

THE USE AND ACCEPTANCE OF ARTIFICIAL INTELLIGENCE (AI) IN HUMAN RESOURCE MANAGEMENT (HRM) – COMPREHENSIVE FINDINGS FROM MIXED-METHOD 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 comprehensive research reveals the final outcomes (Phase 1 and 2) in capturing the perspectives of AI-HR professionals on the use and acceptance factors of AI in HRM.

Finding: This paper elicits the significant findings of a mixed-method (QUALquant) research involving adoption determinants identified through thematic analysis from qualitative research and the exempting factors extracted from quantitative research. The research confirms seminal correlations of Performance Expectancy, Social Influence, Effort Expectancy, Facilitating Condition, Perceived Risks and Status Quo Bias on HR professionals' adoption behaviours.

Research Value: This paper appoints practical literatures to capture the interests of HR practitioners, AI vendors and researchers, and facilitate organisational changes towards innovation.

Practical Implication: The findings of this research generate an inception for AI-HR collaboration while revealing underlying issues regarding adoption. It also provides updated information to related studies on similar fields of how digitalisation transforms and impacts businesses' performance. Additionally, organisations would be able to have insights into the deployment of AI in HRM by apprehending the factors influencing the Use and Acceptance of AI-powered technologies.

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

1. INTRODUCTION

Despite the tremendous disruption AI potentials in HRM, the advanced technologies are yet to be widely applied in HR. In effect, recent empirical research has postulated that AI technologies are in a surge of adoption after the occurrence of the pandemic (Barnes, 2020). Enamating from the aspiration of ascertaining the emerging impacts of AI in the realm of HRM, this research centred on exploring and investigating AI adoption factors through conducting the mixed-method research. Underpinned by the theory of UTAUT and psychological elements, the thesis further proposed a potential AI-powered HR framework stemmed from the AI-influential adoption factors.

At Phase 1, exploratory research was employed where the qualitative results postulated the adoption factors through thematic analysis. This initial research validated the supposition of UTAUT's factors and Perceived Risk element anticipated in Literature Review. Furthermore, the research discovered another emerging psychological component impacting adoption decision of Status Quo Bias. The findings, therein, reshaped the original conceptual framework by including the uncharted psychological component.

At Phase 2, the quantitative research subsequently provided a statistically confirmative findings of the adoption elements. Particularly, the diminution of constructs through exploratory factor analysis (EFA) authenticated the relationship between the charted factors with adoption intention. The refined model was evaluated through multivariant regression analysis to examine the significant level and the congruence of the model. Hypothesis testing was sequentially deployed when the research reached the satisfactory model. In brief, the empirical data analysis emerged from this research professed a relatively clear and consistent picture of how AI technologies are transforming and impacting adoption decision in HR field. On the ground of the findings, the results delineated a prospective mechanism for AI diffusion in HRM. Hence, this chapter significantly communicates and elucidates the primary outputs of the thesis delved on the extant milieu and literature within digitalisation era.

2. 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 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). 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 domain 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 in require, 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). 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. 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. 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). 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’ resumes and call out the questions related to the potential positions.

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).

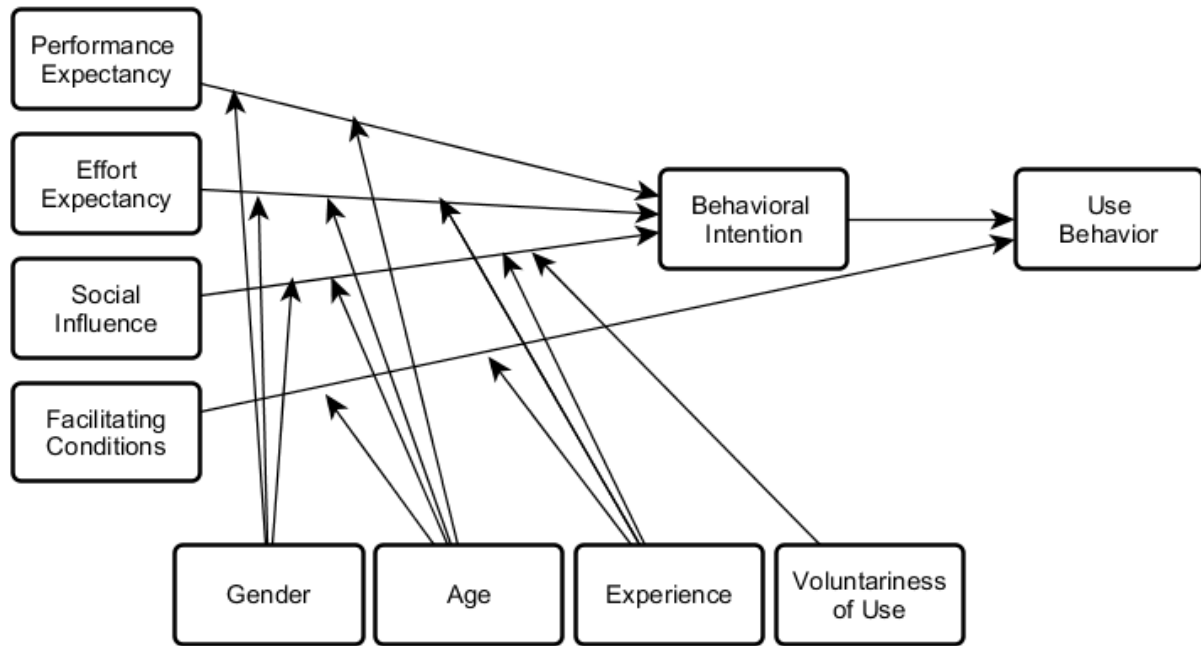


Figure 1: The Unified theory of acceptance and use of technology Model (UTAUT) (Venkatesh et al., 2003)

Since UTAUT has been deployed in multiple research 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 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.

Status Quo Bias (SQB) – (From extended LR after conducting Qualitative Research)

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. It is also defined as a predisposition to adhere to the incumbent circumstances or decision potentially initiated from people's uncertainty and conceivable switching benefits (Hsieh & Lin, 2020). In another theoretical perspective, the prominent prospect theory postulated two key features of human behavioural toward decision making process which are "non-rational" and "reference- dependent" (Tversky, 1979, p.263). This contributes to clarify the paradox in human decision making by psychologically addressing this construct as a typical hindrance of technology adoption. 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). Recent study by Balakrishnan et al. (2021) further proved the direct

relationship between status quo and human attitudes in the study of AI-power voice assistant adoption. The study presented consistent with the previous research on cloud system adoption when the new system was introduced (Fan et al., 2015).

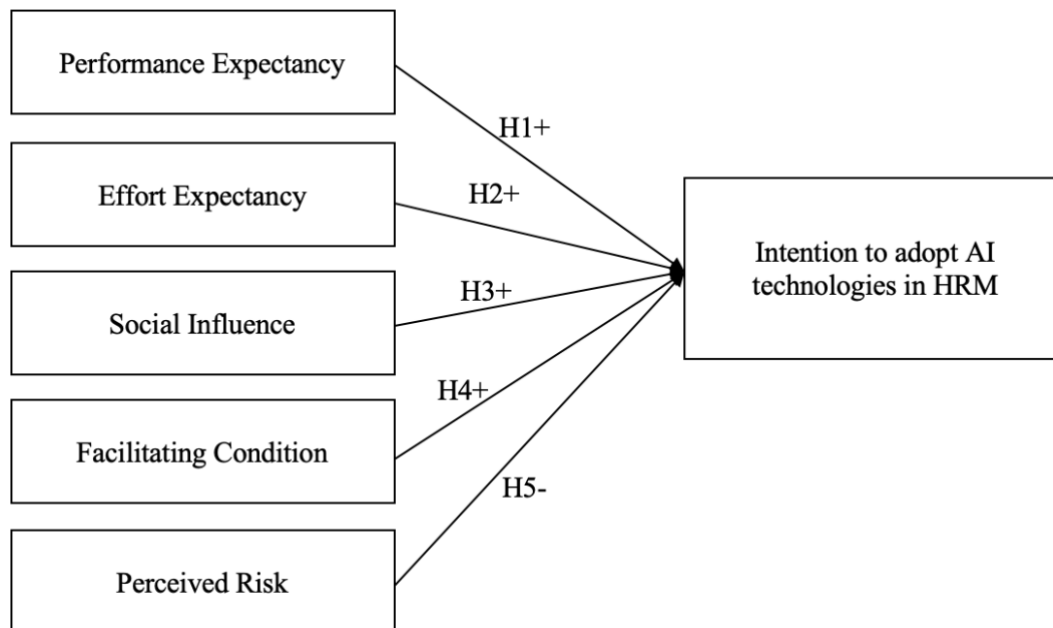


Figure 2: Preliminarily Conceptual Framework

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

3. RESEARCH METHOD

Reflectively on the research topic, factors impacting the use and acceptance of AI present a variety of challenges and opportunities for HR practices transformation. In this case, both findings from data collected from the individual method separately supplement the main theme research. In other words, the research aims to gain a comprehensive understanding and measurement tool for the preparation within the HR field in relation to organisations' AI adopting factors within the intervention of the emerging technology. The arrangement of how data could be gathered to appropriately satisfy research's aims is considered critical. When concluding with the selected mixed methodology, the method design to ideally gather valuable data extraction must be determined to maintain the consistency and logical data-collection path.

According to Creswell and Plano Clark, there are four frameworks to instruct the testification of mixed research methods namely triangulation, explanatory, exploratory, and embedded (Creswell, JW, Plano Clark, 2007). Each mixed-method design illustrates the specific approaches to how data could be collected for research analysis purposes. In particular, the most prevalent design is the triangulation mixed method where both quantitative and qualitative data will be collected at the same time and the data will be analysed parallelly. For the explanatory design, quantitative data will be collected first since findings obtained from the quantitative analysis will direct the selection of research participants in the qualitative investigation (Johansson et al., 2019). The exploratory design is the opposite of the previously mentioned design where qualitative data will be first gathered, and quantitative data will be sequentially collected to build the connection with the in-depth exploration of qualitative results at the beginning.

The final mixed method design is embedded style which allows researchers to use a specific type of data to support the other type of (Creswell, JW, Plano Clark, 2007). To be specific, a traditional research strategy will lead and frame the direction of the research while the supplemental data could be assembled "before, during or after the collection and analysis" to improve the results of the research study (Wellington, 2013, p.1496). Embedded design is considered compatible with the data analysis purpose of the researcher in this research. The research strategy design allows scholars to use a specific type of data to support the other type of (Creswell, JW, Plano Clark, 2007).

By the mentioned virtue, it best fits when scholars select one main research strategy to measure the variables while using the other one to enhance or compliment the previous result findings. For that

reason, the **sequential embedded mixed method** allows the researcher to flexibly use the data collected from both qualitative and quantitative approaches concurrently to support the finding without following specific orders of research conduction. Specific case studies among organisations' HRM research samples are selected adopting a qualitative approach to have an in-depth understanding of the perceptions of factors impacting AI use and acceptance in HRM from AI-HR related professionals. The quantitative data collected from HRM the board will subsequently examine the proposed factors. Noticeably, the mixed-method studies might not integrate both qualitative and quantitative research strategies. The **Figure 3** illustrates the holistic research strategy to address the research questions.

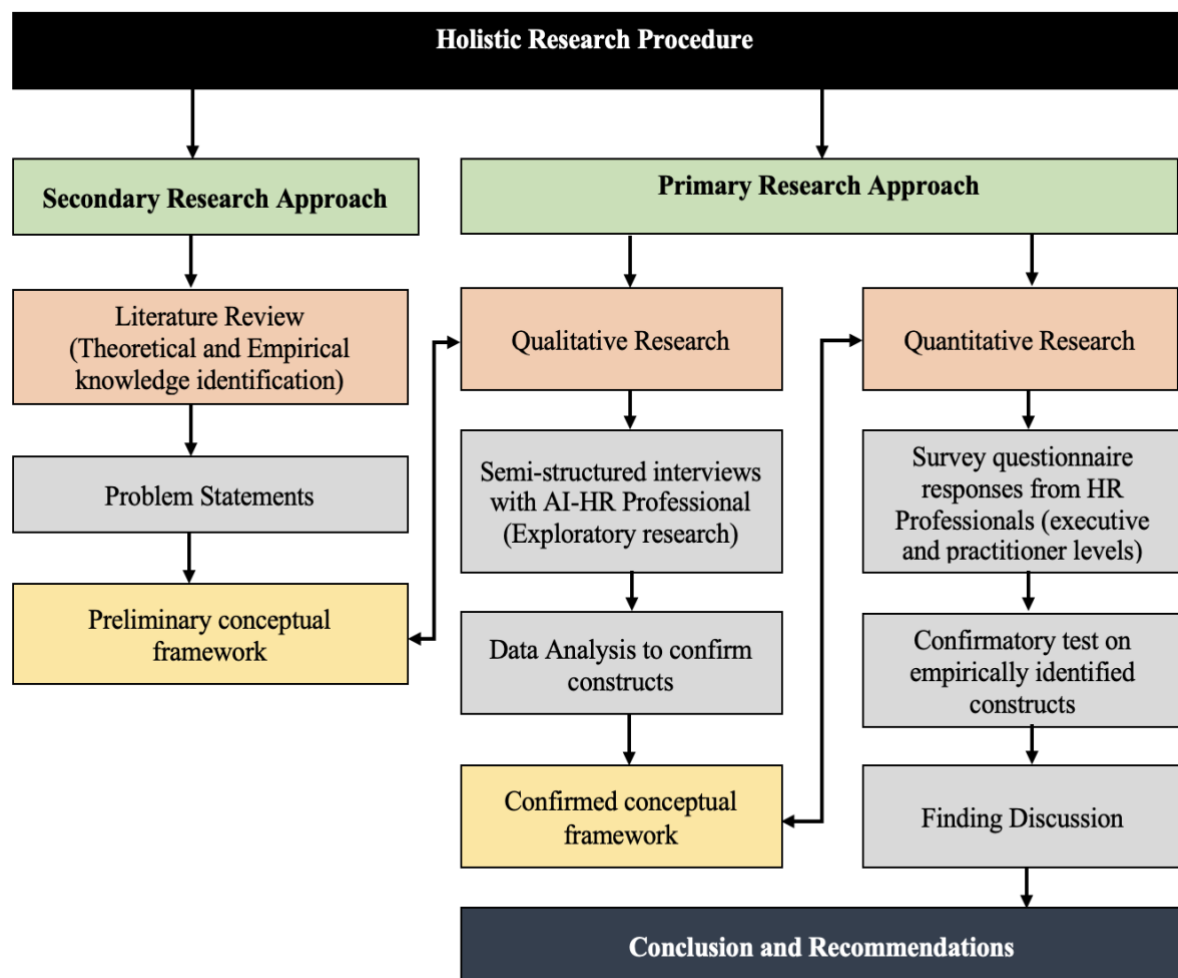


Figure 3: Designed Integration Strategy of Research Approaches (designed by researcher)

4. RESEARCH DESIGN AND TIMEFRAME

Research Design

The research adopts a sequential mixed method research design which is delivered into two phases. The first phase comprises qualitative data gathering among a sample of AI-HR professionals to acquire AI market knowledge in HRM. The semi-structured interviews are conducted at the exploratory stage of the research (Phase 1). The qualitative research was formulated on semi-structured interviews with a total of eighteen (18) participants varies across industries and organisational scopes in West Midland, 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.

At Phase 2, The survey questionnaire was designed and conducted through Qualtrics, a recommended platform for this research, and the pilot testing conducted with experienced research experts regarding its validity and relevance. In all, two hundred and twenty-five (225) candidates participated in the quantitative research. Among that, there was sixty-seven (67) candidates who did not comprehensively complete the survey, eleven (11) candidates who did not meet the inclusion criteria and one (1) candidate decided to withdraw at the end of the survey. Eventually, the total number of validated collected surveys for this research was one hundred forty-six (146). At this stage, quantitative data is set up in place based on themes established in the first phase and at the same time reflecting the conceptual UTAUT model to have a broader idea about the demographic information supporting the findings analysed from the qualitative data collected. The analysis and findings acquired from this quantitative research are conceived from Statistical Package for the Social Science (SPSS) analysis to synthesise the sophisticated and robust data.

Research Timeframe

Phase 1 (February 2022 to June 2022): Qualitative Research was officially launched where empirical data were collected through interviews with selected AI-HR professionals and meticulously analysed to ensure thematic analysis reached its saturation point. Within this timeframe, AI was prospectively introduced into the market and considered as a bedrock for significant development and business adoption for the forthcoming years (Chui, 2022). The milestone indicated an emerging of the AI concept and was potentially categorised in the *Innovator stage* in the Diffusion of Innovation Model.

Phase 2 (September 2022 to January 2023): Quantitative Research was conducted where the surveys were disseminated online to HR Professionals within West Midland areas and the raw data were gathered via Qualtrics platforms. Notably, there was a significant transition of AI diffusion degree during this period of time. According to the Annual Report on AI Index of Stanford University, 2022 to the beginning of 2023 was denoted as the “era of deployment” of AI due to its enlargement in monthly releasing models (Perrault, 2023). Dovetailing to this, AI had been potentially progressing to *Early Adopter stage* where its applications were on the tremendous growth in the market.

The **Figure 4** illustrates the progression of AI diffusion within the timeframe conducting the thesis. Notably, the two distinct phases of this research had incidentally occurred in different evolvement stages of AI developments, which provides a significant triaxiality lens for data interpretation. Echoing the growing evidence of agile AI progression, the findings of this research illustrate the precarious and proceeding attributes of technology advancements as long as their impacts on the nature of research in related fields of technology adoption. The research will progress with data interpretation and discussion in each Innovation phase, specifically *Innovators: Qualitative Research* and *Early Adopter: Quantitative Research*.

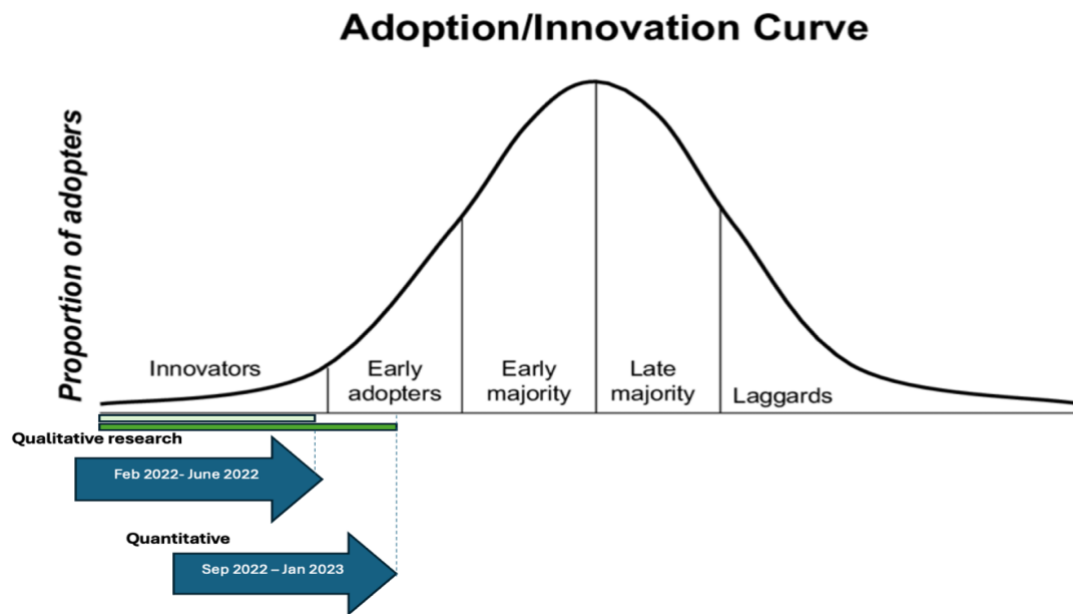


Figure 4: Relations of research milestones in accordance with AI development trend based on DOI Model (2022-2023) (Rogers et al., 2003).

5. RESEARCH FINDINGS

The predetermined conceptualisation and theoretical research model established in this research could be reasonably confirmed in response to the results distilled through empirical data analysis. Although not all hypotheses were acceded, the majorities were verified to solidly correlated with adoption intention of HR professionals as reflected in research's literature review. In fact, whilst the qualitative research revealed the motives and potential impulsion of AI-HR inclusive adoption criteria, the quantitative research denoted the influential elements onto AI adoption mechanism in the extant HRM context. This showcased a concrete evident illustrating in the accomplishment of (1) *the high proportion of identifying related themes in compared to the priori codebook*; (2) *the suitability of EFA and coefficient correlation analysis*; and (3) *the equivalently positive support for the majority of hypotheses*.

Echoing the empirical findings, the research retains the theoretical model of UTAUT with the two accepted constructs and two psychological factors of Perceived Risk (PR) and Status Quo Bias (SQB). The retained model in this research elicits correlations among the variables which will be elucidated in causation impacts rooted from chorological explanations. Amalgamating the results from theoretical and empirical data analysis from this thesis, the primary clusters of discussion are reflected through the impact of Social Influence (SI), Performance Expectancy (PE), Perceived Risk (PR) and Status Quo Bias (SQB) onto AI-adoption decision of HR professionals.

1. Finding 1 - Qualitative Research

Anchoring to the data outputs extracted from thematic analysis, the findings revealed the predetermined themes aligned with theoretical model of this thesis. Evidently, the final themes extracted from the interviews appeared consistent with the five factors specified in the priori codebook (Coverage percentages of FC=88.89%, SI=100%, PE=72.22%, EE= 88.89%, and PR= 88.89%). In addition, the qualitative research successfully recognised the emerging theme of Status Quo Bias (SQB) with 94.45% of coverage percentage (Appendix 1). Conceding to the empirical results, the qualitative phase of the thesis portrays an ideal relationship among the predetermined and spotted constructs within this study. Hence, the results confirm the clusters of UTAUT's factors, PR and SQB factors as pressures for AI adoption in HRM. The **Figure 5** exhibits the outcome of data analysis from qualitative research.

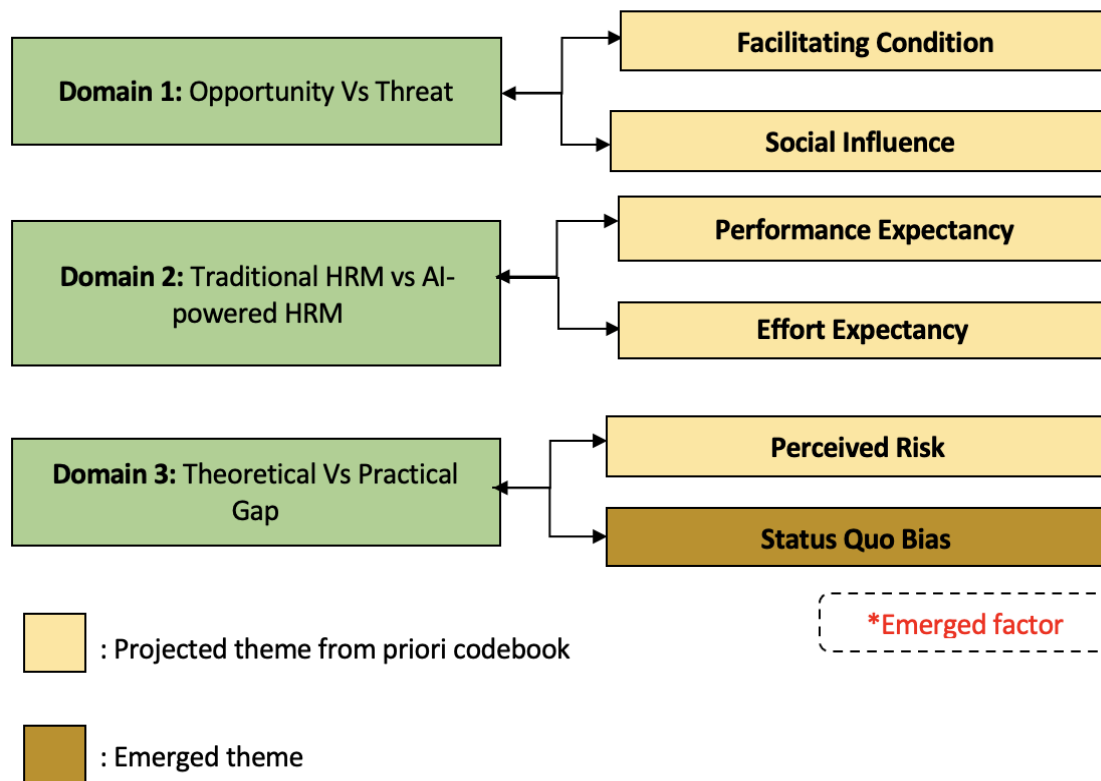


Figure 5: Finalised model from qualitative research

Dovetailing to the theoretical literature and apriori codebook (Appendix 2), 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 2** 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 2: 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. Presently above, all the indicated factors possessed the strong correlations with AI adoption intention in HRM. Based on the coverage percentages of theme segmentations, SI (100%) and SQB (94.45%) are core influential factors in AI adoption. Intriguingly, the two dominant factors belong to the two opposing adoption groups. To elaborate, Domains 1 and 2 illustrates the positive factors (FC, SI, PE and EE) impacting on adoption intention while Domain 3 contains the two adverse factors (PR and SQB) of AI adoption.

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 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 recognitions 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 apriori codebook discussed in this research.
2. **Traditional HRM vs AI-powered HRM:** By extracting the participants' perceptions regarding the two-opposing concept 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 apriori 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 apriori 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.

2. Finding 2 - Quantitative Research

AI Adoption Intention in HR (ITA) was measured based on the six (6) main constructs identified in the qualitative research. Within each construct, the represented variables were applied to directly illustrate the correlation between the independent variables and dependent variable. In fact, the attachment of each variable to the main constructs were examined and illustrated in prior research in related fields regarding technology adoption (discussed in the extended literature review). **Table 3** illustrates how the variables were coded on SPSS software:

Table 3: Coding process for selected constructs on SPSS (generated by the researcher)

Independent Variables	Coding	Measurement codes
Construct 1: Effort Expectancy (EE)		
Ease of Use	EOU	EOU1 - EOU4
Job Compatibility	JC	JC1 - JC4
Construct 2: Facilitating condition (FC)		
Leadership Support	LS	LS1 – LS4
Innovation Driven	ID	ID1 – ID4
Construct 3: Performance Expectancy (PE)		
Cost Effectiveness	CE	CE1 - CE4
Task Versatility	TV	TV1 – TV4
Construct 4: Social Influence (SI)		
Employer Branding	EB	EB1 - EB4
Subjective Norms	SN	SN1 – SN4
Construct 5: Status Quo Bias (SQB)		
Cognitive Misperception	CM	CM1 – CM4
Perceived Cost	PC	PC1 – PC4
Psychology Commitment	PYC	PYC1 – PYC4
Construct 6: Perceived Risk (PR)		
Bias Concern	BC	BC1 - BC4
Fear of the Unknown	FU	FU1 – FU4
Perceived Unemployment	PU	PU1 – PU4
Privacy Concerns	PRC	PRC1 – PRC4
Dependent Variable		
Intention to adopt AI		
	ITA	ITA1 – ITA4

Dependent variable: To measure ITA, the research applied three-item measurement which was utilised in the prior research regarding technology adoption by Venkatesh (Venkatesh et al., 2003). In Particular, the measurement associates to users' attitudes toward the decision of applying the novel technology within organisations. The three items are: (1) "I plan to use AI technologies in the future", (2) "I intend

to use AI technologies in the future” and (3) “I predict I would use AI technologies in the future”. A 5 Point-Likert scale, ranging from level 1 “Strongly Disagree” to level 5 “Strongly Agree”, was subsequently used to evaluate the items. The results were next applied in the Cronbach’s Alpha Coefficient test to examine the reliability and validity of the measured items.

Independent variables: In a similar line, the six constructs represented the adoption influential drivers of AI in HRM were measured by applying four-item measurement on each distinct variable (except for EB variable with three-item measurement) inspired by earlier research. Specifically, according to **Table 3**, Construct 1 (EE) includes two variables (EOU and JC), Construct 2 (FC) includes two variables (LS and ID), Construct 3 (PE) includes two variables (CE and TV), Construct 4 (SI) includes two variables (EB and SN), Construct 5 (SQB) includes three variables (CM, PC and PYC) and finally Construct 6 (PR) includes 4 variables (BC, FU, PU and PRC). The total fifteen (15) adoption variables were derived from the nature of the constructs whose relationships were strengthened from prior research. The meticulous measurement and analysis of each construct contributed to illuminate the final research question regarding the degree of use and acceptance of AI by HR professionals. The answers therein were evaluated accordingly with the dependent variables by using the 5 Point-Likert scale that ranges from “Strongly Disagree” to “Strongly Agree”. They were subsequently examined the consistency and validity through Cronbach’s Alpha Coefficient test.

Multiple Regression Analysis

In regression analysis, there are certain indexes to be envisaged to access correlation coefficients of individual pair of variables, level of significance and the number of cases (Uyanık & Güler, 2013). To be specific, the criteria are adopted in accordance with the following rules:

- **R square or Adjusted R square:** applied to visualise the degree of variance of two variables. The coefficient of determination was computed through square R value. The Adjusted R square reflects the explanation level of dependent variable by independent variables in regression model. This index ranges from 0 to 1 indicating the meaningful of statistical model.

- **Significance of F:** applied to examine the suitability degree of the model to conduct the regression. If significance is less than 0.05 (<0.05), multiple regression is concluded to be appropriate for the data set. This index could be traced in ANOVA Table from SPSS.

- **Significance of t:** used to test the statistical meaning of coefficient. If significance is <0.05 , independent variable is concluded to influence dependent variable. This index can be found in Coefficient table.

Table 4: Model Summary (extracted from SPSS)

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.755 ^a	.570	.552	.42373	1.795

a. Predictors: (Constant), PR, SI, EE, FC, PE, SQB

b. Dependent Variable: IU

In social sciences, it is entrenched that if the Adjusted R Square is larger than 35%, it indicates a respectable amount of variance explained (Pallant, 2010). In this case, according to **Table 4**, the Adjusted R square was 0.552 (55.2%) which depicted that 55.2% variance of the Intention to Adopt AI could be explained by independent variables.

Table 5: ANOVA Table (extracted from SPSS)

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33.101	6	5.517	30.726	<.001 ^b
	Residual	24.957	139	.180		
	Total	58.059	145			

a. Dependent Variable: IU

b. Predictors: (Constant), PR, SI, EE, FC, PE, SQB

The research progressed with accessing ANOVA table to examine model appropriateness to conduct regression analysis. As shown in **Table 5**, the significance value of F was smaller than 0.05 (sig. = 0.000) which indicated that multiple regression model is suitable for this research in accordance with the data set. In this regard, Standardised Coefficients Beta values were subsequently scrutinized. **Table 6** demonstrates the Correlation Coefficients between groups of variables.

Table 6: Coefficients Table (extracted from SPSS)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.601	.373		1.611	.109		
	EE	-.095	.060	-.097	-1.587	.115	.819	1.220
	FC	.085	.063	.090	1.356	.177	.706	1.417
	PE	.276	.077	.248	3.574	<.001	.643	1.556
	SI	.299	.060	.328	4.951	<.001	.703	1.422
	SQB	-.420	.095	-.326	-4.424	<.001	.569	1.757
	PR	-.109	.054	-.121	-2.017	.046	.854	1.172

a. Dependent Variable: IU

According to the result from Coefficient Table, the coefficient of **Effort Expectancy** was smaller than zero ($\beta = -0.097$) which means that this variable has a negative impact on dependent variable. Additionally, the significant value was also greater than 0.05 (sig. = 0.115) demonstrating that Effort Expectancy cannot significantly explain the Intention. **Therefore, hypothesis 1 was not supported by the data.**

The coefficient of **Facilitating Condition** was greater than zero ($\beta = 0.09$) which indicated that this variable has a positive motivation effect on the dependent variable. However, its significant value was greater than 0.05 (sig. = 0.177), this variable has minimal statistical meaning in explaining the intention. **Therefore, hypothesis 2 was not supported by the data.**

The coefficient of **Performance Expectancy** was greater than zero ($\beta = 0.248$) which addressed that this variable has a positive motivation effect on dependent variable. As its significant value was also smaller than 0.05 (sig. = 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 3 was supported by the data.**

The coefficient of **Social Influence** was greater than zero ($\beta = 0.328$) which stated that this variable has a positive motivation effect on dependent variable. As its significant value was also smaller than 0.05 (sig. = 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 4 was supported by the data.**

The coefficient of **Status Quo Bias** was smaller than zero ($\beta = -0.326$) which signified that this variable has a negative effect on dependent variable. As its significant value was smaller than 0.05 (sig. = 0.001), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 5 was supported by the data.**

The coefficient of **Perceived Risk** was smaller than zero ($\beta = -0.121$) which stated that this variable has a negative effect on dependent variable. As its significant value was also smaller than 0.05 (sig. = 0.046), this variable has statistical meaning in explaining the intention. **Therefore, hypothesis 6 was supported by the data.**

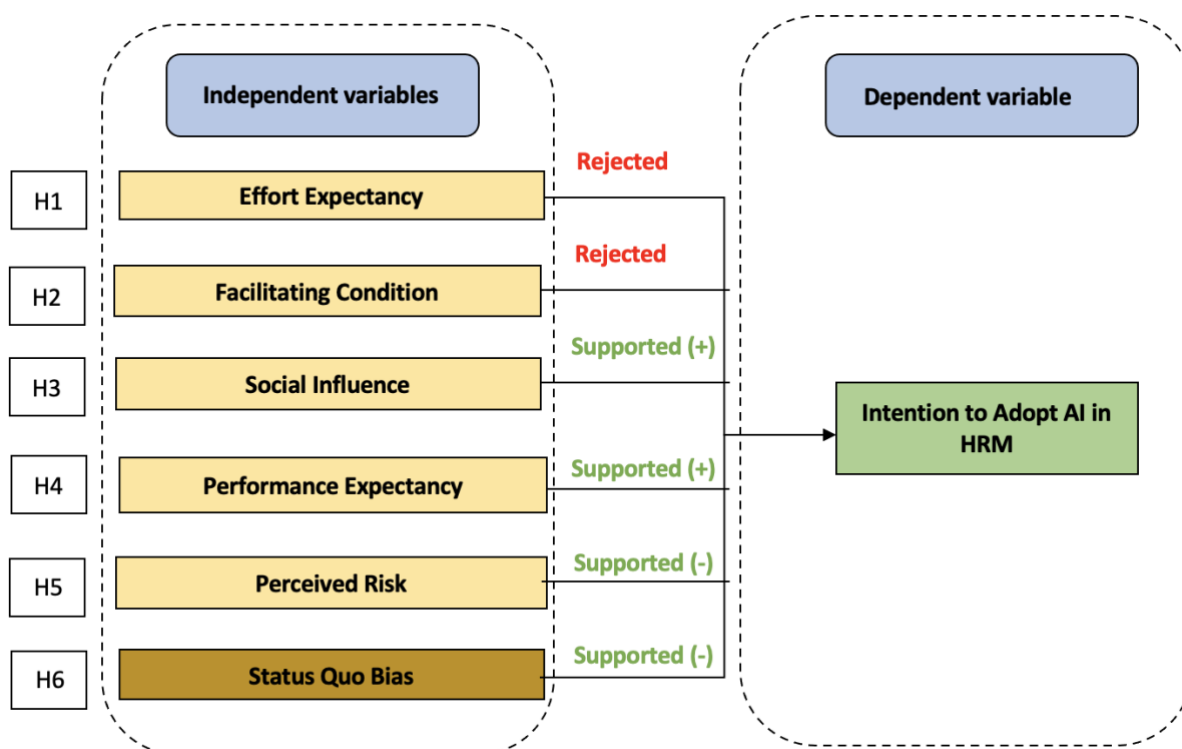


Figure 6: Finalised model from quantitative research

From this standpoint, the results and statistical analysis showcased has elaborated the answers for RQ3 “*To what extent AI is utilised and accepted by HR Professionals?*”. In addition, the research therein achieved the overarching objective of confirming the impact of exploratory factors from qualitative research on AI adoption intention in HRM (summarised in **Figure 6**). In brief, SI, PE, PR and STQ were confirmed to have a strong correlation to AI adoption intentions of HR professionals whilst EE and FC were not significantly performed a statistical correlation impacting the adoption intention in HRM.

6. RESEARCH DISCUSSION

Recapitulating from the empirical findings, this research has successfully illuminated the ulterior influence of AI-powered technologies in HR realm. Particularly, the degree of AI use and acceptance in HRM and the impacting factors on AI-HR deployment were demystified and elaborated within the two phases of the research. In tandem with the exploration of adoption factors, the research provides a practical bridge portraying a potential collaboration mechanism between HR functions and AI technologies. The discussion, therein, concentrates on synthesising the three research questions explicitly structuring the research design and outset. **Figure 7** exhibits the exhaustive anatomy dedicating to examine the problem statements shaped in the three primary research questions (RQs).

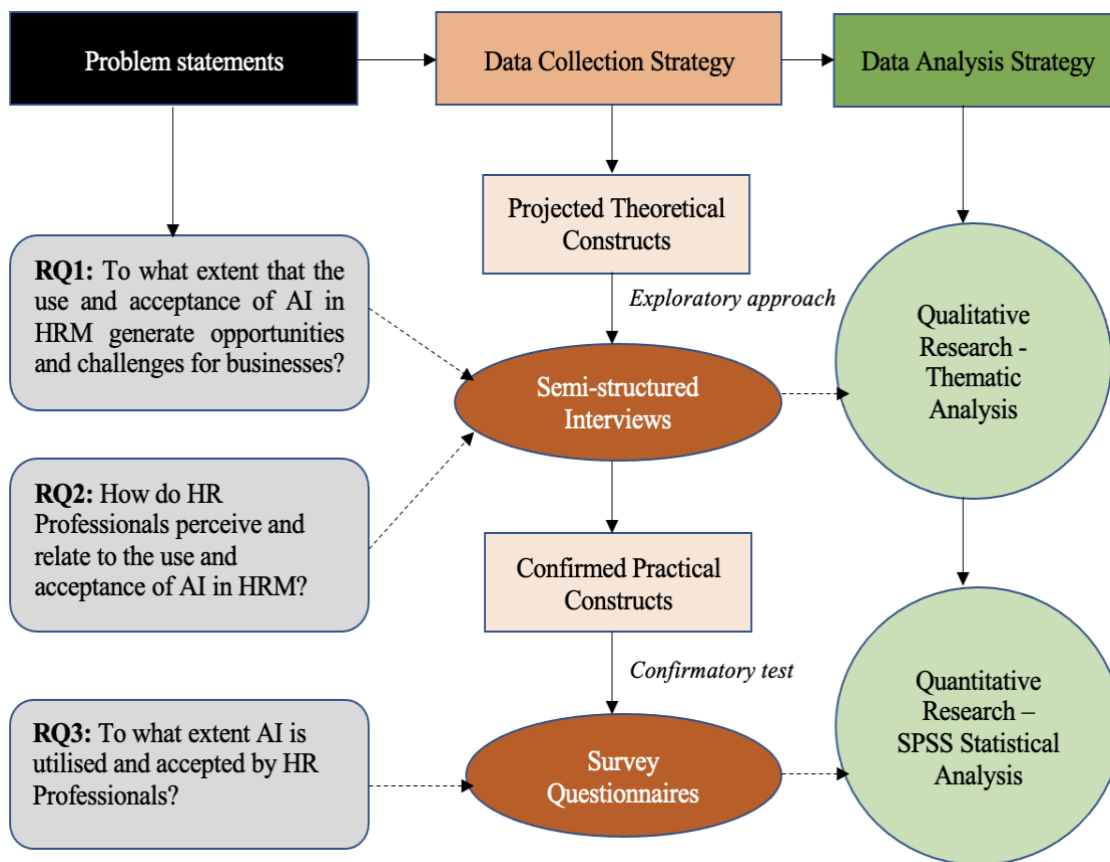


Figure 7: Comprehensive Research Framework Establishment (designed by researcher)

Discussions from Qualitative Research: Innovators Stage of AI adoption in HRM

Discussion 1: Opportunities and Challenges of AI adoption in HRM (RQ1)

By the virtue of the findings from qualitative research, the six influential factors on the use and acceptance of AI and how these factors possibly affect its deployment in HRM were confirmed (Appendix 1). Based on the coverage percentages of theme segmentations, SI (100%) and SQB (94.45%) are core influential factors in AI adoption. Intriguingly, the two dominant factors belong to the two opposing adoption groups with SI (positive factor) and SQB (adverse factor). The findings mold a concrete elicitation of the positive and negatives risks of AI adoption in HRM and highlights the affiliation in RQ1: “To what extent that the use and acceptance of AI in HRM generate opportunities and challenges for businesses?”

Contextually speaking, the Covid-19 pandemic has enlarged the scale of remote working for most businesses in all fields due to the requirement of social distancing and even brought existence crisis threats to all organisations failing to adapt. Lanham Napier, the CEO and co-founder of BuildGroup, states that the pandemic has been escalating and challenging the resilience of many business models struggling to compete against “centric companies that can leverage data and machine learning” to generate essential insights and improve capacity (Napier et al., 2020). The present incident has become the accelerator for the working pattern transformation, which provides a hindsight for businesses to reexamine procedures of management. The situation appoints and explains the seminal impact of **Social Influence (SI)** in shaping novel approaches in HRM. This poses a necessary radicalisation in HRM by cautiously scrutinising to the management approach to prepare for novel working patterns (Akinjiyan, 2019).

The pandemic could be considered as an epitome of how data make sense and turn into valuable sources for HR to conduct necessary analysis without approaching physically people due to the virus spread (Dataquest, 2020b). This reflects on the empirical data collected from qualitative research. In fact, **Effort Expectancy (EE)**, **Performance Expectancy (PE)** and **Facilitating Condition (FC)** were, therefore, reflected as significant elements in AI-HR adoption by HR professionals in this duration. By the dint of the global issues, the potentials related to digital adoption were envisaged to upgrade business performance. This is in line with McCafferty (2021)’s work emphasising on the gap that some organisation are exploring how technology can perform at work and while the others concentrating on building approaches to work with it. **Table 7** presents the collective opportunities and challenges of AI-HR adoption.

Table 7: Opportunities and Challenges of AI-powered HRM compared to Traditional HRM

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 AI-HR related professionals: Obsolete (Old fashion) Human errors Human Biases Lack of historical reflection
	Advantages in conventional HRM Process	Transparency Sympathy Simplification Human interaction	
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 AI-HR related professionals: Cost saving Complexity
	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	

At this junction, the study elicits the triggering mechanism of HR professionals in reevaluating the HR functions and context in the measurement of AI-HR potentials. Subsequently, HRM practices are more likely to make a decision and establish critical approaches on using and accepting AI in HRM. In essence, multiple functions in management could be streamlined and digitalised through various sectors applying AI (Martin and Leurent, 2017). Conceding to this, the findings from qualitative research are consistent

with the predetermined AI adoption factors embedding in UTAUT Model. The study at this stage indicates that HRM encapsulates a crucial capability in augmenting conventional HR functions. This position requires innovations to be accelerated in HR professionals' perceptions.

Discussion 2: HR Professionals' Perceptions on the Use and Acceptance of AI in HRM (RQ2)

It is argued that AI progress potentially leads to the transformation of business models and economic mechanisms, by enhancing the business performance (Jatobá et al., 2019). Despite the discern of AI-HR advantages disclosed in the research interviews, HR professionals exhibited a transparent hesitation when considering AI application in HR. In reality, organisations are expected to take prompt actions on embracing the advanced technology and selecting whether to become a “first mover” or a “fast follower” with AI adoption strategy (Buck & Morrow, 2018). AI-powered technologies could augment analytical tasks and would eventually evolve to perform more intuitive and empathetic tasks, which might pose a rudimentary threat to the human employment (Huang and Rust, 2018). By the cause of dramatic influence on the potential applications of AI, employees may perceive the new technology advancement as a detrimental impact in HR field. The mentioned perceptions could be perceived as a hindrance for businesses to adopt AI into their organisations. In fact, the empirical work from this study revealed a relatively clear and consistent picture of how **Perceived Risk (PR)** and **Status Quo Bias (SQB)** are the major concerns of HR professionals. Thus, the notions of PR and SQB negatively impact AI-HR strategic collaboration. The finding highlights the critical influence of the anteceded psychological determinants in HR professionals' perception.

This proposition is also in line with the position that certain perception regarding risks are triggered when the users are introduced with novel technological subjective (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. This visualises a practical gap between the proposed benefits of AI technologies and the hindrance of application owing to the factor of PR. Significantly, an emerging factor of SQB 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 illustrated the typical hindrance of technology adoption (Eidelman & Crandall, 2012). This explains why the issue posed 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. Reflecting upon Diffusion of Innovation (DOI) theory, the AI-HR adoption determinants possess a symmetry to **Innovator Stage** as described in Research Timeframe section.

Discussions from Quantitative Research: Early Adoption Stage of AI adoption in HRM

Discussion 3: HR Professionals in determining the level of AI-HR collaboration (Use and Acceptance) (RQ3)

In the first instance, AI-HR collaboration for innovation is not an original tacit resource for replacing human factor in the business sustainable circle. Instead, technological adoption theories postulate that innovation adoption, upgrading internal structure, is essential strategic advancement that drives business performance capabilities. Therefore, HR scrutinises more on the contemporary core functions such as Recruitment and Performance Evaluation. In effect, the extension of AI algorithms has depicted a wide ramification of functions which could be adopted within HRM. Theoretically, AI technologies 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). **Figure 8** demonstrates potential AI deployment in HR realm.

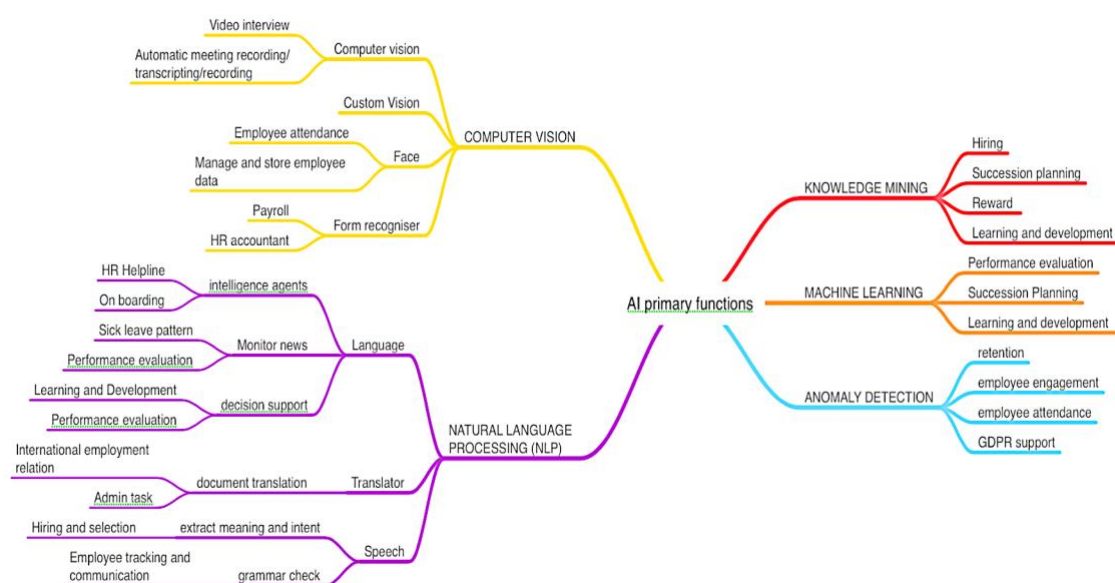


Figure 8: AI-powered HR functions map based on core AI capacities (designed by researcher)

Conversely, the empirical data in the quantitative research continues to communicate another angle of the influential adoption factors in HRM. At this second phase, the statistical evinces that AI-HR coalition are significantly affiliated with Social Influence (SI) ($\beta = 0.328$ sig. at the 0.001), Performance Expectancy (PE) ($\beta = 0.248$ sig. at the 0.001), Perceived Risk (PR) ($\beta = -0.121$ sig. at the 0.001) and Status Quo Bias (SQB) ($\beta = -0.326$ sig. at the 0.001) while Effort Expectancy (EE) and Facilitating Condition (FC) (both sig. less than 0.001) illustrated a minimal statistical meaning in the AI adoption decision of HR professionals. From this standpoint, the research findings are twofold: *(1) it shadows the two adoption factors, dominantly influencing HR professionals, which are SI and SQB. This could be reflected in the findings of the qualitative research from this study. (2) It narrows the adoption factors with the diminishing of FC and EE in AI-HR coalition model.*

As explained in the Research Timeframe, the two phases of conducting the mixed method research aligned with conspicuous milestones of AI advancements in the market. If Phase 1 was launched at the beginning 2022, Phase 2 was occurring at the end of 2022 to early 2023. In fact, ChatGPT was introduced by the end of November 2022, which marked another foundation for AI perceptual evolvments (Ray, 2023). This was not immune to HR realm when demonstrating a marginalisation on FC and EE as adoption factors at this stage. In fact, Venkatesh has early emphasised the importance of FC in exposing users' perceptions on the availability of required resources and advocacy dedicated by organisational capacity, equipment, and essential supports for an individual to perform a task (Venkatesh et al., 2003, 2012). Therefore, FC has been deployed as a crucial element contributing to the positiveness of individual behaviour toward future intentions and decisions. Nevertheless, the plethora of free AI applications and services in the market, therein, potentially explains for the atrophy role of FC in HR professionals' adoption perception.

In this regard, EE is postulated as users' perception on how incentives could be produced, which is measured by the enhancement of the targeted function (Im et al., 2008). Simply put, EE provides a potential mechanism for an individual to enrich the perceptions of the adopted technologies by endowing a sense of easiness in how contemporary performance is positively altered with the intervention of novel technologies. In practice, the significant growth of digital-supported networks has brought more considerations to business operational models in terms of how to deploy effectively and efficiently the

availability of those assistant networks to maximise business success. Internet of things (IoT) and the new introduction of 5G network recently in the market have allowed AI adoptions to expand to potential consumers. According to Dataquest Report 2020, AI and 5G network will be the combo of the future of work and when users are using the 5G network, “there are one or two AI elements that are also making it work” (Dataquest, 2020b). Echoing the growing evidence supporting AI effort expectancy (EE), this provides a potential mechanism explaining the neglect of EE factor in HR professionals’ mindset in evaluating AI adoption elements.

RESEARCH CONCLUSION

The AI-HR adoption research validated the projected adoption variables from UTAUT: **Effort Expectancy (EE)**, **Performance Expectancy (PE)**, **Social Influence (SI)** and **Facilitating Condition (FC)**; and additional two psychological constructs of **Perceived Risk (PR)** and **Status Quo Bias (SQB)**. The analysis also revealed a consistent picture of the paradox perceptions regarding AI technologies from the preponderance of HR Professionals. There were certain controversial opinions regarding the adoption of AI technologies across diverse HR functions, which were closely discussed. The quantitative research statistically examined the investigated constructs of phase one. The results from the second study narrows down the predetermined constructs with the diminution of EE and FC factors.

The thesis contributes to provide the empirical evidence and validation for theoretical linkage of AI adoption factors in HRM. It also pictures the current levels of AI understanding from HR Professionals and the critical adoption concerns in the province of AI-powered HRM. The empirical work further facilitates related implication frameworks for policymakers, AI suppliers and users to foster a sustainability working environment for AI and HR in digitalisation era. The research eventually notifies organisations about the emerging impact of AI in the field of HR as a prominent facilitator in shaping overall organisation and manpower management strategies. Importantly, longitudinal study is suggested for future researcher since the nature of technology-related research is interminable and therefore, the information collected is valid when being reconciled in a certain timeframe.

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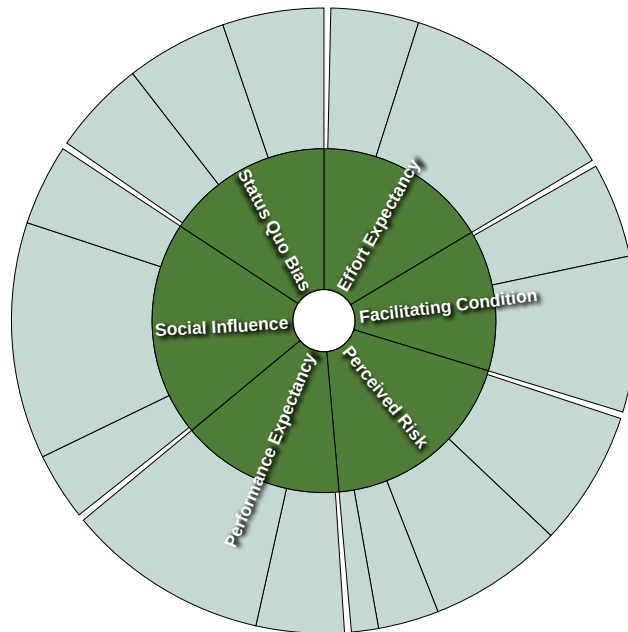
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Appendix

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



Appendix 2: Apriori Codebook (designed by researcher)

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