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A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership

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Abstract

Purpose – This paper aims to explore employee perceptions of companies engaged in services and banking of the role of change leadership on the application of artificial intelligence (AI) that will impact the performance and work engagement in conditions that are experiencing rapid changes.

Design/methodology/approach – This study has used a quantitative research approach, and data analysis uses an approach structural equation modeling (SEM) supported by program computer software AMOS 22.0. A total of 357 respondents were involved in this study, but only 254 were qualified. In this study, the respondent is an employee of companies engaged in the services and banking sector in the East Java, Indonesia region.

Findings – The results reveal that AI has a significant positive effect on employee performance and work engagement. Change leadership positively moderates the influence of AI on employee performance and work engagement.

Originality/value – The development of this model has a novelty by including the moderating variable of the role of change leadership because, in conditions that are experiencing rapid changes, the role of leaders is essential. After all, leaders are decision-makers in the organization. The development of this concept focuses on studies of companies engaged in services and banking. Employee performance is an essential determinant in the organization because it will improve organizational performance. In addition, the application of AI in organizations will experience turmoil, so that the critical role of leaders is needed to achieve success with employee work engagement.

Keywords Artificial intelligence, Change leadership, Employee performance, Work engagement

Paper type Research paper

Introduction

Nowadays, the challenge for 21st-century organizations lies in the company ability to innovate in the face of a highly dynamic market in which competitive positions are constantly evolving (Stank *et al.*, 2019). In the context of globalization and internationalization of markets, innovation, product or service quality and customer requirements have led companies to integrate IT into their managerial approach (Bolwijn *et al.*, 2018; Rachinger *et al.*, 2019; Stank *et al.*, 2019). Innovation is essential for organizations to sustain an advantage in highly competitive environments (Kistyanto *et al.*, 2021). Organizations have always aspired to assign more tasks to machines in order to reduce costs and improve efficiency. It started with assembly lines, which replaced human labor in mechanical and repetitive tasks previously known as "manual labour" (Dopico *et al.*, 2016; Lee *et al.*, 2018).

The digital revolution has already produced its effects by transforming the world into a modern one characterized by data supremacy in every business activity (Wamba-Taguimdje

et al., 2020). Data are no longer confined to data centers. With sensors of any kind, any object or environment is henceforth capable of measuring and producing data (Dopico *et al.*, 2016; Lee *et al.*, 2018; Sheth, 2016). Industrial and digital (information) revolutions have undoubtedly had a financial impact on virtually every aspect of our society, life, business and employment (Blanchet, 2016; Yoav Shoham *et al.*, 2018). This implies the use of digital resources, which vary depending on the moment: big data, artificial intelligence (AI), 3D printing, quantum computing or virtual reality (Nicolás-Agustín *et al.*, 2021). Today, AI remains the most spectacular IT application, a technology that has gone through an unequaled development over the last decades (Blanchet, 2016; Lee *et al.*, 2018; Wiljer and Hakim, 2019). It is defined as a set of "theories and techniques used to create machines capable of simulating intelligence. AI is a general term that involves using a computer to model intelligent behaviour with minimal human intervention" (Benko and Lányi, 2009; Haenlein and Kaplan, 2019; McCorduck *et al.*, 1977).

AI has drawn controversy, both among practitioners and among academics. Calo (2015) argues that AI will replace millions of jobs and possibly increase the number of unemployed, bringing new challenges, such as rebuilding infrastructure, protecting vehicle safety and adapting laws and regulations. AI can develop HR functions but has many risks, such as changing humans to machines, underestimating humans and the system being too high (Reilly, 2018). On the other hand, Nilson (2006) states that AI can help companies improve their performance. IDC estimates that 40% of digital transformation initiatives in 2019 will use AI services and that 75% of business applications will use AI by 2021 (Crews, 2019). To improve productivity and develop new services, organizations will have to rely even more on AI to improve their performance (CIGREF, 2016, 2018; Crews, 2019). Thus, the growth of AI does not replace the humans' roles but makes their work more efficient and effective. HR applications by AI have the talent to investigate, predict, identify and be a resource essential that is more influential in achieving success late (Ernst and Young, 2018). Empirically Frey and Osborne (2013) documented a decline in employment in routine jobs; such work can be done quickly and more effectively by sophisticated algorithms (AI).

Apart from having an impact on improving employee performance, AI can also make employees engage more with their work. Hughes *et al.* (2019) stated that the AI management system could deliver employees to engage in work indicated by direction, monitoring and rewards. During the COVID-19 pandemic, digital and social media played an essential role in engaging consumers. As a result of COVID-19, consumer engagement with social media sites has risen (Rather, 2021).

Employee engagement in the new work environment is shaped by Millennials, a generation of individuals who are very comfortable with online networking technologies (Kaplan and Haenlein, 2010). Meanwhile, understanding the role social media may play in fostering employee engagement is in its infancy. Leonardi *et al.* (2013) explain that to date, scholars have conducted most studies of social media within computer-supported cooperative work and human-computer interaction communities. Not many studies have looked at how social media usage impacts employee engagement and overall organizational performance (Haddud *et al.*, 2016).

The relationship between AI on employee performance and work engagement might not be straightforward and can be strengthened or weakened by other variables. Therefore, this study selects change leadership as a moderating mechanism in explaining the effect of AI on employee performance and work engagement. The organization success depends upon leadership Dhamija *et al.* (2021). The implementation of AI in the organization will be maximized because of the role of a leader. The phenomenon of leadership includes an individual's ability to influence others – i.e. followers – to help achieve organizational objectives (Erkutlu and Chafra, 2018). Hambrick and Mason (1984) stated that an organization is reflected in its top management. The use of social media technologies has

increased across organizations as executives and managers attempt to leverage the power of the information and knowledge within their companies (Leonardi, 2015). The traditional managerial skill that emphasizes improving efficiency alone is no longer sufficient in today's dynamic environment, which is technologically equipped (Dhamija *et al.*, 2021). As an event-based construct, change leadership plays an essential role in implementing changes that are planned, episodic and top-down oriented (Onyeneke and Abe, 2021).

Viewed as a critical growth factor, AI can allow an organization to detect fraud (e.g. banking and other sectors) (CIGREF, 2018; Pwc, 2019). Job performance in the service and banking industry typically requires an interaction between employees and customers (Auh, 2005). Based on this characteristic of the service industry, service employees have been considered a critical resource for determining perceptions of service quality among customers (Auh, 2005). Thus, the job performance of service employees is essential to achieving customer satisfaction and delivering high-quality service and obtaining repeat business (Lee *et al.*, 2011). Although this industry has recorded rapid growth in the last ten years, it has also experienced many challenges (Shah and Tyagi, 2017), mainly due to its high complexity and results-based performance focus. As the industry demands high job performance, employees are under tremendous pressure and constant stress due to their over-rules and fear of losing their jobs if they do not achieve the set goals. Other challenges, such as low income, poor career progression, an unsafe work environment and job insecurity, add to employee work stress and reduce morale. Therefore, employees in this industry often feel dissatisfaction, leading to reduced individual work performance (O'Bien and Marion, 2009), especially during the COVID-19 pandemic in Indonesia (Rahman *et al.*, 2020).

The bank is a highly regulated financial institution incorporated with the economy's high social value systems and monetary regulatory authority (Akther and Rahman, 2021). In Indonesia, the implementation of Bank Indonesia (BI) tasks in the monetary, banking and payment system sectors is supported by the internal management sector, continuously developing and improving. The demand for this sector has become even more significant, given that the challenges faced by BI in the future are not easy, especially given the very complex problems faced by the national economy (Rahman *et al.*, 2020). The development of technology and information and the banking business provides all Indonesian people by developing services through ATM, mobile banking and Internet banking (Kustina *et al.*, 2018). This is conducted to expand services for the customers spread across Indonesia and the features of the transactions developed are more varied. However, digital progress has happened significantly since 2011 after the Hannover fair and advent of 4.0 (Dubey *et al.*, 2020). Moreover, coronavirus disease 2019 (COVID-19) has taught us an important lesson and forced firms to adopt digital modes in every function, including HRM (Bag *et al.*, 2021a).

Although still far from equaling "Human Intelligence" as a whole and its complexity, AI is highly effective in carrying out specific tasks, and its impact on the world and organizations is undoubtedly considerable (Blanchet, 2016; Lee *et al.*, 2018; Wiljer and Hakim, 2019; Zhong, 2008). Research in AI on employee performance and work engagement moderated by change leadership has never been studied before. Built on the philosophies of dynamic capabilities theory (Teece *et al.*, 1997), this study adds to the literature on intelligence by examining an under-explored type of intelligence (i.e. AI) on employee performance and work engagement in the banking and services industry sector in East Java, Indonesia region. It reveals change leadership as the psychological mechanism that can influence AI on employee performance and work engagement. Therefore, the objective of this study is to fill this gap by answering the following research questions:

RQ1. Do AI capabilities influence employee performance and work engagement?

RQ2. What moderating effect will the change leadership variable in AI implementation have on employee performance and work engagement?

Our study aims to analyze the effects of AI capabilities on improving employee performance and work engagement moderated by change leadership. This analysis will be particularly concerned with the business value of AI-enabled transformation projects in organizations. The first section highlights this research background: issues regarding the use of AI on employee performance and work engagement moderated by change leadership in banking and other sectors. The second section reviews the theoretical background surrounding AI, change leadership, work engagement and employee performance. The development of hypotheses relevant to AI, change leadership, work engagement and employee performance has been presented in the subsequent section. The fourth section presented research and methodological issues adopted for this research. The results of empirical findings and discussion were presented before the conclusion section.

Literature review

Dynamic capability view. In organizational theories, dynamic capabilities allow organizations to adapt an organization's resource base purposefully. The concept was defined by Teece *et al.*, in their 1997 paper Dynamic Capabilities and Strategic Management, as "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments". In a broader context, the survival of organizations or firms is mainly dependent upon the mixing and matching of existing resources and capabilities to explore new avenues for better long-term growth (Rhemananda *et al.*, 2020). Varied dynamic environments possess dynamic capabilities (Rotondo *et al.*, 2019) related to innovation, replication and reconfiguration (Rogiers *et al.*, 2020). Identification of dynamic capabilities, especially from the context of human resources, is necessary because it governs the growth and development of organizations or firms (Ruel *et al.*, 2007). Contemporarily, organizational capacities are very much dependent on the employees or staff's emotional skills and organizational behavior, wherein the dynamic capability view fits ineffectively (Schilke, 2014a, b). The association between dynamic capabilities and their related outcomes is expected to be moderated by various internal and external organizational factors (Bowman and Ambrosini, 2003), including intellectual capital, organizational culture and behavior, trustworthy, ethical leadership and managerial effectiveness (Wamba *et al.*, 2020).

Artificial intelligence. From the beginning of computer science, researchers like Alan Turing considered the possibility of a computer playing chess as a test of the machine's intelligence. Thus, he published "Intelligent Machinery" in 1948 and "Computing Machinery and Intelligence" in 1950, both of which will inspire future scientific research in AI (Turing, 2009). AI means the use of technological devices aimed at reproducing the cognitive abilities of humans to achieve objectives autonomously, considering any constraints that may be encountered (Benko and Lányi, 2009; Haenlein and Kaplan, 2019; McCorduck *et al.*, 1977).

Announced in the 1960s, AI has made significant progress that was eventually confirmed since the 2000s with the emergence of "Machine Learning" (automatic learning: machines 'learn' from the datasets offered to them), whose latest development is "Deep Learning" (which relies on neural networks) (Buchanan, 2005; Pwc, 2019; Yoav Shoham *et al.*, 2018). Combined with big data, these types of AI perform operations and actions that exceed human actions in terms of speed and relevance. Many sectors and services are already or will soon be affected by these technological innovations; they include transport with autonomous vehicles (Falcone *et al.*, 2007), health with disease detection programs (cancers and other diseases) through Machine Learning and Deep Learning (Jiang *et al.*, 2017; Koh and Tan, 2011), customer relationship with the use of conversational agents (Rubin *et al.*, 2010), natural processing language and automatic email processing by virtual robots (Gabrilovich and Markovitch, 2009), security with facial recognition and artificial vision technologies and urbanism with a smart city (Jain *et al.*, 2004; Khashman, 2009; Srivastava *et al.*, 2017).

Viewed as a critical growth factor, AI can allow any organization to achieve the following: (1) increase the efficiency of operations, maintenance and supply chain operations, optimize and improve the customer experience, improve products and services (with new features), as well as item recommendation processes (retail and other industries) (Kuzey *et al.*, 2014; Pwc, 2019); (2) improve rapid and automatic adaptation to changing market conditions, create new business models, optimize the relationship between supplies and needs with better forecasting and planning capacity (Kuzey *et al.*, 2014; Pwc, 2019); (3) detect fraud (banking and other sectors), automate threat intelligence and information systems, automate IT function (IT system and processes) and optimize sales processes (CIGREF, 2018; Pwc, 2019); (4) diagnose and treat pathologies (Koh and Tan, 2011), anticipate a disease and its evolution, promote the recommendation of personalized treatments, assist in decision-making by advising on the diagnosis, prevent by anticipating epidemics and acting on pharmaceutical vigilance (Jiang *et al.*, 2017; Johnson *et al.*, 2018); (5) automate quality management investigation and recommendation, manage supply, logistics and fleet assets (logistics or transport and most industries) (Di Francescomarino and Maggi, 2020; Rubin *et al.*, 2010; Sikdar, 2018); and (6) and to the rescue, helping to process natural and man-made disasters-related data in ways that support informed disaster management (disaster relief operation) (Behl *et al.*, 2021).

Change leadership. As an event-based construct, change leadership plays an essential role in implementing changes that are planned, episodic and top-down oriented. The term "change leadership" was coined within more recent literature (e.g. Higgs and Rowland, 2005; Herold *et al.*, 2008) and generally stems from change process literature, which deals with actions undertaken by change agents toward the implementation of a specific planned change. Many process pieces of literature focus on the roles that managers and change agents have as change leaders, and how through a sequential process, change leaders can influence the implementation and outcome of a change at hand. However, the diverging point of emphasis from process to leadership-oriented literature was the realization that the successful implementation of change does not occur through a linear or step-based implementation process. Instead, successful change requires a complex responsive process; thus, more facilitating and engaging leadership models are preferable (Dumas and Beinecke, 2018; Higgs and Rowland, 2011).

Hooper and Potter (2000) define change leadership, namely developing a vision for the future, devising strategies to make the vision a reality and mobilizing energy throughout the organization's members to achieve the same goals. This approach is known more in terms of emotional attunement. Change leadership is the ability of a leader which includes cognitive or rational processes (cognitive intelligence), the need for meaning in people's work and life (spiritual intelligence), emotions or feelings (emotional intelligence) and will actions or behaviors (behavioral skills) to achieve organizational goals (Gill, 2002).

Building on change process literature, researchers have prescribed leadership behaviors that facilitate change. These include developing a clear and concise change vision, encouraging active participation, persuasive communication, mobilizing coalition to support and promote the change, showing concern for individuals who have trouble with the change, providing change-related support, evaluating the change implementation and consolidating the change successes (Onyeneke and Abe, 2021). The activities above are facilitated by those in change leadership positions (Kotter, 2011; Herold *et al.*, 2008).

The difference between "change management" and "change leadership" and the distinction between the two are quite significant. Almost everyone uses change management, which refers to a set of essential tools or structures intended to keep any change effort under control. The goal is often to minimize the distractions and impacts of the change. On the other hand, change leadership concerns the driving forces, visions and processes of large-scale fuel transformation (Kotter, 2011).

There is a very fundamental difference, and it is massive, between what is known today as "change management" and what we have been calling for some time "change leadership." The world uses change management, which is a set of processes and a set of tools and a set of mechanisms that are designed to make sure that when a company try to make some changes, A, it does not get out of control, and B, the number of problems associated with it—company know, rebellion among the ranks, bleeding of cash that company cannot afford—does not happen. Hence, it is a way of making a significant change and keeping it, in a sense, under control. Change leadership is much more associated with putting an engine on the whole change process and making it go faster, more innovative, more efficiently. It is more associated, therefore, with large-scale changes. Change management tends to be more associated with minor changes when it works well (Kotter, 2011).

As we all know right now, the world talks about, thinks about and does change management. The world, as we all know, does not do much change leadership since change leadership is associated with the more enormous leaps that we have to make, associated with windows of opportunity that are coming at us faster, staying open less time, more considerable hazards and bullets coming at us faster. Hence, the leader has to make a more significant leap at a faster speed. Change leadership will be a big challenge in the future, and the fact that almost nobody is perfect at it is a big deal (Kotter, 2011).

Employee performance. In short, job performance can be defined as the behaviors that employees display at work that amount to the delivery of outcomes desired by the organization regarding job quality, job quantity and job time (Na-Nan *et al.*, 2018). According to Peterson and Plowman (1953), job quality involves meeting the set criteria and standards for procurement, production, quality inspection and delivery of goods and services. Job quantity refers to the units of output produced by employees' behaviors, such as the product quantity, waste quantity and sales figures (Peterson and Plowman, 1953). Job time concerns the amount of time required to complete work-related activities about the difficulty of the tasks. Employees satisfy job-time goals as long as the required tasks are carried out accurately and within a reasonable amount of time and products or services are delivered on schedule (Peterson and Plowman, 1953).

Work engagement. The term work engagement was first conceptualized by William Kahn (1990) and defined as the harnessing of employees' selves to their work roles by which they employ and express themselves physically, cognitively and emotionally during role performances (Kahn, 1990). After Kahn, different approaches to work engagement were proposed that each emphasizes a distinct aspect of work engagement (Schaufeli, 2013). Work engagement is defined as a positive, fulfilling work-related state of mind characterized by vigor, dedication and absorption (Schaufeli *et al.*, 2002). Vigor is characterized by high energy levels and mental resilience while working, the willingness to invest effort in one's work and persistence even in the face of difficulties. Dedication refers to being strongly involved in one's work and experiencing a sense of significance, enthusiasm, inspiration, pride and challenge. Finally, absorption is characterized by being fully once treated and happily engrossed in one's work, whereby time passes quickly, and one has difficulties detaching oneself from work (Maslach *et al.*, 2001).

Development of hypotheses

Artificial intelligence and employee performance. Studying the relationship between IT and organizational performance remains topical, although it has evolved over the years. Today, with the spectacular innovations that AI has brought in its wake, some authors generally combine several theories and models for studying the influence of AI on organizational performance and identifying the business value of transformation projects enabled by the same. A literature review enables us to select suitable theoretical foundations. It included

paradox productivity (Kijek and Kijek, 2019; Polák, 2017; Triplett, 1999), process-oriented perspective (Mooney *et al.*, 1996), resource-based view (Barney *et al.*, 2001; Grant, 1991) and dynamics capabilities (Kim *et al.*, 2011).

AI improves business intelligence and performance (Selene and Gong, 2014). Existing research and popular press have documented the potential advantages of utilizing AI in organizations in improving productivity and streamlining organizational processes and tasks (Arslan *et al.*, 2021). To improve productivity and develop new services, organizations will have to rely even more on AI to improve their performance (CIGREF, 2016, 2018; Crews, 2019). As part of an organization's ecosystem, AI can impact, particularly on performance, on relationships between organizations and their customers, prospects and partners (Kelly *et al.*, 2019; Rubin *et al.*, 2010). The findings of study Bag *et al.* (2021a) indicate that sustainable electronic, human resource management (e-HRM) systems can improve firm performance. The results of the study Wamba-Taguimdje *et al.* (2020) have highlighted such AI benefits in organizations, and more specifically, its ability to improve performance at both the organizational (financial, marketing and administrative) and process levels. The study conducted by Malik *et al.* (2021) also revealed that AI has a positive impact on work-related flexibility and autonomy, creativity and innovation and overall enhancement in job performance. Therefore:

H1. Artificial intelligence will be positively related to employee performance.

Artificial intelligence and work engagement. Hughes *et al.* (2019) stated that the AI management system could deliver employees to engage in work indicated by direction, monitoring and rewards. Employee engagement in the new work environment is shaped by Millennials, a generation of individuals who are very comfortable with online networking technologies (Kaplan and Haenlein, 2010). The emergence of internal social media platforms or applications creates opportunities for organizations to promote collaboration between employees and improve employee engagement (Haddud *et al.*, 2016). Employees' use of internal social media contributes to enhanced perceived transparency of the organization and organizational identification, leading to employee engagement (Men *et al.*, 2020).

AI technologies for social media marketing can influence and predict the behavior of users and provide a broad scope of suitable analytics ability to social media users in terms of sense-making, decision-making and insight generation that help to engage the users (Capatina *et al.*, 2020). Organizations are pursuing business intelligence insights to engage with consumers on social media sites. In today's digitalized era, the marketplace has transformed into market space (Prentice *et al.*, 2020). Bag *et al.* (2021d) empirically tests and further establishes that deploying AI technologies impacts user engagement and conversion positively. AI could be used in engagement marketing that is personalized for each customer. Thus

H2. Artificial intelligence will be positively related to work engagement.

The moderating role of change leadership. The implications of technological developments and innovations for humans are increasingly becoming complex, with the role of machines changing from valuable tools for production or usage to playing a critical role in different spheres of organizational and economic life (e.g. Coupe, 2019; Arslan *et al.*, 2021). Few studies in the technology adoption domain have advocated for probing the moderating effect of individual differences (in terms of leadership) on technology adoption, rather than only focusing on their direct effect (Bhatt, 2021). The phenomenon of leadership includes an individual's ability to influence others – i.e. followers – to help achieve organizational objectives (Erkutlu and Chafra, 2018). Hambrick and Mason (1984) stated that an organization is reflected in its top management. As part of an organization's ecosystem, AI can impact, particularly on performance, on the relationships between organizations and their customers, prospects and partners (Kelly *et al.*, 2019; Rubin *et al.*, 2010). AI is an

indispensable factor in the evolution of processes, optimization and flexibility of operations in organizations (Kelly *et al.*, 2019; Rubin *et al.*, 2010). Several studies have understood how computer algorithms can give bosses insight into how their employees feel (Waddell, 2016) and research has explored how automatically sensed behavior can predict job performance (Schmid *et al.*, 2015).

Given the rapid technological advances, particularly in the field of AI, the idea of entrusting more complex tasks to machines no longer seems as far-fetched as it was several years ago. As a set or combination of several different IT configurations and capabilities in different areas of an organization's business, AI has already proven its effectiveness in automating monotonous and repetitive tasks, usually performed by specialists like human resources administrators, salespeople and small contractors (CIGREF, 2018; Pwc, 2019; Rachinger *et al.*, 2019). It is expected that in the future, organizations and their leaders increasingly deal with an "economy of power" whereby the search for a position on the market will guide any organization's action planning to safeguard its decision autonomy, strategic leeway and increased competitive advantage (Liu *et al.*, 2015; Turulja and Bajgoric, 2018). Such a position implies a competitive advantage in the market and resources that allow the valuation of that advantage. Therefore, researchers, practitioners and organizations are interested in examining how information technology and its capabilities improve organizational performance (e.g. Farhanghi *et al.*, 2013; Ruiz-Mercader *et al.*, 2006; Turulja and Bajgoric, 2018).

Hughes *et al.* (2019) stated that the AI management system could deliver employees to engage in work indicated by direction, monitoring and rewards. Reuteman (2014) wrote an organizational leadership piece on Gordon Bethune (Continental Airlines), which discusses explicitly employee engagement and provides research findings based on quantitative measures (e.g. earnings per share growth rates) for companies citing actively engaged employees. A study by Korzynski (2015) indicates that employee engagement is positively associated with the time leaders spend on internal online networking platforms and the code of online networking conduct. Employee engagement in the new work environment is shaped by Millennials, a generation of individuals who are very comfortable with online networking technologies (Kaplan and Haenlein, 2010) (see Figure 1). Hence this study hypothesizes:

H3. The relationship between artificial intelligence and employee performance will be positively moderated by change leadership.
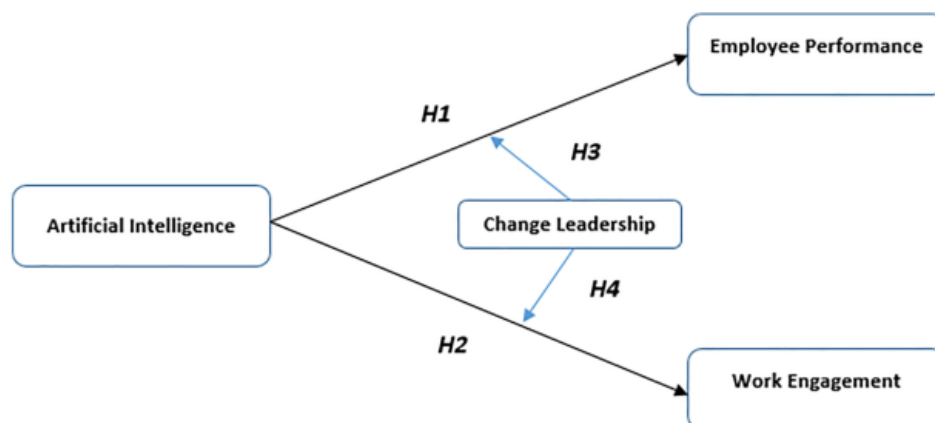

Figure 1.
Research model

H4. The relationship between artificial intelligence and work engagement will be positively moderated by change leadership.

Methods

Design and data collection

This study was quantitative research. This research uses the technique of non-probability sampling, with purposive sampling and judgment sampling approaches. Besides the nature of the problem, the reason for selecting a purposive sample instead of adopting a probability sampling technique is because of its simplicity, rules and costs, contrasted to the probability sampling techniques (Bagozzi and Yi, 2012). Moreover, it was easier to collect the data due to the access demands these banks or services industry sector adopt when requesting formal lists of their employee or clients (Abu Zayyad *et al.*, 2020). The sampling approach is consistent with Abu Zayyad *et al.* (2020) research, which also used a purposive sampling technique in the banking or services industry (Raza *et al.*, 2020). For convenience in data collection, data collection through online-based questionnaires was created via Google Form and was spread out through online social media such as email, Instagram and WhatsApp. A pilot survey was first performed to check the model, and after observing good results, the research team started the final survey in September 2020 and completed it in early February 2021.

This study's population is employees working in companies engaged in the banking and services industry sector in East Java, Indonesia. Roscoe (1975) proposes the following rules of thumb for determining sample size: sample sizes larger than 30 and less than 500 are appropriate for most research (Sekaran and Bougie, 2016, P. 264). The ethical consideration procedure begins by appointing several people to enable researchers to access several banking and services industry sector employees in the East Java region, Indonesia. The principal investigator must have a partner or family working in the banking and services industry sector in the East Java region, Indonesia. So that researchers can distribute the questionnaire through people who have been appointed and deemed appropriate. After receiving approval from the colleague or family of the person appointed by the researcher before, the researcher conducted data collection through online interviews, opinion polls and online-based questionnaires (e.g. Rahman *et al.*, 2020). Requirements that must be met to be a research sample are employees who work at the institution where the research is conducted for at least one year.

Participants and demographic profile

In this study, 357 respondents were collected, but only 254 were qualified. A total of five demographic components were presented using the frequency test. The five demographic profiles were the type of company, gender, latest education, age and length of work.

In general, most respondents' occupations in this study were working for non-banking companies, amounting to 136 people (53.5%). At the same time, respondents who work in banking are 118 people (46.5%). Respondents are 128 male (50.4%) and 126 female (49.6%) respondents. In general, most of the respondents' highest education in this study was undergraduates 164 (64.6%). Meanwhile, the smallest percentage of respondent has master degree 15 (5.9%). Then, 46 people (18.1%) are high school graduates and 29 (11.4%) are diploma graduates. Most respondents were aged 20–25 years, as many as 100 people (39.4%). Then, the ages of 26–30 amounted to 85 people (33.5%). The third place is respondents aged 31–35 with a total of 41 people (16.1%), and finally, respondents aged 36–40, amounting to 28 people (11%). In general, most respondents' length of work in this study was 1–3 years, with as many as 155 people (61%). A total of 79 people (31.1) worked 4–6 years. Meanwhile, the lowest percentage was 20 people (7.9%) with 7–9 years of work.

Measure of constructs
Artificial intelligence. This study uses a 7-item scale to measure AI by Paschen *et al.* (2019). *Change leadership:* change leadership was measured using Herold *et al.* (2008) change leadership scale. This scale includes 7-items covering what leaders due to implement a given change effectively. *Employee performance:* this study assessed employee performance with a 7-item scale (job quality 1-item, job quantity 3-item and job time 3-item) developed by Na-Nan *et al.* (2018). *Work engagement:* this study uses a 9-item scale to measure work engagement. Vigor was measured through 3-items; dedication through 3-items; and for absorption through 3-items were adapted dimensions of engagement by Schaufeli *et al.* (2006) shortened version (Utrecht Work Engagement Scale–9 [UWES-9]). All items were rated on a 5-point Likert scale (1 = strongly disagree and 5 = strongly agree), with respondents indicating their agreement or disagreement with each statement (Sekaran and Bougie, 2016, P. 215). *Control variables:* to avoid potential confounding effects, we controlled for gender (1 = male, 2 = female); latest education (1 = high school graduates, 2 = diploma, 3 = undergraduate, 4 = master); age (1 = 20–25 years, 2 = 26–30 years, 3 = 31–35 years, 4 = 36–40 years); and length of work (1 = 1–3 years, 2 = 4–6 years, 3 = 7–9 years).

Non-response bias
Non-response bias is another set of problems, which occurs when the survey data are gathered in different phases. We followed the guidelines of Armstrong and Overton (1977) to perform the non-response bias test. In this study, 30 were early responders and considered "early wave", whereas 224 were late respondents and considered "late wave". The research team compared the two waves of responses using the "test of homogeneity of variances" in SPSS 23.0 to see if the distribution of our variable differs based on the two waves. Findings did not indicate statistically significant differences between early and late respondents ($p > 0.05$). The non-response bias test was performed as per Eckstein *et al.* (2015) and Dubey *et al.* (2019) guidelines.

Data analysis
The data were analyzed in three steps. First, the validity test used confirmatory factor analysis (CFA) for each construct to assess the loading factor of each indicator and the reliability and validity of the variables were checked to verify the robustness and suitability of the questionnaire. Second, a procedure was adopted to overcome common method bias and goodness-of-fit model to examine the fit of the four-factor model. Third, the structural model was set up according to theoretical hypotheses and tested with the technique of structural equation modeling (SEM). SEM was adopted to assess both direct and moderating effects rather than regression, as moderating effects could not be evaluated with regression because of measurement error (Hair *et al.*, 2014; Wijayati *et al.*, 2020). In SEM, several methods can be used to assess the moderating effect. One of the easiest methods to estimate the moderating effect is the method developed by Ping (1995). The moderating effect test was carried out in several ways: the full SEM model without interaction variables and then by adding interaction variables. According to Ghozali (2017), in general, the model used to analyze the effect of interaction variables is moderated regression analysis (MRA). The model's fit and effects of the relationships between AI, employee performance, work engagement and change leadership were explored with AMOS version 22.0.

Result
Reliability and validity analyses
Table 1 presents factor loadings of all items, composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV) and average shared variance (ASV) of all

Variable and scale item all indicators	Loading factor	CR	AVE	MSV	ASV
Artificial intelligence (AI)					
Artificial intelligence can help me find lost data	0.573	0.875	0.503	0.442	0.361
Artificial intelligence provides accurate data and information	0.642				
Artificial intelligence can help me in making important decisions in the company	0.636				
Artificial intelligence can help display hard-to-measure data	0.647				
Artificial intelligence can protect the privacy of yourself and others	0.593				
Artificial intelligence can help me in getting the job done	0.527				
The authorities can easily audit artificial intelligence	0.605				
Change leadership (CL)					
My leader developed a clear vision for what was going to be achieved by our department	0.609	0.906	0.581	0.343	0.298
My leader made it clear to those in our department why the ministerial strategic plan (MSP) was necessary	0.664				
My leader made a case for the urgency of the MSP prior to implementation	0.594				
My leader built a broad coalition upfront to support the MSP	0.671				
My leader empowered people to implement the MSP	0.677				
My leader carefully monitored and communicated the progress of the MSP implementation	0.633				
My leader gave individual attention to those who had trouble with the implementation of the MSP	0.641				
Employee performance (EP)					
Tasks are completed as per the specifications and standards	0.572	0.886	0.527	0.371	0.307
Products or services meet the expectations of customers	0.586				
The units of output meet organizational expectations	0.577				
The units of output under my responsibility correspond to my skills and ability	0.575				
Tasks are generally completed on schedule	0.575				
Tasks are carried out within a reasonable amount of time	0.596				
The delivery of goods or services is conducted in a timely fashion	0.609				
Work engagement (WE)					
At my work, I feel bursting with energy	0.560	0.902	0.507	0.483	0.312
At my job, I feel strong and vigorous	0.574				
When I get up in the morning, I feel like going to work	0.581				
I am enthusiastic about my job	0.572				
My job inspires me	0.562				
I am proud of the work that I do	0.582				
I feel happy when I am working intensely	0.557				
I am immersed in my work	0.556				
I get carried away when I am working	0.546				

Table 1.
Reliabilities and factor loadings of constructs

constructs. Specifically, all items' loadings were above 0.5. The CR of each construct ranged from 0.875 to 0.906 and was above 0.7. Meanwhile, AVE for each construct ranged from 0.503 to 0.581 and was over 0.5. These results presented that the measures have good convergent validity. This study further tested the discriminant validity of the measurement. Discriminant validity refers to the extent that a latent variable differs from other latent variables, which may be measured by comparing the variable's square root of AVE with its

most significant correlation coefficient. Preferable discriminant validity is acknowledged when the former is more significant than the latter. Discriminant validity assessment has become a generally accepted prerequisite to analyze relationships between latent variables. All the ASV and MSV values were found to be less than their respective AVE values confirming the discriminant validity of the constructs. Thus, construct validity was established for all the study constructs.

Table 2 presents the means, standard deviations and inter-correlations among the study variables. Significant positive correlations were found between the predictor, moderator and outcome variables, providing preliminary support for the study hypotheses. The highest correlation was found between AI and work engagement ($r = 0.35$, $p < 0.001$). From the results of respondents' answers based on the Likert-scale answer selection criteria, we then interpreted using the three-box method, then the range of five must be divided by three resulting in a range of 1.33 (1.00–2.33 = low; 2.34–3.67 = moderate; 3.68–5.00 = high) and then used as the basis for the interpretation of the average value of the variable (Kistyanto et al., 2021). Based on respondents' assessment regarding research variables (AI = 4.15; CL = 4.24; EP = 4.26; WE = 4.18), all the latent variables are high categories.

Common method bias
A common questionnaire was used to collect the responses from participants. Common method bias is a common problem in survey-based research when data are collected using the same technique (same informants) (Ketokivi and Schroeder, 2004; Dubey et al., 2020). In the study, data were collected from a single source for both exogenous and endogenous variables, creating a common method bias problem. For that purpose, we conducted Harman's single factor test to ensure that there is no common method bias (Podsakoff and Organ, 1986). Using SPSS 23.0 software, we put all constructs into the principal component factor analysis and ran the analysis. Common method bias exists when one factor explains more than 50% of the variance in the study variables (Podsakoff et al., 2003). This test result indicated a restrictive extraction that a single factor only explains the variance of 33.51%, which indicates the data do not have a common method bias problem.

Full model test without interaction
The full SEM model test is a test that is carried out on all exogenous and endogenous variables that have been combined into one and intact through variance and covariance matrices, and the whole model is also called the research model. To find out the results of the data processing done using AMOS 22.0 can be seen in Figure 2.

Full model test with interaction
Ping's (1995) complete model analysis consists of several stages, namely: (1) estimating without including interaction variables so that only estimating models with exogenous

Variable	Mean (SD)	1	2	3	4	5	6	7	8
Age	1.99 (1.000)	1							
Gender	1.50 (0.501)	0.18	1						
Latest education	2.58 (0.852)	0.26	0.29*	1					
Length of work	1.47 (0.639)	0.20**	0.30	0.34**	1				
AI	4.15 (0.811)	0.27*	0.35***	0.20	0.32**	1			
CL	4.24 (0.736)	0.31**	0.27*	0.32**	0.34*	0.36**	1		
EP	4.26 (0.683)	0.16	0.25	0.29**	0.19	0.30**	0.31**	1	
WE	4.18 (0.782)	0.27**	0.35***	0.17*	0.31**	0.14*	0.34***	0.32**	1

Note(s): *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$
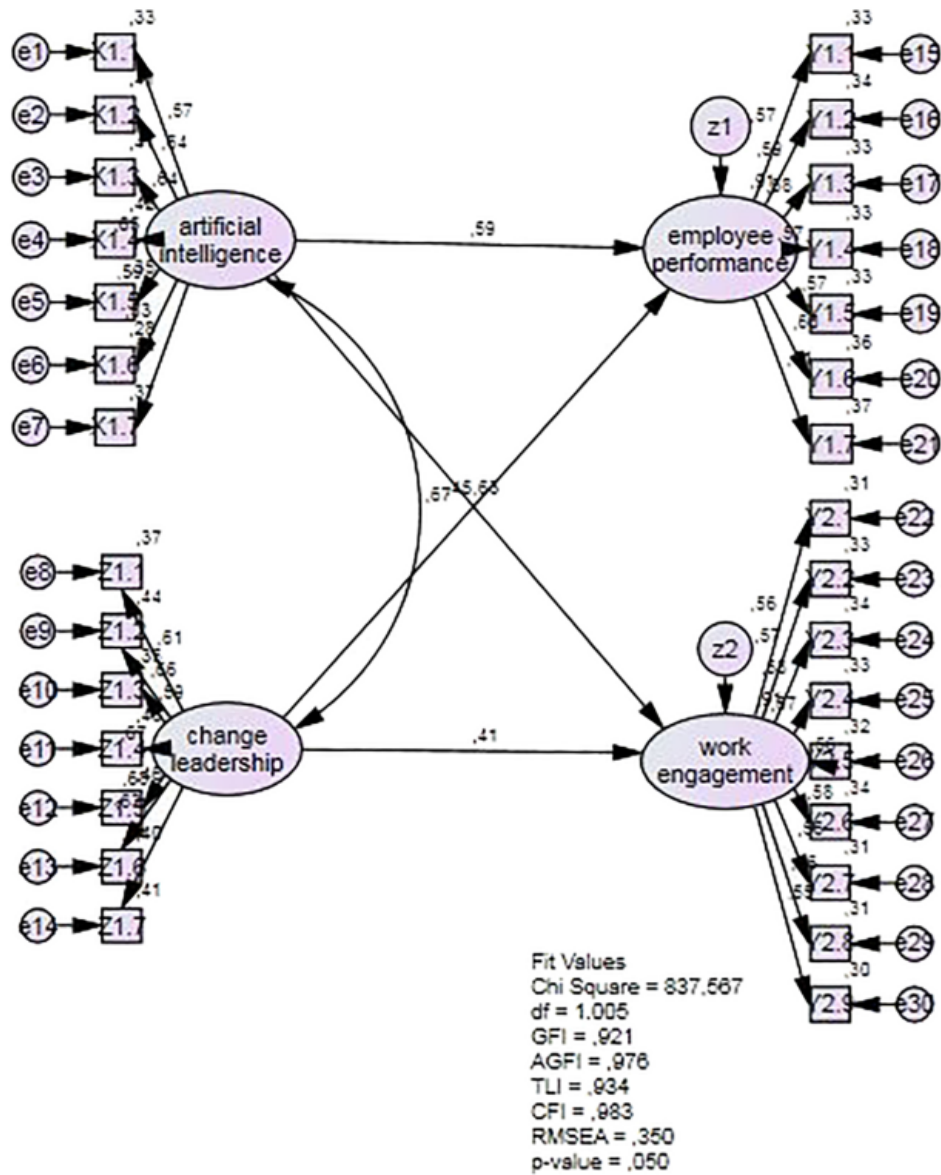
Table 2.
Descriptive statistics
and correlations

Figure 2.
Full model without
interaction

Fit Values
Chi Square = 837.567
df = 1.005
GFI = .921
AGFI = .976
TLI = .934
CFI = .983
RMSEA = .350
p-value = .050

variables to predict endogenous variables; (2) the resulting output of this model is used to calculate the loading factor value of the interaction latent variable (λinteraction) and the error variance (θq) from the value of the interaction latent variable indicator with the formula:

$$\lambda\text{interaction} = (\lambda X) \times (\lambda Z)$$
$$= 4.223 \times 4.489$$
$$= 18.957$$

$$\begin{aligned}
\Theta q &= (\lambda X)^2 \text{VAR}(X)(\theta Z) + (\lambda Z)^2 \text{VAR}(Z)(\theta X) + (\theta X)(\theta Z) \\
&= (17.83373)(0.22)(2.083) + (20.15112)(0.185)(2.887) + (2.887)(2.083) \\
&= 8.172 + 10.762 + 6.013 \\
&= 24.948
\end{aligned}$$

(3) Create a new variable with the name "moderating". The results of manual calculations of the interaction factor loading and error variance values are included in the full model with moderating variables. The calculation results of this step are shown in Figure 3.

The goodness-of-fit model

To examine the fit of the four-factor model (AI, employee performance, work engagement, change leadership), we performed CFA. The four-factor model tested on the overall sample shows a good fit with the data (see Table 3). The goodness-of-fit indices in Table 2 shows acceptable model fit (CMIN/DF = 1.109 ($p < 0.001$), CFI = 0.973, GFI = 0.901, AGFI = 0.969, NFI = 0.933, TLI = 0.923, RMSEA = 0.046), confirming unidimensionality of the measurement model (Hair and Anderson, 2010).

Hypothesis testing

To test the hypotheses, the study used a SEM approach. Results (Table 4) concluded a significant positive effect of AI on employee performance ($\beta = 0.466$; CR = 5.216), supporting H1. The positive-marked coefficient means the higher of use implemented AI in work; then, the higher their employee performance and vice versa. Moreover, the effects of AI on work engagement ($\beta = 0.565$; CR = 5.260), supporting H2. The positive-marked coefficient means the higher of use implemented AI in work; then, the higher their employee work engagement and vice versa. Similarly, Table 4 showed a significant relationship between change leadership on employee performance and work engagement.

Lastly, results from Table 4 show that change leadership significantly moderated the relationship between AI and employee performance ($\beta = 0.004$; CR = 6.836). A positive coefficient means the better the level of change leadership in the company; then, this will make the effect of using AI further increase employee performance and vice versa. Change leadership also moderated the relationship between AI and work engagement ($\beta = 0.005$; CR = 6.834). A positive coefficient means the better the level of change leadership in the company. Then, this will make the effect of using AI further increase employee work engagement and vice versa. The study concluded that change leadership moderates the positive influence of the relationship between AI on employee performance and work engagement. Accordingly, H3 and H4 were supported. Hence, based on these results, H1, H2, H3 and H4 are accepted.

Discussion

Advancement in information technology has changed the conventional ways of service delivery in service firms (Raza *et al.*, 2020). Therefore, banks also started to focus on customized digital services to their customers through the Internet (Shankar and Jebarajakirthy, 2019). The outcome of this study shows that deploying AI has a significant positive impact on employee performance. In this study, the intended use of AI technology is only in virtual programs or processes, not in the form of physical robots. Based on the in-depth and detailed analysis, AI and its technologies offer a wide range of options, benefits and services, to improve employee performance in the banking and services industry sector in the East Java, Indonesia region. In the era of Industry 4.0, many AI systems owned by companies are easier to operate, and even employees can provide a service to their customers through
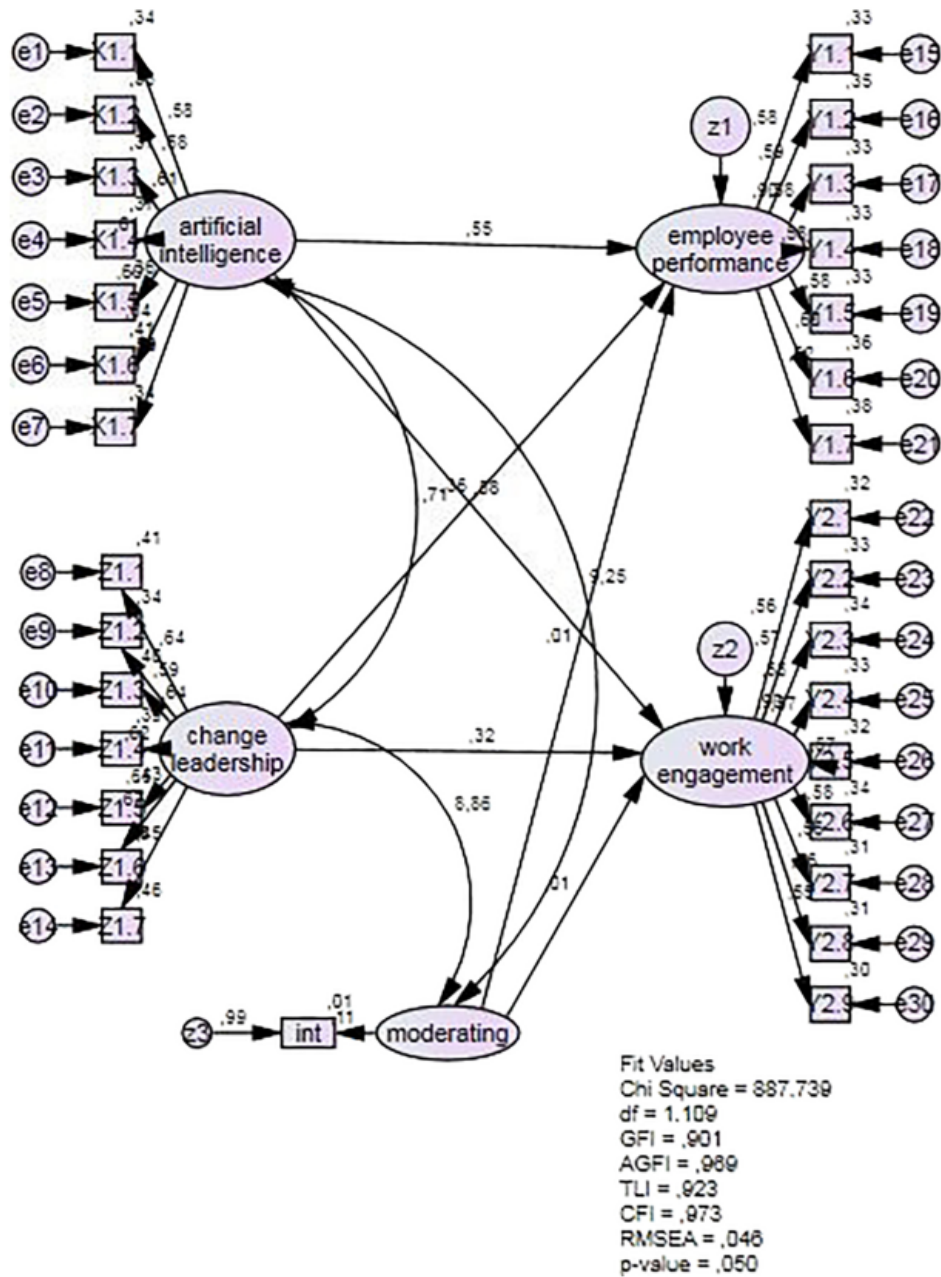
Figure 3.
Full SEM model

their smartphone or gadget that has the system used by the company installed. The deployment of AI in this regard has transformed the process into an intelligent, optimized, self-reactive, effective, efficient and automatic one, eliminating many processes that had previously been done manually, on paper and requiring significant resources. Due to its efficiency and quality in terms of innovation, AI deployment often covers the entire value

chain of the organization: research and development, maintenance, operation, sales or marketing, planning and production, demand forecasting and services.

This is also similar to an analysis conducted by Wamba-Taguimdje *et al.* (2020) reveal the vastness of AI's potential in organizations, such as (1) increment of the efficiency of operations, maintenance and supply chain operations; (2) optimization and improvement of the customer experience, products and services through new functionality, automation and optimization of sales and article recommendation processes; (3) improvement of rapid and automatic adaptation to changing market conditions, creation of new business models; (4) optimization of the relationship between supplies and needs with improved forecasting and planning capacity; (5) detection of fraud in the banking and other sectors; (6) automation of threat and SI monitoring and information systems; (7) diagnosis and diseases treatment, reduction of medical errors and improvement of the quality of patient care.

Findings of the hypotheses testing reveal that deploying AI has a significant positive impact on work engagement. AI assists organizations in predictive maintenance and improving employee engagement. The primary beneficiaries of AI's innovations are commerce, trade, distribution, communication, marketing and advertising. Digital technology positively impacts employee work engagement in East Java, Indonesia's banking and services industry sector. The COVID-19 pandemic has changed employee work patterns, and they now prefer to work from home to maintain social distancing. In this way, social media provides a better option to the employee in terms of work engagement.

This is in agreement with past research; the emergence of social media platforms or applications creates opportunities for organizations to promote collaboration between employees and improve employee engagement (Haddud *et al.*, 2016). Furthermore, the unit could track media usage to determine how often and for how long a particular app is used and each employee's engagement. The research conducted by Men *et al.* (2020) showed that regardless of employees level of satisfaction with their relationships with the organization, the more employees read the company's and co-workers posts, interact with the content by liking, sharing and commenting on the posts and engage in one-on-one conversations or

The goodness-of-fit index	Result	Cut-off value	Model evaluation
CMIN/DF	1.109	≤2.00	Good fit
RMSEA	0.046	≤0.08	Good fit
GFI	0.901	≥0.90	Good fit
AGFI	0.969	≥0.90	Good fit
NFI	0.933	≥0.90	Good fit
IFI	0.940	≥0.90	Good fit
TLI	0.923	≥0.90	Good fit
CFI	0.973	≥0.95	Good fit

Table 3.
Results of feasibility test of CFA full model SEM

Relationships	Estimate	S.E.	C.R.	P	Outcome
AI → EP	0.466	0.089	5.216	***	H1 accept
AI → WE	0.565	0.107	5.260	***	H2 accept
CL → EP	0.305	0.087	3.510	***	
CL → WE	0.304	0.097	3.126	0.002	
Moderating → EP	0.004	0.001	6.836	***	H3 accept
Moderating → WE	0.005	0.001	6.834	***	H4 accept
Note(s): *** $p < 0.001$					

Table 4.
Estimates from the structural model

group discussions on internal social media, the more they feel absorbed, attentive, dedicated, connected and involved in the organization.

The third and fourth hypotheses highlighted the moderating effect of change leadership on employee performance and work engagement in the banking and services industry sector in the East Java, Indonesia region. These findings suggest that change leadership being visionary and development-oriented reinforces the influence of AI on employee performance and work engagement. Change leadership is characterized by a leader's ability to improve existing systems by optimizing technology and maintaining good relationships with subordinates by motivating them. Empirical data also show that the relationship between AI and employee performance is increasing because leaders can see the technology system information and motivate employees. Change leadership can be a driving force for improving employee performance because it focuses on the relationship between leaders and subordinates and covers all organizational systems.

The results also show that the role of change leadership is proven to increase the application of AI at the level of employee work engagement. Leaders who are trained on how to use technology (e.g. social media) will ultimately increase the level of employee work engagement to drive maximum business results. The number of hours leaders spend on the social media platform is a predictor for a higher evaluation of employee engagement. Thomas *et al.* (2009) argue that communication in social media influences trust between leaders and their subordinates, and the role of change leadership, in turn, is needed to build employee engagement. Therefore, leaders develop swift trust through actions on online networking platforms, which will facilitate employee engagement. Even though rules and policies on online networking impose some limitations, they also ensure protection and a feeling of safety that is important for employee engagement. It can be assumed that even if an organization implements social media policies, this necessarily means that its leaders have enough skills not to reduce employee work engagement. Finally, it emerges that all these capabilities can have significant influences on processes, which, if well managed upstream by managers and leaders of organizations, can lead to high levels of employee work engagement, employee performance and the achievement of business value from AI-based organizational transformation projects.

Theoretical implications

Our study has several theoretical implications to be considered in future research. We used the theory of dynamic capability view to developing the research model. It is one of the first studies exploring the role of change leadership as a moderating factor in applying AI to employee performance and work engagement. To date, studies from various disciplines have contributed to our understanding of leadership in the digital era (Banks *et al.*, 2019). These contributions have varied from theoretical and practical contributions to methodological advances in the means through which leadership is studied, including close versus distant leadership (Shamir, 1995). In management and applied psychology, research has explored how various forms of leadership facilitate group performance across different types of electronic media (Raghuram *et al.*, 2019). Such research has quite a history in various domains, even leadership. For example, experimental work has investigated the effectiveness of leadership in face-to-face, desktop videoconferencing, or text-based chatting (Hambley *et al.*, 2007; Sosik, 1997). However, this research has not been leveraged sufficiently to understand better the various facets of leadership as a phenomenon (Banks *et al.*, 2019).

We found that critical resources such as the ability to use technology and a leader's ability can lead to the development of dynamic capabilities, here the level of use of AI and the role of change leadership which sustainable. Such dynamic capabilities are essential for a firm's survival in this volatile business environment and critical for improving employee

performance and engagement. In a broader context, organizations or firms' survival depends mainly upon mixing and matching existing resources to develop capabilities to explore further avenues for better long-term growth (Rhemananda *et al.*, 2020; Bag *et al.*, 2021a).

Practical implications
In identifying some of the practical implications from the study's findings, it seems that the role of change leadership is proven to improve employee performance and employee work engagement levels because of the implementation of the use of AI and its technology. Some experts argue that, due to technological changes in communication, within a few years, all leaders will need to work in an online working environment, and the role of a leader will change from the traditional leader to a leading interweaves who participates in online collaboration supporting employees in a variety of networks (Miller, 2005). In addition, companies must find ways to facilitate their leaders in using AI technology and need to provide training and support leaders and employees in using AI platforms and technology tools. Some of the things that can be done include preparing and training its leaders, employee and stakeholders to get acquainted with the specificities of AI transformation; employee recruitment and retaining the new talent needed for AI; managing changes in employment and skills in the company; accompany not only the new AI-induced operation modes but also significant changes in the role of leaders at different levels. Change leadership in the AI implementation process will be expected to assist in developing a clear vision of what is to be achieved and why the strategic plan is needed. This makes a case for the urgency of the strategic plan prior to implementation, building broad coalitions, empowering people to implement the strategic plan, monitoring and communicating the progress of implementing the strategic plan carefully and paying individual attention to those who have problems with implementing the strategic plan.

Given that policymakers are encouraging the development of AI and emerging technologies related infrastructure – a case in point is Indonesia and several other developed markets that are aggressively investing in AI infrastructure. Therefore, policymakers need to invest in key skills, given that skills related to emerging technologies are still with most of the developed markets, and emerging and developing economies lack such skills. Adopting and leveraging emerging technologies such as AI and robots by various sectors may lead to fewer people commuting to work. As we have seen during the current pandemic, organizations are utilizing emerging technologies for performing various functions and facilitating work from home. With this in mind, policymakers need to work closely with organizations and facilitate the development of sound HRM practices conducive to utilizing and adopting emerging technologies (Arslan *et al.*, 2021).

Managerial implications
Based on the results of research in the banking and service sector, a key managerial implication from the current paper relates to the importance of AI can help find lost data, provides accurate data and information, help in making important decisions in the company, help display hard-to-measure data, protect the company privacy, help in getting the fast job done and be easily audited by the authorities. Application of AI denotes the use of technological inputs to accomplish varied activities (recruitment, selection, training, performance appraisals, career growth and development) of human resources or employees in every organization (Carrero *et al.*, 2019).

According to Wamba-Taguimdje *et al.* (2020), the benefits of implementing AI and its technologies in the banking sector: automate transactions by quadrupling the number of transactions processed; estimate revenue growth; expand financial services customer base;

port customer acquisition by focusing on new digital services; reduce delays for the deployment of new mobile applications; foster innovation by limiting software costs through a corporate license agreement; improve customer experience; reduce operating costs through a wide range of customer services and operational improvements; reduce customer service costs while increasing revenue through better service; detect and combat fraud and money laundering. The benefits of implementing AI and its technologies in the service industry sector: accelerate the way to collect and analyze social media data; increase the chances of detecting threats and alerting security or law enforcement in time to intervene; give the better coverage of the social media world, with a broader range of data sources; give a sharper view of the context of individual messages and increase productivity for its customers.

Limitations and future directions

This study has limitations that could be addressed with future research. First, the study's limited scope – solely on the East Java, Indonesia region – raises concerns about the population's representative. Other than that, the respondents of this study are only employees in the banking and service sector. Future research can be more interesting if it uses a sample not only of the employee of companies engaged in the services and banking sector but those from various sectors of work; and expands the scope of study beyond East Java, Indonesia, to increase overall understanding. Future studies can use a combination of case studies and in-depth interviews or focus groups to provide a more complete and richer understanding of how employees' usage of AI may contribute to employee performance and engagement moderated by change leadership. A qualitative examination of employees' AI usage could also unearth other outcomes from implementing change leadership practices.

It is further necessary to note that trust has been highlighted as one of the major issues when working with emerging technologies such as AI (Arslan *et al.*, 2021). Similarly, trust-related issues have been well documented in the existing literature on the adoption of Internet banking (Yousafzai *et al.*, 2009), where it is suggested that trust plays a vital role in the adoption of Internet banking. Suggestions for further research to add variables related to trust in this research model due to a lack of prior practice-based evidence on practical strategies in such circumstances due to the newness of the topic.

Conclusion

Managing information in an electronic format using AI and its technology will result in great effectiveness for the organization, especially concerning various resources like time and money. Administrative processes involve a high volume of activities, which increases the burden on every department. However, the digitalization related activities capacitate to reduce the workload of employee professionals, improve employee performance and increase the level of work involved, which otherwise are carried out manually.

Change leadership is, first and foremost, a persuasive and promotive process through which change agents build the understanding of a change event. Change leadership in the AI implementation process will be expected to assist in developing a clear vision of what is to be achieved, why the strategic plan is needed. This makes a case for the urgency of the strategic plan prior to implementation, building broad coalitions, empowering people to implement the strategic plan, monitoring and communicating the progress of implementing the strategic plan carefully and paying individual attention to those who have problems with implementing the strategic plan.

The findings show that the relationship between the use of AI on employee performance and job engagement is positively significant. The findings also indicate that change leadership moderates the positive effect between the use of AI on employee performance and

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J.R. and Tchatchouang Wanko, C.E. (2020), "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects", *Business Process Management Journal*, Vol. 26 No. 7, pp. 1893-1924.

Wijayati, D.T., Kautsar, A. and Karwanto, K. (2020), "Emotional intelligence, work family conflict, and job satisfaction on junior high school teacher's performance", *International Journal of Higher Education*, Vol. 9 No. 1, pp. 179-188.

Wiljer, D. and Hakim, Z. (2019), "Developing an artificial intelligence–enabled health care practice: rewiring health care professions for better care", *Journal of Medical Imaging and Radiation Sciences*, Vol. 50 No. 4, pp. 1-7.

Yoav Shoham, R.P., Brynjolfsson, E., Clark, J., Manyika, J., Niebles, J.C., Lyons, T., Etchemendy, J., Grosz, B. and Bauer, Z. (2018), "Artificial intelligence index 2018", available at: https://creativecommons.org/licenses/by-nd/4.0/legalcode.

Yousafzai, S., Pallister, J. and Foxall, G. (2009), "Multidimensional role of trust in Internet banking adoption", *The Service Industries Journal*, Vol. 29 No. 5, pp. 591-605.

Zhong, Y. (2008), "Structuralism? functionalism? behaviorism? or mechanism? looking for a better approach to AI", *International Journal of Intelligent Computing and Cybernetics*, Vol. 1 No. 3, pp. 325-336.

Further reading

Bag, S., Gupta, S., Kumar, A. and Sivarajah, U. (2021b), "An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance", *Industrial Marketing Management*, Vol. 92, pp. 178-189.

Bag, S., Pretorius, J.H.C., Gupta, S. and Dwivedi, Y.K. (2021c), "Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities", *Technological Forecasting and Social Change*, Vol. 163, pp. 1-14.

Szabla, D. (2007), "A multidimensional view of resistance to organizational change: exploring cognitive, emotional, and intentional responses to planned change across perceived change leadership strategies", *Human Resource Development Quarterly*, Vol. 18 No. 4, pp. 525-558.

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18 van der Voet, J.. "Change Leadership and Public Sector Organizational Change: Examining the Interactions of Transformational Leadership Style and Red Tape", The American Review of Public Administration, 2015.
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28 Oscar Hengxuan Chi, Asim Saldamli, Dogan Gursoy. "Impact of the COVID-19 pandemic on management-level hotel employees' work behaviors: Moderating effects of working-from-home", International Journal of Hospitality Management, 2021
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