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Artificial Intelligence-Driven Talent Management System: Exploring the Risks and Options for Constructing a Theoretical Foundation

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Abstract: AI (Artificial intelligence) has the potential to improve strategies to talent management by implementing advanced automated systems for workforce management. AI can make this improvement a reality. The objective of this study is to discover the new requirements for generating a new AI-oriented artefact so that the issues pertaining to talent management are effectively addressed. The design artefact is an intelligent Human Resource Management (HRM) automation solution for talent career management primarily based on a talent intelligent module. Improving connections between professional assessment and planning features is the key goal of this initiative. Utilising a design science methodology we investigate the use of organised machine learning approaches. This technique is the key component of a complete AI solution framework that would be further informed through a suggested moderation of technology-organisation-environment (TOE) theory with the theory of diffusion of innovation (DOI). This framework was devised in order solve AI-related problems. Aside from the automated components available in talent management solutions, this study will make recommendations for practical approaches researchers may follow to fulfil a company's specific requirements for talent growth.

Keywords: risk management; talent management; AI; design artefact; SMEs; design research

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1. Introduction

Employing artificial intelligence (AI) in the area of talent management (TM) is already widely acknowledged as an important research topic. The terms "cognitive technologies" and "artificial intelligence" have both become common terminologies in business, research, and technology. These technologies play a significant role in determining how people and technology interact for business operations (Kuzior and Kwilinski 2022). Applications of cognitive technologies as AI offer technical advancements which are evident in business and research (Kuzior and Kwilinski 2022).

Many modern technologies address the difficulties in creating systematic automated information support solutions. AI has seldom been fully applied yet to enhance employment management practices (Vrontis et al. 2022). The abilities of AI have been recently investigated in terms of the development of interventions from the perspective of the job market (Jarrahi 2018), although many disruptive innovations to improve the current frameworks of talent systems have not been thoroughly studied. For the objective of modernising workforce management, the development of general-purpose AI technology have been applied for implementing changes (Agrawal et al. 2018). When developing new AI-based apps for human resource management, developers have encountered a variety of challenges, including dehumanisation, unfair requirements, and biased algorithms; as a result, it is necessary to carry out detailed research (Tambe et al. 2019).

According to one recent market study, at least 300 Human Resource (HR) technology set-ups are developing AI technologies for managing people. About 60 of these companies have prospered in terms of customers and venture capital financing (Bailie and Butler 2018). One AI-powered talent intelligence platform that aids businesses in finding, developing, and retaining top talent has secured $220 million and is currently valued at around $2 billion (Charlwood and Guenole 2022). Businesses have already begun to make large investments in AI for talent management. A start-up in HR technology has "quietly become a billion-dollar unicorn" after automating work processes to improve several practices, including the recruitment and selection of potential candidates (Kelly 2021). Accenture has made a strategic investment in the London-based company Beamery, which is valued at $800 million and provides options for its recruitment operating system. Accenture's investment is in the form of a capital contribution (Lunden 2021). AI has already begun to be incorporated into the processes and systems of large international technology organisations, which are currently in the process of employing new personnel (van der Lugt 2021). This indicates AI will be an essential part of talent management operations in organisations, which emphasises the importance of the subject for future analysis. On the other hand, the job market is always full with so people seeking work.

These job seekers include new graduates as well as people looking for better or different opportunities. People looking for work are frequently searching for better jobs due to the economy's ongoing changes. Job seekers conduct a variety of tasks as part of their personal objectives and tasks, including preparing a curriculum vitae (CV), choosing a career path, deciding which organisation that would be the greatest fit for an application, practicing for interviews, and assessing job offers. Although the use of AI in TM is still in its infancy, there is potential for it to be applied in a number of different contexts. A variety of AI-based career advising systems have been created, for instance Job Finder, which uses machine learning to connect job searchers with relevant employment based on their preferences and skill sets (Liu et al. 2017). Each of these tasks has elements that, when combined, will provide matrices that can produce an indicator value. The majority of study in this area places more focus on recruiters' attempts to find the best applicants.

One of the most common HRM strategies for doing analysis on large amounts of data is known as machine learning (ML). ML is concerned with how computers can adjust to new conditions, as well as how they can recognise and extrapolate patterns (Makridakis et al. 2018). ML performs an automated process of pattern recognition, which is the fundamental component of machine learning (Jordan and Mitchell 2015). The goal of AI is not only to comprehend how people think, comprehend, learn, and behave logically and intelligently, but also to construct intelligent beings able to think, write, perceive, understand, anticipate, and influence the environment around them (Hassani et al. 2020).

An innovative technical strategy that makes use of AI has the potential to solve the problem of managing such data by converting it into insights that can be used for managerial and operational decisions. In this research, we offer a new AI strategy for talent management that makes use of machine learning to merge various data sources in order to deliver more insightful predictions. The use of AI reveals issues such as discrimination, biased algorithms, and dehumanisation (Charlwood and Guenole 2022; Fritts and Cabrera 2021). Therefore, when designing and evaluating the AI solution, it is important to consider both the potential benefits and risks in such systems. Decision-makers should ensure that AI systems are designed in such a way that minimises the risk of perpetuating existing biases and discrimination (Shrestha et al. 2019). Furthermore, it is important to monitor AI-based solutions consistently to ensure they are functioning as intended morally with a modicum of human ethics and not generate unintended consequences.

This study aims to design a new AI solution and investigate its suitability in the context of TM. We plan to develop a methodological framework for the deployment of talent management AI software solutions for SMEs. Key components of talent management and related processes integrating talent management systems will be extracted from the latest relevant literature and validated with secondary data collected from open sources, for example Scopus database/search engine, social media and other sources that make big training and development datasets freely available. The emerging themes for the proposed proof-of-concept prototype will be compared with existing software solutions available in the market for talent management.

The remaining portion of this paper is organised as below. The essential background literature is discussed in Section 2, which provides an overview of the solution artefact design. The methodology of the research study is broken down in depth, and the next part delves into the specifics of the design artefact, placing our contribution within the framework of earlier work that is pertinent to the topic at hand. Following the discussion, which concentrates on the general contributions of the study, the conclusion is documented, and it states the main themes covered here.

2. Background of the Study

AI helps organisations to manage large volumes of data more effectively, as well as to identify patterns and extract information that would be difficult to discern using traditional methods. In talent management, AI can serve to improve the accuracy of job candidates' assessments, as well as to identify potential personnel who may be a good match for vacant positions (Jia et al. 2018). In this way, AI oriented management solutions have the potential to improve organisational efficiency by reducing the time and resources required to screen job applicants and identify suitable candidates. Despite the potential advantages of AI in HR, there are risks that must be taken into account. For instance, AI-based systems may engage in discriminating and biased behaviour (Chamorro-Premuzic et al. 2019). It is crucial to take into account both the advantages and disadvantages of employing such systems when devising and assessing AI-powered talent management solutions. In particular, decision-makers should ensure that AI systems function in such a way that minimises the risk of perpetuating biases and discriminatory practices. When compared to various other HR procedures, talent management is one in which the impact of AI can be seen as a driving force for substantial improvements in terms of practices. However, if AI is to be applied in this process, we will need to effectively outline a conceptual solution model to meet its key requirements. Table 1 below summarises existing studies on this subject.

Table 1. Existing studies in AI for talent management.

Studies Done on AI Applications in Talent Management	Used ML Approaches	Key Findings of the Papers
(Fritts and Cabrera 2021)	ML concepts identification	Examines the issue of recruitment algorithms with an eye toward the under-explored concerns of HR managers.
(Xiao and Yi 2021)	Tensorflow platform for supervised ML	Implements a design using AI to career planning or related areas.
(Joshi et al. 2020)	Support Vector Machine (SVM)	Builds AI solutions for career-related services.
(Zhao et al. 2021)	Algorithm model design	AI for addressing fairness concerns for designing recruitment systems
(Aleisa et al. 2022)	A minimum viable product (MVP), Natural Language Processing (NLP), and explanatory knowledge derived system.	AI architecture that holds AI models and a data repository for recruiting models
(Shafagatova and Van Looy 2021)	Supervised ML	AI for "process-oriented appraisals and rewards"
(Meng and Dai 2021)	Supervised ML	Utilises the design routine of modular design, real-time evaluation, and standard analysis for assessing people's emotional stability

2.1. Ethical, Cultural, Relational and Personal Implications of AI

The importance of AI in enhancing workplace processes has been the subject of a great number of studies (Pereira et al. 2021). The promise and reality of AI in workforce management are worlds apart when it comes to acquiring, managing, and retaining people, particularly in scenarios involving complexity, data set limits, and fairness (Tambe et al. 2019). To rapidly improve talent management and take advantage of the potential of diverse data sets through the use of AI technologies, it is essential to develop information systems- solutions that allow organisations to establishing more ethical HR systems and at the same achieve greater efficiencies (Chamorro-Premuzic et al. 2019). This suggests that it is vital to have ethical AI solutions implemented in talent management strategies in order to oversee the process of hiring and selecting new staff. A dynamic talent management system is required given the unpredictability of the labor market due to the recent great resignations post pandemic (Kuzior et al. 2022), the rapid changes occurring in corporate strategy, and the introduction of new technology into the workplace. This indicate that the AI implementation Many researchers in the field of artificial intelligence have voiced a range of ethical concerns about technologies like predictive analytics algorithms to make decisions that significantly affect the lives of people (Mittelstadt et al. 2016). It suggests the requirements of generating more realistic solutions that would meet the requirements of three workforce principles that overlap: causal reasoning, randomisation and experiments, and employee contributions (Tambe et al. 2019).

The three key aspects of talent management are employee acquisition, employee development, and employee retention. AI may eliminate technical challenges in each of these domains by making processes more rapid and effective. The deployment of AI, however, presents a distinct set of obstacles that require careful consideration. Employers must examine potential acceptance and implementation obstacles associated with AI. Individuals may not trust and accept decisions made by artificial intelligence; this issue is known as algorithm aversion (Kim-Schmid and Raveendhran 2022).

Employers also struggle to increase employee engagement and minimise staff burnout due to the difficulty of capturing appropriate engagement measurements (Kim-Schmid and Raveendhran 2022). Strategies for mitigating risks include assisting users in interacting with AI products and promoting diversity on engineering teams. Employers may be held accountable for inadvertent employment discrimination perpetrated by AI-powered systems. The most important factor for management to evaluate is if tracking can improve employee results without raising evaluation problems. Organizations utilise AI tools for personnel management should carefully monitor forthcoming laws and implement proactive risk management measures (Kim-Schmid and Raveendhran 2022).

The European Union has already taken some efforts, releasing a "White Paper on Artificial Intelligence" outlining a European approach to AI excellence and trust. Robots can assist people in tough situations and enhance manufacturing operations. They must, however, be able to talk about a reliable artificial intelligence (Kuzior 2022). The document illustrates how AI may improve public service quality and consistency. Citizens must trust AI with a predictable ethical and regulatory framework that protects fundamental rights and freedoms. Ethics as a competitive advantage for European company raises the question of whether ethics are being used to advance business (Ulnicane 2022). While The Kingdom of Saudi Arabia releases AI Ethics Principles for public consultation. The Saudi Authority for Data and Artificial Intelligence (SDAIA) created them as a practical roadmap to integrate AI ethics across the AI system development life cycle. AI Ethics principles emphasise the need of using AI and tech innovation into the Kingdom's services for inhabitants and visitors. After evaluating worldwide and domestic AI standards and guidelines, SDAIA created a framework to advance AI while preventing irresponsible use (zawya 2022).

2.2. Application of AI in Talent Management

Employment has been radically changed as a result of what is known as the 'fourth industrial revolution', which was driven by demographics, technological changes, and globalisation. This has had far-reaching implications for workers. A positive outlook on the future is possible in spite of the concerns raised about technological unemployment, the changing demands of the labour market in light of the growth of Industry 4.0, and the need for new competencies needed to run current technology. Humanistic and ethical studies should be included into engineering curricula alongside more traditional practical training. It is important to incorporate both technological and social advances (Kuzior 2022). Recent years have seen a rise in the number of applications of AI within the scope of talent management. It is crucial for organisations to identify patterns in their data that may help them make more educated decisions about the development and retaining of talent pools, in addition to automating routine chores using AI apps, such as advertising openings and screening applicants' resumes.

2.2.1. Talent Acquisition

The selection and acquisition of qualified candidates with high performance levels is the focus of the TA process. Technological improvements have greatly enhanced the TA function. Many companies and human resources departments heavily rely on social media and internet platforms like LinkedIn, Facebook, and Twitter when hiring new personnel. Moreover, several websites and apps like Naukri, Glassdoor, and Indeed, offer a platform for companies and job seekers to communicate with one another where recruitment is the goal (Horton and Tambe 2015). The amount of time recruiters spend on these tasks is greatly reduced when chatbots screen prospects and conduct the first interviews with job seekers. Robotic systems such as Vera and Sophia are equipped with speech recognition and natural language processing technologies, which enables them to carry out automated recruiting procedures. These machines are able to conduct interviews with hundreds of prospective employees and create a list of individuals who are most suitable for the position (Mathew et al. 2021a). Recent research has found that candidates are more likely to apply for jobs online via technology-based platforms like social media, corporate websites, mobile applications, and chatbot talent assistants than they are using conventional recruiting methods (van Esch et al. 2021). Automated selection and assessment systems based on artificial intelligence produce more accurate and objective findings (Mathew et al. 2021b). Employer branding may be accomplished by utilising a comprehensive social media presence, interactive career pages, and highlighting existing employee testimonials and corporate achievements, all of which are useful for recruiting qualified candidates.

2.2.2. Talent Development

Following the completion of the recruitment process, it is extremely important to train individuals in order to improve their skills or expertise for future employment and to provide them with an engaging environment. Technology is increasingly being utilised by organisations for the purpose of talent development, such as m-learning and e-learning software, both of which may be used to educate staff members whenever and wherever they want (Paul 2014). Gamification is also utilised for the purpose of staff training and provides an objective evaluation. The performance of employees is continuously monitored and feedback is provided, using software powered by AI. This programme supports employees in gaining a better grasp of their current skill levels as well as the several career paths available within the company (Simpson and Jenkins 2015). Several different technologies, for instance file sharing, project management systems, and wikis, facilitate collaborative work. This helps to keep employees interested in their job and updated on the progress of their projects inside the virtual office (Gaonkar et al. 2022).

In addition to helping employers attract and choose highly qualified candidates, AI and related automation technologies help employers manage vast amounts of employee data, provide staff with prompt and effective training, and support managers in making better decisions for their teams. Technology's supportive role in the HRM function eventually fosters positive employee outcomes including enhanced engagement, work satisfaction, devotion/loyalty, and performance. As a consequence, it is possible to improve an organisation's productivity, efficiency, cost-effectiveness, customer satisfaction, and quality of services provided. Conversely, organisations must make sure that all moral, legal, and ethical guidelines around the use of these technologies in HRM are followed. This is so that both the working environment and employees are not compromised by these technologies.

2.2.3. Talent Retention

According to the U.S. Bureau of Labor Statistics, in August 2022, 4.2 million employees departed their jobs willingly. (Kim-Schmid and Raveendhran 2022) Concurrently, there were 10.1 million available jobs. Due to the Great Resignation and more current trends like as "quiet quitting", traditional methods for attracting exceptional talents in this intensely competitive market have not always been effective (Kim-Schmid and Raveendhran 2022). PwC (2022) Middle East Workforce Hopes & Fears Survey of 1565 workers reveals a discrepancy between employee and employer expectations. Gen Z in the Middle East favoured remote or primarily remote work. 75% of Kuwaiti, 60% of Qatari, 58% of Saudi, and 46% of UAE employees say their country lacks specialised talents. PwC advise corporations to address employee hopes and fears. Businesses must be aware of a new generation of workers who will transfer employment for fewer opportunities. (PwC 2022). Therefore, human resource managers have a challenging problem when it comes to the subject of retaining high-performing employees. These personnel need to be engaged and motivated in order for the business to run efficiently, and to keep talent on board, HR managers are employing retention techniques such as challenging work, competitive salaries/wages structures, training for future skills, timely feedback, awards and recognition, etc. Technology is assisting in refining these processes through the use of a wide range of AI- and TM-based cloud apps. The data from predictive analytics provided by these types of software act as an early warning system for HR managers, allowing them to forecast employee attrition. Employee attrition may be minimised by conducting early intervention prior to an employee resigning. Pulse surveys may be carried out in a short amount of time if technology can offer information on the current thinking and motivation of employees.

2.3. Risks Management for AI Adoption

AI refers to a collection of algorithms and methods that have the ability to automatically aggregate, analyse, and learn from data. These insights may then be put to use in pursuing certain objectives and engaging in particular activities (Kaplan and Haenlein 2019). AI algorithms may offer companies analytical tools that help them grasp the consequences of risks, develop automated suggestions to minimise and manage these risks (Canhoto and Clear 2020), and enhance the resilience of their organization (Chowdhury et al. 2022). From the viewpoint of risk management, AI algorithms can provide businesses with analytical tools and help managers make decision more efficiently (Jarrahi 2018). This is accomplished by: (1) reducing aggregating latency, which is also known as automatically gathering and consolidating digital data streams (Osamy et al. 2022); (2) curtailing processing latency, also referred to as automatically processing and summarising huge volumes of data; and (3) decreasing processing latency (Osamy et al. 2022).

The ability of AI to foresee and learn for AI risk management is still in its early phases because there has not been much attention paid to building automated solutions for making decisions (Žigienė et al. 2019). One such challenge is the market for e-risk management, which is characterised by a number of factors: a lack of competent individuals; a limited budget and financial resources; insufficient access to technology; paucity of senior management commitment and leadership; a lack of expertise; a lack of knowledge and awareness among managers and teams; supervision; a fear of the unknown; not having enough organisational dynamism; and a failure to adequately prepare for the digital world (Rodríguez-Espíndola et al. 2022).

2.4. AI in Small and Medium-Sized Enterprises

Using AI in HR has been evident for a few decades. There is a growing demand for the automated process of talent management, which is increasing the planned uses and broadening the breadth of services. Several sectors have adopted talent intelligence, such as higher educational systems, labor markets, and private and public sector agencies that offer a talent management system. As the need for assistance grows, it is vital for them to use digital services to reduce the cost of resources while also making a significant contribution to workforce management (Toni and Vuorinen 2020). Fierce competition in the contemporary business world has increased the use of information technology from integrated manufacturing operations to managing people. Managing people and getting the best out of their skills and potential remain a challenge for strategic human resources. A rapid pace use of technology in business operations and market uncertainty accelerates the demand for multi-taskers and employees with flexibility to learn new skills as business assumptions and processes change (Pauli and Pocztowski 2019). Hence, the focus has been further narrowed down from employees' performance management to talent management. Talent management is defined as the efforts made to plan, attract, select and train the talent required to meet current and future human capital needs (Pauli and Pocztowski 2019).

Talent management is driven from organisational objectives that senior management and/or shareholders want to be achieved. Translating organisational objectives into departmental targets and emphasise daily activities and operational targets must also align with individual work performance requirements if the talent management system is going to work (Baublyte 2010). Moreover, an employee could not be expected to perform a new task perfectly unless he or she receives relevant training and a career-building program. Moreover, such training programs must be integrated with a centralised talent management system. Talent management is a complex system that requires integration with a company's vision and mission statements, objectives, human resources processes and policies, and business operations (Kimanzi and Gamede 2020). Such a multidimensional integration is not possible without the deployment of supporting technologies. Talent management software solutions are offered by IT companies worldwide. These software solutions for talent management generally follow certain human resource management standards and cover legal aspects of local labor laws. Talent management solutions cover four broad aspects, namely recruitment, employee performance management, training/development, and employees' salaries/wages and recognition (Schweyer 2004).

SMEs are important pillars of a country's economic progress and social cohesion. It has been estimated that approximately 400 million people are employed by this sector throughout the world. These enterprises have to make their processes more responsive to competition and market/industry uncertainty to sustain their viability compared with large corporations or multinationals. This responsiveness depends on the operational and human resource flexibility to adopt technologies at the operational level and enrich the talent inventory. Capital investments and infrastructural resources are not available for SMEs compared to large corporations. Redefining organisational objectives, repurposing, retooling and pivoting human capital are the strategies adopted by SMEs. All these strategies require flexibility of operations and human resources. Hence, a comprehensive framework is required to address the ever-changing talent management requirements that may help SMEs to so that they can cope with a market or industry's needs.

By utilising design principles that produce more user-friendly forms, AI technology streamlines the application process and makes it simpler for job seekers to complete an application. This significantly reduces the volume of applications that prospective candidates leave unfinished or unsubmitted. Technology has been a key factor in candidate rediscovery by maintaining a database of prior candidates. AI from a pool of current applicants may be used to evaluate these applications, and if and when openings for new positions in the company emerge, a qualified candidate may be found. HR professionals may identify competent people faster than ever before, saving a substantial amount of time, as opposed to wasting time and money seeking for new talent. The widespread usage of AI technologies in HR operations is now evident in the talent acquisition context.

2.5. Theories in Technological Adoption

The literature that has been published explored the adoption of new technologies and innovations from a variety of perspectives. The theory that is referred to as the Diffusion of Innovation (DOI) focuses on the process by which an invention is disseminated across a social system over the period of time in various ways (Chang 2010). In the context of user technology adoption, the Technology Acceptance Model (TAM) takes account of the theorised causal links between individuals' subjective beliefs, intentions, and behaviours (Davis 1989). Meanwhile, the Unified Theory of Acceptance and Use of Technology (UTAUT) provides additional drivers of behavioural intention, including performance and effort expectation, social influence, and enabling factors (Venkatesh et al. 2003). The Adaptive Structuring Theory (AST) model investigates how organisations' staff adapt to the norms and resources of information technology in order to carry out the designated activities. The Technology-Organisation-Environment (TOE) framework examines the role that technical, organisational, and environmental contexts play in making decisions about cutting-edge innovations.

The task-technology fit model is used to find out if the capabilities of a certain piece of technology are a good match for the prerequisites of a specific job (Goodhue and Thompson 1995). However, the primary focus of these theories is on the subjective viewpoints of individuals and specific activities (such as dissemination of innovative ideas) and they completely disregard the power or ideas that individuals possess. None of them address the particulars of the adoption of information technology since they were written before information technology use became widespread, so their accuracy is questionable.

2.6. TOE Framework and DOI Theory

This study employs an integrated framework based on TOE and DOI theory. The technology viewpoint of the TOE model takes into account the external and internal technical resources necessary for the implementation of technology (Depietro et al. 1990). The technological factors discussed are reliability, security, capability, quality, relative cost advantages, and the compatibility of TM solution and technology benefits. The organisational perspective puts considerable emphasis on a variety of factors, namely the scope and size of the firm, the formalisation and centralisation of the workplace, the complexity of its organisational structure, the quality of HR available, the support of senior management, and the readiness of the organisation.

The DOI hypothesis is an innovative framework applied to support studies that aim to elucidate the elements that contribute to the spread of innovation(s) through the application of technology (Rogers et al. 2014). (DOI) theory examines the possibility of an organisation adopting a new technology based on its relative advantages because it is new, as well as its observations of complexity, compatibility, and amount of time spent trialling and observing it (Bradford and Florin 2003). DOI theory can be used in a substantial way and is relatively effective when it comes to accurately predicting the adoption of a variety of different systems already in place. Research designs for studies that make use of the DOI theory can either be quantitative or a mixed methods approach. Previous research does not provide a theoretical model for the incorporation of AI into TM, which is an example of technological innovation. It is necessary to investigate AI for TM from the three aforementioned viewpoints of the TOE framework in Figure 1.

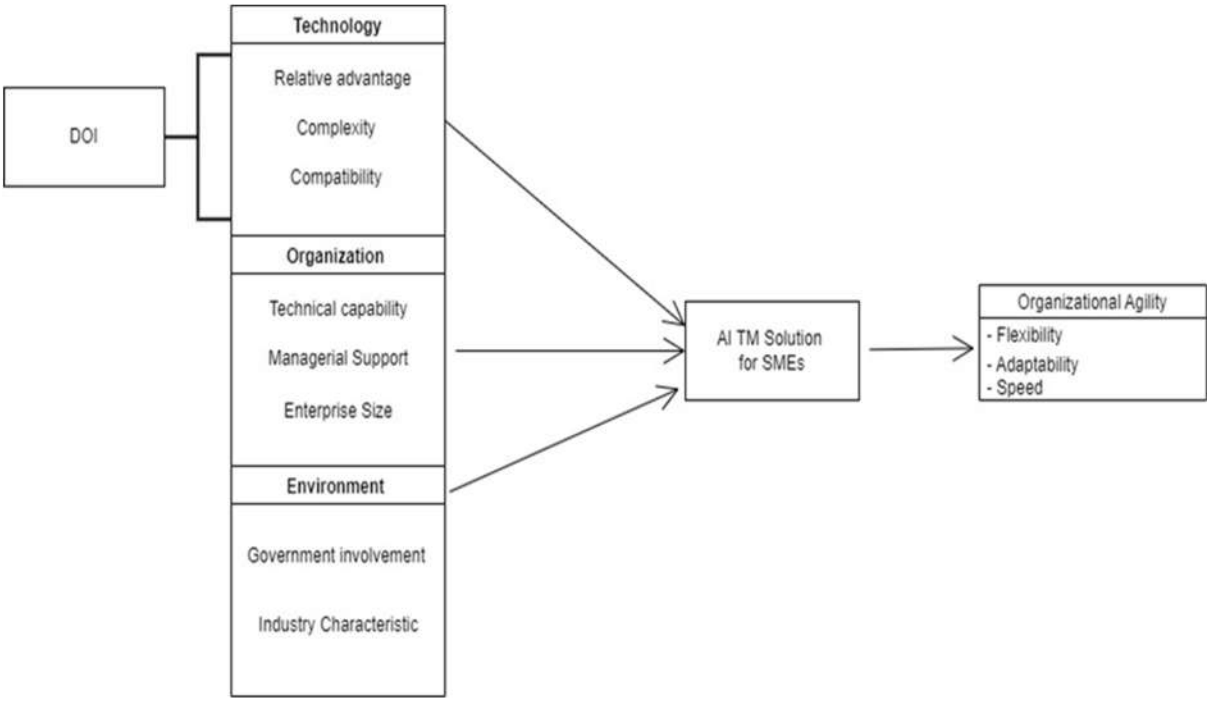

Figure 1. Conceptual Framework.

2.6.1. Technological Factors

AI can play a significant part in the global dissemination of innovative services and have competitive benefits. AI has been utilised thus far in chatbots for customer care, speech and voice services for customers, and automatic network operation (Riikkinen et al. 2018). These applications help businesses become more efficient while also reducing their operating costs or overheads, improving the quality of services, and enriching the experiences of their clients. When humans have a higher level of awareness, they may be more willing to accept the changes brought about by AI and actively engage in them.

As shown in Figure 1, complexity is the extent to which the invention is seen as being relatively difficult to comprehend and employ (Rogers 2002). To put it another way, complexity refers to the challenges or barriers that exist when AI adoption arises. The greater the ease with which the technology can be incorporated into company processes, the greater the likelihood that it will be adopted (Venkatesh 2022). The immaturity of AI, the scarcity of technological expertise and IT specialists, the length of time it takes to develop, and its high cost all contribute to its difficult nature. The immaturity of AI is the main problem that deters its widespread use, as suggested by its characteristics. Previous research has reported that the level of IT maturity has a major impact on the strategic decisions that companies make regarding the acquisition and deployment of IT/IS. When a new technology has reached its maturity stage, businesses have a better understanding of how to implement it. Businesses are more inclined to employ cutting-edge technology if they are confident in their ability to work productively with third-party providers (Blut and Wang 2020).

Compatibility presented in Figure 1 is a crucial factor in determining the rate of innovation uptake (Senarathna et al. 2018). It refers to the extent to which the innovation is able to deliver value and experience while at the same time being consistent with the requirements of those who might embrace it (Rogers 1995). According to the DOI theory, the adoption rate of an innovation is positively correlated with the degree to which it is compatible with previous experiences and current needs. In other words, the degree of compatibility has a direct bearing on how quickly something is embraced (Olatokun and Igbinedion 2009).

2.6.2. Organizational Factors

The term "technical capability" presented in Figure 1 refers to the tangible assets required to implement new ideas. Some examples are computer hardware and software, data, and networking (Senarathna et al. 2018). It is also a representation of the collective resources that a company owns in order to provide itself with a foundation that will benefit business applications (Chen et al. 2021). Having strong technical competence helps to reduce the complexity of integration, which enables a company's IT department to deploy artificial intelligence technologies in a timely and effective way (Chen et al. 2021).

Managerial support is the commitment of managers is an essential component of any significant organizational change since it affects how resources and services are structured and delivered (Garrison et al. 2015). According to some findings, managerial support is an essential component in both the introduction of an information system (IS) and the use of information technology (IT) (Myers and Avison 2002).

Managerial capability shown in Figure 1 contains education and training components in addition to project coordination. Managerial capability is an example of an intangible asset extremely important for the successful use of IT (Gangwar et al. 2015). The difficulty of AI application can be controlled if managers are able to recognise the potential of new AI technology to enhance the professional abilities of employees, then modify staffing and recruit relevant technical professionals, rationally allocate resources, prioritise training, and establish circumstances for adopting AI (Chen et al. 2021).

2.6.3. Environmental Factors

Environmental context listed in Figure 1 encompasses the market/industry, the companies that compete in it, the regulations, and relationships with the government (Priambodo et al. 2021). Institutional theory emphasises how significant institutional contexts are in terms of their influence on the structure and activities of organisations. Because of the external isomorphic pressures originating from the government, competitors, and customers, businesses are likely to adopt and employ AI (Chen et al. 2021).

2.6.4. Talent and Organisational Agility

Organisational agility presented in Figure 1 is defined as the adaptability and response of an organisation to a changing environment (Harraf et al. 2015). Organisational agility is the ability to generate growth and profit that can be sustained by a business (Teece et al. 2016). Organisational agility is about being able to adapt quickly in a changing environment so a company can compete in different markets and industries. This can include both entrepreneurial qualities and a strong sense of mission with some organisational reorganisation and technological adoption shifting required (Mathiassen and Pries-Heje 2006).

3. Design Science Methodology

Design science research (DSR) is acknowledged as a significant and viable research paradigm in information systems (Gregor and Hevner 2013); Hevner et al. (2004) described that DSR is a scientific approach to problem-solving that emphasizes the development of new knowledge to design and evaluate solution artifact as stated in Figure 2. The main goals of DSR are to: (1) developing new artifacts or software system model, method or construct for real-world problems; (2) evaluating effectiveness of these solution artifact and (3) generating new knowledge about the design of new systems solution. Following an ensemble artefact design (Miah et al. 2017; Miah 2010), the first step in this process is to develop a conceptual model that describes how AI can be used to improve talent management. This model will be based on a review of the literature on AI and talent management. Next, the feasibility of using AI in talent management will be assessed, through datasets. This will involve conducting reports in the field to identify the challenges and opportunities associated with AI-based solutions. Finally, a prototype AI-based solution will be developed and tested in two problem contexts (e.g., using design principles defined by (Miah et al. 2019; Fahd et al. 2021). As presented in Figure 2, the results of this study will contribute to the body of knowledge and to our understanding of how AI can be used to improve talent management in SMEs.

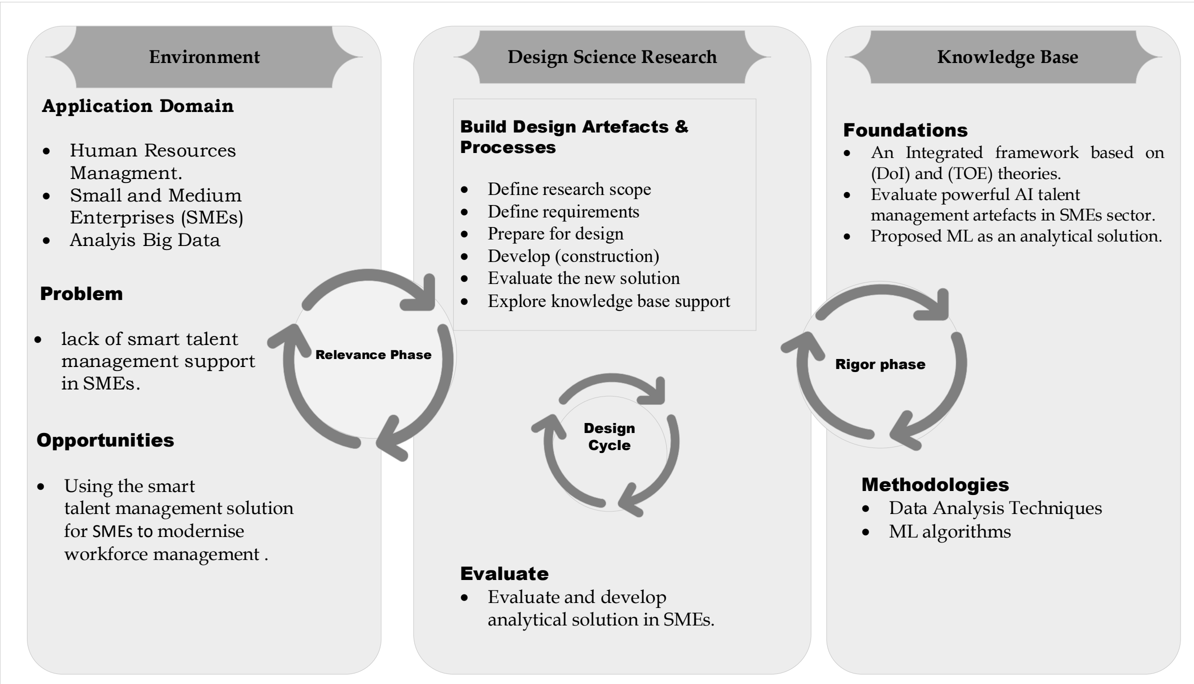

Figure 2. Modified Design science research cycles.

Many design research approaches for undertaking development studies have been introduced in DSR, although their styles varies due to the emphasis on designing artefacts (Miah et al. 2017). Peffers et al. (2007) for instance, presented a six-activity-based methodology: problem identification, solution objective definition, design and development, demonstration, evaluation, and design communication. Gregor and Hevner (2013) claimed that Peffers et al. (2007) design research methodology provided a well-defined research process that provides a valuable synthesising generic model from problem identification mentioned in Figure 2, to solution design and evaluation (Hevner et al. 2004). In this extensively cited study, Hevner et al. (2004) established seven design guidelines as shown in Table 2 which provides processes for influencing the design activities required to complete the artefact design. March and Smith (1995) claimed that design research might result in four different sorts of artefacts: constructs, models, methodologies, and instantiations. According to Miah et al. (2017), "a construct as artefact is formed when there is a need for study to develop a fundamental language of concepts". A model is "a structure of conceptual concepts that typically explains artefacts, actions, and circumstances". (p. 24). "A method is an artefact of design study when there is a requirement for descriptions or specifications of methods or ways of executing goal-directed activities in order to solve or address challenges". An instantiation as an artefact that is "created when a specific solution product is developed and deployed". As shown in Table 2, Hevner et al. (2004) outlined seven guidelines for developing and evaluating an innovative IS artefact:

Table 2. Hevner's seven guidance in a summarized form.

DSR Adopted Guideline	Its Relevant to the Proposed Solution
Guideline 1: Design as an Artifact: Design:	Design-science research must result in a valid construct, model, technique, or instance.
Guideline 2: Problem Relevance:	The objective of design-science research is to create technological response to significant business issues. Identified is a genuine issue domain that supports the specified software solution prototype.
Guideline 3: Design Evaluation:	The utility, quality, and feasibility of a AI design need to be stringently shown by well-executed assessment procedures in order to satisfy the requirements. For prototype testing with industry various stakeholders, a descriptive assessment approach will be used with utilizing secondary data.
Guideline 4: Research Contributions:	The models utilised for the AI artifact's features were designed by domain specialists with information gleaned from actual practice, through prototyping.
Guideline 5: Research Rigor:	DSR is dependent on the use of rigors procedures in the creation and assessment of the AI design artefact informing through IS theories.
Guideline 6: Design as a Search Process:	The search for a functional artefact necessitates the utilisation of accessible ways to achieve desired purposes in compliance with the issue domain,
Guideline7: Communication of Research:	DSR will help successfully communicated about the research outcome to both technical and managerial groups.

3.1. Big Data in Talent Management

Talent analytics is the practice of attempting to discover trends in an organisation's workforce via the study of data pertaining to its personnel. It is also known as "people research", "workforce analytics", and other designations (Kaur and Fink 2017). The term "talent analytics" is also referred to as "people analytics", "HR analytics", "workforce analytics", "people research and analytics", and "HR business intelligence". There is no universally accepted definition (Marler and Boudreau 2017). The findings obtained by analysing data are provided by talent analytics in three different ways: descriptive, predictive, and prescriptive analytics. Hence, individuals' career pathway decisions and future intentions are very closely linked to data within big data. HR managers will be able to better comprehend employees' career interests and assist their career planning and management better by conducting quantitative analyses of all the information that we can obtain about them. Enterprises may combine conventional career management with big data-driven career management to fully examine a worker's career path, give personalised career counselling, and minimise talent turnover, resulting in a win-win scenario for both the organisations and employees.

3.2. Risk Mitigation

In order to combat ingrained biases, leaders should think about including factors like gender and ethnicity into AI algorithms and proactively setting different standards for certain groups. Organisations could use a variety of viewpoints to reduce AI bias by promoting diversity throughout the design and implementation phases. These tools can dramatically destroy employee privacy if they are deployed incorrectly. According to studies, when tracking is carried out by an AI system without any human participation or control, employees are more receptive to it. Even accidental job discrimination caused by AI-driven technologies can result in employer liability with serious legal consequences. Leaders should focus on whether tracking may improve employee informational outcomes without raising evaluation issues:

- Create a legally enforceable code of ethics for AI that takes into account human conventions, values, and cultures.
- Ensure human oversight and monitoring of AI choices respecting fundamental rights, equality, and non-discrimination.
- Install a high-quality talent management system to guarantee ethically sound AI decision-making and dataset quality.
- Convert AI's moral code into a programming language, and continuously train and test AI systems to guarantee that it is being used correctly.
- Ensure that AI systems do not infringe on people's autonomy and freedom (e.g., decision-making).
- Before a product is launched, make sure that it complies with ethical standards that have been trained for and tested.

4. Proposed AI Oriented TM Approach

An evolving prototype is an innovative design approach for transforming system requirements into a workable solution model whereby potential users may see the advantages or conceptual outcome. The understanding required to identify the problems with a present system and create an artefact solution is covered in the prototype design. Three phases are considered for the creation of the minimum viable product (MVP). These phases will include the following desired services: the talent pool, talent personality traits assessment, career guidance chatbots, skills and knowledge building, CV screening software, interview screening, and jobs or opportunities matchmaking. The bots are software tools that have been created in natural language and have the ability to carry on conversations by themselves (Khan and Das 2018). It is mostly divided into three different types. The first thing that must be done is to obtain information from the end-user. This can be done either vocally or by typing in natural language. The second step is to get the bot to provide output in the form of spoken words, while the third step is to process the input through the software in order to get output that is accurate and simple to comprehend. Most of the time, these counselling bots are utilised for generating predictions and questions regarding a career, such as which industry would be the best choice and which courses are the most recent and relevant. This system's principal function is to understand human speech with the assistance of natural language processing so that the results can be delivered to the user.

Figure 3 presents the proposed framework, which depicts how the output (an AI-driven talent intelligence solution) will be converted from the input (numerical data). When our big data has been pre-processed (for instance, through data cleansing, data integration, and the removal of stop words), it is ready for the sampling process; after that, it will be ready to be separated into datasets for training and testing. The proposed framework is shown in Figure 3, which shows how the input (an AI-driven talent intelligence solution) is going to be transformed into the output, numerical data. After our big data has been preprocessed (for example, by means of data purification, data integration, and stop word removal), it is ready to be sampled, and after that, it will be ready to be divided into datasets for training and testing. Using methods from the field of data analytics, such as visualisation and forecasting, it's possible to build a draught model from scratch. After doing an examination to determine whether or not it is accurate, the model will then be modified into an exact representation that may be used for generating predictions, plans, and decisions. The first method generates novel, nontrivial patterns and information, while the second method generates models and roles for the systems. Clustering, summarisation, and modelling dependencies are three of the most important activities involved in descriptive data mining. Classification, regression, monitoring changes, and identifying deviations from the norm are the core activities of predictive data mining.

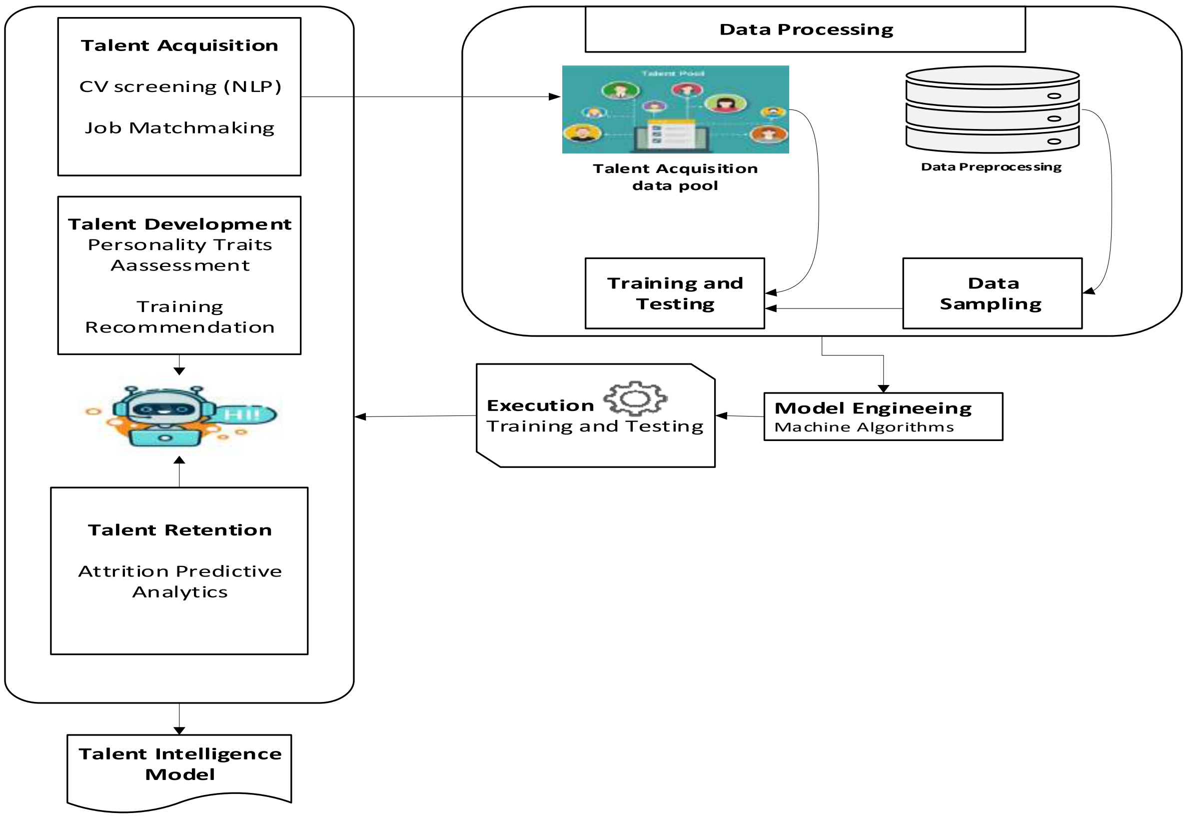

Figure 3. The proposed AI Framework.

- CV Screening: Supervised learning algorithms such as Support Vector Machines (SVMs) and Decision Trees can be used to classify and score resumes based on their relevance and suitability for a particular job.
- Job Matchmaking: Unsupervised learning algorithms such as K-Means Clustering and Collaborative Filtering can be used to identify and match job seekers with job opportunities based on their skills, experience, and preferences.
- Personality trait Assessment: One common approach is to use machine learning algorithms, such as decision trees or support vector machines, to classify and score individuals based on their answers to a series of personality trait-related questions. These algorithms can be trained on a large dataset of personality trait assessments to accurately predict an individual's personality traits based on their responses to the questions. Another approach is to use natural language processing (NLP) techniques to analyze written or spoken responses and extract personality traits based on the words and phrases used. This approach can be particularly useful for assessing personality traits in unstructured data, such as open-ended responses to interview questions.
- Career Guidance Chatbot: Natural Language Processing (NLP) algorithms such as Text Classification and Sentiment Analysis can be used to identify and analyze the questions and concerns of talent, and to provide personalized and relevant career guidance.
- Attrition Predictive: Supervised learning algorithms such as Random Forests and Gradient Boosting can be used to predict the likelihood of talent attrition based on various factors such as salary, job satisfaction, and career development opportunities.
- Talent Training Recommendation: Collaborative Filtering algorithms can be used to identify and recommend relevant training courses and programs for employees based on their skills, experience, and career goals.

5. Discussion and Conclusions

The proposed hybrid ML approach taking a current talent analytics approaches a step ahead, integrating talent acquisition and talent development with the common functionality of the talent retention (which is often the common features of the traditional talent analytics), streamlining and utilizing multiple data sources. addressing risk management issues, we aimed to create a basis of design research that leads to enable innovation with the new AI-driven TM artefact. Our project facilitates moderisation of the daily operations of TM for managers in SMEs. AI functionalities can assist professional talent managers by identifying, forecasting, and investigating talent management and performance-related trends. There is a growing demand for automated talent management processes. Various sectors have adopted talent intelligence, including SMEs, labour markets, the private sector, and the government. SMEs requires innovative ways to enhance employee's productivity in the workplace. Smart technologies have the potential to assist in mentoring both current professionals and future talent. There is no doubt that AI has the potential to assist career counselors with some of their daily tasks. Moreover, AI can be used to develop a chatbot that can answer frequently asked questions about careers, job applications, and resumes. Few studies have been conducted on employing AI to develop and evaluate powerful TM solutions within SMEs domain. Therefore, researchers have not been able to design a suitable AI-driven TM solution that may contribute to changes in SMEs. Despite advances in technology, the use of AI in the procedures involved in HRM is somewhat limited at present. Compared to various other HR procedures, TM is one in which the impact of AI can be seen as a driving force for substantial improvements in the practices. However, if AI is to be applied in this process, we will need to effectively outline a conceptual solution model to meet its key requirements. In addition, there is a lack of conceptual clarity as a result of the restricted scope of the research that has previously been conducted in this subfield. As a result, it is important to develop research in this domain and, more specifically, to create a practical solution framework that may assist managers/professionals in adopting AI to improve TM processes and practices in the SMEs.

The scope of the study is mainly focused on the practical approaches towards designing AI based TM system and limited to the need of the SMEs. Additionally, the nature of this study does not involve an empirical data. Therefore, there is a need for more thorough, interdisciplinary study on the use of AI in talent management, including investigations into its practical use, long-term implications on HR, and ethical, social and legal ramifications.

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