal a disruptive threat, and vice versa. However, as evident from Table 2, we found that scholars, across conceptual and empirical research, perceive a *more* beneficial (objective) outcome from AI adoption (mean = 0.6961) compared to a reactive outcome (mean = 0.4804). This further suggests the following. First, organizations in general are *evolving to adopt* AI as the latter intrudes into HR domain.

Secondly, those organizations that are open to adoption have created certain *ex-ante* governance mechanisms that facilitate their *ex-post* adaptation process and reduce negative employee reactions. To highlight, governance interventions that *aimed at* better work-life balance via AI assisted enhanced accuracy and speed of execution, facilitate AI adoption. Likewise *driven by the need to reduce* employee turnover, organizations adopting AI applications that enhance workplace collaboration, augment skill sets for changing nature of jobs, and increase hiring process efficiencies, have contributed to reducing negative employee reactions (Sajjadiani, Sojourner, Kammeyer-Mueller, & Mykerezi, 2019; Somers, 1999). Concurrently, guided by the organizational profitability perspective, AI-induced efficiency gains from reduced or distributed staffing costs and enhanced team performance reinforce objective outcomes (Tarafdar, Beath and Ross, 2019). In contrast, *AI-enabled governance* interventions, such as enhanced workplace surveillance and role incongruencies, threat of unemployment to less skilled workforce, and actual job losses trigger reactionary outcomes. Therefore, we posit that *AI induced outcomes are contingent upon the nature and creation of the governance mechanism that drives its adoption and application-based usages in the organizational context*. Those mechanisms can be driven by organizations or can be initiated by individuals (Anandarajan, 2002; Davis, 1989). Therefore, we focus on the precise causal configurations that augur these different outcomes.

A closer observation of the dominant configurations (in Table 4) suggests the following. First, objective outcomes are predominantly associated with *organizational driver subtheme* while reactive outcomes are associated with *individual driver subtheme*. Organizational drivers, such as *corporate investments, choice of technology, adaptive use intention, training for users, skill acquisition channels, degree of reconstitution of use, and centralization of firm's key HR decisions*, are indicative of a conscious and collective thought process, intent upon creating the necessary mechanisms to govern and ameliorate the impact of AI introduction. That in turn leads to beneficial organizational outcomes. In contrast, individual drivers, such as *attitude towards workplace surveillance, emotional response to robots, domain expertise of lead users, and leadership,* are indicative of a biased, incoherent, and more individualistic governance approach, that is spontaneous in introducing AI and insensitive to employee emotions. Consequently, such individualistic governance leads to reactive responses. Therefore, we propose that *organization-driven collective governance of AI interventions leads to favorable outcomes for both the organization and the employees, while individually-initiated AI adoption more often than not leads to reactive outcomes. Secondly,* organizational drivers exhibit a consistent focus on the *non-robotic type AI* while individual drivers exhibit a higher inclination towards robotic type AI. This is insightful and suggests that organizations, while acting through a collective mind, choose to expose their human resources to AI in a phased manner. In contrast, individual drivers/initiatives expose their human resources to robotic AIs relatively early, which comes as a shock. Assuming that robotic AI (like EPA robots, service robots, and robotic interactive HR systems) are less benign to traditional job roles compared to their non-Robotic peers (like Bigdata driven HR analytics, algorithm management, and predictive analytics), a phased introduction and adoption of the latter allows the employees of the organization to learn and adapt to the change and then contribute to organizational objectives (Shah, Irani and Sharif, 2017). In contrast, the sudden introduction of robotic AIs, replaces jobs and limits the human resources of the time to learn and adapt, which eventually leads to employee belligerency and reactive outcomes (Aleksander, 2017; Bergvall-Kåreborn & Howcroft, 2014). Thus, we propose that *a phased introduction of AIs, through collective endeavors, beginning with non-robotic AIs, shall lead to superior organizational outcomes*. *Thirdly*, and in continuation to the aforesaid configuration, organizational drivers are more aligned to *applications* based on non-robotic AIs and which leads to objective outcomes. Concurrently, we observe a clear emphasis on themes emphasizing adoption processes (e.g. appropriation, skill reproduction, discursive persuasion, digital transformation, shadow learning, training, and people equity) with the introduction of non-robotic applications and which leads to objective outcomes (Beane and Orlikowski, 2015). In contrast, individual driver themes with more emphasis on robotic application themes pay less emphasis on adoption processes per se, which leads to reactive outcomes. Thus, we propose that *organization level initiatives (drivers) towards establishing proper* *adoption processes to harness the benefits of non-robotic AI applications lead to superior organizational outcomes*.

With regard to thematic variances along the temporal axis, we compared the *later stage empirical studies leading to objective outcomes* with other corresponding cases since it denotes the best configuration for successful adoption and adaptation of AI in HRM context. Our review suggests the following. First, successful organizations (with objective outcomes) have progressively moved from collective emphasis on non-robotic *application* to non-robotic *adoption* processes, with organizational and individual drivers getting a peripheral role. This suggests that organizations are *evolving to be more process-driven than people-driven,* and the various *non-robotic application* driven outcomes/innovations are adopted to different situations for the collective benefit of the firm (Dougherty and Dunne, 2012). In contrast, the not so successful firms (with reactive outcomes) are still muddling with *people-driven robotic applications* having progressively rejected non-robotic applications and adoption (Compagni, Mele and Ravasi, 2015). Secondly, later-stage conceptual studies continue to emphasize on the need for *simultaneous* non-robotic application and adoption for organizational success while their empirical peers focus more on adoption processes. This variance is indicative of the *exploration – exploitation conundrum* where theory advises to hedge by investing (on application) for future, while practical considerations lead to exploiting the extant applications (via adoption) into different commercial contexts.

Third, comparing the later-stage conceptual-empirical studies with objective outcomes with those of reactive outcomes, we found that the reactive outcome group has rendered only a peripheral treatment to adoption process, that too in conceptual articles. When we compared the later-stage reactive outcomes with their early-stage peers, we found that adoption process was emphasized in both conceptual and empirical papers. However, early-stage conceptual papers looked into adoption for robotic AI, while the empirical papers looked into adoption and application for non-robotic AIs, both being individually driven. Furthermore, the non-robotic application-adoption themes of early-stage empirical group change decisively to robotic application in later empirical research. But their conceptual counterparts suggest a dominant non-robotic – application theme and a peripheral robotic – adoption theme. The configurations in early stage empirical research with reactive outcomes appear to provide an answer to the exploration – exploitation conundrum as stated above. Intrapreneurial/individually-driven (top-down) simultaneous application – adoption of even non-robotic AIs is likely to augur reactive outcomes, specially when the underlying technology is new (early-stage), and the management is *in a hurry to adopt and exploit*. This is because a perception of threat precedes entrepreneurial opportunity identification (Spencer, 2018). The same trend (of reactive outcomes) is visible when intrapreneurs (despite organizational support) swing to develop robotic applications (in empirical research), while their conceptual counterpart suggests moderation via incremental (peripheral configurations) adoption of robotic AI.

In general, we observe a relatively greater configurational similarity between early-stage conceptual and later-stage empirical research while a greater degree of dissimilarity exists between similar *types* or *dissimilar types* but *in similar time frames*. Furthermore, collective (organizationally driven) decision to exploit non-robotic AI-based technology is more objectively beneficial to the organization than individually-pioneered development of new applications based on robotic AI technologies, which triggers negative employee reactions. Finally, given *suitable time to adapt*, as is indicative of the configurational convergence between early-stage conceptual and later-stage empirical works, AI-based technological interventions are likely to generate more opportunities for human resources, thereby enabling *organizational adaptation*.

6.1. Academic and managerial implications

Our review of the literature affords several key insights for theory and practice alike. First and foremost, inferring from the *incremental and benign changes in the evolving causal configurations*, we are inclined to say that the field of AI-HRM is at the cusp of a benign pluriverse, with extant and potential benefits and opportunities accruing to both the organization (hence to the capitalist in the capitalist – labor debate) and to the employees. By adopting AI systems, organizations gain efficiency, which translate to better product and service quality and to capital formation. By adapting to AI-based applications, the human resources gain newer skills to be more efficient as well as effective, that manifests through creativity and innovation. Human creativity and innovation, in the context of AI-HRM is a trait, acquired in the process of competitive interaction with *the machine*. While acquired traits may not be inherited, but with large scale imitation, the same can be institutionalized (Briscoe & Safford, 2008), which facilitates co-evolution (Pacheco, York, Dean, & Sarasvathy, 2010).

The question of creativity-innovation based evolution brings forth the second insight centering round the human element. As more and more human resources collectively adapt to AI as part of the organizational adoption process, more and more commercially viable applications are likely to be innovated both within the firm as well as outside its boundary (Dougherty and Dunne, 2012). Innovation being the tool of entrepreneurs, we may witness proliferation of spinoffs, startups, and AI-based business models by intrapreneurs, who may leave their existing jobs to fuel their creative passion. These new business models may disrupt incumbents and their invested capital in the process. *While AI may not supplant human ingenuity and entrepreneurship, new organizational forms may threaten existing ones – an antithesis to the threat of AI to human resources.* We draw this inference from the evolving configurations suggesting that objective outcomes are influenced by non-robotic adoption process, while *reactive outcomes are influenced by robotic applications, driven by individuals*.

Thirdly and building on the organizational adoption process to non-robotic AI, we may witness a proliferation of systems and processes aimed at encouraging prosocial organizational behavior. To explicate, creative and innovatively enhanced human resources (as a consequence of competitively interacting with AI systems) may accrue socio economic capital and which they may want to share with a distressed colleague, triggering a virtuous cycle. By extension, such behavior may also trigger the creation of informal governance mechanisms aimed at containing some of the darker aspects of organization like sexual harassment, threats and intimidation, and which often go unreported due to lack of supporting mechanisms.

Fourthly, while AI systems may trigger positive mutation and evolution of the human resources, one has to be mindful of the harmful mutations. As emerging but non-mainstream literature suggests, there are apprehensions that AI systems can be *rigged* to perform tasks which are harmful to the human resources and the organization at large. AI systems can be manipulated with biased inputs that identify certain characteristics conducive of nepotism. When that happens, the healthy sense of competitive evolution may get affected, as a vicious cycle of malignant action and reaction follows between organization and human resources. While evidence to the above is difficult to obtain (hence scarcity in mainstream literature), negative biases and manipulations of AI systems do have the potential to spiral out of control, necessitating regulatory interventions, which may stifle creativity and innovation (Kim, 2018).

Finally, given the pros and cons of AI-HR interactions, it is important that organizations do not *rush* to adopt AI systems. An earlier than expected adoption may trigger unwanted opportunism and biases against a technology that has potential to do good or being ethically neutral at worse (Khalil, 1993). A *phased and collectively driven adoption* shall provide the necessary time to the human resources to adapt and then start exhibiting creativity and innovation via AI-based applications (Fayard, Gkeredakis and Levina, 2016). Indeed, organizations should be aware of and take lessons from scriptures. God might not have banished Adam and Eve from the Paradise, if they had taken the forbidden knowledge apple *at a time ordained by God*. An earlier than expected adoption may lead to suboptimal adaption and negative consequences thereof. Organizations should be mindful of the same.

Insert Table 3B about here

Insert Table 4 about here

6.2. Limitations and future directions

Our review of the AI-HRM literature has some limitations, which, along with our effort to predict the evolutionary trajectory of causal configurations, provides scope for future research. First, we restricted our review to reputed journals and repositories like WoS. While this approach enhanced authenticity and verifiability of our findings, it risks losing out on new, critical, and often unconventionally reported information/findings, appearing in peripheral or non-English journals. Secondly, while abstracting themes, we found that the same phenomenon can be viewed from different thematic lenses. For example, the bias of the top management towards adoption of any specific AI technology can trigger employee opposition. This can be viewed from the lens of specific technological context, organizational and individual drivers, and suboptimal objective outcomes due to employee reactions. In effect, the distinction between (negative) individual drivers and reactive outcomes as antecedents to (suboptimal) objective outcomes blur. Our choice of causal configurations through QCA and the separation of the two outcomes mitigate this problem to some extent. However, we recognize the basic issue and sound the caveat to future researchers, who may want to adopt our configurations, without controlling for necessary causality. Third, and as already highlighted, we found instances of negatively correlated constructs appearing simultaneously in the truth table. We believe this to be an outcome of emerging contingencies, which, at the time of the present research, is a peripheral issue. Further, even the significant negative correlations are not equal to 100%, thus, in a way, anticipating such peripheral contingencies. Finally, we have presented (in Tables 3A and 3B) the dominant configurations based on consistency and coverage. But there are a large number of minor configurations with lower coverage, meaning these configurations are reported in one-off articles. Ignoring these recessive configurations may not be prudent as they, over a period of time, may gain strength and disrupt the dominant configurations. Alternatively, the presence of large number of minor configurations is reminiscent of the Darwinian conditions of evolution. Closely monitoring these configurations may provide timely insights on the emergence of subsequent favorable mutations beneficial to both the organization and its human elements.

In terms of future directions, we envisage several possibilities. If past trends are an indication of future, we expect to see more conceptual or empirical papers contextually embedded in either new technologies or in specific industries, with individual or organizational decision makers playing a more dominant role in technology absorption and adoption. In line with our categorization, we expect to see more research on non-robotic AI applications and adoption than on robotic AI (Aleksander, 2017). Research on reactive outcomes shall continue to theorize on the effect of organizational and individual drivers, on increasing adoption and application of robotic AI in the labor-intensive manufacturing industries, typically in the emerging market context. With a large population and labor forces, such adoption (or failed adaptation) may trigger the environmental drivers like policymakers to respond with punitive regulations. As Table 3 (A & B) suggests, research involving the environmental drivers has been scarce, compared to that on other drivers, and may serve as a legitimate scope of future exploration. Likewise, involvement of stakeholders is also relatively lower in AI-HRM linkages. Taken together, future research may investigate the roles of institutions (as an environmental driver) as more rules and regulations emerge to formalize the interaction between AI and HRM. It appears that a nascent equilibrium is slowly emerging in the AI-HRM literature, as empirical research and their conceptual peers tend to exhibit incremental advancement and convergence over a long term temporal scale. As increasing number of research in AI-HRM emerge, we expect to see clearer compartmentalization the identified themes, enabling more precise theorization in the future.

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Table 1: Search Syntax in AI and HRM

Items	Key Words
AI and AI Related	"HR", "HRM", "HCM", "human resource management", "human capital", "hiring", "talent", "workforce", "training", "employee", "employer", recruit*, talent*, "workforce", interview*, "performance management", "performance appraisal", "team performance", emotion*, "skilling", "labor", "worker", "human resources", "training", "organizational behavior", “behavior”, "labor union", "worker union", "personnel management", "leadership", "executive", "team", "group", "human capital management", "skill development", "workforce learning", "job evaluation", "role evaluation", "knowledge management", "change management", "organizational capability", gigwork*, "staffing", "job satisfaction", and "organization commitment behavior".
HRM and HRM Related	"decision sciences", "automation", robot*, chatbot*, “chat bot”, cobot*, "virtual reality", "intelligent machines", "intelligent machine", "digital", "machine learning", "neural", "AI", "algorithm", "decision system", "Artificial Intelligence", "augmented reality", "deep learning", "big data", "NLP", "self-service technology", "internet of things", "expert system", "enterprise cognitive computing", "visual recognition", "voice interaction", "facial recognition", "face recognition", "conversational agent", "automated service interactions", "smart device", "neural network", "swarm intelligence", "artificial", "EPM technology", "IR 4.0", "virtual team", "virtual world", and "predictive analytics".

Table 2: Descriptive Statistics and Pearson's Correlation Matrix

Variables	Mean	SD	Context	Stake-holder	Driver Env	Driver Org	Driver Indiv	Type Robotic	Type Non-Robotic	Application	Adoption Process	Outcome Objective	Outcome Reactive
Context	0.7353	0.4434	1.0000										
Stakeholder	0.2745	0.4485	-0.0293	1.0000									
Driver Environmental	0.1078	0.3117	-0.0063	0.0694	1.0000								
Driver Organizational	0.4804	0.5021	0.0876	-0.1078	-0.0812	1.0000							
Driver Individual	0.6373	0.4832	0.1482	0.0986	-0.2636*	-0.1316	1.0000						
Type Robotic	0.4118	0.4946	-0.0850	0.1549	0.0302	-0.1267	-0.0317	1.0000					
Type Non Robotic	0.5588	0.4990	0.0935	-0.0729	-0.0730	0.0639	-0.0954	-0.6608*	1.0000				
Application	0.6078	0.4906	0.2008*	0.0891	0.0203	0.1694	-0.1048	0.1824	0.0547	1.0000			
Adoption Process	0.6765	0.4701	-0.0349	0.0028	-0.0298	-0.0481	0.0449	-0.0601	0.0608	-0.3409*	1.0000		
Outcome Objective	0.6961	0.4622	0.0867	-0.0712	0.0923	0.2940*	-0.3655*	-0.0535	0.0997	0.2114*	-0.1380	1.0000	
Outcome Reactive	0.4804	0.5021	0.0876	0.1561	-0.0180	-0.2961*	0.5214*	0.1525	-0.1337	-0.0717	-0.0062	-0.6872*	1.0000
Number of Observation	100	100	100	100	100	100	100	100	100	100	100	100	100

(* implies p at 5% level of significance)

Table 3A: The Emergent Configurations for Objective Outcomes from Fuzzy Set Qualitative Comparative Analysis

Objective Organizational Outcomes			
Types	Prime Implicants	Consistency	Unique Coverage
Early Stage Conceptual (ECO)	~STAKEHOLDERS*~ENV_DRIVERS*ORG_DRIVERS*~IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * ~APPLICATION * ADOPTION PROCESS	1.0000	0.1111
	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ~ORG_DRIVERS * ~IND_DRIVERS * TYPE_ROBOTIC * ~TYPE_D&A * APPLICATION * ~ADOPTION PROCESS	1.0000	0.1111
Early Stage Empirical (EEO)	CONTEXT * ~ENV_DRIVERS * ORG_DRIVERS * IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION * ~ADOPTION PROCESS	1.0000	0.1667
	CONTEXT * ~STAKEHOLDERS * ORG_DRIVERS * ~IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION * ADOPTION PROCESS	1.0000	0.1667
Later Stage Conceptual (LCO)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ORG_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION * ADOPTION PROCESS	1.0000	0.1739
Later Stage Empirical (LEO)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * ~APPLICATION * ADOPTION PROCESS	0.8333	0.1852
	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ORG_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * ~APPLICATION * ADOPTION PROCESS	1.0000	0.1481

Table 3B: The Emergent Configurations for Reaction Outcomes from Fuzzy Set Qualitative Comparative Analysis

Reactive Organizational Outcomes			
Types	Prime Implicants	Consistency	Unique Coverage
Early Stage Conceptual (ECR)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ~ORG_DRIVERS * IND_DRIVERS * TYPE_ROBOTIC * ~TYPE_D&A * ~APPLICATION * ADOPTION PROCESS	1.0000	0.2000
Early Stage Empirical (EER)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION * ADOPTION PROCESS	1.0000	0.2143
Later Stage Conceptual (LCR)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION * ~ADOPTION PROCESS	1.0000	0.1667
	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ~ORG_DRIVERS * IND_DRIVERS * ~TYPE_ROBOTIC * TYPE_D&A * APPLICATION	1.0000	0.1667
	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ~ORG_DRIVERS * IND_DRIVERS * TYPE_ROBOTIC * ~TYPE_D&A * ~APPLICATION * ADOPTION PROCESS	1.0000	0.1667
Later Stage Empirical (LER)	CONTEXT * ~STAKEHOLDERS * ~ENV_DRIVERS * ORG_DRIVERS * IND_DRIVERS * TYPE_ROBOTIC * ~TYPE_D&A * APPLICATION	1.0000	0.1667

Here CONTEXT implies the theme “context”, STAKEHOLDERS implied the theme “stakeholders”, ENV_DRIVERS, ORG_DRIVERS, and IND_DRIVERS imply the nested/sub themes of “environmental drivers”, “organizational”, and “human or individual drivers” respectively, within the theme “drivers”, TYPE_ROBOTIC and TYPE_D&A refer to nested/sub themes “Robotic type” and “Non-Robotic type” within the theme “types”, APPLICATION implies the theme “application” and ADOPTION PROCESS refers to the theme “adoption process”.

Further, the notations have their usual meanings i.e. (*) implies “and”, (~) implies “not”. Therefore, (CONTEXT * STAKEHOLDERS * ENV_DRIVERS * ORG_DRIVERS * ~IND_DRIVERS * TYPE_ROBOTIC * ~TYPE_D&A * APPLICATION * ADOPTION PROCESS) implies the prime implicants “context” *and* “stakeholders” *and* “environmental drivers” *and* “organizational drivers” *and* “robotic type” *and* “application” *and* “adoption process” but *not* “individual/human drivers”, *not* “non-robotic type” leads to Reactive Outcomes, which has 100% consistency but with low (least dominant) coverage.
We have kept consistency threshold at 0.5 and coverage/frequency threshold at 1.00. We have analyzed using TOSMANA V.1.61 (release date, June 13, 2019).

Table 4: Stylized Representation of the Evolution of Conceptual and Empirical Research on AI-HRM

↓ Themes\Types-Time →	Early Stage Conceptual	Early Stage Empirical	Later Stage Conceptual	Later Stage Empirical	Early Stage Conceptual	Early Stage Empirical	Later Stage Conceptual	Later Stage Empirical
Context	•	●	●	●	●	●	●	●
Stakeholder								
Driver Environmental								
Driver Organizational	•	●	●	•				●
Driver Individual		•		•	●	●	●	●
Type Robotic	•				●		•	●
Type Non Robotic	•	●	●	●		●	●	
Application	•	●	●			●	●	●
Adoption Process	•	•	●	●	●	●	•	
Outcome Objective	●	●	●	●				
Outcome Reactive					●	●	●	●

Note: 1. Only the “AND” themes are included for **visual clarity** and “NOT” themes are excluded/kept as BLANKS.

2. As per convention “●” implies the presence of the dominant “AND” theme, while “•” represents the peripheral/recessive theme.

Figure 1: Theoretical Framework with Themes, Nested Subthemes and Underlying Concepts