

THE USE AND ACCEPTANCE OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT – THE FIRST PHASE: QUALITATIVE RESEARCH

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ABSTRACT

Research aim: This research aims to investigate the emerging impact of Artificial Intelligence (AI) technologies in the realm of Human Resource Management (HRM).

Methodology/design/approach: The research considers the insights perspectives of HR professionals through conducting a mixed research method as an overarching analysis tool. This qualitative research reveals the first outcomes (Phase I) in capturing the perspectives of AI-HR professionals on the use and acceptance factors of AI in HRM.

Finding: This paper elicits the empirical findings of Qualitative Research (Phase one) with significant involving adoption determinants identified through thematic analysis. The research confirms significant correlations of Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Condition and Perceived Risks on HR professionals' adoption behaviours.

Research Value: This paper appoints practical information to capture the interests of HR practitioners, AI vendors and researchers, and facilitates organizational changes towards innovation.

Practical Implication: The findings of this research will generate an inception for AI-HR collaboration while revealing underlying issues regarding adoption. It also provides updated information to related studies in similar fields of how digitalisation transforms and impacts businesses' performance. Additionally, organisations would be able to have insights into the application of AI in HRM by understanding the factors that influence the use and acceptance of this powerful technology.

Keywords: Artificial Intelligence (AI), Human Resource Management (HRM), automation, innovation, technology, machine learning (ML), deep learning (DL), the use and acceptance of technology (UTAUT)

INTRODUCTION

In recent years, Artificial Intelligence has become a major factor in transforming and challenging human resource management. The dominance of these advanced technologies has significantly affected and challenged the traditional working processes of a large majority of different types of organisations. Reflecting on the business market during the dynamic incident of the Covid-19 pandemic, HR is recommended to be a pioneer in AI adoption due to its strategic roles in engaging, training, and sharpening employees' mindsets to be able to familiarize themselves with the new way of working in the digital era. Even though the disruptions of AI applications in HRM have been recently discussed in forums, research and articles are yet to be widely applied and they are still searching for their time and place to be appropriately deployed by businesses. In effect, recent empirical research has postulated that machine learning, AI and advanced technologies are in a surge of adoption after the occurrence of the pandemic (Barnes, 2020). To a considerable extent, the temporary incident of the pandemic has challenged businesses in terms of internal capacity and manpower management. HR functions in response to the pandemic have seen havoc for businesses since HRM requires close-knit work with human factors. Nonetheless, several firms have decided to take solid movement towards AI technologies as a strategic solution.

Owing to the significance level of the novel element, the current use and acceptance of AI in HRM is an emerging incident that is worth investigating. The investigation on how AI technologies are being deployed would possibly generate a significant impact on how other businesses could construct their management and assign manpower sources in this digital era (Program, 2021). To elaborate on the adoption factors of the emerging advanced technologies in AI, this research is aiming to explore the potential adoption factors. The research is conducted by analysing perspectives from HR Professionals through conducting mixed research methods as an overarching analysis tool. This paper reveals the empirical findings of Qualitative Research (Phase one) with significant involving determinants identified through thematic analysis. The exploration in this field will also close the gap between the proposed scenarios of the willingness and ability in AI adoption for the digital evolution. Based on the result of the research, potential opportunities, and challenges of AI adoption in current businesses will be elucidated.

LITERATURE REVIEW

1. Empirical Review

Artificial Intelligence (AI)

Artificial Intelligence has been tailored to one of the current emerging realms in the business world. It has been currently used in different technology-related research fields, however, there is not yet a universal consensus on coining a definition on the term (Kirsh, 1991). AI refers to the potentials of tasks to be performed by machine or program with relevant human activities namely planning, problem-solving, reasoning, analysing and manipulation that generates creativity and social intelligence (John McCarthy, 2008). In fact, the term “intelligence” has empirical and emerging content and therefore the concept is a barely stable (Thórisson & Talbot, 2018). The subject includes complicated terms to be followed and its definition has been evolving (Russell, 2010).

Through years, with the increase in the amount of data and information to be processed, functions of AI have been enlarged in diverse fields such as the engineering (Pham & P.T.N. Pham, 1999), medicine (Lajoie S. P., and Vivet, M, 2002), education (W. Wang & Siau, 2017), science (W. Wang & Siau, 2017), business and law (Soni et al., 2020). AI can integrate assorted fields by multi-layered algorithms allowing machines to perform brainy human tasks by undergoing artificial neural networks (Nisar, 2018). The side of learning ability and problem-solving by machines could be upgraded to an “advanced level” where machine learnings are programmed to perform more sensible human tasks (AlSheibani et al., 2018). In the business context, AI is envisaged as an accelerator to upgrade the investigation ability on data and provide a contextual field for human’s decision-making processes. The technology has been successfully applied in five domains of Machine Learning, Computer Vision, Knowledge Mining, Natural Language Processing (NLP) and Anomaly Detection. (P. Wang, 2019).

Types of AI

Since AI applications are applied in diverse circumstances with divergent problem-solution elements required, it is complicated to label the constitution of AI. In fact, AI can be divided into two types which are *Narrow AI* and *Artificial General Intelligence (AGI)*. The first type of AI is considered as “Weak AI” which is defined as limited-context AI operations whose functions are mostly simulated human intelligence (Buitin, 2003). Particularly, Narrow AI is designed to concentrate and complete specific tasks with the assistance of machine learning and deep learning. The technology has been utilised and applied in different economical aspects of human life such as search engines and digital personal assistants (Alexa or Siri).

The second type of AI is categorised as “Strong AI” which is described as a machine with human intelligence. Its ability can be exploited to assist humans with difficult situations or conundrums (R.L. Adams, 2017). Russel and Norvig stated that this type of AI is applying a "universal algorithm for learning and acting in any environment” and it will be continuing to shape the feature of the cognitive intelligence (Buitin, 2003).

Dominant AI Capacities

In recent years, the AI taxonomy system has become more diverse in multidisciplinary aspects. AI functionalities and categorisations have been applied discretely subjected to professions, industries, and business practices. According to (Pournader et al., 2021), AI functions are classified into eight themes including Optimisation, Planning and Scheduling, Expert systems, Machine Learning, Natural Language Processing, Speech, Vision, Simulation and Modelling. The algorithms deployed in each category, vary depending on different types and the availability of input data. Despite the diversity of AI nomenclature, there are five leitmotifs which are considered the fundamentals of AI which are Machine Learning, Anomaly detection, Computer vision, Natural language processing and Knowledge mining (Wang, X., Han, Y., Leung, V.C.M., Niyato, D., Yan, X., Chen, 2020). They are imperatively encapsulating the demand of the business market. The mentioned concepts are illustrated at **Table 1**:

Table 1: AI’s dominant capacities (generated by researcher)

AI themes	Functions
Machine Learning (ML)	The capability of computer learning to make projections and cogitate results based on input data
Anomaly detection	The capability to detect anomalies or unusual activities
Computer vision	The capability to recognise and interpret the meaning of objects/words through images, videos, and camera
Natural language processing (NLP)	The capability to process and respond to spoken or written languages
Knowledge mining	The capability to extricate data from a wide range of unstructured data for future repercussion analysis

Showcases of AI applications in HRM

The Covid-19 pandemic could be demonstrated as an invisible hand pushing HR toward the digital trend to maintain the competitive edge. It is argued that the incident has accelerated the global- mega trends including “the flexible workforce, the digitalization of business models, and AI and machine learning” which tremendously impact the future of HR by the disruptive forces (Minbaeva, 2020). Recent research has shown an increase in AI applications in HRM thanks to the data-driven aspects brought by AI to offer more insights to HR functions. The empowerment of data-driven AI to business performance has been confirmed by HR leaders who adopted the technology into HRM (V. Chaturvedi & Joshi, 2018). It is stated that the transformation encourages “people to communicate across geographic boundaries and share information” and therefore, it enhances the strategic role of HR in “supporting the organisation in achieving its business strategy” (Parry & Tyson, 2011). The following part illustrates how AI technologies are applied in various HRM practices.

The capacity of processing high volumes of data allows AI users to extract potential patterns for decision making and planning. There are multiple AI algorithms to power the use of Big Data Analytics such as case-based reasoning, logic programming, text mining or neural network. In the current labour market, Oracle Taleo and IBM Kenexa BrassRing are considered as effective bias- eliminated recruiting tools used to search for numerous candidates’ experience without “the need for detailed application forms, using statistical natural language processing (NLP) to extract resume or social media data for review” (V. Chaturvedi & Joshi, 2018). In practice, to generate equal job opportunities, Johnson & Johnson has used Textio’s AI tool to detach male-oriented language in job descriptions to increase gender diversity, which consequently attracted 90,000 female candidates within a year (Black & van Esch, 2021). L’Oréal also followed the same suit by applying the Textio tool to remove gender-biased language and successfully achieve the “gender diversity it had never before attained” (Duan et al., 2019).

In addition, the invention of the cobot/chatbot has reinforced recruiters in communications and managing the workforce. In fact, during the pandemic, Burger King Brazil has successfully deployed AI and Cloud services to handle employees’ questions and concerns via a virtual agent. The AI tool assists the company to engage with 18,000 employees by just being connected to their WhatsApp accounts (IBM Institute for Business Value, 2020). Apart from this, humans hardly avoid unconscious biases generated in decision making and therefore, a “good bot” could answer not only candidates’ questions, but it can analyse candidates’ résumés and call out the questions related to the potential positions. That is how assessment tools, or “blind CVs” could extract biases with the help of bots (Faragher, 2018). Orientation and training supporting new hires could be delivered with the help of an AI-bot which can answer general

enquiries as well as “recommending team members for the new employee to talk to” for further assistance (Gikopoulos, 2019).

In reality, Google has been successfully deploying AI to establish better hiring strategies by adjusting the algorithms towards “learning ability and intellectual humility” traits from candidates after realising that university brands and final examination grades are not utmost factors for expecting-achieved performance in the work (Oracle, 2017). Additionally, IBM has successfully applied AI in onboarding by pressingly matching new hires’ questions with experienced employees working in the company by providing their names, locations and contact details (Amritaa & Achwani, 2018). The recruitment workflow with the help of Knowledge Mining through a matching algorithm that can “compare skills extracted from a job requisition with those extracted from candidate résumés or CVs, returning a match score” allows recruiters to acquire a quick assessment when a candidate fits with the criteria (Feinzig, 2020). HireVue, for example, has applied AI tool to analyse candidates’ “answers, body language, tone, emotional state and keywords” during interviews with the applicants, which eventually results in higher judgements on candidates’ “honesty and emotional intelligence” (Ahmed, 2018).

2. Theoretical Review

The Unified theory of acceptance and use of technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) has been considered as a comprehensive and profound framework by virtue of its high explanatory power and greater projective capacity of technology acceptance and use (Barrane et al., 2018; Palau-Saumell et al., 2019). Developed in 2003, Venkatesh successfully introduced the UTAUT framework by integrating and refining eight predominant models in the affiliated field to formulate the final model selecting cardinal elements from the preceding dominant model’s (Venkatesh et al., 2003). The eight examined models constituting UTAUT include Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Acceptance Model (TAM) (Davis, 1986), Motivational Model (MM) (Davis et al., 1992), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), Model of Personal Computer Utilization (MPCU) (Thompson et al., 1991), Diffusion of Innovation Theory (DOI) (Rogers, 1962), and Social Cognitive Theory (SCT) (Compeau & Higgins, 1995).

The nature of the model is to effectively describe the acceptance of IT service in its introduction phase. By dint of the framework’s versatility, multitudes of research have been established on the foundation of UTAUT to examine technological factors’ use and acceptance presenting in various realms

(Alwahaishi & Snášel, 2013, 2013; Chen et al., 2021; D. C. Lee et al., 2017; Wrycza et al., 2017; Yu, 2012; Zuberi et al., 2007). Additionally, the UTUAT framework is posited to be likely to rectify potential limitations presented in previous affiliating models. In fact, by the virtue of its prevalence, the model is suggested to be an effective instrument for the management board to measure the presence of novel technology in the market while also explaining and envisaging adopters' behaviours on technology acceptance. The explanatory power of UTAUT is scrutinised to be higher than TAM (20%-30%), increasing the explanation of adopter's intention-and-behaviour likelihood up to 40%–50% (Barrane et al., 2018).

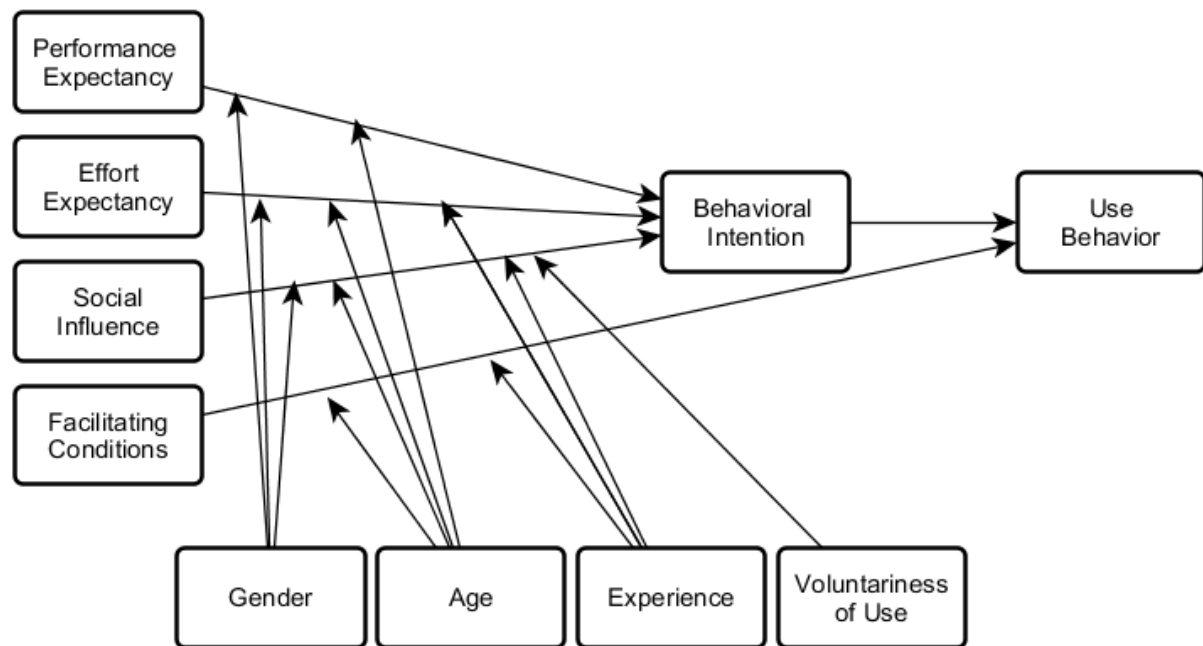


Figure 1: The Unified theory of acceptance and use of technology Model (UTAUT)
(Venkatesh et al., 2003)

Since UTAUT has been deployed in multiple researches in analogous technology fields such as online mobile banking payment (J. M. Lee et al., 2019), blockchain (Christopher, 2019) or cloud computing (Rastogi et al., 2018), the findings provide a potential mechanism for the applied context of AI. The researcher aims at driving the further development of UTAUT on the current dynamic of AI in HRM with a modified UTAUT framework. Conceptual framework and Hypothesis formulation were followingly introduced based on two key drivers. The first driver was shaped based on the original UTAUT model dovetailing with potential key variables established from consonant study fields.

Perceived risk (PR)

According to Vimalkumar et al. (2021), PR refers to probability of losing something which consequently induces insecurity in people's decision making. Motivational theorists also incline on PR as a central construct in determining the level of individual engagement in performing a behaviour. While the vast majority of motivation notions centralise on the facilitating factors, PR is considered as an explicit construct regulated by multidimensional psychological effect rooted in individual anxiety, fear, uncertainty and concerns (Al-Saedi et al., 2019; Hasan et al., 2021; Thusi & Maduku, 2020). Prior research has linked this subjective notion with the individual decision-making process in technology adoption. In fact, an empirical study about mobile banking adoption demonstrated seven types of risk pertaining to technology adoption namely Performance risk, Financial risk, Time risk, Psychological risk, Social Risk, Privacy Risk, and Security Risk (Akturan & Tezcan, 2012).

Alongside with related research of technology acceptance, the construct PR in this thesis per se possesses a negative impact on the intention to apply AI technologies. Users usually encounter high level of psychological risks when confronting novel technologies such as fear and avoiding feelings (Morosan, 2012). The psychology factor awakens discouraging emotions against behavioural intentions (Udo et al., 2010). In practice, through the empirical results from this research, certain features related to the PR construct were detected including users' concerns and fear toward biases, privacy, fear of the unknown and perceived employment. In the next section, the relationship among the discussed factors will be illuminated to confirm the reciprocation among the considered variables.

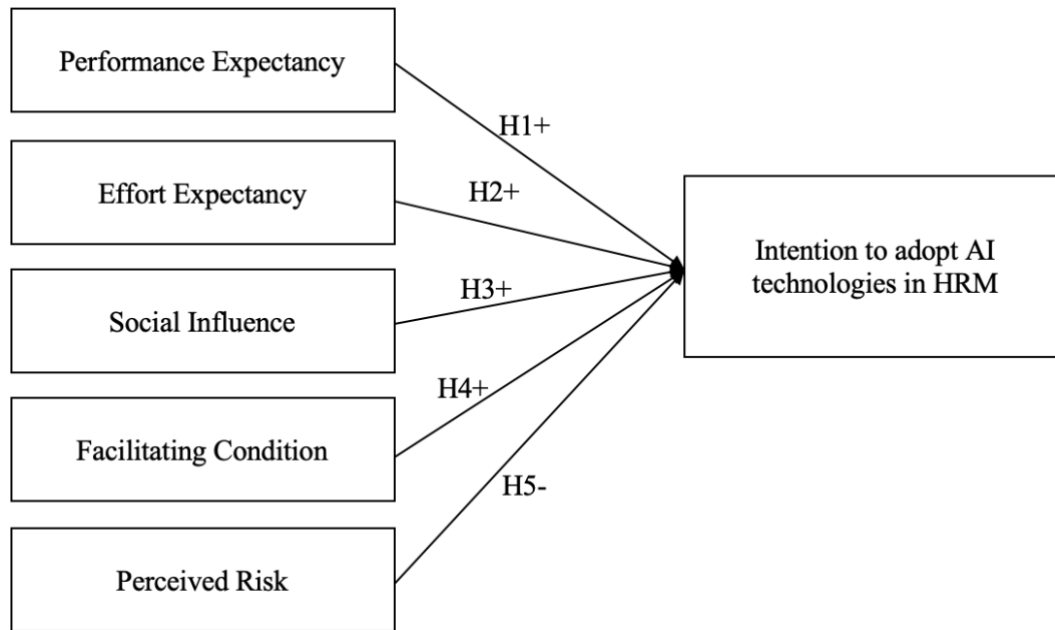


Figure 2: Preliminarily Conceptual Framework

Anchoring to the empirical and theoretical reviews, the preliminary conceptual framework is established with the preliminarily conceptual framework (**Figure 2**) and the hypotheses as follow:

H1: PE is positively related to AI adoption in HRM

H2: EE is positively related to AI adoption in HRM

H3: SI is positively related to AI adoption in HRM

H4: FC is positively related to AI adoption in HRM

H5: PR is negatively related to AI adoption in HRM

QUALITATIVE RESEARCH METHOD

Qualitative Research Overview

From a theoretical standpoint, the Literature Review pinpointed four constructs extracted majorly from the UTAUT Model and a significantly related factor of Perceived Risk (PR), which is psychologically linked with the motive of technology adoption in businesses. The other factors belong to the UTAUT model which are Effort Expectancy (EE), Performance Expectancy (EE), Facilitating Condition (FC), and Social Influence (SI) (Venkatesh et al., 2003). Furthermore, Perceived Risk (PR) is the additional variable, not included in UTAUT, which is argued to potentially affect adoption behaviour (Hasan et al., 2021; Terblanche, 2020). The mentioned factors possess sub-categories that constituted the formation of the main themes. The articulation and classification of subthemes are based on the previous examined studies related to technology adoption and the integrated association tied to the connotation of each considered factor. Subsequently, the researcher will provide a detailed analysis formulated on the primary data collected through semi-structured with AI-HR Professionals. The demographic data gathered was used to synthesise the overall characteristics of AI perceptions from the chosen sample. The rest of the primary data was used to examine, assemble, confirm, and establish central themes for the conceptual framework.

Demographic Information

The qualitative research was formulated on semi-structured interviews with a total of eighteen participants varying across industries and organisational scopes in England. Specifically, the participants were selected based on their expertise and experiences in HRM and AI which essentially serves the purpose of this phase of exploratory research. There were eight HR professionals from large organisations (more than one thousand employees), six HR professionals from SMEs (around two hundred and fifty employees), three senior HR consultants and an AI leader in the industry. The interviews were either conducted via face-to-face or video recordings on MS Team so that the researcher could comprehensively capture the reactions, thoughts and feelings of the participants which assisted in reflections while conducting data analysis. The overall information of the research interviews can be viewed as follow:

Table 2: Demographic Information (extracted from empirical data)

Sample Characteristics	Frequency (n)	Proportion (%)
Total: (overall sample)	18	100%
Gender		
Male	6	33.33%
Female	12	66.67%
Working Experience		
>10 years	8	44.44%
5-10 years	3	16.67%
< 3 years	7	38.89%
Relations to HR Professions		
HR Executives	7	38.89%
HR Practitioners	7	38.89%
HR-AI Related professionals	4	22.22%
Interview mode		
MS Team	16	88.89%
Face-to-Face	2	11.11%

The **Table 2** illustrates the attributes of the research participants selected to measure the perceptions of AI adoption within HRM. Since this stage of the research concentrates on exploring the emergence of AI concepts in the HR market, the focal point is to reach the discursive understandings from different HR-related angles. Echoing that subtext, not only HR Executives' opinions were taken into considerations, but an equal sample of HR practitioners was deployed to extract the insights from AI-HR contextualisation. It is argued that the evolvement of learning organisations in recent years have contributed to enhance and facilitate flat-structured organisations where traditional top-down decisions could be flexibly altered with a bottom-up decision-making process (Kodama, 2018). Technically, the employees are endowed with more authority and legal rights to voice opinions in organisational decision making. Distinctly, the disruptive intervention of AI in HRM has subsequently drawn attention of organisation management, especially the working employees due to the potential impacts of the advanced technologies on their jobs (Basu et al., 2022). Since this phenomenon has proposed an institutional level of transformations, both perceptions from HR executive and practitioner levels are equally significant for the comprehensive understanding of the research subjects.

To broaden the scope of perceptions apprehension, a third group of participants, involving three HR consultants and an AI leader were invited to participate in the research. This is to provide ancillary angles as a reflective tool for the current perceptions of HR professionals towards AI applications. In addition, the research interview questions were designed not only to depict the main themes but the current awareness and perceptions of the participants about the emerging concept of AI. Therefore, the collaborations of the grouped participants will concede various points pertaining to the behavioural adoption intention. This mechanism will provide a broad spectrum of this research orientation in terms of advanced technology maturity in the HRM field.

Thematic Establishment with NVivo

Researcher adopted NVivo 12 software to conduct qualitative research analysis. The analysis tool accommodate the researcher to obtain a flexible platform to analyse rich and wide ranges of data (Malik, 2012). NVivo facilitates the use and organising information in terms of linking nodes, themes, and case studies to visualise the relationship of the empirical data (Edwards-Jones, 2014). Thanks to the discussed advantages, NVivo was employed to analyse the narrations of participants from collected interviews. By applying the software, themes were identified and linked with theoretical and empirical literature whilst answering the thesis' questions. Descriptive coding was adopted which enables the classification of theme based on the a priori codebook when analysing and interpreting interview narrations (Roberts et al., 2019). The codebook for this research utilised knowledge retrieved from related theories based on the exploration research nature. In addition, the validation of established codes was ensured to be primarily data-driven and maintained throughout eighteen semi-structured interviews.

Table 3: Research A priori Codebook (adapted research strategy of (Olajide, 2018))

Parent codes	Sub-codes
Perceptions on manual HRM	Performance Expectancy of traditional HRM • Current deployed Employee Management System • Preferability of the current HR functions in manipulation and capacity
	Effort expectancy of traditional HRM • Hindrances of the current HR functions in manipulation and capacity • Dexterity and flexibility of manual HRM application
Perceptions on AI-powered HRM	Performance Expectancy of AI-deployed HRM • Applied or potentially applied AI-powered technologies in HRM • Projected HR function of AI applications and justifications
	Effort expectancy of AI-deployed HRM • Consideration on cost effectiveness • Consideration on job dexterity and flexibility of AI-powered HRM application
Projections of AI adoption in HRM	Facilitating factors • Organisational support for AI applications in HRM • Innovation integration level in HRM
	Social Influence • Employer branding concerns on AI adoption in HRM • Competition pressure of AI adoption in HRM
Emerging Risks of AI Adoption	Fears and threats induced by AI deployment • Potential biases in decision making • Control level of personal information • Job evolvment and replacement • Lack of skills and deskills possibility

The **Table 3** illustrates the codebook with four parent codes sieved from the research literature and questions. The initial foundation of sub-codes was formulated on literature review and empirical data collection. In this vein, the codebook generates an integrating centre of articulating the research questions, related theories, and primary data. A concrete codification structure was applied to establish codename with a high concentration on the possibility of forming affiliated themes. Collected data was subsequently uploaded and explored on NVivo software for coding, node generation, and theme establishment following the guidance of the a priori codebook.

RESEARCH FINDINGS

Through this qualitative study, the researcher synthesised the empirical data within the scope of the thesis into three sections. Each section comprises subcategories and themes used for quantitative research as a measurement tool at phase two of quantitative research. The research findings will be presented through three contradictory pairs of perceptions namely: *Opportunity Vs Threat; Traditional HRM vs AI-powered HRM; and Theoretical Vs Practical Gap*. By communicating the research findings, relationships among identified adoption factors will be reviewed, refined, and illustrated. Main findings of this research are depicted below.

First Angle: Opportunity Vs Threat

To comprehensively capture the overall perceptions of the participants, the questions were designed not only based on the a priori codebook, but it also centred on the colloquial understandings regarding the novel concept of AI. The participants were questioned the initial relations of the AI by providing a noun or an adjective for their answers. The **Table 4** summarised the answers and perceptions of the participants who were questioned about AI opportunities, threats, and the potential for job replacements in HR. The arrangement of data is in response with chronological order.

Table 4: Participants' perceptions of AI (extracted from empirical data)

Interviewees	AI Concept relation	Threat or Opportunity	AI will replace human jobs	Positions
Participant 1	Future	Opportunity	Agreed	HR Practitioner
Participant 2	Advanced machine	Opportunity	Agreed	HR Consultant
Participant 3	Advanced technology	Opportunity	Agreed	HR Practitioner
Participant 4	Advanced technology	Opportunity	Agreed	HR Executive
Participant 5	Automation	Neutral	Agreed	HR Practitioner
Participant 6	Advanced and smart object	Threat	Agreed	HR Practitioner
Participant 7	Siri, machine	Threat	Agreed	HR Executive
Participant 8	Robots, non-human	Threat	Agreed	HR Executive
Participant 9	Automation	Opportunity	Agreed	HR Practitioner
Participant 10	Technologies taking over	Threat	Agreed	HR Executive
Participant 11	Norms	Opportunity	Agreed	HR Practitioner
Participant 12	Self-service machine & robots	Opportunity	Agreed	HR Practitioner
Participant 13	Automation	Opportunity	Agreed	HR Executive
Participant 14	Robots	Opportunity	Agreed	HR Consultant
Participant 15	Utopia	Opportunity	Disagreed	HR Executive
Participant 16	Robots	Neutral	Disagreed	HR Consultant
Participant 17	Umbrella of innovative technologies	Opportunity	Disagreed	AI leader
Participant 18	Robots and automation	Opportunity	Disagreed	HR Practitioner

According to the collected results, the concepts of AI were significantly separated pertaining to the HR professional participants' understandings of AI functions. As defined in LR Chapter, AI is an umbrella technological term for diverse algorithm-based softwares served multiple analytics' purposes (Braun et al., 2019). In this sort of orientation, it could be observed that the insights of AI technologies in HRM was not fully captured. The fundamental knowledge derived from HR professionals illustrated partial contributions and functions of AI as reflected in this research's Literature Review discussing AI technologies' capacities and deployments. Sporadic parts of AI functions were mentioned, and the answers were investigated to be corresponding with the amplification of ubiquitous conceptions related to AI. In particular, "robot", "automation" or "advanced technologies" were terms which were majorly used by the participants. In practice, AI technologies are asserted to be pervasively evolving and becoming a buzzword in the 21st century (Mehrotra, 2022). The relation map (**Figure 3**) illustrates a connection of overarching research regarding AI in HRM through time.

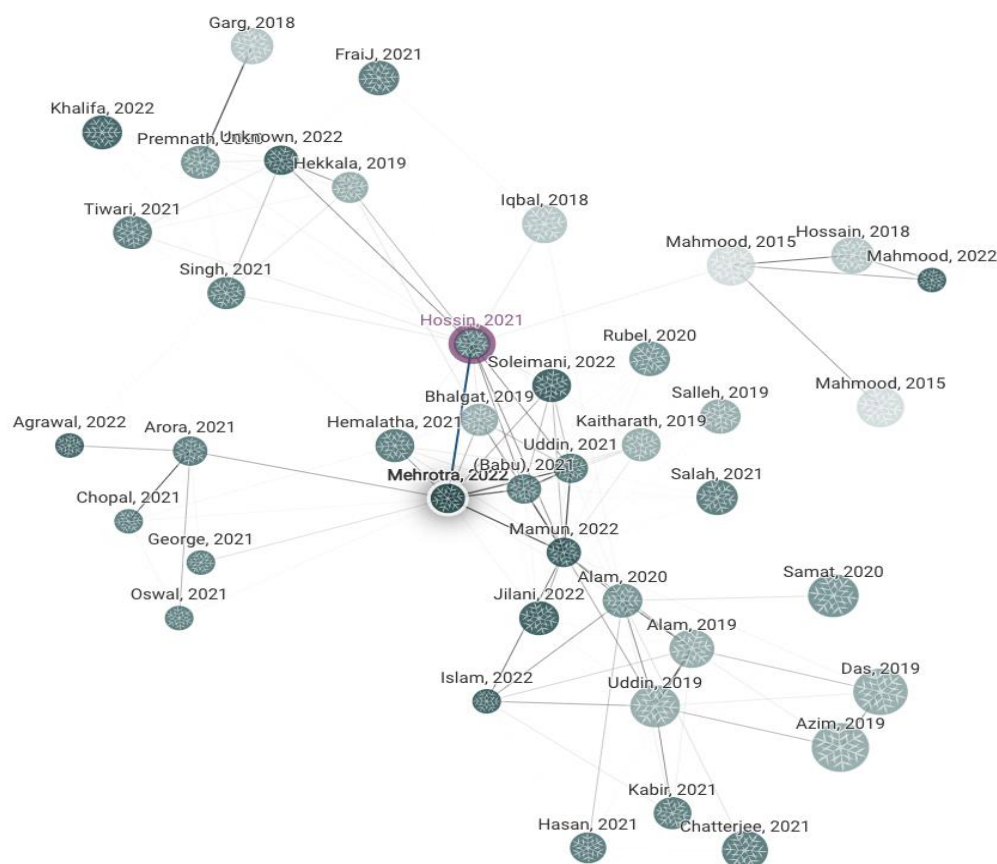


Figure 3: Interconnection network of research about Artificial Intelligence in Human Resource – Connected Paper Platform powered by (Microsoft Azure, 2022)

As can be seen from **Figure 3**, research regarding AI applications within the field of HR initiated in 2015 with two researches conducted by the same scholar (Microsoft Azure, 2022). The accretion of interest in the realm has perceived a surge starting since 2019. This could be reasonably explained due to the unexpected emergence of the global pandemic of Covid-19 with its challenges on universal business performance management. HRM managers and practitioners are indicated to be critically impacted due to their substantial role in providing ingenious approaches to maintain business performance (Cross & Swart, 2022). In essence, hybrid-working and alternative business approaches were effectively articulated with the support of advanced technologies during the pandemic period (Aliman, 2020).

“[...] regard to recruitment, again it is completely changed whenever I interview someone, one of the first questions asked is “how do you work? Are you all in the office? Are you hybrid? Are you remote?” So, I think the pandemic has changed a lot, not only in HR but within businesses alike” - P18.

While the majority of the participants evinced the potentials of AI by describing the novel element as Opportunity, only four participants out of eighteen participants fortified the applications of AI would be a threat in HR Field. Two respondents expressed a neutral discernment about the application of the advanced technologies. This postulates that AI diffusion and recognition level is germinating and is under consideration of applications in the HR Field. In essence, multilateral aspects of HR functions are being analysed and found to be congruent with autonomous and algorithm-customised natures of AI (Bharati, 2020). Thereby, the empirical data revealed a relatively clear and consistent picture of a positive impact of AI within HR perspectives:

“Artificial intelligence has to be seen as an opportunity by companies and organisations, by HR leaders and HR departments. It has to be an opportunity to be more proactive.” - P2.

“It is an opportunity definitely. I think it's just identifying the right AI for the right thing, and I think it's very positive and certainly plays a part.” - P13.

Paradoxically to the above discussion, there is a high level of uncertainty when the discussion progressed to the acceptance of AI in HR Field. Notably, 75% participants who considered AI applications as Threat belongs to HR Executives group. To exemplify, P7, P8 and P10, HR Executives confirmed that:

“For me, I wouldn't see it as an opportunity [...] It depends on which element [...] because they do have errors.” – P8.

“I think it's now becoming a threat [...] the companies don't treat their colleagues well and it's because they don't need them now because technology is replacing that. So, I do see it as a threat.” – P10.

“Yes. It is a threat [...] “because it's administered by humans.” – P7.

It could be indicated from the above statements that adoption-concerned foundation stems from Perceived Risk (PR) and Effort Expectancy (EE) factors. In essence, humanitarian and functional issues are inferred from the HR perspectives, which appears to be consistent with Bias Concerns, Perceived Unemployment (sub-themes of PR) and Job Compatibility (sub-theme of EE). The respondent demonstrates reasonable fear assumptions regarding the novel technologies which is assimilated to the emerging factor of Fear of The Unknown (FOTU) - This factor will be lately discussed in upcoming section regarding **Theoretical vs Practical Gap**. In fact, the growth of AI terminology and applications could be argued to be newly emerged and in the intersection of Innovator and Early Adopter. Due to the inchoate context, fear and doubtfulness are subconsciously unavoidable elements influencing the decision-making process.

Echoing the DOI theory, leaders contribute a critical role in becoming a foundation for behaviour changes in transition period (Rogers, 1962). In this vein, the circumstance demonstrates a potentially detrimental inclination on the adoption of AI element in terms of leadership unfavourableness. Nevertheless, in the era of advanced technologies and changing market, leadership roles are speculated to be actively testing potential hypothesis rather than solely concentrating on quantifiable values such as costs and profits (Schoemaker et al., 2018). The justification is in line with the earlier discussion regarding Leadership Support (sub-theme of Facilitating Condition (FC)) in determining adoption behaviour. However, according to the empirical data, the HR professionals simultaneously depicted a significant influence on leadership regarding adopting AI technologies in organisations.

Seventeen of out eighteen participants agreed when being asked whether innovation is required in HR functions. At this realm, the majority of the participants acknowledged AI as an unavoidable factor for HRM in the future due to recognition of its competitive edge in building brand and staying relevant. This could be considered as an empirical validation of the interconnection between innovation transformation

and competitive approach (Akter et al., 2021). This is in line with Black & van Esch (2021)'s proposition that SI is a crucial societal factors that generates a leveraging effect for innovation adoption. In fact, a recent research centred on AI adoption in Recruitment confirmed the concrete relations between the use of novel technology with employer reputation (Kot et al., 2021). The above discussions strengthen the hypothesis of FC and SI factors critically involved in AI adoption behaviour of HR professionals.

Second Angle: Traditional HRM vs AI-powered HRM

Extant studies suggests that manual HRM is being constantly challenged due to the incongruence of features in the new economic world (Cross & Swart, 2022). It is posited that automatic and repetitive tasks are largely constituted in manual HRM, which impedes organisational productivity (Mohamed et al., 2022). In addition, the impact of the global pandemic has generated a conundrum for HRM to rejuvenise the strategic HRM across core functions due to alternatives in working conditions and performance management (Hamouche, 2021). Anchoring to this, the participants were asked to discuss their stances about the nature of manual HRM with its advantages and disadvantages before approaching the main research theme. This is to investigate potential milieu triggering the intentional behaviour towards accepting AI technologies in HRM. The **Table 5** presents the summarised stances of the participants towards the mentioned domains.

Table 5: Participants' opinions: Traditional HRM vs AI-powered HRM (generated by researcher)

HR Related Fields	Related Questions	Summarised points from empirical data	Most concerns on the subject
Traditional HRM	Disadvantages in conventional HRM Process	Time-consuming Human errors Human Biases Paper-based Obsolete (Old fashion) Tediousness High human effort Long process Difficulty in managing large information Slow in decision making process Lack of historical reflection Cost inefficiency	HR Executives: Cost inefficiency Slow in decision making process Simplification HR Practitioners: Time-consuming Paper-based High human effort Tediousness Transparency
	Advantages in conventional HRM Process	Transparency Sympathy Simplification Human interaction	AI-HR related professionals: Obsolete (Old fashion) Human errors Human Biases Lack of historical reflection
AI-powered HRM	Disadvantages in AI-powered HRM Process	Human Biases Complexity Lack of human interaction Costly Privacy concerns Trust matters Job insecurity	HR Executives: Costly Enhance Social Image Fast in decision making process Efficiency Speediness HR Practitioners: Less human efforts Less human errors Large data storage Trust matters Job insecurity Human Biases Privacy concerns
	Advantages in AI-powered HRM Process	Efficiency Speediness Less human efforts Less human errors Consistency Large data storage Easy to use Fast in decision making process Cost saving Enhance Social Image	AI-HR related professionals: Cost saving Complexity

By comparing two distinct angles of manual HRM and AI-powered HRM, a parameter of AI demand in HR could be visualised and resonated. In essence, the literature discussed in chapter 2 ascertained that agility is in line with organisational effectiveness in responding towards dynamic changes in innovative economy (Heilmann et al., 2020). Hence, the absence of performance improvement to HRM could vulnerate business performance in a long run. Reflecting upon the collected data, twelve out of eighteen respondents indicated the extant downsides of conventional HRM while expressing their thoughts regarding manual HR practices.

“So manual HR, my opinion is that it's time-consuming and it's not cost-effective and obviously it's introducing a level of increased risk because manual interventions are obvious off to my things go wrong so slow as the stone hints our processes and I guess stops us from being able to spend time doing some of the more strategic stuff that we'd like today.” – P15.

“It's time-consuming and it's costly [...]. It's quite difficult in complete honesty here. I'm sure the machine would make it easier for workers without the mental repercussions afterwards.” – P7.

Manual HRM was therein portrayed to presently obtain certain obstacles for HR professionals in terms of effectively and efficiently processing tasks. According to the collected data, over 76% of the participants encounters limitations and inconvenience in manual HRM. The empirical context has pictured the high recognition of the downsides stem from the conventional HR practices. The scenario is argued to generate a leverage for HR evolvement to overcome the extant obstacles. Reflecting upon the discussed literature within this thesis, the AI-leverage factor could be argued to be the Innovation Driven (ID), a sub-theme of Facilitating Condition (FC), to positively influence adoption intentions from HR professionals.

Indeed, HRM is deemed to be bewildered by the abundance of data and the increasing demand to perpetually optimise the processes (Radonjić et al., 2022). In line with this, the study further found that the awareness of AI-augmented HR functions was highly reflected in participants' expressions towards the questions regarding AI technologies. In fact, when being questioned about AI applications in HRM, sixteen out of eighteen participants could depict some substantial AI applications currently available within HR field.

“The advantages of artificial intelligence could help us predict employees' retention, employees' behaviour. What kind of employees stays with us? [...] if we start making records of those as well, then we can predict that “what's the next steps that our employees going to take?” “How they navigate their decisions within our company?” [...] So, there are a lot of things that can be taken out from the data if we are linking it with artificial intelligence or if we are utilising it in a more appropriate manner to make or to take useful information out of it.”. - P13

The extant HRM obstacles were subsequently compared with AI-powered HRM to capture the insights of the participants regarding the emerging AI factor. Based on the empirical data, Cost-effectiveness (CE), Task Versatility (TV), Job Compatible (JC) and Ease of Use (EOU) were identified to be

prominent variables extracted from respondents' answers regarding AI capacities in HRM. Following the conceptualisation by Kim (2022), this thesis defines CE, TV, JC and EOU as primary components of Performance Expectancy (PE) and Effort Expectancy (EE). Particularly, CE and TV are two proposed variables of PE while JC and EOU are the sub-themes of EE as entrenched in the a priori codebook. In this junction, the empirical evidence reinforces the literature extracted from UTAUT model since PE and EE were the two primary factors critically directing users' intention toward technological transformation (Venkatesh et al., 2003). Sixteen out of eighteen participants in this research cited the augmented performance in HR practices through the listed PE and EE features.

In line with Figueroa-Armijos et al. (2022), the practical views undergird the argument that EE and PE positively facilitate AI adoption in HRM. The above analysis has highlighted the emerging motives for AI-powered HRM transformation by comparing the distinct conceptions of traditional and AI-powered HRM. Within this section, the findings also strengthen the proposed hypotheses that FC, PE, and EE are the influential factors in behavioural intention. In the next section, the researcher aims to provide more insights regarding opportunity and challenges concerns based on participants' propositions about AI in HR functions.

Third Angle: Theoretical Vs Practical Gap

The study progresses further to explore the main issues of the extant AI applications within the HR market by excavating the gap between theoretical and practical applications. The interview questions were successively designed to elaborate the diffusion of AI technologies and the intention of adoption in specific HR functions. Technically, the participants were examined for their insights while discussing the potential opportunities and challenges of AI applications in HR functions. This provides a potential mechanism for the researcher to articulate AI capacities with HR functions and capture AI pervasion scope. In addition, the intention to apply or expand AI applications in the future were questioned to measure the gravitation of AI and its maturity in HR field.

Data analysis reveals that primary HR bundles of practices were considered across eighteen participants. Specifically, there were a variety of HR functions aligning with AI technologies listed by the participants including Recruitment, Learning and Development and Administration tasks. Notably, eight out of eighteen respondents considered recruitment to be the most congruent function to involved with AI technologies. In practice, recruitment is envisaged to be contemporarily the most ubiquitous functions integrating with AI capacities. It is depicted that there is a proliferation of interest reflected in recent

studies regarding AI in Recruitment owing to its applicational germination. It is also noteworthy that Administration tasks such as (answering common employment enquiries or managing leaves) were deemed to be in high demand of AI-augmentation. Above 50% of the participants expressed their approval of adopting AI technologies to erode inefficiency and counter-productivity features in administrative tasks. The remaining dominant HR functions such as L&D, Retention and Compensation captured a small proportion of favourableness of AI applications across participants.

In nature, there are two prominent spectrums which constitute HRM, which profoundly orient and summarise this business function's activities: operational and decisional (**Table 6**). In this study, the researcher defines operational spectrum to be HR functions which could deal with quantifiable or transactional HR aspects such as Payrolls or Administrations. In contrast, decisional spectrum is illustrated in the form of fusion between quantifiable and situational factors. Particularly, Training and Development is required the inspection of quantifiable feature from goal-based accomplishments and relational feature from employees' performance at work. The former factor is easily devolved to transactional attribute by its ability to quantify the number of tasks assigned. On the contrary, the latter factor requires the inclusion of the perusal of employees' strengths, weaknesses, and the deliberation of contextual elements such as working and environmental conditions.

Table 6: Operational and Decisional Spectrums imbedded in HRM (generated by researcher)

Operational spectrum related functions	Decisional spectrum related functions
Quantifiable	Quantifiable + Situational
(Examples of performed tasks)	(Examples of performed tasks)
Sick Leave Management	Training and Development
Employment Contract	Job Mobility
Personal Employment Data Management	Recruitment and Selection
Pay Rolls	Performance Management
Attendance Management	Succession Planning
General Data Support (GDPR)	Retention

Reflecting upon the empirical data, HR professionals perceived a high expectation to eliminate repetitiveness constituted from HR tasks, which significantly links with quantifiable aspects. In addition, administration tasks captured the highest proportion compared to other functions. Although recruitment placed at the second echelon, there are components within the function could be quantified based on the previous argument. The expectations in AI-powered HRM appear compatible with main AI capacities. The relation map (**Figure 4**) represents the potential interconnections of five main AI capacities: Computer Vision, NLP, Knowledge Mining, Machine Learning and Anomaly Detection with HR functions.

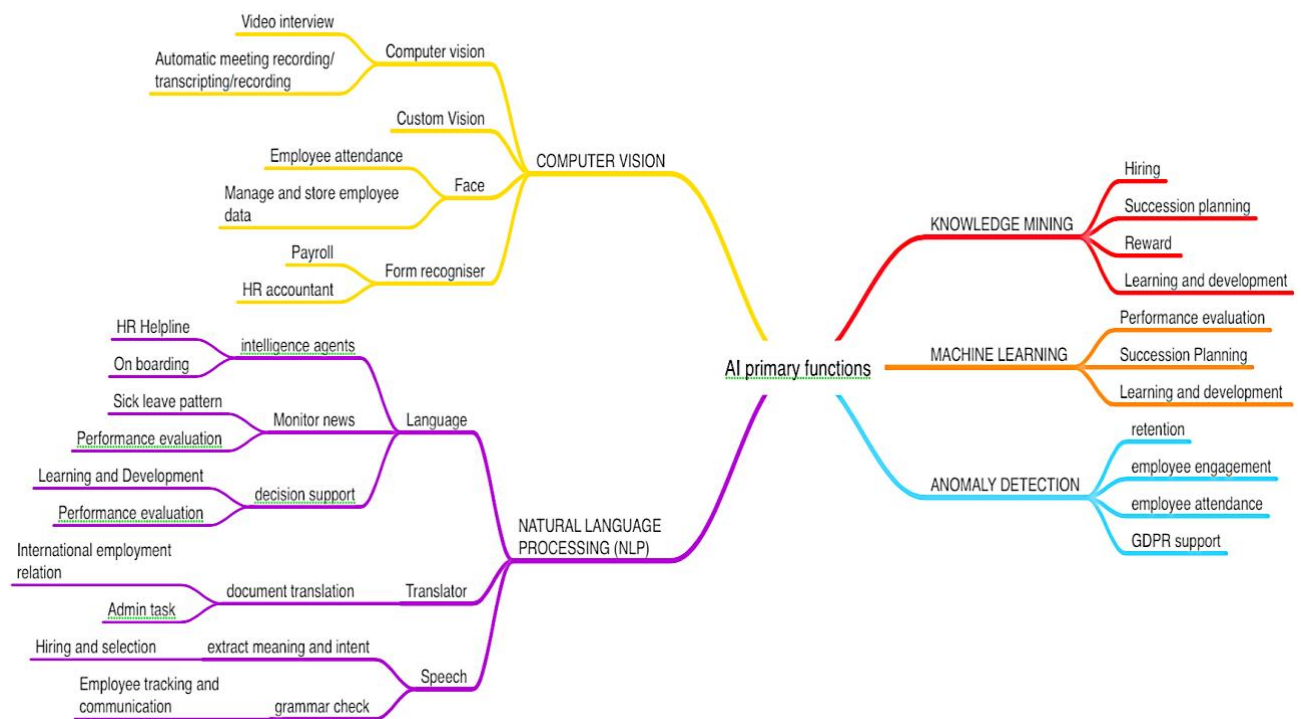


Figure 4: AI-powered HR functions map based on core AI capacities (generated by researcher)

Theoretically, AI technologies herein could be considered as an ultimate key to penetrate and upgrade current HR processes with a variety of technical solutions. The thriving of studies regarding AI in HRM and the high awareness and diffusion of its terminology in HR market has also been confirmed in the previous arguments within this study (Arslan et al., 2022; Basu et al., 2022; Hmoud & Várallyai, 2020). Conversely, the empirical data continues to reveal significant influential factors of adoption decision on AI-powered HRM. In fact, the participants were also asked to discuss their critical concerns regarding the preventions of AI adoption in HRM. Despite the positive assertions regarding the high demand in AI

adoption, the empirical data reveals several factors which impact on participants' decision in accepting AI technologies in HRM. In fact, thematic analysis confirms four types of risks highlighted by the participants in this research as presented in the Table:

Table 7: Sample responses of emerging risks of AI-powered application in HRM

Perceived Risk	Sample responses
Bias Concern	<i>"There is debate around things like subconscious bias because the person whose programme these things got subconscious bias that then feeds through into the programmes"</i> <i>"I think there's something about fairness and bias. [...] the data used to train these models often has got bias embedded within it, and [...] it can amplify and extend and genuinely cause real-world harm and poor outcomes to people"</i>
Privacy concern	<i>"People might perceive any risk [...] about the level of information and ways in which data and information are held in relation to those solutions. I think people will always have ongoing challenges with that."</i> <i>"I think privacy concern is increasing. There are a lot more cases where I suppose the media have made that fear amplified because there's always new stories that certain details have been leaked, a firewall has been breached and data is in the public domain."</i>
Fear of the unknown	<i>"I think without knowing exactly what it means and what it entails [...] probably a bit of a threat in my mind because I just don't know that"</i> <i>"I do see artificial intelligence can be a scary concept for some [...] it's more about being scared of the unknown rather than actually having any real basis for the fear."</i>
Perceived Unemployment	<i>"Artificial intelligence, I believe it's something that's meant to be smarter than us. And like I said earlier, something that will replace us slowly."</i> <i>"The fear I think is on the part of HR practitioners. [...] if you are introducing technology that replaces what you can currently do, then you will have a natural fear that your job is going to be eroded and eventually you'll be redundant."</i>

As presented in **Table 7**, there are several concerns regarding the adoption of AI in HRM despite the insistence on improving manual HR performance. In essence, these findings appear to be consistent with the projected themes in the literature review that BC, PRC, FU and PU are associated obstacles when approaching technology transformation. This proposition is also in line with the position that certain perceptions regarding risks are triggered when the users are introduced with novel technological subjects

(Pitardi & Marriott, 2021). The participants acknowledged the possible threats delivered by AI in terms of unemployment, privacy data exposure, potential bias from machine and human; and general fear in terms of the unknown matter due to the uncertainty nature as shown in the above table. This visualises a practical gap between the proposed benefits of AI technologies and the hindrance of application owing to the factor of PR. Therein, the collected evidence reinforces the literature and projected antecedents stated in the a priori codebook.

Significantly, an emerging factor of Status Quo Bias was explored within this study as a converse adoption mechanism toward AI advancements. Samuelson & Zeckhauser (1988) first coined the concept of SQB which refers to the bias triggered in individual decision making by remaining the current status quo as a mechanism towards changes. Paramount to this definition is the assertion that this is a psychological construct which illustrated the typical hindrance of technology adoption (Eidelman & Crandall, 2012). The issue posed by the existence of inertia tendency which facilitates the maintenance of status quo despite the pressure to alter the status (Greta L. Polites and Elena Karahanna, 2012). This concept was supplementarily adjoined in LR as it is validated within this section. In effect, thematic analysis results explored in this thesis established a new realm of AI influential adoption factor, which is not envisaged within the preceding framework. **Table 8** illustrates the new theme (SQB) emerging from the qualitative research.

Table 8: Sample responses of Status Quo Bias's factors influencing AI-HRM collaboration

Status Quo Bias	Sample responses
Psychology Commitment	<i>"I also refer that interaction. It's a lot better and sometimes you get the problem resolved a lot quicker and [...] when you're speaking to a human, you feel more valued, which is what I prefer."</i> <i>"I must admit, last year we did put together a spreadsheet. That we felt probably better to manage it and we're not having to deal the machine all the time"</i> <i>"Everything is working fine, so I don't necessarily see that needs to be improved. [...] I believe everything seems to be working just fine now about that."</i>
Cognitive Misperception	<i>"I'm thinking of something smarter than us up then as humans. [...] that was very scary to me because [...] artificial intelligence, I believe it's something that's meant to be smarter than us."</i> <i>"The first thing that comes to my mind is the movie The Matrix. And Tesla Self-service machines and robots. That's the first thing that comes to mind when I think about artificial intelligence [...] there are also people that could use AI for bad reasons."</i>
Perceived cost	<i>"[...] I implemented was a career development portal which was quite expensive and obviously, I do have a training budget and I have to weigh up the losing majority of my training budget to implement this [...] for the company and cost-wise."</i> <i>"Also because of cost, because to adopt AI, first thing it will cost [...] it will be huge cost upfront, although long term it might be better because you're not going to pay salary to [...] hundred people using AI."</i>

Psychology Commitment (PYC) is a theme that scholars have been emphasising in technological adoption studies. Within this study, the factor represents the implication of psychological attachment with the current HR functions.

Cognitive Misperception (CM): within this research, this theme is described as incorrect interpretations and understandings of AI applications in HRM leading to adoption stagnancy. As further supplemented in LR, this concept entrenches the distortion understanding formulated by the prevailing value and belief (Hsieh & Lin, 2018).

Perceived Cost (PC): Notably, finance is a significant factor for implementing AI-powered HRM. In this study, PC represents the costs exhibit investments and commitments, which accelerates SQB (Hsieh & Lin, 2020).

The empirical results are not surprising as AI-powered HRM is a new concept which will confront a diversity of potentially psychological impacts. The above discussed features provide further evidence to Samuelson & Zeckhauser (1988)'s assertions for SQB as a negative element in technological adoption. Particularly, it is argued that SQB were manifested in influences of rational decision making, psychology commitment, and cognitive misperceptions to the status quo position. With the provided findings, the thesis broadens the existing conceptual framework on SQB as an impacting factor on AI adoption in HRM. Within this section, the empirical data also strengthen the factor of PR to be a critical factor in measuring intentional behaviours.

QUALITATIVE RESEARCH CONCLUSION

Anchoring to the theoretical literature and the a priori codebook, the thematic analysis conducted through eighteen semi-structured interviews with AI-HR Professionals reveals a high degree of AI advancements' awareness in HR field across businesses. The **Table 9** illustrates the six empirically identified factors that impact the adoption of AI technologies in HR field. The nexus between AI and HRM is presented as follow:

Table 9: Finalised constructs based on Qualitative Research's results

Finalised Constructs	Proposed evaluating factors	Interview sources	Frequency	Percentage Coverage	Importance Level Evaluation
Effort Expectancy	Ease of use Job Compatibility	P1, P2, P3, P4, P5, P6, P7, P9, P10, P11, P12, P13, P14, P15, P16, P17	16	88.89%	Importance
Performance Expectancy	Cost-effectiveness Task Versatility	P1, P2, P4, P5, P6, P8, P9, P10, P12, P13, P14, P15, P16	13	72.22%	Moderately Importance
Social Influence	Employer Branding Subjective Norms	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18	18	100%	Highly Importance
Facilitating Condition	Leadership Support Innovation Driven	P1, P2, P3, P4, P5, P6, P8, P7, P10, P11, P12, P13, P15, P16, P17, P18	16	88.89%	Importance
Perceived Risk	Bias Concerns Fear of the Unknown Perceived Unemployment Privacy Concern	P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P17, P18	16	88.89%	Importance
Status Quo Bias	Cognitive misperception Perceived Cost Psychology Commitment	P1, P2, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P15, P14, P16, P17, P18	17	94.45%	Highly Importance

The frequency analysis reveals that the generic constructs of EE, PE, SI, PE, PR and SQB are key reasons which influence on AI adoption intention in HRM (Illustration of factors' weights can be viewed at **Appendix 1**). Most notoriously, SI and STQ are considered as highly important factors to impact on users' decision making. The findings in this qualitative research contribute to establish a foundation to quantitatively examine the impact of the influential factors on AI-HRM collaboration. In addition, the research outcomes synthesise the insights of the critical issues in relation to degree of AI diffusion in the HR realm. Particularly, the empirical results demonstrate a profound picture of how AI is penetrating and impacting HRM as presented in **three** critical angles distilled from this qualitative research.

1. **Opportunity Vs Threat:** By examining the participants' evaluations on AI factor in HRM over the lens of Opportunity and Threat, the research confirms a positive inclinations in AI-HRM collaboration. The empirical data in this section addressed a high recognition of AI terminology diffusion after the global incident of the Covid-19 pandemic, which triggers a mechanism for alternative working patterns. Critical adoption factors including FC (supported by LS and ID) and SI (supported by EB and SN) were confirmed within this section to positively influence AI-powered HRM to be executed. These findings are consistent with theoretical literature and the a priori codebook discussed in this research.
2. **Traditional HRM vs AI-powered HRM:** By extracting the participants' perceptions regarding the two-opposing concepts of traditional and AI-powered HRM, the research confirms a positive expectation in AI-HRM collaboration. The empirical data in this sphere addressed the contemporary limitations in manual HRM whilst asserting the expectations in higher productivity with AI-augmented HRM. In this vein, critical adoption factors comprising PE (supported by CE and TV) and EE (supported by EOU and JC) were strengthened to positively influence AI-powered HRM to be executed. These findings are consistent with theoretical literature and the a priori codebook discussed in this research.
3. **Theoretical vs Practical Gap:** By examining the adoption intention, the research elaborates the AI-HRM adoption issues between theory and practice. The empirical results in this stance addressed the emerging risks associated with AI-powered HRM implementation. The critical counter-adoption factor of PR (supported by BC, FU, PRC, and PU) was reinforced to negatively AI-HRM collaboration. These findings are consistent with theoretical literature and the a priori codebook discussed in this research. Importantly, SQB (supported by CM, PYC, and PC) is a novel theme discovered through thematic analysis within this section. The factor was proven to negatively influence AI-powered HRM execution. The emerging finding was subsequently reviewed and adjoined in LR Chapter in this research.

The findings of this research confirm the significance of predetermined factors of EE, PE, SI, PE, PR in terms of impacting HR professionals' adoption intention. It further discovered the factor of SQB to potentially influence AI adoption predisposition in HRM. The phase one of this research critically contributes to establish a concrete foundation for the second phase of the quantitative research to examine the correlations coefficient of dependent and independent variables. At this junction, interested scholars and parties could delve into the results of the first phase to initially deliberate compatible AI adoption strategies. The constructs extracted from this stage are in the process of analysing to investigate potential discrepancies while applying the second research method. (7713 words)

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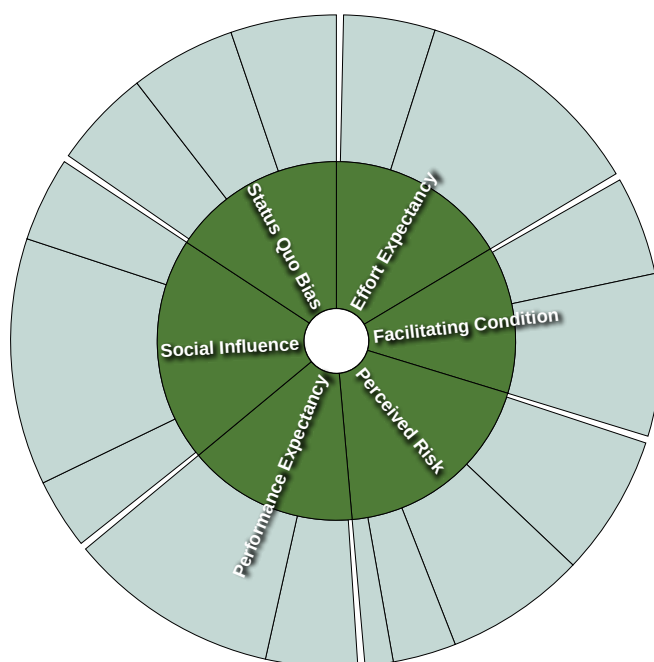
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Appendix



Appendix 1: Illustrations of factors weights (extracted from NVivo)