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An Analysis Of Artificial Intelligence For Employee Engagement And Productivity

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ABSTRACT

Working remotely has become the norm in the modern day, elevating the significance of artificial intelligence (AI). Thus, the purpose of this research is to apply the resource-based view (RBV) to the topic of artificial intelligence (AI) and how it impacts employee engagement and productivity by investigating how employees perceive change leadership in this area. Only 359 out of 467 banking sector workers in India's West Sumatra province were eligible to participate. There is a direct correlation between AI and employee engagement ($p < 0.05$) and productivity ($p < 0.05$), as well as between employee engagement and productivity ($p < 0.05$), according to the partial least squares (PLS) study. The effect of AI on employee productivity is mediated by employee engagement ($p < 0.05$), but the moderating effect provided by change leadership is not significant ($p > 0.05$) in increasing employee productivity. These findings will help managers create a positive work environment through the application of AI, resulting in higher employee engagement and productivity. Specifically, these findings help organizations integrate AI more effectively and provide managers with a comprehensive understanding of the considerations needed to increase productivity through employee engagement for organizational competitiveness.
Keywords : information technology, leadership, organizational behavior, employee performance, banking industry

INTRODUCTION

The post-pandemic worldwide has accelerated the application of artificial intelligence (AI). McKinsey & Company (Alexander et al., 2021) claims that the post-pandemic has seen most large companies shift to a hybrid work model that combines remote work with the help of technology such as AI and working at the company’s location. For example, before the pandemic, around 62% of employees liked working at the company’s location, but after the pandemic, only 37% showed their preference for working at the company’s location. With the use of AI, employees work faster, more effectively, and more efficiently (Arslan et al., 2022). On the other hand, Prentice et al. (2023) explained that companies must rely on AI to increase employee productivity. AI is quite good at getting some jobs done. Although it is still far from equaling “human intelligence” in its overall complexity and complexity, its impact on the world and com- panies is significant (Arslan et al., 2022). Chen et al. (2022) found that it is crucial to improve companies’ ability to adopt AI to create and maintain competitiveness. In line with the resource-based view (RBV), the HR de- partment has the opportunity to create a company’s competitive advan- tage by having unique and valuable resources (Chen et al., 2022; Barney et al., 2011). One example of a unique and valuable resource is AI, which can help employees carry out work (Chaudhuri et al., 2021). Most of the literature explaining the impact of AI on workers remains theoretical, although some claim that employees can become more ef-fective and productive at work with the use of AI (Huang & Rust, 2018; Hughes et al., 2019; Wijayati et al., 2022). AI is a facilitator in explaining employee performance (Prentice et al., 2023; Wijayati et al., 2022). Meanwhile, there is still limited research investigating how AI is related to employee productivity, which is part of employee performance (Zhang et al., 2020). Besides, AI also has the potential to increase employee engagement. Hughes et al. (2019) provide evidence of employees' work engagement through an AI management system in the form of rewards, monitoring, and guidance. One example of the ap- plication of AI is the use of social media, which has an impact on employee engagement and overall organizational performance (Men et al., 2020). Employee engagement facilitated by the application of AI to increase employee performance can be strengthened by a leader (Wijayati et al., 2022; Dhamija et al., 2023). Thus, companies can optimize the application of AI using leaders. Onyeneke and Abe (2021) believe that top management is a reflection of the organization. In today's technologically advanced and dynamic world, traditional top management skills that prioritize efficiency alone are no longer suf- ficient (Dhamija et al., 2023). For this reason, one needs a change leader who can implement top-down, episodic, and planned changes (Onyeneke & Abe, 2021). Previous research has directly explored the application of AI to employee engagement and performance with a strong push from change leadership. Therefore, there is a need for further study regarding the application of AI to employees to provide a better understanding. Thus, employee performance may be the level of employee productivity, which can be indirectly increased through employee involvement by utilizing AI services that are strengthened by change leadership based on the RBV view.

LITERATURE REVIEW AND HYPOTHESES

The resource-based view (RBV) provides the belief that to produce competitive advantage and company performance, encouragement is needed from the resources and capabilities of the or- ganization (Barney et al., 2011; Abrokwah-Larbi & Awuku-Larbi, 2024; Chen et al., 2022). An organization requires tangible resources, such as equipment or facilities, and financial assets, such as debt and equity. These tangible resource s cannot create a competitive advantage by themselves, although they are necessary but not sufficient to create capabilities; to complete them, one requires synergy, coordination, and strategic orientation (Mikalef & Gupta, 2021). In the sense of the word, it is important to com- bine these two resources so that the organiza- tion can increase the value of its resources to greater than per resource. RBV explains that the characteristics of resources that can create com- petitive advantage and improve company performance are resources that are valuable, rare, inimitable, and irreplaceable, which will thus produce value (Barney et al., 2011; Chaudhuri et al., 2021). Barney et al. (2011) concluded that RBV is concretely known as a company resource theory that can be used as a basis for company strategy. RBV is most widely used in the fields of information systems and information technology (Abrokwah-Larbi & Awuku-Larbi, 2024; Chen et al., 2022). According to Belhadi et al. (2024), AI is increas- ingly becoming an important and intangible resource for more productive business progress. In line with Chaudhuri et al. (2021), AI is the driver of business competitive advantage because AI is a valuable, unusual, unique, and priceless resource. According to Belhadi et al. (2024), Mikalef and Gupta (2021), and Chen et al. (2022), firm capabilities act as a mediating factor between firm per- formance and resources. Company capability is essential for business operations because this ca- pability will contribute to deploying the resourc- es needed for company performance (Mikalef & Gupta, 2021). In contrast to previous studies, this study focuses on employee engagement and change leadership as the company's ability to create value that comes from AI as a valuable resource it has to increase employee productivity as a measure of company performance. Zhang et al. (2020) explain productivity as a term used to describe employee performance. Similar to Farooq and Sultana (2022), productivity is de termined by performance behavior, external oportunities, and contextual factors combined with the amount of production produced. Employee productivity is influenced by the length of time a person spends at work and the extent to which a person operates effectively during that time (Zhao et al., 2021). This means that employee productiv- ity is related to being effective and efficient at work. Increasing employee productivity is the main or- ganizational purpose because it can benefit employees and organizations (Farooq & Sultana, 2022). AI can measure each employee's productivity, which can improve worker effectiveness and ef- ficiency (Tong et al., 2021). AI is the application of technology to replicate human cognitive capac- ity for achieving goals independently while still considering potential limitations (Wijayati et al., 2022; Arslan et al., 2022). So, AI is human intelligence poured into the use of machines through innovative technological orientation. By using AI as a resource to improve performance, manage- ment can assess and differentiate the production of competent key employees (Zhou et al., 2021). AI contributes to businesses by connecting each employee's performance to strategic objectives that trigger employees to boost their productivity (Zhao et al., 2021). In addition, AI promotes employee engagement. Men et al. (2020) explain the utilization of social media apps and platforms to encourage employee collaboration and increase employee engagement. Employee engagement is defined as the positive thoughts of employees characterized by having a spirit of enthusiasm for work, inspira- tion, pride, meaning, joy at work, and difficulty disengaging from work (Kaur et al., 2020). In line with RBV, to make employees meaningful, companies can use all the resources they have, both tangible and intangible, such as providing AI facilities to develop special learning programs for employees so that employees can adapt these programs to tastes and their needs, which can accelerate and increase the acqui- sition of new skills (Soltani et al., 2020). As a result, AI increases employee engagement and accelerates their learning rate (Kashive et al., 2021). Engaged workers demonstrate behaviours that have a beneficial impact on the busi- ness, such as customer satisfaction, operational effectiveness and efficiency, and revenue devel- opment. This shows that organizations must encourage employee engagement by using their resource s to gain a lasting competitive advantage (Saks, 2006). Furthermore, the RBV emphasizes that the capabilities possessed by employees will make employees increasingly engaged in key business processes and routines, namely controlling how resources interact to convert input into output (Wheelen & Hunger, 2012; Kassa & Tsigu, 2022). High employee work engagement is also related to productivity (Jindo et al., 2020). The RBV states that to gain a competitive edge, businesses must make the most of their resourc- es by giving their employees relevant, quality job training and formal education; however, doing this takes money and time (Kassa & Tsigu, 2022). For this, other strategies are needed, such as using AI as an information and communication technology to help employees meet challenging goals, such as providing exceptional quality of service or employees involved in difficult jobs (Li et al., 2021; Prentice et al., 2023). Utilization of AI services has the potential to increase work engagement and work results in a fast, accurate, reliable, and target- ed manner (Fu et al., 2022; Huang & Rust, 2018). Change leadership relates to the ability to use technology to improve existing procedures while inspiring subordinates and fostering healthy work- ing relationships (Wijayati et al., 2022). Wijayati et al. (2022) show that leadership of change may im- prove how AI affects employee performance; the leader of change is a visionary, one of whom has a vision for the use of information system technol- ogy, which is the driving force in improving work results. Nevertheless, prior research has not clarified how leadership of change affects the use of AI to increase employee productivity in the banking sector.

Research and Methodology

This study examines the effect of the application of AI on employee engagement and productivity by considering the function of change leadership, as shown in Figure 1. Thus, the hypotheses formed are:

H1: AI positively and significantly affects employee productivity.

H2: AI positively and significantly affects employee engagement.

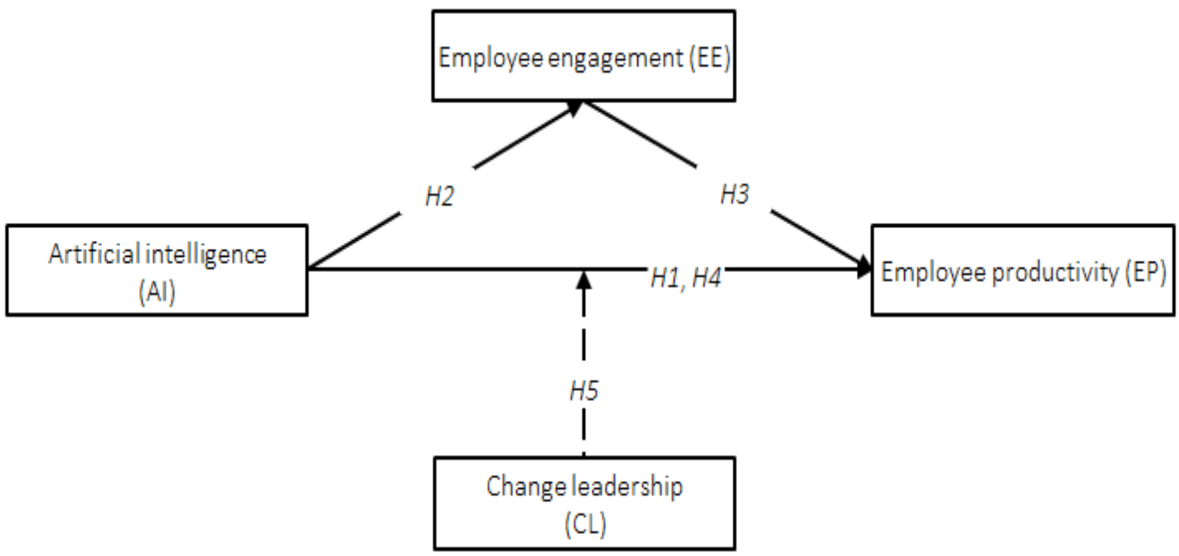

Figure 1. Research model

H3: Employee engagement positively and signifi- cantly affects employee productivity.

H4: AI positively and significantly affects em- ployee productivity through employee engagement.

H5: AI positively and significantly affects em- ployee productivity moderated by change leadership.

This study targeted Indian government owned banks in the West Sumatra region, includ- ing Bank of India India, Canara Bank, Union Bank of India India, and Bank Bank of Baroda. Government owned banks were chosen because of their developments, such as improving the quality of services accessed using technology and information such as automatic teller machines, mobile banking, and online banking (Xu et al., 2020). Many frauds have occurred as a result of the proliferation of this service; AI can help identify fraud in any company, including companies operating in the banking sector (Omoge et al., 2022). The next reason is the assessment of banking industry performance seen from interactions between employees and customers (Xu et al., 2020). Therefore, it is necessary to pay attention to relationships with customers. Omoge et al. (2022) explained that the application of AI is critical in customer service because AI can give rise to customer relationship management. Besides, AI is a modern phenomenon that has received little attention, especially in the context of banking systems in developing countries (Wijayati et al., 2022). Then, AI, accord- ing to Xu et al. (2020), is changing banks' methods of delivering products and services to customers, and AI is greatly influencing the banking business and will continue to do so. Employees of Bank of India India, Canara Bank, Union Bank of India India, and Bank Bank of Baroda are the units of analysis in this paper. Sekaran and Bougie (2016) explain the gen- eral rules for determining sample size: most stud- ies should use sample sizes greater than 30 and less than 500. Based on this, the data were collected from 467 respondents. However, only 359 respondents were analyzed because these respondents met the criteria for sampling (the paper employed a non-probability sampling technique with a pur- posive sampling method, with the required crite- ria being the application of AI and digital technol- ogies during office operating hours). The reason for using the purposive sampling method refers to the opinion of Bagozzi and Yi (2012) that apart from the nature of the problem, purposive sam- pling was chosen due to its affordability, rules, and ease of usage in comparison to probability sam- pling techniques. This is consistent with Omoge et al. (2022), who applied purposive sampling in the banking industry. The data collection procedure began with the clos- est relatives who worked at Bank of India India, Canara Bank, Union Bank of India India, and Bank Bank of Baroda in Mumbai

Table 1. Measurement of constructs

Constructs	Position	Items	Indicator nature	Source	Scale
AI	Independent	7	Reflective	Wijayati et al. (2022)	Likert
EE	Mediator	4	Reflective	Kaur et al. (2020)	Likert
EP	Dependent	7	Reflective	Bashir et al. (2024)	Likert
CL	Moderator	7	Reflective	Onyeneke and Abe (2021)	Likert

Note: **EE = employee engagement; EP = employee productivity; CL = change leadership.**

with the aim of gaining access to other bank employees as research respondents. The data collection process was carried out during break times without disturbing the bank's operational hours, and respondents' answers were kept confidential and anonymous, according to the opening statement (Satrianto et al., 2023). After obtaining permission from the respondents, the data were col- lected through an online questionnaire-based survey. A scale of 5-point Likert was used to measure each research construct (variable), with the number one signifying "strongly disagree" and the number five signifying "strongly agree." Items for building AI are taken from Wijayati et al. (2022), employee engagement was adopted from Kaur et al. (2020), and measuring employee productivity refers to Bashir et al. (2024). Finally, change leadership was adopted from Onyeneke and Abe (2021) (See Table 1). The constructs are first-order reflective measurement models based on prior research. The data analysis technique used is structural equation modeling (SEM). One of the advantages is that it can analyze confirmatory factors and simulta- neous multiple regression (Hair et al., 2021). This paper uses a variance based approach with par- tial least squares (PLS). PLS-SEM has been widely operated in behavioral sciences such as management science, especially in human resource management and marketing (Satrianto et al., 2023). As confirmed by Hair et al. (2021), PLS-SEM extends theoretical models and is a good methodological strategy for primary research. Furthermore, re- search models that use mediation and moderation are more successfully evaluated through the appli- cation of PLS-SEM (Hair et al., 2021). Therefore, testing this research model is suitable for the PLS- SEM approach. PLS-SEM evaluation consists of an assessment of the attributes of the suggested measurement model (such as validity and reliability) conducted before the structural model (hypothesis test) is evaluated. The first evaluation of the measurement model for reflective indicators is to check the internal consistency. It evaluates the validity of an indicator by examining the outer loading value in the PLS algorithm. The threshold value is 0.7; if the specified threshold value is not reached, the item is removed (Hair et al., 2021). Apart from that, convergent validity assesses the extent to which certain construct indicators converge or have a high proportion of variance (Hair et al., 2021). The component for assessing convergent validity is evaluating the values of composite reliability (CR) and average variance extracted (AVE). The threshold values set by Hair et al. (2021) for CR and AVE are 0.7 and 0.5, respectively. The final evaluation of the measurement model is to assess discriminant validity. When a construct is truly unique from other constructs, discriminant valid- ity is achieved. It quantifies the number of indica- tors that represent only one construct (Henseler et al., 2015). This study uses the HTMT ratio to re- port discriminant validity based on the suggestion of Henseler et al. (2015). There is a serious problem with discriminant validity if the HTMT value is greater than 0.85. The structural model was evaluated using the coef- ficient of determination (R2), effect size (f2), pre- dictive relevance (Q2), and hypotheses testing. The R2 value measures how well the combination of exogenous constructs explains the variance in the endogenous constructs used to determine predic- tion accuracy (Hair et al., 2021). The R2 value of around 0.67 is substantial; the R2 value of 0.3333 is considered average; the R2 value of around 0.19 and below is considered weak (Hair et al., 2021). To ensure whether the exogenous construct makes a significant contribution to the endogenous construct, it is evaluated using the effect size (f2). The effect size grouping consists of large effect sizes with an f2 value of 0.35 or higher, medium effect sizes having an f2 value of 0.15 to 0.35, and small effect sizes having an f2 value of 0.02 to 0.150 (Hair et al., 2021). Moreover, Stone Geisser's Q2 can be applied to evaluate the model's predictive power. If the Q2 score is higher than zero, predictive relevance is attained (Hair et al., 2021). Finally, hypothesis testing is estimated through the boot- strapping of 5000 samples displayed using the beta coefficient (β), standard deviation (SD), t-statistics, and p-value (Hair et al., 2021). If the t-statistic val- ue exceeds 1.96, the hypothesis is accepted (Hair et al., 2021).

3. RESULTS

The findings show that around 60% of respondents were women. Out of all the respondents, 36% had bachelor's degrees, followed by associate degrees (23%). Next, 45% of the total respondents have work experience in the banking industry for 3-5 years, serving as frontline (29%) and customer service (22%) employees, and the majority are aged between 30-35 years with a percentage of 48% of the total respondents. In addition, 62% of respondents are married with two children (78%), and more than half of respondents earn more than IDR 4.000.000 per month. Before doing the SEM PLS assessment, the study first checked the common method bias. In survey based research, common method bias often oc- curs (Chang et al., 2020) because the exogenous and endogenous variable data were collected at the same time and came from the same informant (Podsakoff et al., 2003; Chang et al., 2020). Because of this, Harman's single factor test is required to ensure that bias in the common method does not exist (Podsakoff et al., 2003; Chang et al., 2020). When more than 50% of the variance in a research variable can be explained by one factor, common method bias may be present (Podsakoff et al., 2003). Harman's single factor test was ana- lyzed with the help of SPSS software. The results showed that only one factor was able to explain a variance of 28.053%; this indicates no bias. Table 2 presents the outer loadings of all items, CR, and AVE of all constructs. In particular, each construct item possesses an outer loading value higher than 0.7, except for AI1, AI2, EE4, EP2, EP3, EP4,EP7, CL6, and CL7. The CR value for each construct is greater than 0.7. Besides, the AVE value for each construct varies with values above 0.5. Thus, this finding has a good convergent valid- ity value. Discriminant validity is also supported because the HTMT value is smaller than 0.85, as suggested by Henseler et al. (2015), as in Table 3.

Table 2. Convergent validity

Construct and item all indicators	Outer Loading	CR	AVE
AI			
AI helps me while I am making crucial decisions for the firm.	0.765		
Data challenging to measure can be presented with AI	0.787		
AI can safeguard both my and others' privacy.	0.860		

AI can assist me in completing the task.	0.802	0.905	0.657
AI is easily auditable by the authorities.	0.836		

EE

I have been acknowledged for my hard work.	0.889	0.900	0.750
Organizational mission gives me hope that the work I perform matters.	0.906		
My ideas and opinions are always taken into consideration when working.	0.799		

EP

I perform above my manager's expectations	0.789	0.855	0.663
I am aware of the products and services that my firm provides.	0.816		
I am aware of what my customers want.	0.838		

CL

My leader created a detailed plan outlining what our department would do.	0.837	0.927	0.719
The head of our department explained the need for the ministerial strategic plan.	0.848		
My leader contended that the ministerial strategy plan has to be put into action right away.	0.798		
My leader formed an extensive alliance up front to back the ministerial strategic plan.	0.878		
My leader gave others the authority to carry out the ministerial strategic plan.	0.874		

Note: EE = employee engagement; EP = employee productiv- ity; CL = change leadership.

Table 3. HTMT ratio (Discriminant validity)

Construct	AI	CL	EE	EP
AI				
CL	0.073			
EE	0.544	0.061		
EP	0.680	0.160	0.675	

Note: EE = employee engagement; EP = employee productiv- ity; CL = change leadership.

The model has predictive accuracy, as shown by its R2 value greater than 0.19. Thus, the combi- nation of AI and employee engagement in ex- plaining the variance in employee productivity is substantial. Based on the analysis results, AI explains 56% of the variance in employee engagement while AI and employee engagement together explain 60% of the variance in employee productivity. The f2 value of AI on employee productivity is 0.056, which has a small effect size. Likewise, the f2 value of change leadership on employee productivity is 0.025, and the f2 value of em- ployee engagement on employee productivity is 0.034, except for the f2 value of AI on employee engagement, which is 1.899 with a large effect size. Next, the Q2 value of employee engagement is 0.244, and the Q2 value of employee productivity is 0.348. Thus, every Q2 score exceeds the zero value, meaning less error is generated by the model, which in turn results in a high prediction value (Hair et al., 2021). Based on path coefficients (see Table 4), all suggested hypotheses were validated. The analysis shows that the hypothesis can be accepted if its significance is at the level of 0.001 to 0.05, the direction of the sign is positive, and the t-statistic value is at the level of 1.96.

4.DISCUSSION

The results show that the use of AI has a significant impact on the productivity of bank employees. Based on comprehensive and extensive investigations, AI and its technological tools provide various customer service options, benefits, and conveniences that make employees effective and efficient in doing their work. Zhao et al. (2021) and Zhou et al. (2021) stated that AI contribu- tion is enormous to employees and organizations. Moreover, in the current 4.0 era, the banking in- dustry already has its own AI system that is easier to use. That way, just using a smartphone or gadget that has the company's AI system installed, employees can serve their customers. In this way, the application of AI has changed the need for large resources; many operational procedures that were carried out manually and used a lot of paper have now been eliminated. Nowadays, with the use of AI, processes become effective, efficient, reactive, optimal, intelligent, and automatic. In line with Chen et al. (2022), AI is a collection of implicit resources that are very valuable for employees in gaining an organizational competitive advantage. Thus, technological progress is a resource used to increase the productivity and expertise of organizations and their employees. As explained by Tong et al. (2021), employees will perform well and gain the latest capabilities as the organization gets closer to AI. The use of AI significantly increases employee involvement in work, as during the pandemic, there was a change in employees' working habits, and now they are already in the habit of working from home with the help of AI. In this case, AI offers many options for employees to interact at work,

Table 4. Hypotheses testing

Pathway of model	Effect of Estimated	Standard Deviation	T Statistics	Significant	Results
Direct effect					
H_1 AI → EP	0.328	0.079	4.149	0.000	Accepted
H_2 AI → EE	0.809	0.024	33.040	0.000	Accepted
H_3 EE → EP	0.253	0.087	2.923	0.004	Accepted
Mediation effect					
H_4 AI → EE → EP	0.205	0.071	2.876	0.004	Accepted
Moderation effect					
H_5 AI*CL → EP	0.058	0.108	0.534	0.594	Rejected

Note: EE = employee engagement; EP = employee productivity; CL = change leadership.

one of which is by using social media. According to Men et al. (2020), the use of social media brings opportunities for companies to encourage employee cooperation so that employees become engaged in their work. Employee engagement facilitated by AI will become an intangible asset to achieve a competitive advantage, as explained by the RBV view (Soltani et al., 2020). According to Kashive et al. (2021), AI provides support for acquiring and retaining talented employees by hiring them with appropriate skills. Moreover, nowadays, choosing the best people for a job is crucial for the success of a business. Besides, AI in the banking industry can help identify employee growth opportunities, training needs, and further progress to increase employee engagement. Thus, AI is positively related to employee engagement at work (Wijayati et al., 2022). The association between employee engagement and productivity is supported. This means that employees with higher engagement will produce higher levels of productivity. When employees are engaged in work, they will try to contribute to the success of the company and will be highly motivated to do more than what is asked (Kassa & Tsigu, 2022; Jindo et al., 2020). Both at the individual level, teams and companies will benefit greatly from high levels of employee engagement. This is consistent with the RBV belief that an en- gaged employee may give the company a competitive edge and strategic advantage (Saks, 2006; Wheelen

& Hunger, 2012). Besides, AI's relationship to employee productiv- ity is supported by the mediating role of employee engagement. This is consistent with Fu et al. (2022) that in the age of technological advancements, employee engagement is crucial and affects worker productivity. Furthermore, employee engagement in an AI work environment will create a spirit and joy at work because working with AI becomes easier and faster so that employees can complete their work effectively and efficiently and more produc- tively (Li et al., 2021; Prentice et al., 2023; Huang & Rust, 2018). This study also analyzed the moderating role of change leadership. The findings show that change leadership does not moderate the path of AI to employee productivity. There are various possibilities underlying these results. For example, Choi et al. (2016) and Sandee (2016) claimed that Indonesia lacks advanced infrastructure facilities because it is a developing country. As a result, the banking industry lacks potential qualified and trained hu- man resources, thereby limiting leaders who do not have much orientation toward change leader- ship methods. Janah et al. (2020) also mentioned a strong tendency among professionals in the Indonesian banking industry toward autocratic leadership.

CONCLUSION AND FUTURE RESEARCH

This study looks into the effects of change leadership on AI for worker productivity and worker engagement. The results show that directly, AI has a positive and significant impact on employee engagement and employee productivity in the banking industry. Indirectly, employee engagement has a mediating role in this relationship, except that the impact of AI on employee productivity is not moderated by change leadership. These results highlight how important it is to incorporate resource based views in the creation and implementation of AI on the job site. Additionally, the rejected hypothesis emphasizes the need to conduct additional research and analysis regarding the moderating impact of change leadership on the relationship between AI and employee productivity. In summary, this study advances understanding of the advantages and difficulties of integrating AI inside the banking industry and highlights the potential for applying the resource-based view to future research in this field. The research findings have important theoretical ramifications for comprehending how AI influences employee productivity in the banking sector. Initially, this paper adds to knowledge regarding the use of resource-based views in AI and employee productivity. Then, this study extends pre- vious literature by looking at the mediating role of employee engagement in influencing the impact of AI on productivity. Additionally, it emphasizes how important it is to consider other contextual elements, such as company traditions or employee inspiration when analyzing how AI affects employee productivity". Besides, the leadership of change does not moderate the relationship between AI and employee productivity. Furthermore, the findings provide some suggestions for banking practitioners. Not only tangible resources should be paid attention to, but intangible resources are also critical. The application of AI is helpful in company operations, for example, finding lost data, identifying and stopping fraud and money laundering, providing accurate information, helping the banking industry in making important decisions, protecting banking privacy, helping complete tasks quickly, and making it easier for professionals to audit them. Not only that, but the use of AI can also help human resource activities, from the recruitment process to career development.

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