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RESEARCH ARTICLE

Human Resource Artificial Intelligence Implementation and Organizational Performance in Malaysia

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Abstract: The purpose of this study is to examine the effects of perception on human resource (HR) artificial intelligence (AI) implementation on organizational performance in Malaysia. There are three dimensions of perception of HR AI implementation, namely, talent acquisition process, human capital development process, and performance management process. Data were collected online from 352 respondents with HR backgrounds in Malaysia and analyzed using partial least square structural equation modeling (SmartPLS). The results indicated that AI implementation in the talent acquisition process, human capital development process, and performance management process has a significant positive effect on organizational performance in Malaysia. This study makes a significant contribution to the HRM process literature by examining the effects of HR AI implementation on organizational performance. It provides vital insights to business organizations to consider implementing AI in their Human Resource Management (HRM) processes for a successful business. Studies that have investigated HRM functions and been published are rarely based on countries like Malaysia. Therefore, this study corroborates the assertion to conduct more empirical studies on the adoption of AI in HRM processes and its potential influences on organizational performance in Malaysia.

Keywords: Perception on human resource artificial intelligence implementation, organizational performance, talent acquisition process, human capital development process, and performance management process.

In the age of globalization, technology plays an important role and is a vital force in modern business expansion. How business is traditionally conducted is now being challenged because local firms no longer compete with one another within the country, but they must constantly compete on a global level (Erixon, 2018). Organizations nowadays need to adopt technology to ensure they develop a competitive advantage in the global competitive environment (Wong et al., 2020).

According to the findings of the McKinsey Global Survey, the implementation of artificial intelligence (AI) in business organizations continues to increase approximately by 25% yearly (McKinsey Global Institute, 2017). Other than that, a majority of C-level executives whose companies have implemented AI agree that the adoption of AI has generated more returns in business and even reduced costs (Cam et al., 2019). AI is a set of techniques that allow computers to complete tasks that do not require the reasoning skills that human intelligence brings (Grzonka et al., 2018). It operates in many different forms, such as robots, bots, or software (Madakam et al., 2019) to support different applications.

AI and big data are now seemingly inseparable, and big data is becoming usual in today's business world, in operations, customer service, marketing, and even human resources (HR) (Elish & Boyd, 2018). In recent years, HR professionals have been making good use of big data and recognize that data-driven insights can bring a major positive influence by minimizing risk and improving the decision-making process in terms of organizational performance and talent management. AI eliminates biased decisions and assists HR professionals in making impactful actions by reducing manual analysis and providing recommendations based on data instead of human emotion (Chaturvedi & Joshi, 2017). Hence, with the deep and instant insights that AI provides, HR professionals will be able to retain, engage, and hire competent talents to improve the performance of the organization (He, 2018).

The move for better employee management began during the industrial revolution in the 18th century when machinery was first introduced and employees were starting to comprehend how technology might affect their jobs (Pandian, 2018). In later years, due to technological development, the subject of how both AI and human resource management (HRM) processes can be combined has gained public attention and been discussed extensively in terms of how HRM processes can be optimized with the help of technology (Galanaki et al., 2019). With advanced technology, processes such as talent acquisition, human capital development, and performance management will be further automated. Humans have limited abilities, and accomplishing all necessary tasks within a specified time is not easy. Also, ensuring that all tasks reach completion the correct way might be beyond human abilities as people are not machines (Grace et al., 2018). People have certain limitations such as biases, presumptions, and time constraints that may hinder the effectiveness of the HRM processes in the organization (McRobert et al., 2018). Moreover, human limitations could also cause the loss of potential talents for certain jobs, offer unsuitable development opportunities to talents, and provide biased performance evaluation (Osei et al., 2019).

Despite the limitations, many organizations are of the view that people will always be the human capital of the company and should always be at the center of every organization's focus (Çunaku, 2019). In other words, without accurate and suitable techniques to keep human capital engaged, the organization might meet with failure (Li & Tang, 2017).

HR 4.0, which is a game-changer in the human resources dimension, has been embraced by many global companies, such as Google and IBM. Also, majority of Malaysia's neighboring countries are in the process of bridging the gap between HR 3.0 and 4.0 (Jayashree et al., 2020). HR 4.0 emerges as an industry strategy to adapt and survive in the Industry 4.0 market, which blends real and virtual global information, information technology (IT), and management knowledge (Liboni et al., 2019). Most Malaysian companies, however, still lack awareness in the ways to implement HR 4.0 elements, AI particularly, in their company processes, which leads to difficulty in venturing into the era of digital innovation (Jayashree et al., 2020). Within the next few years, Malaysia may face elimination from competing in the global environment, putting the survival of many Malaysian companies at stake (Ghafar et al., 2020) if awareness of AI implementation remains at the surface level.

There are several past studies that have explored the general HRM processes linked with job satisfaction and productivity in Malaysia, but there is limited empirical research emphasizing the adoption of AI in the human capital development process, talent acquisition process, and performance management process (Ibrahim et al., 2018). This gives rise to a need for such an empirical study to be conducted. It is essential to note that this research is a replication of the perception study on the adoption of AI in HRM processes and its potential influences on organizational performance, focusing specifically on companies in Malaysia (Halid et al., 2020).

Despite the topic of AI being widely discussed in studies in recent decades, these studies are generally related to very specific industries. For example, there are several studies that have focused on industries like healthcare (He et al., 2019; Xiang et al., 2020), education (Yang, 2019), electric power (Sozontov et al., 2019), and manufacturing (Lee et al., 2018). Besides, studies that have investigated HRM functions and been published are rarely based in countries like Malaysia (Mohan, 2017). There have been numerous studies regarding the implementation of AI in countries such as Pakistan (Maqbool et al., 2020), India (Premnath & Chully, 2020) and China (Zhang, 2020), but the HRM processes focused in these studies are quite different, thus yielding a variety of findings. For instance, extensive research has been published on the topic of AI execution in the recruitment process (Nawaz, 2019; Upadhyay & Khandelwal, 2018; Vedapradha et al., 2019; Wilfred, 2018), performance appraisal process (Gui, 2020), and training program (Collado-Mesa et al., 2018).

The variables focused in this study are the core HR processes such as talent acquisition, human capital development, and performance management, where research previously published is not extensive. Therefore, this study aims to answer the research question, "What are the perceived influences of implementing AI in HRM processes on organizational performance?" Answering this question will provide full-scale knowledge to other scholars as the focus of this study is not limited to any industry but emphasizes on HRM processes. Furthermore, the findings will encourage Malaysian companies to be better prepared to enter the world of HR 4.0 and reduce the possibility of elimination from competing in the global competitive environment. It is hoped that the findings from this study will be useful to Malaysian companies in terms of increasing awareness of implementing AI within the company, especially in HRM, to improve the efficiency of completing HR-related tasks and streamline HRM processes.

Theoretical Underpinnings

The foundation for the study is the 5P's model established by Pryor et al. (2007). The 5P's model is based on the five constitutional aspects of purpose, principles, processes, people, and performance. Pryor et al. (2007) claimed that aligning and balancing these five components will lead to company success. Figure 1 illustrates the connection between strategy (which is Purpose), structure (which includes Principles as internal structures and Processes as external structures), influence of structure on employee behavior (which is People), and the subsequent results, which represent Performance (Gülenç & Kozak, 2016). The overall implication of the model is that strategy drives structure, structure drives behavior, and behavior drives results (Pryor et al., 2007). Besides, all of the arrows moving backward to Purpose represent the feedback mechanism for guiding an organization toward its company goals. In short, the main purpose of this model is to guide an organization toward employee performance excellence and long-term survival (Pryor et al., 2010).

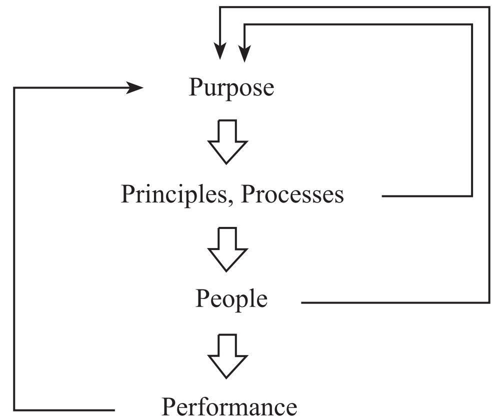

Figure 1. The 5P's Model

Note: Adapted from Pryor et al. (2007)

Purpose, the first element of the 5P's model, represents the purpose of a company and includes mission, vision, objectives, tactics, and SWOT analysis of the company (Gülenç & Kozak, 2016). Pryor et al. (2007) have declared that these elements are important at the organizational level to set a strategic direction for employees to achieve because the fundamental strategic management progression is a model the company will employ for long-term survival and success. According to Pryor et al. (2010), business leaders in the organization should develop the strategic direction and goals of the organization as well as the approaches to attain those goals.

Next, Gülenç and Kozak (2016) pointed out that principles refer to the guiding philosophies, attitudes, or assumptions about how the company should operate its business and the core values with which employees are expected to make a commitment. In other words, principles are the operational protocols that the company sets to achieve its purpose (Pryor et al., 2007). Principles are crucial to effective execution, consistent with key company processes, and involved in a more integrated methodology because they are paired with operating guidelines for behavior that must be fitted throughout the organization (Shil et al., 2020).

Processes involve the company structures, procedures, systems, and methods of operation, which are being streamlined and used to enhance products or perform services the organization offers to achieve employee performance excellence (Pryor et al., 2007). In other words, processes are the transformation of inputs into outputs such that the manner of task completion by employees and every activity of the organization is a part of a large process related to the wider goals of the organization (Shil et al., 2020). Pryor et al. (2010) claimed that performance appraisal methods, communication patterns, and production systems are examples of processes in which people are a significant part.

Gülenç and Kozak (2016) have also stated that people are the employees who work individually or as a team to perform tasks consistent with the principles and processes of an organization in order to attain organization goals. People would include employees, suppliers, customers, and those who are also defined as the process owners. Hence, people are critical elements that enhance workplace productivity as employee performance is seen to have increased, as shown in Figure 1 (Pryor et al., 2007). Business leaders demonstrate good performance if they are able to harmoniously manage purposes, principles, processes, and people.

Lastly, performance, the last component of the model, represents the ultimate result with regard to employee performance, resulting in organizational long-term survival and profitability (Pryor et al., 2007). Gülenç and Kozak (2016) stated that performance is defined as the expected consequence that indicates all measurements, criteria, and status of the organization and is employed in decision-making. Pryor et al. (2010) further declared that performance results support the strategic management process in a particular way to provide feedback and control. Hence, HR professionals in organizations always emphasize performance assessment to facilitate a follow-up of performances and the monitoring of employees' development.

In this study, the purpose reflects the aim of companies in Malaysia to survive and compete with their rivals in trying to achieve Industry 4.0. Hence, the companies consistently abide by the principles they have set to achieve this purpose. Next, to streamline company processes, the companies implement AI in their HRM processes to enhance efficiency and reduce bias. It can be said that employees are vital people who operate the processes for beneficial results and higher performance.

Literature Review

AI is a software engineering domain that is established based on intellectual science which is evolving, with research in areas of machine learning, robotics, natural language processing, and image processing (Lee et al., 2018). Due to the development of the machine learning ability of AI, a significant level of algorithmic developments has been achieved, bringing substantial benefits to many aspects of the industry in the last few years (Samarasinghe & Medis, 2020). Moreover, based on computational power and algorithmic advancement, AI has developed in such a way that machines are able to execute tasks more effectively and efficiently than humans (Leyer et al., 2020). According to Bhardwaj et al. (2020), the components of AI show differentiation from ordinary software as AI encompasses high-speed computation, advanced algorithms, and huge amounts of quality data. Besides, AI provides stability and accuracy to daily business processes as it uses algorithms that integrate quality data and quick computational services (Deng et al., 2020). The implementation of AI will provide better insights to organizations on how to operate and execute processes to increase their competitive edge (Kaczmarek-Śliwińska, 2019). In fact, the evolution of any organization depends on how efficiently and intelligently it blends manpower, processes, and machinery to achieve maximum value at minimum cost (Zehir et al., 2020).

The implementation of AI in business organizations has become more prevalent due to boosted data volumes, enhanced algorithms, and improvements in computing storage and power (Ghoreishi & Happonen, 2020). From a global perspective, a business will not be able to survive in a competitive market without advanced technology, and the implementation of AI has become an essential component in propelling the business to success (Lee et al., 2019). It is estimated that AI will add approximately $13 trillion to the global economy over the next decade, raising global gross domestic product (GDP) by roughly 1.2% a year by 2030 (Fountaine et al., 2019). AI may broaden performance gaps between countries, and AI leaders could obtain an additional 25% in economic benefits comparatively (Bughin et al., 2018).

AI is known too as the "fourth industrial revolution" or Industry 4.0 (Xing & Marwala, 2017). Today, Malaysia is preparing itself for Industry 4.0 by taking steps to embrace newer technology, that is, AI, to improve competitiveness against other countries (Omar et al., 2017). The Malaysian government has acknowledged the importance of digitalized technology for the country's economy, specifically in the industrial sector (Ooi et al., 2018). Based on the "2016 GE Global Innovation Barometer" report, a large number of Malaysian executives in the manufacturing industry are optimistic about transforming their current manufacturing systems to the new technological advancement driven by Industry 4.0 (Mohamad et al., 2018).

The influences of AI Implementation on Company Processes

The organizational competencies for Industry 4.0 have been designed along with components that include the methodological, social, and personal domains (Hecklau et al., 2017). The ability to develop networks, solve problems, and invest in innovation in the industry can be addressed by implementing AI in company processes, specifically in HRM (Kinkel et al., 2017). Social and technological attributes no longer exist separately, based on the presumption that digitalization is an essential work integrated criterion in an organization, specifically the use of virtual learning environment (VLE), augmented reality, and collaborative environments between service robots and humans (Liboni et al., 2019). A proposed model for Industry 4.0 where HRM becomes the center of the human-technology interface relationship has been proposed by Dregger et al. (2016), and shown in Figure 2.

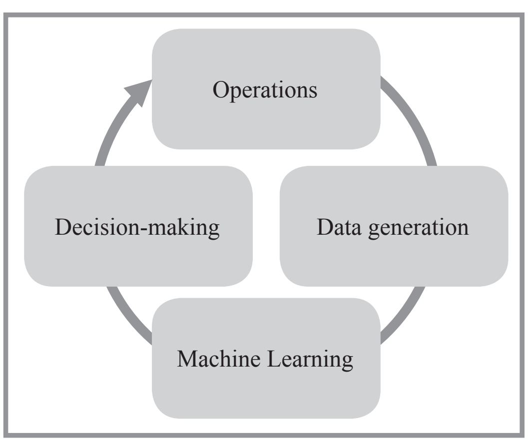

Figure 2. The Life Cycle of an AI-Supported HR Practice
Note. Adapted from Tambe et al. (2019)

Most organizations are looking for AI solutions for their business as AI plays a critical role in terms of operations and data generalization that relate to developing algorithms to accelerate HR processes (Matsa & Gullamajji, 2019). Furthermore, several companies, such as Google and IBM, are implementing AI in their HRM processes to easily access information and reduce the workload and time spent by HR managers (Premnath & Arun, 2020).

Tambe et al. (2019) affirmed that the AI life cycle of HR practices consists of four stages: operations, data generation, machine learning, and decision-making. Operations refer to the application of data science tools in HR's many operations, which involve much capital. Of interest under operations will be whether the organization secures good candidates, offers jobs to those with potential, and whether it can predict which talents are likely to stay or leave. These HR processes will cost the organization if it is unable to operate the processes effectively. Each of the operations involves administrative tasks that will ultimately influence performance. The next stage involves data generation. As volumes of data will be generated, the human resource information systems are a critical input for this stage. The input will be obtained from multiple databases, converted to a common format, and compiled before conducting data analytics. Tambe et al. (2019) further claimed that machine learning (ML) refers to a broad set of techniques that can be adapted from data to create algorithms to perform better tasks and execute predictions. The final stage of the life cycle is decision-making which deals with the outcomes from the ML model in an organization's daily operations. By leveraging the empirical evidence from scientific data when executing HRM processes in the company, HR managers could make better judgment calls in decision-making.

Hypothesis Development

AI Implementation in HRM Processes

AI has been extensively explored in several business processes, especially in the field of HR, and its adoption in HRM processes increases the efficiency of employees in an organization (Bibi, 2019). The role of AI in HRM processes will generally be seen starting from talent acquisition to performance management of employees in the organization (Jia et al., 2018). AI-based human resource applications will help the organization dynamically increase employee performance, engagement, and retention (Jain, 2018). They will also assist in reducing turnover, time, errors, and biases in professional decision-making (Eubanks, 2018). The reluctance to implement AI in HRM processes can have a devastating impact on the organization's overall growth, and HR leaders should address this issue of human and machine interactions in the workplace (Bibi, 2019). In today's business world, AI is a blueprint for the success of HR (Lengnick-Hall et al., 2018). Organizations have been hiring, managing, and engaging their workforce in recent years by modernizing through AI (Balabanova & Balabanov, 2020). The adoption of AI in HRM processes has become widespread, and the implementation of AI provides vital, wide-ranging prospects to improve HRM processes in terms of talent acquisition, training and development, performance management, and decision-making (Saxena, 2020). The advancements of AI, machine learning, and predictive analysis in HR processes facilitate HR professionals to execute traditional HR practices with much more ease and decreased time span (Nankervis et al., 2021). AI can also assist the organization in the execution of various tasks like scheduling interviews, group meetings, analytics, reporting on relevant data for the purpose of improving hiring procedures, personalize learning and development programs, granting rewards, minimizing employee turnover, and increasing employee engagement with the job (Bibi, 2019). In the HR industry, the emphasis is on data-driven technology, with AI solutions reaching new heights and creating significant impacts on business organizations (Ashraf, 2020). Therefore, the adoption of AI in HRM processes will help the organization enhance its competitiveness and performance (Donkor et al., 2017).

AI Implementation in Talent Acquisition Process

Predicting the best potential hire is critical in every organization (Aboramadan et al., 2020). The talent acquisition process that is equipped with an AI-based system will assist an organization in publishing available positions on its website or portal, conducting preliminary candidate screening, organizing interview scheduling, as well as assessing, preparing, and generating new hire data (Balasundaram & Venkatagiri, 2020). The adoption of AI-integrated systems assists HR professionals in analyzing resumes received and selecting the best candidate that fits the job by comparing the qualifications of the candidates with those of existing employees in the same job position (Matsa & Gullamajji, 2019). With the implementation of AI in the talent acquisition process, HR professionals will no longer be involved in the tedious and tiresome task of screening the resumes of potential candidates by hand, making phone calls, or replying to candidates' emails when selecting and hiring new talents (Bibi, 2019). The use of AI will help to simplify the manual process and send out automated messages according to the qualifications and requirements of the job set out in the system beforehand (Veena & Sharma, 2018). Along the process, it will help eliminate human intervention and result in zero human bias (Chaturvedi & Joshi, 2017). Besides, the use of AI in the talent acquisition process will help HR personnel save a lot of time when selecting qualified candidates (Matsa & Gullamajji, 2019). Monotonous and stressful work can be reduced as AI-related software can scan, read, and evaluate applicants and weed out incompetent candidates quickly (Barboza, 2019). By using AI in talent acquisition, HR departments are significantly enhancing the quality of hiring decisions (Garg et al., 2018). Furthermore, organizations will be able to save a considerable amount of money and avoid paying the price of poor hiring decisions (Amritaa & Achwani, 2018).

According to Johnson et al. (2020), the adoption of AI in the talent acquisition process will increase efficiency and timeliness in terms of reducing the costs of hiring by streamlining the process. For example, by executing AI, HR professionals can use the scanning system to determine if the candidates are qualified for the jobs when they meet the minimum job requirements and convey the status to the applicants in the screening process (Veena & Sharma, 2018). Premnath and Chully (2020) proved there is a positive influence of AI implementation in the talent acquisition process on organizational performance, whereby AI will assist the company in enhancing efficiency in the hiring process and thus lead to increased organizational performance. Another positive influence on organizational performance is that AI will help the company to attract applicants and the degree of fit assessments (Johnson et al., 2020). Based on the study by Balasundaram and Venkatagiri (2020), AI can help HR professionals to design the website to draw applicants as the hiring messages can be tailored to aim for candidates with specific skill sets. Therefore, we hypothesized that:

H1. AI implementation in the talent acquisition process positively affects organizational performance

AI Implementation in Human Capital Development Process

With rapid technological alterations happening in these recent years, it is important to ensure employees are aware of constant improvements in executing tasks in an organization (Barboza, 2019). Hence, learning and development provided to talents to improve their professional skills must be enforced within the company (Sekerin et al., 2018). HR managers can also determine the best timeframe for new scheduled lessons to fit the individual preferences of employees (Maity, 2019). The use of AI in the human capital development process has become a powerful avenue in organizations because the learning and development programs are more effective compared to traditional training programs (Matsa & Gullamajji, 2019). By utilizing AI-based algorithms, learning programs can be customized as the company will be better able to monitor and investigate the skills, attitudes, and behaviors of different employees at different ranks (Wolor et al., 2020). AI can assist in planning, organizing, coordinating, and developing programs for all talents in such a way that it categorizes the talents based on their competencies. Next, AI will also help the employer and employee discover the gaps in their performance, knowledge, and competencies by providing feedback after the learning programs and thus help them to enhance their work processes (Wang & Lin, 2020). Wamba-Taguimdje et al. (2020) stated that organizational performance would increase when the company adopts AI-based human capital development tools to cope with the increased volumes and changes in learning and development contents. This statement is supported by Sima et al. (2020) because they claimed that AI tools would enhance organizational performance by providing the workforce with up-to-date skills. Hence, we hypothesized that:

H2. AI implementation in the human capital development process positively affects organizational performance

AI Implementation in Performance Management Process

The traditional performance appraisal is being made obsolete due to the adoption and usage of AI in recent years (Matsa & Gullamajji, 2019). In past decades, company managers could possibly show bias during performance appraisal and raise the error rate of measuring performance (Dal Corso et al., 2019). Great efficiency and productivity are critical traits of successful talents, but many organizations may find it difficult to figure out which talents have those important traits (Barboza, 2019). However, by using AI, HR managers will be able to identify, assess, and develop better results. Top companies such as Microsoft and Deloitte have been successful in using AI-based applications to evaluate the performances of employees (Matsa & Gullamajji, 2019). By adopting AI-based systems, the performance management processes will be improved in terms of mailing performance review forms to employers and employees, data scrutiny, scheduling performance interviews, and publishing predefined performance reports to managers (Balasundaram & Venkatagiri, 2020). Furthermore, AI-driven reviews of employee performance can occur on a real-time basis with systems that monitor the targets and the execution of AI, which will lead to incentive specifications and immediate acknowledgment of good performance, as well as prevent any oversight by the leaders (Bibi, 2019). On the other hand, if the performance targets or standards are not met, the system will signify interventions before the problem escalates or even solve the problem before it spirals out of control (Buck & Morrow, 2018). AI can also forecast the performance indicators of employees with potential and inform HR professionals of employees who need to change to more suitable positions (Bhardwaj et al., 2020). Real-time responses will allow HR professionals to recognize, evaluate, and rectify operational inefficiencies by employing AI tools (Bibi, 2019). Hence, we hypothesized that:

H3. AI implementation in the performance management process positively affects organizational performance.

Method

Population

In order to measure and study the targeted sample of this research, the first step is to determine the estimated number of the target population, that is, employees that are working in Malaysia. In this study, the target population takes into account employees who are working in Malaysian companies. According to Hirschmann (2022), the number of employees in Malaysia is approximately 14.96 million people in 2020 overall. The sample frame selected to conduct this study includes supervisors, executives, managers, and senior managers who are responsible for measuring employee performance in a company (Tarmidi & Arsjah, 2019). Apart from that, superiors who are responsible for regularly checking in with employees on goal-oriented progress, delivering positive feedback and feedforward, conducting performance conversations, and communicating organizations' performance standards and expectations to employees will also have the power to directly measure employee performance (Sari & Amalia, 2019). Measuring the performance of employees is the responsibility of both management and the human resources department. The sampling frame of this research is drawn to find out the influences of perception on HR AI implementation on employee performance in Malaysia. As stated by Tarmidi and Arsjah (2019), there is a link between employee performance and organizational performance. Although supervisors, executives, managers, and senior managers are not directly related to HR, they are people managers and are key stakeholders in the design and implementation of the AI systems in HR. Thus, the perceptions of these people managers are of value to the study to ensure that these users of potential AI in HR processes have a voice in the design and adoption of such a system. The views may differ or may align with the HR practitioners; therefore, by including these people managers, the perception of the adoption of AI in HR processes will be more complete.

Sample

To assess the minimum required sample size in terms of statistical power, we used G*Power (Faul et al., 2009). The model of this study had three predictors. By using G*Power with an effect size of 0.15, alpha of 0.05, and a power of 0.95, the minimum sample size needed was only 119. Thus, we can safely say that our study with a sample size of 352 has a power of more than 0.95 and is large enough, and the findings can be used with confidence. Although the sampling frame of this research, which includes supervisors, executives, managers, and senior managers, could not possibly constitute 14.8 million people, Andrade (2020) argued that a sample that is larger than necessary will be a better representative of the population and will contribute more precise results.

Sampling Design

We conducted an online survey via social networking sites to recruit participants using a nonprobability snowball sampling method. This procedure takes samples that are either related to or referred to by earlier samples (Taherdoost, 2016). In this research, snowball sampling was chosen because this technique helped gain representation from various levels, backgrounds, genders, and age groups, and covered a wide geographical area (Asiamah et al., 2017).

Data Collection Procedure

Data collection was held over a two-week period in November 2020. It should be pointed out that a conditional movement control order (CMCO) was being imposed in Malaysia at that time, from May 4, 2020, until December 2020. The Malaysian government temporarily stopped or restricted "nonessential activities." Specifically, all employers were urged to implement flexible working hours as part of the effort to prevent congestion at public transportation stations and vehicles. In addition, public and private sector employees were encouraged to work from home as the new normal (Bernama, 2020). We foresaw that CMCO might adversely impact recruitment and data collection if we were to focus on specific companies. Research activities were affected, and numerous procedural adjustments had to be made (Weissman et al., 2020). Therefore, to ensure compliance with safety requirements, switching to online data collection was deemed necessary.

Using a snowball sampling technique, the first participant fulfilling the inclusion criterion was selected to complete the self-report survey administered via the Internet (link: https://forms.gle/KAqFfEePpxccbPbQ7) through social networking sites like Facebook and LinkedIn. The respondent was then asked to recommend other suitable participants within the sample frame to answer the survey. A total of 358 responses were received from respondents, of which 352 responses were usable. Six responses were not usable due to respondents not having the authority to measure employee performance directly and incomplete questionnaires. The response rate for the study was 81.86% after the screening process to eliminate noise data. The questionnaires, data collection procedures, informed consent forms, and instructions were reviewed and approved by the Scientific and Ethical Review Committee of the University of Hertfordshire, United Kingdom (ref no: cBUS/UG/CP/04802). Table 1 illustrates the summary of the demographic profile of the 352 respondents. In the age category, respondents aged between 31 and 40 years formed the largest group (35.5%), but only 2% of respondents were from the group aged 60 years and above. Majority of respondents worked in accounting and finance departments, followed by production departments (22.7% and 22.4%, respectively). In addition, 42% of respondents worked as supervisors, 31.3% of respondents were executives, 18.5% of respondents worked as managers, and 8.2% of respondents were senior managers.

Measures

Organizational Performance

This construct is comprised of five items adapted from several sources using the 5-Point Likert Scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The following items were used: "Using AI in company processes will help the company to attain its goals effectively," developed by Almatrooshi et al. (2016); "Using AI in company processes will increase the return on investment (ROI) of employees in the company," adapted from Ojo et al. (2018); "Using AI in company processes will increase the productivity of employees," adapted from Matsa and Gullamajji (2019); as well as "Using AI in company processes will definitely increase organizational performance" and "AI should be adopted in company processes to increase organizational performance" which were adapted from Halid et al. (2020). The Cronbach alpha coefficient was .86.

Table 1

Demographic Profile of Respondents

		Frequency	%
Age	18-25 years old	19	5.4
	26-30 years old	64	18.2
	31-40 years old	125	35.5
	41-50 years old	109	31.0
	51-60 years old	28	8.0
	60 years old and above	7	2.0
Department	Human Resource	16	4.5
	Performance Management	20	5.7
	Sales	51	14.5
	Marketing	60	17.0
	Accounting and Finance	80	22.7
	Production	79	22.4
	Research and Development	37	10.5
	Purchasing	9	2.6
Job Position	Supervisors	148	42.0
	Executives	110	31.3
	Managers	65	18.5
	Senior Managers	29	8.2

AI Implementation in Talent Acquisition Process

This construct is comprised of four items adapted from several sources using the 5-Point Likert Scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The following items were used: "Using AI in the talent acquisition process will reduce the time per hire and repetitive task screening of candidates' resumes or scheduling interviews with candidates," adapted from Barboza (2019); "Using AI in the talent acquisition process will improve quality of hire through standardized job matching," adapted from Matsa and Gullamajji (2019); "Using AI in the talent acquisition process will reduce cost per hire because of the capability of targeting the right hire in a timely manner," adapted from Amritaa and Achwani (2018); and "Using AI in the talent acquisition process AI will help to eliminate hiring bias by implementing blind applicant screening," adapted from Chaturvedi and Joshi (2017). The Cronbach alpha coefficient was .92.

AI Implementation in Human Capital Development Process

This construct is comprised of four items adapted from several sources using the 5-Point Likert Scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The following items were used: "Using AI in the human capital development process will assist in identifying talent gaps to provide accurate learning and development programs to employees" and "Using AI in the human capital development process will shorten learning processes by suggesting specific modules employees need to improve their skills for the jobs they are doing" which were adapted from Wolor et al. (2020); "Using AI in the human capital development process will improve employees' training experience and provide valuable feedback on potential areas to improve" which was adapted from Wang and Lin (2020); as well as "Using AI in the human capital development process will improve absorption and implementation of learning content in the job" which was adapted from Maity (2019). The Cronbach alpha coefficient was .81.

AI Implementation in Performance Management Process

This construct is comprised of four items adapted from several sources using the 5-Point Likert Scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The following items were used: "Using AI in the performance management process will assess employee performance based purely on historical performance data and achievement of current performance metrics to conduct bias-free performance reviews," which was adapted from Dal Corso et al. (2019); "Using AI in the performance management process will initiate immediate course correction by delivering prescriptive recommendations," adapted from Buck and Morrow (2018); "Using AI in the performance management process will allow performance assessments to take place in real time and on a consistent basis," adapted from Bibi (2019); and the last item, "Using AI in the performance management process will help forecast the performance indicators of employees with potential and inform HR professionals of the employees who need to change to more suitable positions," adapted from Bhardwaj et al. (2020). The Cronbach alpha coefficient was .86.

Data Analysis

PLS-SEM was applied to examine both the measurement and structural models, using

SmartPLS 3.3.3. We employed PLS-SEM due to the inherent suitability of this approach for exploratory studies, which is the purpose of the current study (Ali et al., 2018). PLS-SEM is a comprehensive analysis approach that can simultaneously assess the measurement and structural models (Hair et al., 2017).

Results

This study conducted a two-step process that includes an assessment of the measurement and structural models.

Assessment of Measurement Model

This section indicates the criteria necessary to affirm the reliability and validity of the measurement model. A total of 352 samples were used to assess both the measurement and structural models. The measurement model used in this study was composed of four reflective constructs, namely, Organizational Performance (OP), Talent Acquisition Process (TAP), Human Capital Development Process (HCDP), and Performance Management Process (PMP). In order to assess reliability, the threshold value of outer loadings, composite reliability (CR) and Cronbach's alpha (CA) should be higher than 0.7. Furthermore, the average variance extracted (AVE) should be higher than 0.5

(Ali et al., 2018) to confirm convergent validity. The results of the assessment of the measurement model, shown in Table 2, indicate that the CR and CA of all constructs in this study were above 0.70. In addition, all item loadings were above the value of 0.5, which, assuming that the CR and AVE met the required thresholds, is acceptable (Ali et al., 2018). All constructs had an AVE above 0.5, which illustrates an acceptable degree of convergent validity as recommended by Fornell and Larcker (1981).

Hair et al. (2017) also recommended the incorporation of discriminant validity during the assessment of reflective measurement models. There are two common ways to ascertain discriminant validity, namely, the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. However, according to Henseler et al. (2015), the HTMT criterion has recently been established as the more conservative approach compared to more traditional assessment methods such as the Fornell-Larcker criterion. For

Table 2

Results of Measurement Model Assessment

Latent Variable	Items	Loading	AVE	CR	CA	Mean	SD
OP	OP1	0.854	0.714	0.926	0.900	4.51	0.51
	OP2	0.840					
	OP3	0.845					
	OP4	0.834					
	OP5	0.852					
TAP	TAP1	0.929	0.800	0.941	0.916	4.47	0.52
	TAP2	0.921					
	TAP3	0.882					
	TAP4	0.843					
HCDP	HCDP1	0.913	0.611	0.860	0.813	4.53	0.48
	HCDP2	0.861					
	HCDP3	0.670					
	HCDP4	0.649					
PMP	PMP1	0.827	0.703	0.904	0.859	4.30	0.51
	PMP2	0.801					
	PMP3	0.862					
	PMP4	0.862					

Note. OP=Organizational Performance, TAP = Talent Acquisition Process, HCDP = Human Capital Development Process, PMP = Performance Management Process

Table 3

Discriminant Validity Using HTMT Ratio

	HCDP	OP	PMP	TAP
HCDP				
OP	0.115			
PMP	0.305	0.458		
TAP	0.273	0.622	0.325	

Note. OP=Organizational Performance, TAP=Talent Acquisition Process, HCDP=Human Capital Development Process, PMP=Performance Management Process

HTMT, discriminant validity is achieved when the correlation between each pair of the latent exogenous constructs is less than 0.85 (stricter threshold) or 0.90 (more lenient threshold; Henseler et al., 2015). To establish discriminant validity, $HTMT_{0.85}$ was used in this study. Table 3 shows the value of HTMT for all constructs is lower than 0.85, therefore confirming discriminant validity.

Assessment of Structural Model

As shown in Table 2, the mean scores and standard deviations (SD) for our study variables were 4.51 for organizational performance (SD = 0.51); 4.47 for talent acquisition process (SD = 0.47); 4.53 for human capital development process (SD = 0.48); and 4.30 for performance management process (SD = 0.451). Before assessing the structural model, the collinearity between research variables was examined to ensure that the structural model did not include any lateral collinearity issue (Hair et al., 2017). Table 5 shows that all inner VIF values were below 5 (Hair et al., 2017), indicating that collinearity among the predictor constructs was not a concern in the structural model.

Assessing the structural model involves reviewing and evaluating the R-squared (R^2) value for the endogenous latent variable, the significance of path coefficients using the p-value and a confidence interval of 95% (CI 0.95), and the effect size (f^2) (Hair et al. 2017). The R^2 value can differ based on the research area, but it is important for the path coefficients to be significant. Chin (1998) proposed the R^2 values of 0.19, 0.33, and 0.67 in the path model as weak, moderate, and substantial, respectively. The results show an R^2 value of 0.392 for organizational performance, which is acceptable, suggesting that 39.2% of the variance for organizational performance can be described by AI implementation in the talent acquisition process, human capital development process, and performance management process.

The next step in the assessment of the structural model involves the evaluation of the path coefficients in relation to the model's latent variables. Table 4 and Figure 3 indicate the results of the hypotheses testing, including the path coefficients and the effect size for each path. The values of 0.02, 0.15, and 0.35 for the effect size can be considered small, moderate, and high, respectively (Cohen, 1988). To determine the path coefficient's significance, resampling techniques (e.g., bootstrapping) can be used. The path coefficients of the structural model were assessed using the bootstrap method with 5000 resamples, as suggested by Hair et al. (2017). The results show that AI implementation in the talent acquisition process ($\beta = 0.505$, $t = 9.739$, $p < 0.05$), human capital development process ($\beta = 0.083$, $t = 1.703$, $p < 0.05$), and performance management process ($\beta = 0.280$, $t = 5.156$, $p < 0.05$) positively affects organizational performance, thus supporting all hypotheses. Therefore, H1, H2, and H3 were verified. The talent acquisition process has the strongest effect on organizational performance based on path coefficient and effect size, followed by performance management and organizational performance. The human capital development process has the weakest effect on organizational performance.

Blindfolding and Predictive Relevance (Q^2)

Another important criterion to assess the predictive capability of the model is Stone-Geisser's Q^2 (Hair et al., 2017). A Q^2 value greater than zero indicates predictive relevance. The results of cross-validated

Table 4

Results of Hypothesis Testing

Hypothesis	Relationship	Coefficient	t-value	95% CI	f^2	Supported	VIF
H1	TAP → OP	0.505	9.739	[0.419, 0.590]	0.374	Yes	1.123
H2	HCDP → OP	0.083	1.703	[0.021, 0.216]	0.020	Yes	1.105
H3	PMP → OP	0.280	5.156	[0.196, 0.373]	0.113	Yes	1.143

Note. OP=Organizational Performance, TAP=Talent Acquisition Process, HCDP=Human Capital Development Process, PMP=Performance Management Process redundancy indicates that the value of Q^2 is greater than zero for the endogenous variables, which is 0.276 and acceptable (Ali et al., 2018). Therefore, the results allude to the predictive capability of the model based on the value of the endogenous constructs.

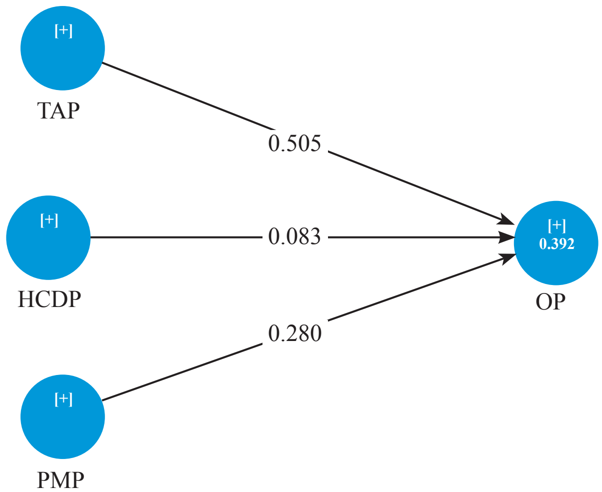

Figure 3. Results of Assessment of Structural Model

Note. OP=Organizational Performance, TAP = Talent Acquisition Process, HCDP = Human Capital Development Process, PMP = Performance Management Process

Discussion

This study aimed to examine the effects of AI implementation in the talent acquisition process, human capital development process, and performance management process on organizational performance in Malaysia. The results show that AI implementation in these processes has a significant positive effect on organizational performance. In the human resource industry, data-driven technology is being emphasized by today's HR leaders, and the capabilities of AI are reaching new heights and bringing numerous significant influences on business organizations (Ashraf, 2020). The findings of this study confirm that the adoption of AI in HRM processes will help organizations to enhance organizational performance and competitiveness. AI is a tool by which human intelligence can be applied in various dimensions to improve employee productivity and performance (Matsa & Gullamajji, 2019). AI implementation in company processes, specifically in HRM, will contribute to person-specific performance data collection in real-time due to digitalization. Work can be assessed by anyone and is more transparent, thus allowing HR professionals to measure employee performance easily. AI has the power to act like a human brain and ensures full efficiency and productivity in HRM processes.

Specifically, the AI implementation in the talent acquisition process is the strongest indicator of organizational performance in Malaysia compared to the other dimensions. Thus, this study confirms the findings of previous studies (Premnath & Chully, 2019; Johnson et al., 2020) regarding the importance of AI implementation in the talent acquisition process for organizational performance. With the assistance of AI, HR professionals will be able to save considerable time in making effective decisions due to a reduction in cost per hire because of the efficiency of job advertisements. Using AI in the talent acquisition process will reduce the time per hire and repetitive tasks like screening a candidate's resume or scheduling interviews with them. The recruitment of high-performing or key talents to perform specific tasks in the workplace can be done through standardized job matching. This can be done through the implementation of blind applicant screening. HR professionals will also be able to eliminate human intervention and achieve zero human bias while selecting the candidate that best fits the job profile, thus increasing organizational performance and quality.

In addition, the findings of H2 reveal that organizational performance will be increased should the company adopt AI-based human capital development tools to cope with the greater volumes and changes in learning and development contents. This supports the claims made by Sima et al. (2020) with regard to AI tools enhancing organizational performance by providing the workforce with up-to-date skills. Using AI in the human capital development process will help identify exactly the talent gap so that accurate learning and development programs for employees can be provided. Hence, this study corroborates the suggestion made by Fernando et al. (2020) that a positive influence exists between the implementation of AI in the human capital development process and employee performance, as employees are constantly aware of the development programs that help them accomplish tasks efficiently in the workplace. Using AI will shorten learning processes by suggesting specific modules employees need to enhance their skills for the jobs they are doing, improve the training experience for employees and provide valuable feedback on potential areas to improve, as well as boost the absorption of learning content for implementation in their jobs.

Furthermore, the findings of this study confirm those of previous studies by Muthuveloo et al. (2017). By adopting AI in the performance management process, ongoing and data-driven conversations to trace organizational performance can be continuously executed instead of just having a one-time discussion at the end of the year. Real time feedback on continuous touch points will assist the organization in reviving the recognition it deserves, and constructive feedback delivered when appropriate and in a timely manner will increase performance (Bibi, 2019). Using AI in the performance management process will also help assess organizational performance purely on historical performance data and achievement of current performance metrics in conducting bias-free performance reviews, and therefore initiate immediate course correction by delivering prescriptive recommendations. With AI in the performance management process, unbiased reviews will aid HR professionals in appreciating the real performers and prioritize their retention (Dal Corso et al., 2019).

Theoretical Implications

With the help of the 5P's model, the present study has provided support to previous studies as well as clarified the roles played by the talent acquisition process, human capital development process, and performance management process in organizational performance in Malaysia. The research topics that are available in the theoretical field regarding the implementation of AI in business organizations have become increasingly popular in these recent years, though research that focuses on specific fields, especially HR, is relatively insufficient. Therefore, from a theoretical point of view, this study will help bridge the knowledge gap on the influences of perception on implementing AI in HRM processes on employee performance. The findings will benefit future researchers who could take it further.

The results of this study are reliable and will be instrumental to other researchers. Pryor et al. (2007) have proven that based on the 5P's model, aligning and balancing the five components, namely, purpose, principles, processes, people, and performance, will lead to achieving company success. The theory is corroborated in this study. It can be seen that the purpose reflects the aim of companies in Malaysia to survive and compete with their rivals in trying to achieve Industry 4.0. The companies consistently adhere to the principles they have set to achieve their purpose. Also, company processes become more streamlined with the implementation of AI in HRM processes, thus enhancing efficiency and reducing bias. Employees, too, are vital people as they operate the processes to gain favorable results and higher performance and productivity (Gülenç & Kozak, 2016). In conclusion, the findings of this study will provide insights for other researchers to focus on areas relevant to this subject matter.

Practical Implications

The results of this research would assist business organizations in Malaysia in making appropriate and effective decisions should they adopt AI in their company processes to increase organizational performance. For instance, it is recommended that they implement AI in their talent acquisition process as the first step. Though companies may initially have to spend a fair amount of capital, the adoption of AI-based tools and their implementation will generate more returns compared to the amount spent (Cam et al., 2019). The reason is that the adoption of AI will increase efficiency and timeliness in terms of reducing the costs of hiring by streamlining the process (Johnson et al., 2020). Business organizations should also adopt AI-based systems in the talent acquisition process to assist HR professionals in publishing available positions on company websites or portals, conducting preliminary candidate screening, organizing interview scheduling, as well as assessing, preparing, and generating new hire data (Balasundaram & Venkatagiri, 2020). Applicants who are drawn to these jobs will be more engaged, leading to a high possibility of increased productivity and organizational performance (Matt et al., 2020).

The outcome of this study also reveals that an AI-based performance management process is necessary to enhance organizational performance. Therefore, business organizations in Malaysia are encouraged to implement AI systems in their performance management process to collect ongoing performance reviews and data continuously throughout the year instead of a one-time data collection at the end of the year. By doing so, the system will be able to signify interventions before the problem escalates or even solve the problem before it becomes uncontrollable (Buck &

Morrow, 2018). Apart from that, business organizations are recommended to adopt AI-based systems in the performance management process. Mailing performance review forms to employers and employees automatically, scheduling performance interviews, and publishing predefined performance reports for managers will make the process more systematic and professional (Balasundaram & Venkatagiri, 2020). AI may also forecast the performance indicators of employees with potential, informing HR professionals of the employees that should be promoted. These employees would then be moved to more suitable job positions and accurate departments. All this will indirectly boost organizational performance (Bhardwaj et al., 2020).

Last but not least, the findings of this study would help business organizations in Malaysia to increase performance through the AI-based human capital development process. With the assistance of AI, business organizations can plan, organize, and coordinate learning and development programs for all talents, as well as help to differentiate one talent from the next based on their competencies (Wolor et al., 2020). HR managers can also determine the best timeframe for new scheduled lessons to fit the individual preferences of employees (Maity, 2019). In fact, AI will inform the employer and employee of the gaps in their performance, knowledge, and competencies by providing feedback after the learning programs, thus helping them enhance their work skills and eventually increase organizational performance (Wang & Lin, 2020).

Limitations and Future Research

This study is constrained by the limited number of studies on AI in Malaysia due to the lack of AI implementation in Malaysian companies. Given that this study was aimed at finding out the perception of the impact of AI in HRM processes on organizational performance in Malaysian companies, it was discovered that most companies in Malaysia are still ill-equipped to reach Industry 4.0. Nevertheless, this study provides some pertinent insights into HRM processes. Future research could modify the dimensions of perception on AI implementation and include other variables such as talent mapping, rewards management, onboarding, and engagement in order to enrich the literature on AI implementation in HRM processes. Furthermore, the research could look into qualitative approaches to gather different insights on the perception of HR AI implementation and organizational performance in Malaysia because the quantitative approach used in this research could have restricted respondents' points of view. Therefore, prospective research could explore the perspectives of participating individuals by interpreting the data from respondents qualitatively. A qualitative approach might give different insights into the perception of HR AI implementation and organizational performance in Malaysia.

Conclusion

This study is greatly significant in that it offers insights into the perception of AI implementation in HRM processes on organizational performance in the context of Malaysian companies. In light of this, our study has revealed that in the incorporation of AI to improve efficiency in completing HR-related tasks and streamlining HRM processes, factors like talent acquisition, human capital development, and performance management are imperative. The talent acquisition process, in particular, is found to have the greatest impact. Nevertheless, as most companies in Malaysia still lack awareness of how to implement AI in their company processes, the challenges they face in venturing into Industry 4.0 have proven to be a stumbling block. Thus, it is important for these business organizations to take appropriate measures and make effective decisions to overcome these challenges in order to be successful in applying AI in their HRM processes and ultimately increase organizational performance. Our results also resonate with the assertion of the 5P's model, which painted a holistic composition with regard to the implementation of AI in HRM processes. Our study, notably, has extended the scope of this model by examining factors such as strategy, structure, and behavior and identifying them as the forces that drive organizational performance.

Declaration of Ownership

This report is our original work.

Conflict of Interest

None.

Ethical Clearance

This study was approved by our institution.

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