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RESEARCH ARTICLE

Transactional and Transformational Leadership Styles and Their Impact on Employees' Acceptance of Predictive Maintenance Analytics: Evidence From an Indonesian Mining Company

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This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

ABSTRACT This study aimed to investigate the role of leadership in the acceptance of predictive maintenance technologies in the coal mining industry. The Unified Theory of Acceptance and Use of Technology (UTAUT) model was used to assess the acceptance, and the Multifactor Leadership Questionnaire (MLQ) 5X was used to assess the perceived leadership styles of managers. The key findings of this study revealed that transactional leadership had a significant effect on performance expectancy, effort expectancy, and social influence, whereas transformational leadership did not significantly impact these aspects. Furthermore, an examination of the subdimensions of transformational and transactional leadership showed that contingent reward, management-by-exception (active), and intellectual stimulation had a considerable influence on the core constructs of the UTAUT model. These findings suggest that for adopting new technologies, the coal mining industry may require a different approach to exert leadership, and a comprehensive approach with consideration of the various subdimensions of leadership may be more effective in promoting acceptance and application of the technologies.

INDEX TERMS Leadership styles, employee, Indonesia, predictive maintenance analytic.

I. INTRODUCTION

The efficiency and productivity of the mining industry can be greatly improved by adopting new technologies. According to Laskier [1], the cost of labor, contractors, and consultants accounts for 65% of the total expenses in the mining industry. In addition, fuel and energy costs make up 10%–15% of the total operating costs. In general, adopting Internet of Things (IoT) technologies in the mining industry is expected to improve the corresponding productivity. For the mining industry, a large amount of heavy equipment is normally utilized during mining operations and regular equipment maintenance is required. Among the IoT technologies, the predictive maintenance approach is often integrated to increase the efficiency of maintenance activities.

Predictive maintenance is a type of maintenance strategy that uses sensors and data analytics to monitor the equipment's condition and predict the time for maintenance, allowing for timely and proactive interventions to avoid equipment failure and downtime [2]. Introduction of the predictive maintenance technology requires a huge investment by the company, although the implemented technology can help avoid equipment failure and downtime, which can save time and money for the company in long term [1], [3]. However, for the investment to pay off, the introduced technology must be accepted and used by the employees.

People may not accept new technologies right away. Moreover, people may resist adopting new technologies due to

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several reasons. First, some people may be hesitant to try new things, especially when they are unfamiliar with the new technology, which can result in fear and anxiety for them when using the new technology [4]. In addition, people may become hesitant to adopt new technologies if the technologies are perceived as too complex or difficult to use, or if they are not sure how they can benefit from using the technologies [5]. To overcome the challenges associated with implementing new technologies, effective leadership is considered to be one of the key factors. A strong leadership style can help guide the implementation of new technology and ensure its acceptance by the employees [6], [7].

Leadership plays a critical role in enhancing employees' acceptance of new technologies. In previous studies on the leadership's role in technology acceptance, several leadership constructs were examined, including transformational and transactional leadership [6], [7], empowering leadership [8], green organizational leadership [9], authentic leadership [10], and leadership support [11], [12], [13]. This study specifically focuses on the impact of transformational and transactional leadership styles on the acceptance of predictive maintenance analytics in the mining industry. The transformational leadership style involves inspiring and motivating followers to not only achieve their goals but also strive for personal growth and development, while the transactional leadership style emphasizes the use of rewards and punishments to manage performance. From these studies, the transformational leadership style has generally been found effective in promoting technology acceptance among employees. Leaders can promote open-mindedness and encourage their subordinates to consider multiple perspectives when analyzing different problems, which can in turn, indirectly affect their acceptance of new technologies [7]. Leaders can also provide training to help employees become comfortable with new technologies and ensure that they can understand how the technology can benefit their work [9], [10], [12]. In essence, an appropriate leadership style can facilitate technology acceptance among employees and ensure that the new technologies can be successfully integrated in the workplace.

Despite the general findings that transformational leadership is important in ensuring employees' technology acceptance, there is no consensus on the mechanism of how the leadership style impacts the employees' technology acceptance. The findings of different studies on this topic suggest that many mechanisms exist that can influence the outcomes, depending on the specific context of the study. Among the published studies, the acceptance of predictive maintenance technology is insufficiently studied, specifically in the context of the mining industry. Moreover, the studies concerning the role of leadership in technology acceptance often utilized the older Technology Acceptance Model (TAM) despite the newer Unified Theory of Acceptance and Use of Technology (UTAUT) model that has significantly higher power in predicting the intention of using new technologies.

The research problem this study attempts to address is the insufficient understanding of the impact of transformational and transactional leadership styles on employees' acceptance of predictive maintenance technology in the mining industry, particularly in the context of an Indonesian mining company. The originality of this study lies in its focus on the specific context of the Indonesian mining industry, the examination of both transformational and transactional leadership styles in relation to technology acceptance, and the use of the UTAUT model instead of the older TAM model. Furthermore, this study aims to identify which subdimensions of these leadership styles are most effective in promoting the acceptance and application of predictive maintenance technology in the mining industry.

The study focuses on a mining company in Sangatta, East Kalimantan, Indonesia, by taking into account the specific context of this company (referred to as "The Company" hereafter). The Company has the biggest coal mining operation in Indonesia, and it is also the target site of this study. The Company started to apply digitalization in its maintenance activities in 2012, and relevant data of the equipment were recorded and transferred to the server manually for further analysis. In 2018, The Company invested 1.5 million USD to introduce a predictive maintenance technology that can monitor heavy equipment in real time while applying analytics to analyze the equipment's health and avoid unexpected downtime.

The real-time monitoring also allowed the company to track how their employees are running the equipment and therefore, preventing potential damages caused by human errors. In addition, it can also track the productivity of the equipment operator by collecting the corresponding usage information for analysis. The equipment should be brought to the workshop for maintenance before failure. However, since the technology tracked not only the equipment but also the behavior of the operators, employees became skeptical of the technology when their perceived productivity and the recorded productivity were found unmatched sometimes. Moreover, if the operators were deemed careless in using the equipment with the results from the technology, they must be retrained, which was often considered an embarrassment among the employees. An incident happened when a truck was brought to the workshop for maintenance according to the adopted technology in a condition that was actually "Okay." This has also affected the employees' trust in the analytics of The Company's novel technology. In this case, The Company should develop a proper leadership strategy to gain back their employees' acceptance of the technology. By examining the influence of transformational and transactional leadership styles on technology acceptance within an Indonesian mining company, this study aims to offer insights that can assist The Company in addressing employee skepticism, enhancing trust in the technology, and fostering a supportive environment for the adoption of predictive maintenance analytics. The transformational leadership style, characterized by its emphasis on inspiration, motivation, and personal growth, could help employees recognize the long-term advantages of the technology and overcome initial reluctance. Conversely, the transactional leadership style, which focuses on rewards and consequences, may prove effective in addressing concerns associated with productivity and equipment utilization.

II. LITERATURE REVIEW

A. APPLICATION OF PREDICTIVE MAINTENANCE TECHNOLOGY

Implementing information technologies, such as predictive maintenance technologies, is claimed to improve productivity in the mining industry [1]. The mining industry relies on heavy equipment that needs to be maintained regularly. For maintenance, three main approaches are often integrated, including corrective maintenance, preventive maintenance, and predictive maintenance [14]. Corrective maintenance is performed after a breakdown or malfunction occurs. However, corrective maintenance can lead to higher costs, especially for those associated with breakdown time, and the repair time is extensively long. Preventive maintenance represents regular maintenance usually scheduled based on historical failure data. As a result, scheduling preventive maintenance in advance is often challenging. In addition, preventive maintenance is relatively less effective.

The predictive maintenance approach is based on IoT technologies. It utilizes intelligent information processing approaches, communication systems, future-oriented techniques, and other elements to determine the necessary maintenance [14], [15]. It also allows for real-time monitoring of the equipment's health, resulting in more efficient maintenance [1]. In principle, the predictive maintenance approach differs from the corrective maintenance approach in that it performs repairs after a breakdown occurs. Predictive maintenance aims to overcome unscheduled downtime, which incurs additional costs for yield loss and maintenance and reduction in production time [2]. Predictive maintenance builds on the idea of relying on data to make maintenance decisions, which is in parallel with the preventive maintenance approach. The preventive maintenance approach focuses on historical data to obtain the failure pattern and make maintenance decisions, whereas the predictive maintenance approach employs analytics for the company's maintenance decision to achieve resource efficiency [3]. Because of the increased efficiency, predictive maintenance can reduce maintenance costs and unexpected downtime while extending the service life of the equipment [14], [16]. According to a previous study [17], the use of predictive maintenance technology led to reduced maintenance costs by up to 38% and improved operational safety in offshore oil drilling, which also involves much heavy equipment (similar to coal mining). In addition, the use of predictive maintenance, which allows for tracking and monitoring of equipment usage, can also prevent careless behaviors that may cause premature wear and tear of the equipment [3].

Data collection, fault detection and diagnostics, and prognostics, are key aspects of the predictive maintenance procedures used to guide maintenance decisions [14]. Data can be collected by observing how the equipment is used. The obtained data is then analyzed to determine the presence of operational faults and the root cause, a process known as diagnostic. Prognostic is another procedure that predicts how long the system would perform to its desired functionality or remaining useful life (RUL) based on the current and historical conditions [14], [16]. Prognostication is mainly performed by detecting the trends of a specific variable. The trend results are then extrapolated to determine the approximate RUL of a specific component [2]. This insight can then be used to adjust scheduled maintenance, which can further reduce unscheduled downtime or extend the equipment's service lift.

B. INTENTION TO USE NEW TECHNOLOGIES

Efforts to determine the factors that drive the intention to perform a specific behavior date back to the development of the Theory of Reasoned Action (TRA) [18]. According to the TRA, intention can be determined by the attitude toward performing the behavior (attitudinal) and subjective norm (normative). Based on the TRA, Davis [5] developed the TAM, which involves two main constructs that drive intention, that is, the perceived usefulness and perceived ease of use. Perceived usefulness is defined as the individual's perception that using a technology will improve their performance, while perceived ease of use refers to the extent to which an individual believes that using a technology will be easy. Compared to the more general TRA, the TAM's purpose is more specific and applies only to the intention to use technologies [19].

By expanding the TRA, Ajzen developed the Theory of Planned Behavior (TPB), adding the perceived behavioral control as a determinant of intention [20]. Perceived behavioral control is defined as an individual's perception of the ease or difficulty of performing the desired behavior. The TPB may include additional predictors if it is proven to contribute to a significant proportion of the variance in intention [20]. Both the TPB and TAM are able to explain the intention to use technologies, and although the TAM can explain more variance, it is not sufficient to conclude that the TAM is better [21]. The Decomposed TPB (DTPB) model, in which the attitudinal, normative, and control beliefs of the original TPB model are decomposed into multidimensional belief constructs, is able to offer a more complete understanding of the information technology usage [22].

The TAM remains the most widely-used model in examining the factors of technology acceptance. However, the TAM needs modification to include other components to be able to consistently explain more than 40% of the system usage, which affects its operation consistency [23]. Moreover, instead of measuring system usage, the TAM actually measures the variance in self-reported usage. This can be problematic as the correlation between actual and self-report usage was found relatively weak [26], indicating that people tend to overestimate how much they actually use the technology.

By integrating the TAM with several other models including the TRA, TPB, DPTB, Motivational Model (MM), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT), Venkatesh et al. [24] formulated the UTAUT model. The UTAUT model has been empirically tested, and four core predictors of intention and usage were identified, including performance expectancy, effort expectancy, social influence, and facilitating conditions.

1) PERFORMANCE EXPECTANCY AND INTENTION TO USE TECHNOLOGIES

Performance expectancy refers to the degree for an individual to believe that using the technology will improve their performance [24]. Performance expectancy is derived from previous models' constructs, including the perceived usefulness in the TAM, extrinsic motivation in the MM, job-fit in the MPCU, relative advantage in the IDT, and outcome expectations in the SCT. The idea that people's intention to use a specific technology is driven by their belief that using the technology will improve their performance has been validated multiple times in previous studies [7], [8], [11]. In both voluntary and mandatory settings, performance expectancy was also found to be the strongest predictor of intention [24]. In the context of adopting predictive maintenance technology, where the use of technology is mandatorily included in the daily job routines, the belief that using the technology will increase the employees' performance should drive their intention to use the technology. Therefore, this study hypothesized that:

H1: Performance expectancy positively affects the intention to use the predictive maintenance technology

2) EFFORT EXPECTANCY AND INTENTION TO USE TECHNOLOGIES

Effort expectancy is defined as the extent of ease associated with using the technology. This construct is similar to the perceived ease of use in the TAM, complexity in the MPCU, and ease of use in the IDT. The basic notion is that when an individual perceives that using a technology will be hassle-free, they will have the intention to use that specific technology. Effort expectancy largely affects the intention to use technologies in the early stage of implementation, and the effect will likely weaken over extended usage [24], [25]. The rationale is that once people start to use a technology and understand how to navigate the technology, the ease of using the technology will become less important [26]. Based on the previous studies, this study hypothesized that:

H2: Effort expectancy positively affects the intention to use the predictive maintenance technology

3) SOCIAL INFLUENCE AND INTENTION TO USE TECHNOLOGIES

As a member of society, people often consider how other people (especially those more relevant ones) will think about them. If an individual perceives that the people who are important to them believe that the individual should use the technology, that individual will want to use the technology. This concept is known as social influence, also known as the subjective norm in the TRA, TAM, and TPB models, or as social factors in the MPCU [24]. Social influence is more likely to drive intention in a mandatory setting than in a voluntary setting. This is because social influence often occurs through compliance [27]. People may choose to use the technology when someone important to them thinks they must, even if it is favored by them. Social influence is also more likely to significantly drive the intention to use technologies before their implementation. Before the technology is implemented, an individual might not have a full grasp of the technology and therefore, they will rely on the opinions of people who are important to them [27]. After they have sufficient knowledge of the technology, the impact of social influence weakens. Based on the previous studies, this study hypothesized that:

H3: Social influence positively affects the intention to use the predictive maintenance technology

4) DIRECT DETERMINANTS OF THE ACTUAL USAGE OF TECHNOLOGIES

Building on the previous concept of the perceived behavioral control (TPB), facilitating conditions (MPCU), and compatibility (IDT), Venkatesh et al. defined the facilitating conditions as the extent to which an individual believes that a sufficient organizational and technical infrastructure exists to support using the technology [24]. In a model with performance expectancy and effort expectancy, facilitating conditions were found to show no significant effect on the intention to use technologies [24]. However, the facilitating conditions were found to directly affect the actual usage instead, especially for older people who might need more assistance. Based on the previous studies, this study hypothesized that:

H4: Facilitating conditions positively affect the actual usage of the predictive maintenance technology

Following the established notion that intention drives behavior, this study also hypothesized that:

H5: Behavioral intention positively affects the actual usage of the predictive maintenance technology

C. TECHNOLOGY ACCEPTANCE AND LEADERSHIP

In the existing literature, the impact of various leadership styles on technology acceptance has been investigated through different theoretical lenses and empirical studies. For example, Khasawneh investigated the impact of technophobia on employees' technology acceptance [6]. The study

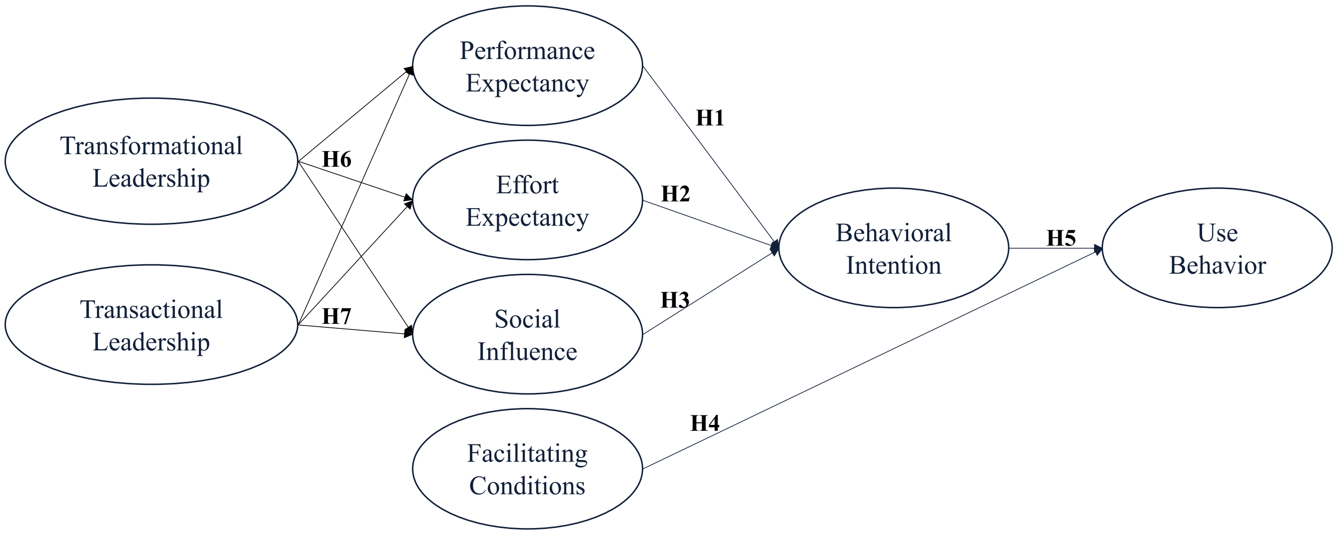

FIGURE 1. Research model.

revealed that technophobia can impede the acceptance of new technologies. However, when employees work under a manager who is genuinely interested in their personal development, their level of technophobia decreases, and technophobia is no longer an issue for their lack of technology acceptance [6]. The study suggests that transformational leaders, by demonstrating genuine interest in their employees' personal development, can create a psychologically safe environment that encourages employees to embrace new technologies and adapt to change. Molino et al. [13] carried out a mixed-method study that focused on examining the role of digital leadership in technology acceptance. In addition to paying attention to technology implementation, leaders must consider the wellbeing of their followers. Leadership support and the supervisors' digital skills are equally important in cultivating employees' technology acceptance [11], [13].

By extending the TAM, Aziz et al. [10] investigated the role of authentic leadership on the employees' acceptance of technology. Authentic leaders, who exhibit a positive attitude, mindset, and self-confidence, can indirectly motivate employees by influencing their perceptions of the benefits of technological changes. This study highlights the importance of leaders who are transparent, genuine, and supportive, as they can instill confidence in employees and create a positive organizational culture that fosters technology acceptance. Focusing on the leader-member exchange quality, Hwang et al. suggested that the higher the quality of the leader-member exchange, the stronger the relationship between the supervisor's influence and employees' intention to use technologies [29].

Similarly, Neufeld et al. [30] also explored the role of leadership style with a focus on charismatic leadership. Their study found that the employees, who perceived that their superior demonstrated inspirational motivation and idealized influence behavior may also show a higher level of performance expectancy, effort expectancy, social influence, and facilitating conditions.

Another study also investigated the impact of empowered leadership on the intention of adopting technologies [8]. According to their findings, employees who believe they have personal empowerment in the workplace tend to find the technology easier to use. However, empowering leadership was found to show no significant effect on perceived usefulness.

III. METHODOLOGY

However, not all leadership styles have been found to be equally effective in promoting technology acceptance. Schepers et al. [7] found that transactional leadership, which emphasizes rewards and punishments for performance, had no effect on perceived usefulness or perceived ease of use in their study. This suggests that leadership styles focused on extrinsic motivation and control may be less effective in fostering a climate of innovation and technology acceptance.

In some cases, the existing literature presents conflicting results. For instance, Halbach and Gong [28] found that the Leadership Practice Inventory (LPI) did not significantly influence bank leaders' intentions to use technologies. However, when individual LPI indicators were evaluated, specific aspects of leadership behavior, such as modeling the way and enabling others to act, were found to be significantly correlated with technology acceptance. This highlights the importance of examining the nuanced dimensions of leadership styles and their potential impact on technology acceptance

In summary, the existing literature demonstrates a strong connection between various leadership styles and technology acceptance, with transformational and authentic leadership styles appearing particularly effective in fostering a positive environment for embracing new technologies. However, the impact of transactional leadership remains less clear, suggesting that further research may be needed to better understand the mechanisms through which different leadership styles influence technology acceptance.Therefore, this study hypothesized that:

H6: Transformational leadership positively affects the core determinants of intention in the UTAUT model

H7: Transactional leadership positively affects the core determinants of intention in the UTAUT model

A. SUBJECT OF THE STUDY

The study focuses on a coal mining company located in Sangatta, East Kalimantan, Indonesia. The company is known to have one of the largest open-pit mining sites in the world. As a coal mining company, it also manages sales to both domestic and international consumers from various industrial sectors.

The mining area covers 84,938 hectares, and its head office is situated in Sangatta, East Kutai Regency, East Borneo Province, Indonesia, with representative offices distributed in Jakarta, Samarinda, and Balikpapan. The company's production capacity reaches an impressive 70 million tons per year, with the support of over 4,499 employees and 21,000 personnel ranging from contractors to its associated companies.

B. DATA COLLECTION

This study aimed to explore the acceptance of the predictive maintenance technology in a coal mining setting. The Company is the largest coal mining company in Indonesia with over 4,499 employees. In this study, online questionnaires were deployed to employees using the company's internal channel. As the predictive maintenance technology is used for heavy equipment in The Company, the subject of this study included the Superintendent, Supervisor, Engineer, Leading Hand, and Tradesperson Mechanical/Auto Electric, who are the users of the equipment and the predictive maintenance technology. This study employs convenience sampling method in acquiring the data. A total of 148 questionnaire responses were collected and considering missing data and outliers, 140 completed responses were used for data analysis in this study. In the 140 respondents, 138 were males and 2 were females. The majority of the respondents were aged over 40 years old. Around 60% of the respondents were graduates of high school or vocational high school, and most of them worked in the coal mine as Tradesperson Mechanical/Auto Electric. Almost half of the respondents (47%) have worked in the company for over 15 years.

C. MEASUREMENTS

The scales for measuring the UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention) were developed based on previous studies [24]. The usage behaviors were measured by a direct question of how often they employed the predictive maintenance technology in their shift routines. The questionnaire items obtained from previous study [24] are modified to fit the context of predictive maintenance app use in coal mining company. Before conducting the full study, these scales were pilot tested to ensure the validity and reliability of the scale items. A total of 14 item scales were used to measure the acceptance using the UTAUT constructs. All the items were measured using a six-point Likert scale ranging from totally disagree (1) to totally agree (6).

The perceived leadership styles were measured using the MLQ version 5X rater-form, MLQ5X [31]. In this study, the Indonesian translation of the MLQ5X was used. The MLQ was used in this study due to its reliability demonstrated in similar previous studies [6], [7]. Transformational leadership was measured by five indicators that included the idealized influence (attributed), idealized influence (behavior), inspirational motivation, intellectual stimulation, and individualized consideration, with each indicator having four items. Transactional leadership was measured using two indicators, the contingent reward and management-by-exception (active), with four items to operationalize each indicator. A six-point Likert scale was used to measure transformational and transactional leadership scales ranging from never (1) to always (6).

IV. DATA ANALYSIS AND RESULTS

The partial least square structural equation modeling (PLS-SEM) using the SmartPLS 3 was selected to analyze the data. The PLS-SEM was chosen due to its less-restrictive distributional assumptions and high degrees of statistical power, compared to the CB-SEM [32]. The PLS-SEM is also more appropriate for predictive models with less developed theory in this study [33].

To generate comparative outcomes, an artificial neural network (ANN) analysis is utilized in conjunction with the PLS-SEM analysis. One advantage of incorporating ANN alongside linear techniques, such as PLS-SEM, is its ability to detect nonlinear relationships [34]. This will enable the study to capture intricate linear and nonlinear relationships between predictors and behavioral intention. The neural network is modeled using SPSS 25.

A. RELIABILITY AND VALIDITY

The reliability and validity of the approach were assessed in terms of indicator loadings, construct reliability, convergent validity, and discriminant validity [35]. Although the recommended factor loadings are above 0.708, indicators with loadings between 0.40 and 0.708 were only removed if the deletion resulted in an increase in composite reliability [36]. Table 1 shows the outer loadings for each indicator. Based on the above criteria, several items were removed because their values were below the threshold or to improve the overall reliability (items removed are marked with asterisks).

Construct reliability was measured using the composite reliability score with a cutoff value of 0.60 [35]. The results showed that all the composite reliability scores were above the threshold, which demonstrated the desired construct reliability. Convergent validity should be at least 0.50 when measured by the average variance extracted (AVE) [35].

TABLE 1. Construct validity and reliability.

Constructs	Indicators	Outer Loadings	Composite Reliability	AVE
Transformational Leadership	Idealized Influence (Attributed) 1	0.654	0.957	0.556
	Idealized Influence (Attributed) 2	0.717		
	Idealized Influence (Attributed) 3	0.677		
	Idealized Influence (Attributed) 4	0.024*		
	Idealized Influence (Behavior) 1	0.588		
	Idealized Influence (Behavior) 2	0.759		
	Idealized Influence (Behavior) 3	0.828		
	Idealized Influence (Behavior) 4	0.771		
	Inspirational Motivation 1	0.758		
	Inspirational Motivation 2	0.790		
	Inspirational Motivation 3	0.792		
	Inspirational Motivation 4	0.848		
	Intellectual Stimulation 1	0.678		
	Intellectual Stimulation 2	0.634		
	Intellectual Stimulation 3	0.760		
	Intellectual Stimulation 4	0.860		
	Individualized Consideration 1	0.792		
	Individualized Consideration 2	0.401*		
	Individualized Consideration 3	0.575		
	Individualized Consideration 4	0.828		
Transactional Leadership	Contingent Reward 1	0.590	0.900	0.533
	Contingent Reward 2	0.727		
	Contingent Reward 3	0.813		
	Contingent Reward 4	0.767		
	Management-by-exception (Active) 1	0.545		
	Management-by-exception (Active) 2	0.843		
	Management-by-exception (Active) 3	0.800		
	Management-by-exception (Active) 4	0.701		
Performance Expectancy	Performance Expectancy 1	0.820	0.833	0.629
	Performance Expectancy 2	0.893		
	Performance Expectancy 3	0.644		
Effort Expectancy	Effort Expectancy 1	0.868	0.909	0.768
	Effort Expectancy 2	0.872		
	Effort Expectancy 3	0.890		
Social Influence	Social Influence 1	0.815	0.862	0.610
	Social Influence 2	0.782		
	Social Influence 3	0.724		

TABLE 1. ***(Continued.)*** **Construct validity and reliability.**

	Social Influence 4	0.801		
Facilitating Conditions	Facilitating Conditions 1	0.824	0.809	0.586
	Facilitating Conditions 2	0.764		
	Facilitating Conditions 3	0.705		
Behavioral Intention	Behavioral Intention 1	0.926	0.965	0.901
	Behavioral Intention 2	0.957		
	Behavioral Intention 3	0.965		

*items deleted in the analysis

TABLE 2. **Construct correlations.**

	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence	Transactional Leadership	Transformational Leadership
Behavioral Intention	*0.949*						
Effort Expectancy	0.532	*0.877*					
Facilitating Conditions	0.517	0.709	*0.766*				
Performance Expectancy	0.547	0.672	0.555	*0.793*			
Social Influence	0.517	0.689	0.607	0.768	*0.781*		
Transactional Leadership	0.429	0.437	0.379	0.482	0.473	*0.730*	
Transformational Leadership	0.344	0.383	0.336	0.445	0.423	0.719	*0.746*

The AVE values for all constructs were also above the threshold, which satisfied the criteria of convergent validity.

The criterion described in Fornell–Larcker was used to assess discriminant validity [37]. According to the criterion, the square root of a construct's AVE must be greater than the correlation between the construct and any other constructs. Based on the correlation of constructs shown in Table 2, the Fornell–Larcker criterion was satisfied.

B. PATH RELATIONSHIP

To examine the relationship between the constructs, the path coefficients should be statistically significant and meaningful in size. The results of the path analysis are summarized in Table 3. Empirical evidence was found in this study for behavioral intention to be significantly affected by performance expectancy ($\beta = 0.276$ and $t = 2.112$) and effort expectancy ($\beta = 0.259$ and $t = 2.335$). However, it was found that social influence did not significantly affect behavioral intention ($\beta = 0.127$ and $t = 0.819$). Supporting the UTAUT model, this study also found evidence that the usage behavior can be influenced by the facilitating conditions ($\beta = 0.218$ and $t = 2.666$) and behavioral intention ($\beta = 0.262$ and $t = 3.120$).

In terms of the impact of perceived leadership styles, it was found that only transactional leadership significantly affected performance expectancy ($\beta = 0.474$ and $t = 2.451$), effort expectancy ($\beta = 0.553$ and $t = 2.676$), and social influence ($\beta = 0.474$ and $t = 2.451$), whereas transformational leadership was not found to significantly affect performance expectancy, effort expectancy, and social influence.

To gain a more detailed understanding of the impact of leadership styles on technology acceptance, a second model was tested by replacing transformational and transactional leadership with their subdimensions. From the results of the second test, it was found that contingent reward significantly can affect performance expectancy ($\beta = 0.314$ and $t = 2.042$) although effort expectancy and social influence were not significantly affected. On the other hand, management-by-exception (active) was found to significantly affect effort expectancy ($\beta = 0.354$ and $t = 2.597$) and social influence ($\beta = 0.284$ and $t = 2.146$), but not performance expectancy. When tested with the subdimensions, intellectual stimulation was also found to affect performance expectancy ($\beta = 0.368$ and $t = 2.256$) and social influence ($\beta = 0.350$ and $t = 2.127$), but not effort expectancy.

C. MODEL FIT

Model fitting was quantified by the coefficient of determination (R^2), effect sizes (f^2), and prediction relevance (Q^2). The coefficient of determination R^2 measures the prediction power ranging from no relationship (0) to perfect relationship (1). The results reveal that employees' perceptions

TABLE 3. Path analysis.

Path Relationship	Coefficient	*t*-value	*p*-value
Performance Expectancy → Behavioral Intention	0.276	2.122	0.034*
Effort Expectancy → Behavioral Intention	0.259	2.335	0.020*
Social Influence → Behavioral Intention	0.127	0.819	0.413
Facilitating Conditions → Usage Behavior	0.218	2.666	0.008*
Behavioral Intention → Usage Behavior	0.262	3.120	0.002*
Transformational Leadership → Performance Expectancy	0.009	0.046	0.963
Transformational Leadership → Effort Expectancy	−0.125	0.525	0.600
Transformational Leadership → Social Influence	−0.076	0.376	0.707
Transactional Leadership → Performance Expectancy	0.474	2.451	0.015*
Transactional Leadership → Effort Expectancy	0.553	2.676	0.008*
Transactional Leadership → Social Influence	0.543	2.806	0.005*

*statistically significant at 95% ($p < 0.05$) means that there is a less than 5% of chance that the observed relationship between the variables may not occur and a 95% confidence level can be achieved that a real relationship between the variables exists.

TABLE 4. Coefficients of determination, effect sizes, and predictive relevance.

Endogenous constructs	Exogenous constructs	R^2	f^2	Q^2
Performance expectancy		0.221		0.121
	Transformational leadership		0.001	
	Transactional leadership		0.045	
Effort expectancy		0.182		0.127
	Transformational leadership		0.003	
	Transactional leadership		0.059	
Social influence		0.213		0.108
	Transformational leadership		0.001	
	Transactional leadership		0.059	
Behavioral intention		0.340		0.311
	Performance expectancy		0.044	
	Effort expectancy		0.049	
	Social influence		0.009	
Usage behavior		0.163		0.131
	Facilitating conditions		0.042	
	Behavioral intention		0.061	

The "rough" rule of thumb for an acceptable R^2 is 0.75, 0.50, and 0.25 for significant, moderate, and weak levels of predictive accuracy, respectively; the rule of thumb values for f^2 are 0.02, 0.15, and 0.35 for small, medium, and large effects, respectively; and values of Q^2 greater than 0 for an endogenous construct suggest that the path model has predictive validity for that construct [33].

of leadership styles accounted for 22%, 18%, and 21% of performance expectancy, effort expectancy, and social influence, respectively, as determined by the R^2 values. Furthermore, the model indicated that 22% of behavioral intention was explained by performance expectancy, effort expectancy, and social influence. Lastly, 16% of usage behavior could be accounted for by facilitating conditions and behavioral intention.

The effect size f^2 represents the change in R^2 value when a specific independent variable is removed from the model, with the values of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively. The predictive relevance Q^2 evaluates the model's prediction power, with the Q^2 values greater than zero indicating acceptable prediction accuracy for the path model. Table 4 presents the results of R^2, f^2, and Q^2 of the model.

D. ANN ANALYSIS

The use of PLS-SEM may at times oversimplify the complex nature of technology adoption decisions made by users due to its inherent linear model [38]. To address this drawback, an ANN analysis was employed to identify and assess the nonlinear relationships within the model.

Similar with the approach in previous studies, the significant predictors identified in the PLS-SEM analysis were included as inputs in the ANN model to determine the relative importance of each predictor variable [39], [40], [41]. The latent variable scores obtained from the PLS-SEM analysis served as inputs for the ANN model. The ANN model utilized multilayer perceptrons and sigmoid activation functions for the input and hidden layers [39]. Hence, a tenfold cross-validation approach was utilized, where 90% data was allocated for training and 10% for testing purposes [34].

To assess the predictive accuracy of the ANN model, the root mean square error (RMSE) was calculated. Table 5 lists the results of the RMSE calculation. Based on the calculation, the ANN model is quite accurate in predicting the intention to use predictive maintenance technology and the actual use.

TABLE 5. RMSE values of artificial neural networks.

	Model I (Input: PE, EE; Output: BI)		**Model II** (Input: FC, BI; Output: UB)	
Network	Training	Testing	Training	Testing
1	0.579809332	0.425648294	0.622624298	0.648705004
2	0.558485015	0.563710237	0.632449307	0.626713037
3	0.64934249	0.427425207	0.649659797	0.632788316
4	0.552530834	0.466234919	0.627845588	0.686179354
5	0.587409216	0.560544848	0.643535084	0.460313903
6	0.57672177	0.726085394	0.626724288	0.560357029
7	0.558354726	0.450703154	0.629341613	0.565957324
8	0.567887313	0.359629439	0.650492503	0.669131409
9	0.56569244	0.465909249	0.641984423	0.625726245
10	0.549559824	0.762583329	0.629829373	0.547937309
Mean	0.574579296	0.520847407	0.635448627	0.602380893
Standard deviation	0.028952481	0.132779997	0.010069945	0.068252165

Note: PE = performance expectancy; EE = effort expectancy; BI = behavioral intention; FC = facilitating conditions; UB = usage behavior.

TABLE 6. Sensitivity analysis: Normalized importance.

	Model I (Output: BI)		**Model II** (Output: UB)	
Network	PE	EE	FC	BI
1	0.855	1.000	1.000	0.983
2	0.812	1.000	1.000	0.836
3	1.000	0.165	0.871	1.000
4	0.852	1.000	0.833	1.000
5	0.809	1.000	0.999	1.000
6	0.826	1.000	0.784	1.000
7	1.000	0.781	0.560	1.000
8	1.000	0.935	1.000	0.894
9	0.875	1.000	0.650	1.000
10	1.000	0.900	0.739	1.000
Average importance	0.903	0.878	0.844	0.971
Normalized importance	100.0%	97.3%	86.9%	100.0%

Note: PE = performance expectancy; EE = effort expectancy; BI = behavioral intention; FC = facilitating conditions; UB = usage behavior.

In addition, a sensitivity analysis was conducted to measure the importance of each predictor variable. The results of the sensitivity analysis are presented in Table 6. Based on the sensitivity analysis, performance expectancy is the most significant predictor of behavioral intention and behavioral intention is the most significant predictor of usage behavior.

V. DISCUSSION

This study attempted to assess the factors of predictive maintenance acceptance among employees in a mining company. Moreover, by utilizing the MLQ5X to measure the perceived leadership style, this study also examined how different leadership styles affected the employees' acceptance.

Similar to the previous studies [7], [8], [11], the results of this study were found to support the hypothesis that performance expectancy has a significant effect on the intention of using the predictive maintenance technology. In other words, employees are more likely to use the predictive maintenance technology if they believe it will improve their performance and help them achieve their goals. This study also showed that performance expectancy is the strongest predictor of intention among other constructs.

Effort expectancy refers to the degree of ease when using a specific technology. It includes factors such as the complexity of the technology, the level of training or support required to use the technology, and the compatibility of the technology with the individual's existing workflow. The current study found that effort expectancy has a significant influence on the individual's intention to use the predictive maintenance technology, which supports hypothesis H2. In other words, employees are more likely to use the predictive maintenance technology if they perceive that it is easy to use [24].

Interestingly, this study found no support for hypothesis H3, which suggests that social influence significantly affects the intention of using technologies. Apparently, the employees' intention of using the predictive maintenance technology was found not to rely on their belief that someone important to them thinks they should use the technology. It is also possible that in this study, the effect of social influence on the intention of using technologies has diminished over time due to employees' previous experiences with the technology [27]. As individuals become more familiar with the technology, they can get less influenced by the social norm around them, as they may have already formed their own opinions about the technology.

The research model in this study included performance expectancy and effort expectancy as the predictors. Therefore, the facilitating conditions were hypothesized to affect the actual usage of the technology rather than the intention to use the technology [24]. Accordingly, this finding suggested that by providing the employees with the necessary resources, support, and infrastructure, the likelihood for the employees to use a certain technology can be increased, which supports hypothesis H4. In addition, the fact that the majority of the respondents in this study were over 40 years old may suggest that age is a factor in technology acceptance, although further analysis is needed to confirm it. Older individuals may be less familiar with new technologies and may require more support and resources to use the technologies effectively. Acceptance of new technologies in the workplace can be promoted by providing adequate facilitating conditions and offering training and support to employees of all ages.

The current study found that there is a strong relationship between individuals' intention of using the technology and the actual usage, which supports hypothesis H5. This is in line with the existing idea that behavioral intention plays a major role in determining a person's behavior [24]. The findings of this study suggested that one should focus on increasing people's intention to use technology for promoting technology adoption, along with necessary support. Companies can also focus on increasing people's perception of the associated benefits and ease of use of the technology. This could be achieved through education and training programs that highlight the benefits of using the predictive maintenance technology and provide clear instructions on how to use it.

This study indicates that the ANN analysis provides a more nuanced and precise understanding of the complex decision-making processes involved in technology adoption by users. While the PLS-SEM has been widely used to explore technology adoption behavior, it has a tendency to oversimplify the relationships among factors due to its inherent linear model. On the contrary, the ANN analysis allowed this study to identify and evaluate nonlinear relationships, leading to a more comprehensive understanding of the factors that influence technology adoption behavior.

The sensitivity analysis results of the ANN analysis support the findings of the PLS-SEM analysis, indicating that performance expectancy is the most significant predictor of behavioral intention and that behavioral intention is the most crucial predictor of the actual usage behavior. Overall, these results have implications for organizations that aim to encourage technology adoption among users. Focusing on the factors that impact performance expectancy and behavioral intention can aid in designing effective strategies to promote technology adoption.

In this study, the role of leadership in the acceptance of the predictive maintenance technology was also investigated. The results showed that transactional leadership had a significant effect on performance expectancy, effort expectancy, and social influence, whereas transformational leadership did not have a significant effect on these factors, which disagrees with hypothesis H6 and supports hypothesis H7. This contradicts with previous research regarding the impact of leadership on technology acceptance. Previous studies typically found that transformational leadership is more effective in promoting acceptance [6], [7], [10].

This difference may be due to the unique characteristics of the coal mining industry, such as the high level of specialization and potential hazards, which may require a different approach to exert leadership. The findings of this study suggested that transactional leadership, which focuses on setting clear goals and expectations and providing rewards and punishments to motivate employees [42], may be more effective in ensuring safety and compliance in the coal mining industry than transformational leadership, which focuses on inspiring and motivating employees to achieve their full potentials [6]. Another possible reason is that the coal mining industry is currently undergoing significant changes and challenges, such as the shift toward renewable energy sources and tightened regulations, which may require a different approach to exert leadership. In this context, transactional leadership, which emphasizes on accountability and results, may be more effective in helping organizations adapt to these changes and challenges than transformational leadership, which emphasizes on creativity and innovation [42].

To gain a deeper understanding of the mechanism of how transformational and transactional leaderships promote technology acceptance, this study tested a second model which included the subdimensions of transformational leadership and transactional leadership. The findings suggested that the different subdimensions of leadership have different effects on the acceptance of the predictive maintenance technology in the coal mining industry. For example, the contingent reward, which is a subdimension of transactional leadership that involves providing rewards and incentives based on performance, was found effective in promoting performance expectancy, but not effort expectancy or social influence. This suggested that this subdimension may be particularly useful in promoting the belief that using the technology will improve job performance. On the other hand, the management-by-exception (active), which is also a subdimension of transactional leadership that involves monitoring employees and intervening to correct deviations from the standards, was found to significantly affect effort expectancy and social influence, but not performance expectancy. This suggested that this subdimension may be effective in promoting the perception of ease of use for the technology, but not the belief that it will improve job performance.

For the first model, no significant impact of transformational leadership was found on performance expectancy, effort expectancy, and social influence. However, when tested using the subdimensions, it was shown that the intellectual stimulation, which is a subdimension of transformational leadership that involves stimulating and encouraging creativity, can significantly affect performance expectancy and social influence, similar to the findings from a previous study [7]. This suggested that this subdimension may be effective in promoting the belief that using the predictive maintenance technology will improve job performance and support from others, but not the perception of ease of use. One possible reason for this finding is that the intellectual stimulation may be more effective in promoting acceptance of complex and innovative technologies, compared to simple and routine technologies. In this case, the intellectual stimulation would be more effective in promoting the acceptance of the predictive maintenance technology (which involves using advanced algorithms and machine learning to predict and avoid equipment failures) than a simple maintenance checklist, which can be easily implemented and followed. Accordingly, the intellectual stimulation may be more effective in promoting the belief that the technology will improve job performance and support from others, but may not have a significant impact on the perceived ease of use of the technology, which may be relatively low for a simple and routine technology.

In general, this study highlighted the importance of considering the specific conditions of the industry in terms of the unique challenges and opportunities it presents, when interpreting the results of the study and comparing them to previous research. It is also important to consider that the impact of leadership on technology acceptance may vary depending on factors such as the individual employee's characteristics, the nature of the technology, and the organizational culture.

VI. CONCLUSION

This study aimed to investigate the role of leadership in the acceptance of the predictive maintenance technology in the coal mining industry. The UTAUT model was used to measure the associated acceptance, and the MLQ5X was used to measure the perceived leadership style of managers. The results showed that transactional leadership had a significant effect on performance expectancy, effort expectancy, and social influence, whereas transformational leadership did not show any significant effect on these factors. In addition, our analysis of the subdimensions of transformational and transactional leadership showed that the contingent reward, management-by-exception (active), and intellectual stimulation had significant effects on performance expectancy, effort expectancy, and social influence, respectively.

These findings suggested that the coal mining industry may require a different approach to exert leadership when adopting new technologies. More specifically, the results of this study indicated that transactional leadership, which emphasizes on accountability and results, may be more effective in promoting the acceptance of the predictive maintenance technology than transformational leadership. In addition, our findings on the subdimensions of leadership suggested that a comprehensive approach that considers various subdimensions may be more effective in promoting acceptance than focusing on only one type of leadership style.

A. PRACTICAL IMPLICATIONS

Overall, the results of this study can provide knowledge and tools for managers and organizations in the coal mining industry to effectively promote the adoption and acceptance of the predictive maintenance technology, and help them overcome the challenges and take advantage of the technology. For example, the results of the PLS-SEM and ANN analysis which point to performance expectancy as the most important predictor of the intention to use predictive maintenance can be considered when crafting strategies to foster the technology adoption. Moreover, the findings on the role of transactional leadership in promoting technology acceptance may be used by managers and organizations in the coal mining industry to develop and implement leadership strategies that are more effective in promoting the implementation of this technology.

In addition, the findings on the subdimensions of leadership could be used to identify the specific aspects of leadership that are most effective in promoting technology acceptance, which can help develop specific leadership strategies according to the unique challenges and opportunities of the coal mining industry. Managers could use these findings to determine the key subdimensions of leadership to promote acceptance of the technology, such as the contingent reward or management-by-exception (active), and to develop leadership practices that are tailored to these subdimensions.

Moreover, this study's focus on a large-scale mining company has practical implications for other mining companies grappling with similar issues. The findings highlight the factors that impact the intention to use predictive maintenance technology, which can aid the industry in enhancing their practices and developing more successful strategies to achieve their objectives.

B. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

It is important to note the potential limitations of this study. First, this study relies on self-report measures, such as surveys and questionnaires, to assess technology acceptance and leadership styles. These measures are subject to response bias and other sources of errors such as social desirability bias, and may not provide a completely accurate or objective assessment of the variables in this study. By adopting more objective measures such as observations and performance data, a more valid and reliable assessment of technology acceptance and leadership styles can be achieved. Moreover, this study is focused on the coal mining industry, and the results may not be applicable for other industries. For example, the challenges and opportunities faced by the coal mining industry and the impact of leadership on technology acceptance may be different from those of other industries. Further research could explore the generalizability of the results of this study by examining the relevant results from other industries.

In this study, no significant effect was found for social influence on the intention of using the predictive maintenance technology. This is due to the impact of the existing experience with the technology since the technology has existed for a while. Social influence is more likely to affect the intention of using technologies during the preimplementation stage or the early stage of technology adoption. Due to the experience, the effect of effort expectancy is also expected to diminish over time [26]. However, this study found that the ease of use of the technology is still important in determining the employees' intention of using the technology. This finding suggested that future research should also focus on exploring the impact of experience on technology acceptance. Collecting data from several time points during the adoption of a certain technology could be an effective way to study the impact of experience on technology acceptance. By comparing data from different time points, one can identify any changes in the factors that influence technology acceptance over time. This may provide valuable insights into how the acceptance of a technology changes as individuals gain more experience, which can help identify key strategies for promoting technology acceptance in the various stages of adoption. In addition, researchers could also study the impact of different leadership styles on technology acceptance over time to check if certain leadership strategies are more effective in promoting technology acceptance in the early stages of adoption or in other later stages.

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