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ASIAN ACADEMY OF MANAGEMENT INTERNATIONAL CONFERENCE

INDONESIA CHAPTER 2025

"Harnessing AI for Ethical Leadership: Keeping the Heart in the Age of Machine"

(ASEAN MANAGEMENT RESEARCH NETWORK)

PROCEEDINGS

ASEAN MALAYSIA 2025 INCLUSIVITY AND SUSTAINABILITY

Asian Academy of Management International Conference Indonesia Chapter 2025

Harnessing AI for Ethical Leadership: Keeping the Heart in the Age of Machine

This conference was organized by the School of Management, Universiti Sains Malaysia, in collaboration with the Asian Academy of Management and Universitas Indonesia.

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MESSAGE FROM THE PRESIDENT

It is with great pleasure and honour that I welcome all contributors to The Asian Academy of Management International Conference – Indonesian Chapter 2025.

Since its establishment in 1995, the Asian Academy of Management (AAM) has consistently received overwhelming support and active participation from researchers and practitioners across various regions of the world. The Asian Academy of Management Conference (AAMC) has been organised biennially as a premier platform for scholarly exchange. Over the years, AAM has also strengthened its international presence through strategic collaborations with global partners, enabling wider participation and richer intellectual engagement.

For AAMC 2025, the Asian Academy of Management, in collaboration with the School of Management, Universiti Sains Malaysia, and Universitas Indonesia, and in conjunction with the ASEAN Management Research Network, proudly organises the Indonesian Chapter. This initiative reflects our continued commitment to strengthening regional academic networks and enhancing meaningful research collaborations within Asia and beyond.

This year's theme, "Harnessing AI for Ethical Leadership: Keeping the Heart in the Age of Machine," reflects the growing influence of artificial intelligence in organisational decision-making, governance, and leadership practices. Notably, as AI technologies become increasingly embedded in business operations and strategic processes, leaders are confronted with complex ethical considerations involving transparency, accountability, fairness, and societal impact. The theme therefore underscores the urgent need to balance technological advancement with human-centred values. It calls upon scholars and practitioners alike to explore how leadership grounded in empathy, integrity, and moral responsibility can guide organisations in leveraging AI responsibly while safeguarding trust and long-term sustainability.

As President of AAM, I sincerely hope that all contributors to the Indonesian Chapter will gain valuable insights, broaden their academic perspectives, and enrich their knowledge through the scholarly papers presented and published in the proceedings. May this Chapter serve as a catalyst for new research ideas, interdisciplinary dialogue, and enduring academic collaborations.

I would like to express my heartfelt appreciation to everyone involved in making this Chapter possible, particularly the dedicated Organising Committee of the Indonesian Chapter 2025, whose commitment and hard work have been instrumental in ensuring its success. Special thanks are also extended to Universiti Sains Malaysia, Universitas Indonesia, our sponsors, and distinguished guest speakers for their unwavering support and contributions.

In closing, I wish all contributors every success in their academic endeavours and hope that this Chapter will further strengthen research excellence, foster meaningful regional partnerships, and inspire impactful management scholarship for the future.

Professor Dr. Noor Hazlina Ahmad,
President, Asian Academy of Management

ABOUT THE CONFERENCE

The Asian Academy of Management International Conference – Indonesia Chapter 2025, organised by the School of Management, Universiti Sains Malaysia, in collaboration with the Asian Academy of Management and Universitas Indonesia, in conjunction with ASEAN Management Research Network, serves as a distinguished international platform that brings together academics and researchers to engage in meaningful scholarly discourse on contemporary management and leadership issues. The conference aims to foster knowledge exchange, strengthen collaboration and advance impactful research across the ASEAN region and beyond.

This year's theme, "Harnessing AI for Ethical Leadership: Keeping the Heart in the Age of Machine," reflects the growing influence of artificial intelligence in organisational decision-making, governance and leadership practices. As AI continues to reshape the business and management landscape, the conference underscores the importance of preserving ethical values, human-centred leadership and moral responsibility in the age of intelligent machines. The theme calls for a balanced integration of technological advancement with empathy, integrity and accountability to ensure sustainable and inclusive organisational outcomes.

The conference provides a valuable scholarly platform for participants to explore innovative research ideas, emerging methodologies and interdisciplinary perspectives related to AI, ethics, leadership, sustainability, and management. It encourages critical reflection on how ethical leadership can guide the responsible adoption of AI while sustaining trust, transparency and positive societal impact. The proceedings of this conference document the collective intellectual contributions presented, reflecting our shared commitment to advancing ethical, impactful and future-oriented management research within the ASEAN context.

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Study On Individuals' Behavioral Intention Opt For Islamic Bank Services: Malaysian Depositors' Perspective

Anwar Bin Allah Pitchay*
Universiti Sains Malaysia, Malaysia
Email: anwarap@usm.my

**Corresponding Author*

Abstract

The sustainable development of Islamic banking services has motivated large numbers of depositors to choose Islamic bank services instead of the conventional bank. There are various factors that can persuade the depositors' choice to choose Islamic bank. The present study examines the factors that persuade individuals' behavioral intention to choose Islamic bank services. Hence, to achieve this objective, this study employs the theory of planned behavior (TPB) as the underlying theory to measure the factors that persuade the depositors' behavioral intention to choose Islamic bank services. A total of 300 questionnaires is distributed to Malaysian Islamic bank depositors in Peninsular Malaysia. The data from the questionnaires are analysed using structural equation modeling (SEM). The result shows three variables predicted the behavioral intention, namely attitude (ATT), subjective norms (SN) and perceived behavioral control (PBC) of the depositors are found significant to persuade depositors' behavioral intention to choose the Islamic bank services. Furthermore, the finding of the study also confirmed the relevant of using TPB to measure the depositors' behavioral intention and this result is fruitful for the body of knowledge in the area of Islamic finance and also provides positive implication for the practitioners.

Keywords: Islamic bank, theory of planned behavior, structural equation modelling.

Introduction

The initial model of Islamic banking system can be traced during the establishment of the Mit-Ghamr Saving Bank in Egypt 1963. In the past five decades, Islamic banking has grown rapidly in term of size and number of investors. The reasons for the expansion are (1) high respond from the countries with high economic growth and relatively unbanked Muslim populations, and (2) fuelled by the large savings accumulated by many oil-exporting countries which are seeking for Shari'ah-compliant financial products. Currently, Islamic banking is operating in more than 50 countries worldwide1(Chong & Liu, 2009).

Malaysia is one of the pioneer countries that introduce Islamic bank industry and it has been in existence for more than 30 years. At present, Malaysia is one of the most developed Islamic banking markets in the world with its annual growth rate of 18-25 percent. Presently

Malaysia has 16 full-fledged Islamic banks, 12 Takaful operators, 5 international Islamic banks and 6 development financial institutions that offering Islamic financial services and products. Its asset represents almost 24 percent of total banking system asset with the value of RM495 billion. Moreover, the total financing reached to RM315.0 billion with a market share of 25.8 percent. Samat (2013) finds that Islamic financing is expected to account for 40 percent of total financing in 2020. This rapid growth and recognition especially from the depositors' lead to a series of questions such as what are the factors that persuade the depositors choosing the Islamic bank instead of the existing conventional bank? Thus, to answer this question, the present study aims to investigate the factors that influence the behavioural intention of Malaysian depositors to choose Islamic bank.

Organisation of the study is as follows; the following section is focusing on the Islamic banking in Malaysia and section three discusses literature review. Section four and five highlight methodology and discussion of the result. Finally, section six provides the conclusion of the study.

Islamic Banking in Malaysia

The Islamic financial system in Malaysia can be traced since 1963 when the government established Tabung Haji (the Pilgrims' Management and Fund Board). This institution is one of the successful Islamic financial intermediaries that provides a systematic mobilisation of Muslims' funds for the purpose of performing pilgrimage in Makkah as well as to encourage the participant to invest in Shari'ah based investment. The impressive performance of Tabung Haji has attracted several organisation to propose to the Malaysian government to establish full fledge Islamic bank. Implementation of this idea required various stage at the early stage such as the government organised many conferences and meetings which comprise of 20 experts in this field in 1981 in order to setup the full fledge Islamic financial institutions in Malaysia. Later, important parties' involvement such as by Bumiputra Congress and the National Steering Committee in 1981, a study has been conducted on the worth of making a new Islamic bank in Malaysia taking into various aspects. The result shows positive outcome and based on this result lead to the establishment of the first full fledge Islamic bank in Malaysia named Bank Islam Malaysia Berhad (BIMB) on July 1983.

BIMB operated like other bank offering products, which comply with Islamic law. The products that offered by BIMB are such as Mudharabah (profit sharing), Murabaha (cost plus), Bai BithamalAjil (home financing), QardAl Hassan (benevolent loan) and many other products which are Shari'ah compliance. Currently, BIMB has more 80 branches throughout the country with more than 1200 employees. Furthermore, in 1992, BIMB is listed in Main Board of Kuala Lumpur Stock Exchange. The rapid development and acceptance among the Malaysian on BIMB services, has attracted the conventional banks to offers Shari'ah compliant products. Hence, in n19993 the government allows the existing commercial banks to open Islamic windows and start using the bank existing infrastructure, staff and branches. The Central Bank of Malaysia has established National Shari'ah Advisory Council on Islamic banking in order to strengthen the regulation and to monitor and, harmonise the Shari'ah interpretation among the banks. The stable and sustainable development of Islamic banking in Malaysia has attracted foreign full fledge Islamic bank, e.g. Al Rajhi, Kuwait Finance House to penetrate into Malaysia Islamic bank main stream

Literature Review

Past Studies Examined Behavioural Intention in the Area of Islamic Economic and Finance

There are various studies have been conducted to measure behavioural intention of individual to react toward an action. Most of the studies are concentrated in the area of social science and at the present we can find several researchers are conducting research on behavioural intention in the area of Islamic economics and finance studies. However, there are limited studies examined behavioural intention in the area of Islamic economics and finance.

Pitchay et. al, (2015) examine the factors that influence the behavioural intentions of Muslim employees to donate through deductions from employment income. Using Theory of Reasoned Action (TRA), we attempt to identify the factors that may influence the behavioural intentions of Muslim employees to contribute to cash Waqf. A total of 380 Muslim employees, both from public and private sectors, from the Klang Valley, were involved in the study. The results show that the attitude and subjects' norms toward behavioural intentions are distinctively noted by the respondent. Furthermore, the structural equation model used in the study verified the structural relationship between attitude, subjective norms and behavioural intentions of Muslim employees. It is also found that the attitude of Muslim employees has more influence compared to subjective norms

Abduh et.al, (2011) investigates the factors that influence depositors' withdrawal behaviour in Islamic banks in Malaysia. This study employed the theory of reasoned action and total of 368 numbers of respondents. The results revealed that both subjective norms and attitude factors significantly influence depositors' decision on deposit withdrawal. Furthermore, the researchers also indicated that subjective norms influence depositors' decision of withdrawal compared to attitude toward behaviour.

Similarly, Amin et.al, (2010) tested the applicable of TRA on Qardhul Hassan financing acceptance among 214 Malaysian bank customers and the effect of price on its acceptance. This study employed TRA and added price as a new variable to examine the extent of price sensitivity among the client. The result shows that the higher the price, the lower the acceptance and vice versa. This indicates lower acceptance follow higher price. The study also finds that attitude and subjective norm are important determinants of bank customers' perception to accept Qard Hassan financing.

Bidin et.al, (2009) equally employed TRA to examine behavioural intention of Muslim employees to contribute Zakah from their salary deduction. This study used 250 business respondents in the state of Kedah. The study examined the extent to which TRA theoretical model help in predicting behavioural intention of Zakah payment on employment income by adding an additional path from subjective norm to attitude toward Zakah. They found that subjective norm and attitude predict behaviour to pay Zakah on income. As suggested by the result of the study, the additional path significantly improved the fitness of the model. This shows that both direct and indirect effect of subjective norms were significant.

Lada et.al, (1999) also employed TRA to examine the intention of using Halal products among the Malaysian consumers involving a survey of 485 respondents in Labuan Malaysia with selected locations by using convenience sampling. Their finding suggested that TRA is useful in predicting intention to choose the Halal products among the consumers. The finding shows that attitude of the consumer is not significant while subjective norm has been found to significantly influence the use of halal products.

Based on the previous studies, the researchers employ the theory of reasoned action (TRA) as the underlying theory to measure the behavioural intention of an individual towards an action. Hence, the present study intends to measure behavioural intention of Malaysian depositors' to choose Islamic banks services. The existing literature shows that there is an extended version of TRA which is call as the theory of planned behaviour (TPB) to measure an individual behavioural intention. Therefore, the following section we discuss the TRA and TPB and, the relevant theory that we employ for the present study.

Theories Relevant to Predicts and Explains Actual Behaviour

There are popular theories that used in the area of social science study to measure intention of an individual. The previous section 3.1 has highlighted the past studies that used to measure intention of an individual. Theory of reasoned action (TRA) and theory of planned behaviour (TPB) are commonly used to measure the behavioural intention of an individual toward his or her action. TRA and TPB (an extended theory of TRA) are related theories which are developed by same the founder. The following are the detail discussion of both theories and the factors that used to predict individual's behaviour which leads to an action.

Theories of Reasoned Action (TRA)

Fishbein & Ajzen (1975) state that attitude can anticipate behaviour if the particular attitude and behaviour are adequately conceptualised and measured. Hence, they introduce Theory of Reasoned Action (TRA), which originally proposed by Fishbein & Ajzen (1975) and later revised by Azjen & Fishbein (1980). TRA is a widely used model in the area of social psychology, which is concerned with the determinants of consciously intended behaviours (Razak & Abduh, 2012). According to Azjen & Fishbein (1980), the TRA model can be expressed as:

$$B \sim I = (AB)\, w1 + (SN)\, w2$$

Where:

B = Behaviour

I = the person's intention to perform the behaviour

AB = the person's attitude toward performing behaviour

SN = Subjective norms

w1 & w2= empirically determined weights

This theory basically incorporates measures of attitudes, intention and behaviour. Behaviour is the actual performance of the action that is being measured. The hypothesis is that the best predictor of the behaviour is behavioural intention, which is a person's conscious decision whether to perform behaviour. Behavioural intention is predicted by two components which are attitude toward the behaviour and the subjective norm. Aizen & Fishbein (1980) describe attitude toward the behaviour as the learned response toward an object or an act, whether it be favourable or unfavourable.

The attitude is the sum of the salient belief about the outcomes of performing the behaviour multiplied by the evaluation of whether these outcomes are perceived as favourable or unfavourable. In other words, if the outcome seems beneficial to the individual, he or she may then intend to or actually participate in a particular behaviour.

Algebraically, it can be written as:

$$AB = \sum bi \;\; ei \text{ , for } i = 1 \text{ to } n$$

Where:

AB = attitude toward performing the behaviour

bi = the person's belief that performing the behaviour will result in outcome i

ei = the person's evaluation of outcome i

n = the number of beliefs

Meanwhile, subjective norm is a person's perception of social pressure to perform a particular behaviour. The subjective norm is the sum of the normative beliefs, which is what specific people or groups of people think the person should do, multiplied by the motivation to comply, or how much the person wishes to comply to his/her normative influence (see Figure 4.1). It means that a person's decision to participate in any behaviour is strongly influenced by the people around them. These people may include friends or a peer group, family, co-worker, community leaders and others significant people. Thus, these attitude and subjective norms form the behavioural intention jointly. The equation for getting the subjective norm is as follow:

$$SN = \sum NBj\ MCj\ , \text{for } j = 1 \text{ Ton}$$

Where:

SN = subjective norm

NBj = the normative belief that a reference group j think that the person should or

Should not perform the behaviour

MCj = the motivation to comply with the influence of referent j

N = the number of relevant reference groups of individuals.

In terms of testing and analysing Theory of Reasoned Action empirically, various previous studies have employed Structural Equation Modelling (SEM). For example, in 2004, Choo et al. use SEM to analyze on Indian consumers' purchase for new food by using Theory of Reasoned Action. Amin et al. (2009) also study the intention of students to enrol for accounting course by using SEM. In addition, Abduh et al. (2011) also apply SEM in their study to find out the factors that influence the depositors' withdrawal behaviour in Islamic banks in Malaysia by using TRA. It indicates that SEM is widely used as an analytical tool for empirically testing the theory of reasoned action in many areas.

Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) is used to help understand people's behavioural intentions and performance. It is also known as social cognitive framework. The behavioural decisions ofTPB are not made spontaneously but are the result of a reasoned process in which behaviour is influenced, albeit indirectly, by attitudes, norms, and perceptions of control over the behaviour.

Specifically, the TPB suggests that behaviour depends on one's plan of action (i.e. intentions) which, in turn, are controlled by attitudes (i.e. positive-negative evaluative appraisals ofthe behaviour), by their PBC (i.e. personal weights assigned to prior obstacles or circumstances), and by subjective norms (i.e. perceived social pressure to perform the behaviour). Therefore, the more favourable the attitude towards such a behaviour, then the stronger the subjective norm with respect to the behaviour, the greater the PBC, and the stronger will be an individual's intention to perform the behaviour under consideration (Ajzen, 1991) .

The TPB has been one of the most widely used and influential models in the study of the attitude-behaviour relationship (Davies et al. 2002). According to Rivis, et. al, (2009) TPB is among the most influential theory for the prediction of pro-social behaviours. Furthermore, the TPB can be criticised from a number of different aspects. First, it is considered to be too logical or rational (Barber, 2011). The TPB assumes that decision making is a rational process and it hypothesises that a person appraises the consequences of acting, forms attitudes, subjective norms towards the act, PBC, and then finally decides to act in a certain way, which is expressed by one's intentions to act; however, individuals may form intentions to behave in ways that are irrational or unreasonable (Gibbons et.al, 1998; Armitage et.al, 2001).

In addition, Rivis et.al, (2009) argue that the TPB appears to perform less well in the prediction of behaviours that are assumed to have a strong affective or irrational component and, therefore, non-rational and emotional aspects of behaviour also need to be taken into account in order to better predict and explain social decision-making and behaviour. Second, the operationalisation of the theory is becoming complicated as cannot measure PBC directly, as opposed to recording control beliefs (Manstead and Parker, 1995). Eagly and Chaiken (1993) mention that the assumption of a causal link between PBC and intentions presumes that individuals decide to engage in behaviour because they feel they can achieve it.

However, Ajzen (1991) argues that TPB model is open to further elaboration if important proximal determinants are identified, stating that "the theory of planned behaviour, is, in principal, open to the inclusion of additional predictors if it can be shown that they capture a significant proportion of the variance in intention or behaviour after the theories' current variables have been taken into account".

Between these two theories, we employed theory of planned behaviour (TPB) due to several reasons. First, TPB is an extended version of TRA; this means the variables that tested in TRA are included in TPB framework. Second, new variable added in TPB framework, i.e. perceived behavioural control (PBC) is important to assess the ease of an individual to engage or to choose Islamic banks services in this case of this study and this variable is not available in TRA. Third, based on past studies, the application of using TPB in the context of Islamic finance and economics is still new and, therefore, using TPB as the theoretical framework for this study could expand the usage and relevant of the theory and, this will contribute toward the body of knowledge and relevant practitioners.

Methodology

Theoretical Framework

This study attempts to examine the behavioural intention of depositors to choose Islamic bank services. Based on the discussion in literature review, it was identified that attitude, subjective norm and perceived behavioural control are the main independent variables that influence the individual behavioural intention. Therefore, based on these factors the theoretical framework of this study has been developed, Figure 1.

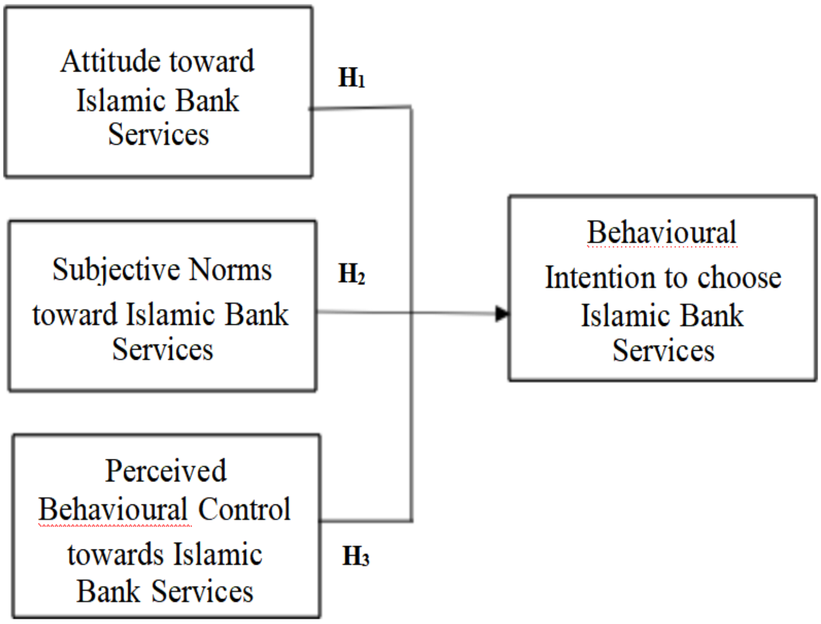

Figure 1: Theoretical Framework-Theory of Planned Behaviour

Hypotheses of the study

Based on the previous studies findings and TPB relationship explanations, we proposed the following hypotheses.

H1 : *There is apositive relationship between attitudes of individual and intention of individual to choose Islamic bank service.*

H2 : *There is a positive relationship between subjective norms of individual and intention of individual to choose Islamic bank service.*

H3 : *There is a positive relationship between perceived behavioural control of individual and intention of individual to choose Islamic bank service.*

Sample Size and Sampling Technique

This study investigate the factors that influence the intention of Islamic bank's depositor to choose Islamic bank service. The relevant respondent participated for this study is comprised of existing depositors of Islamic bank in Malaysia. The data that employed in this study are primary data obtained from survey conducted on Islamic bank's depositor. The questionnaire are collected through a direct survey using self-administered questionnaire and it is distributed using multistage sampling technique. Kalton (1983) argues that the use of this technique is justified by economies achieved in sampling and data collection. The sampling economies is considerable with area sampling, where the list from which elements are selected need to be compiled only in selected final-stage cluster such as city, state, or smaller segments. In this study, the sampling technique is started by cluster sampling in order to choose the states that the enumerator will go to distribute and collect the data. In this case, peninsular state in Malaysia that become the target place to distribute the questionnaire. Peninsular Malaysia is chosen because majority numbers of the Islamic bank branches are situated in peninsular Malaysia compare to Sabah and Sarawak. Since, there is no list of specific respondent, for the next step, the enumerator choose convenience sampling method to distribute the questionnaire direct to the Islamic Banks' depositor in a respected Islamic bank which are randomly choose by the enumerators. Sample size formula for large population used in this study is adapted from (Israel, 1992).

$$\mathbf{n_0 = z2pq / e2}$$

Where:

n0	Sample Size
z	Z-value of α (α in this study is 0.5)
p	variability (variability used in this study is 0.5)
q	1-p
e	Level of precision or sampling error (sampling error tolerated in this study is 5%)

Therefore, the sample size is equal to;

$$\mathbf{n_0 = z2pq / e2 \quad = (1.96)^2 (0.5) (0.5) / (0.05)^2}$$

$$\mathbf{= 385}$$

Thus, as many as 385 respondents collected and intended to be examined in this study. However, due to several technical and important issues such as incomplete information and time constraints, only 300 respondents are able to be tested in this study analysis.

Variable in the Analysis

There are 22 observed variables and 4 latent variables included in the analysis. The latent variables are intention to choose Islamic Bank services (BI), attitude (ATT), subjective norms (SN), and perceived behavioural control (PBC).

i. Behavioural intention or intention to behave (BI). The TPBposits that the most proximal predict for volitional behaviour is one's behaviour intention. There are 6 observed variables refers to BI, e.g. "Islamic Bank product offers flexible and fair treatment of profit/loss situation than conventional bank".

ii. Attitude towards behaviour (ATT). One of the latent variable in TPB that refers to attitude toward engaging in some volitional behaviour. There are 5 observed variables refers to ATT, e.g. "I am willing to use the products offered by Islamic bank rather than conventional bank".

iii. Subjective norms (SN). This latent variable is refers to social norms that perceived social pressure exerted on an individual either to act or not. It is also can be defined as whether important people around him think that behaviour should be performed. There are 6 observed variable refers to SN, e.g. "My parents encourage me to subscribe with Islamic bank products".

iv.Perceived behavioural control (PBC). PBC is additional variable extended from theory of reasoned action. This variable is refers to the level of simplicity of an individual to perform the behaviour. There are 5 observed variables refers to PBC, e.g. "I have high confidence on Islamic bank products".

Data Analysis Techniques

The following techniques are employed to analyse the data obtain through questionnaire survey.

Reliability Test

Reliability test measured the correlation between the scores on the test and hypothetical true value (Norusis, 2006, p.423). This study measured reliability by using Cronbach's alpha and this measurement established the internal consistency among the items in the questionnaire. A minimum score of 0.60 is required for reliability. Measurement of sampling adequacy is based from the result of Kaiser-Meyer-Olkin (KMO).

Structural Equation Modelling (SEM)

SEM is distinctive in its ability to examine a series of dependence relationships simultaneously. It is useful in testing theories which have multiple equations involving dependence relationships. This study used two-stage SEM approach, which involves confirmatory factor analysis (CFA) using measurement model and structural or path analysis of hypothesized relationships using structural model. Structure equation model (SEM) was employed to test the fitness of the theory of planned behaviour with the data that observed among the Islamic Banks' depositors in Malaysia. The use of this statistical tool become widely acceptable and tested in social science researches. This method allows the researchers to assess and modify the theoretical models which provide opportunities to explore new relationship development within the model of theory (Anderson & Gerbing, 1988).

The data was analysed by using SEM analysis. Data of frequencies and percentage were calculated for the demographic variables in order to understand the respondent background that tested in the study. SPSS version 20 was used to analyse the demographic variables. The hypothesized interrelationship among multiple independent and dependent variables were tested. Byrne (2001) and Hair et.al (2010) say that the SEM technique is the best analytical strategy to examine simultaneously multiple effects between independence and dependent variables. SEM is an extension of multivariate regression model. The main differences between the regression models and SEM is that later provides coefficient that estimate the statistical significance and magnitude of the structural relationship between theoretical constructs (Mayhem et.al, 2009). Variables that tested using SEM may influence one another reciprocally, directly or through other variables that stand as intermediaries. SEM is meant to represent causal relationship among variables (Fox, 2002). This study used structural equation modelling software by using AMOS 20.0.

Table 1 shows the model fit measurement and its cut-offvalue. The cut-off value acceptance is suggested by.

Table 1 : Model Fit Indices and It Cut-Off Value

	Name of Index	Level of Acceptance	Literature
1. Absolute Fit	RMSEA*	Range 0.05 to 0.1	Browne and Cudeck (1993)
2. Incremental Fit	CFI**	More than 0.90	Bentler (1990)
3. Parsimonious Fit	Normed $\chi 2$	Less than 5.0	Marsh and Hocevar (1985)

*RMSEA is refers to Root Mean Square of Error Approximation.

**CFI is refers to Comparative Fit Index.

Normed χ^2 is refers to Chi Square/ Degrees of Freedom

Result and Discussion

Reliability Analysis & Sampling Adequacy

Cronbach's Alpha was used to test the reliability of the research instruments. Nunnelly (1978) noted that the cronbach's alpha value should ne greater than the minimum standard of 0.7. Table 2 shows the reliability result for each latest variables tested in this study. The result indicates good estimates of internal consistency reliability as the values are range between 0.899 to 0.915.

Table 2: Reliability Result

Latent Variables	Number of observes variables	Cronbach's Alpha
Behavioural Intention (BI)	6	0.915
Attitude (ATT)	5	0.901
Subjective Norms (SN)	6	0.918
Perceived Behavioural Control (PBC)	5	0.899

The sampling adequacy analysis is measured using Kaiser-Mayor-Olkin (KMO) and Bartlett's Test of Sphericity. Following Table 3 shows the result generated for the study.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.932
Bartlett's Test of Sphericity	Approx. Chi-Square	6942.332
	df	630
	Sig.	.000

Table 3 : KMO and Bartlett's Test

The result shows that the KMO is 0.932 and Bartlett's Test of sphericity is significant (χ^2 =6942.332, p-value <0.01). Kaiser and Rice (1974) suggest that if the KMO result exceed 0.9, it means that the sample size adequacy tested is considered good. Hence, the sample size for the study is good.

Structural Equation Model

Confirmatory Factor Analysis (CFA)

There are 2 main stages that required before we established the SEM analysis; 1) confirmatory factor analysis (CFA) and; 2) path analysis. In the first stage, we need to establish the fitness of the baseline model (or also called as measurement model) before we proceed with the path analysis. The main aims ofthe first stage is to confirm the overall theoretical framework which is related to the tested observe variables with the latent variables. Following Table 4 shows the model fit result of the baseline model. Based on the results show the 3 indexes measured on the baseline model are fit and achieved the cut-off criteria and, hence, this result confirmed that the observed and latent variables in this study are fit for further path analysis stage. Furthermore, this result also confirmed that Islamic bank depositors' choosing behaviour can be approach using theory of planned behaviour framework.

Table 4: Result of Fitness for Measurement Model

	Index	Result	Comments	Literature
1. Absolute Fit	RMSEA*	0.079	Acceptable	Browne and Cudeck (1993)
2. Incremental Fit	CFI**	0.929	Acceptable	Bentler (1990)
3. Parsimonious Fit	Normed $\chi2$	2.851	Acceptable	Marsh and Hocevar (1985)

*RMSEA is refers to Root Mean Square of Error Approximation.

**CFI is refers to Comparative Fit Index.

Normed χ^2 is refers to Chi Square/ Degrees of Freedom

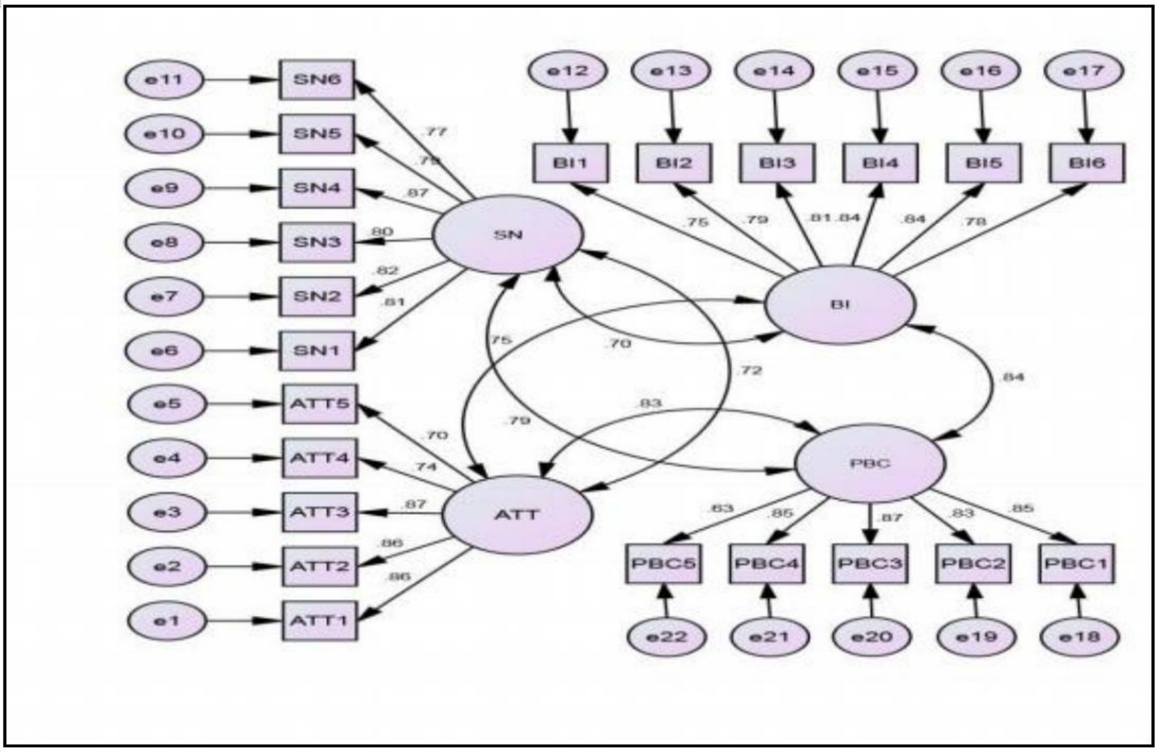

Figure 2: Baseline Model (MM1)

Figure 2 above shows the output of baseline model generated from AMOS 20.0. Besides the above fitness requirement (Table 4), there is another 2 assessments that required to fulfil such as unidimensionality and validity test. First, unidimensionality assessment is to measure the significant acceptance of observe variables with its latent variable. The means every each observe variable must be meaningful with the latent variable and this is measure using the value of factor loading with minimum of 0.5 and above (Byrne, 2001). Thus, the rules of thumb indicate that any factor loading with below 0.5 should be deleted and we need to run again the new baseline model (Byrne, 2001). Table 5 shows the result of tested observe variables which are above 0.5 and this mean the tested observes variable are meaningful to the latent variables. Therefore, the unidimensionality assessment is established.

Table 5: Factor Loadings

Latent Variable	Observe Variables	Factor Loadings
Behavioural Intention (BI)	BI 1	0.75
	BI 2	0.79
	BI 3	0.81
	BI 4	0.83
	BI 5	0.83
	BI 6	0.78
Attitude (ATT)	ATT 1	0.86
	ATT 2	085
	ATT 3	0.86
	ATT 4	0.74
	ATT 5	0.70
Subjective Norms (SN)	SN 1	0.81
	SN 2	0.82
	SN 3	0.79
	SN 4	0.87
	SN 5	0.78
	SN 6	0.76
Perceived Behavioural Control (PBC)	PBC 1	0.85
	PBC 2	0.83
	PBC 3	0.87
	PBC 4	0.84
	PBC 5	0.63

Second assessment is refers to convergent validity which this assessment indicates convergence or share of proportion of variance in common among indicators of a construct. In this regard, factor loading, average variance extracted (AVE) and reliability analysis are used as a measurement. Previous result in Table 2 and 5 have confirmed the criteria for reliability test and factor loading are achieved. Next is the average variance of the items that are explained by the construct on which they are loaded (Byrne, 2001). AVE value of 0.50 and above is considered acceptable. The result of AVE also confirmed that the latest variables examined in this study are fulfilled. The acceptance criteria for AVE is >0.5 and the AVE result for this study is shows in the following Table 6.

Table 6: Average Variance Extracted

	Behavioural Intention (BI)	Attitude (ATT)	Subjective Norms (SN)	Perceived Behavioural Control (PBC)
AVE	0.645	0.654	0.656	0.660

Structural Model (SM)

After the establishment of TPB model's goodness-of-fit, the study proceeds to interpret the parameters estimated using SEM analysis. Table 7 shows the goodness-of-fit result for structural model. The result is similar to measurement model goodness-of-fit. Hence, this allows interpreting the path analysis result which is also generated from the structural model stage. Path coefficients are used to measure the hypothesised relationship between dependent and independent variables. In this study, we have developed 3 hypotheses and the path coefficients results for all relationship are given in Table 8 and Figure 3 shows the structural model output generated from AMOS 20.0.

Table 7: Result of Fitness for Structural Model

	Index	Result	Comments	Literature
1. Absolute Fit	RMSEA*	0.079	Acceptable	Browne and Cudeck (1993)
2. Incremental Fit	CFI**	0.929	Acceptable	Bentler (1990)
3. Parsimonious Fit	Normed $\chi2$	2.851	Acceptable	Marsh and Hocevar (1985)

*RMSEA is refers to Root Mean Square of Error Approximation.

**CFI is refers to Comparative Fit Index.

Normed χ^2 is refers to Chi Square/ Degrees of Freedom.

Table 8: Relationship Model among Variables

Hypotheses	Critical Ratio (C.R.)	P-Value	Decision
i. H1 ATT → BI	5.473	<0.001	Significant
ii. H2 SN → BI	3.613	<0.001	Significant
iii. H3 PBC → BI	10.128	<0.001	Significant

Table 8 above shows the path coefficients results for every tested relationship are found significant. Hence, these path results confirmed that the three objectives examined in the study are achieved. The first hypothesis of the study is between attitude and intention of the depositors' to choose Islamic bank services. We found that attitude of individual is an important factor that influence the behavioural intention of depositors to choose Islamic bank services. The second hypothesis is between subjective norms and behavioural intention of depositors to choose Islamic bank services and this relationship is also significant. Finally, the third hypothesis is between perceived behavioural control and behavioural intention of depositors to choose Islamic bank services and we also found significant. Therefore, based on these results, it is implies that factors within an individual such as attitude and perceived behavioural control and, factor surrounding an individual such as subjective norms are important to influence individual particularly depositors to choose their banking service.

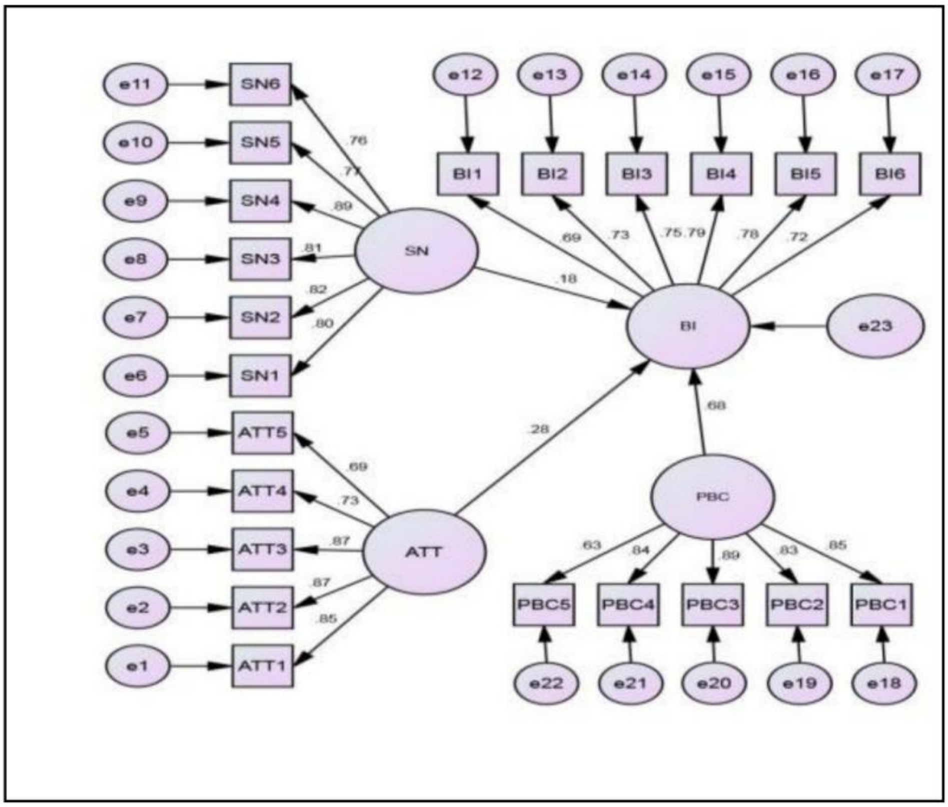

Figure 3 : Structural Model

Conclusion

The current study aimed to explore the factors influence the behavioural intention of Islamic bank depositors to choose Islamic bank services. In order to identify the relevant factors, we employs theory of planned behaviour (TPB) to examined the behavioural intention of depositors. Based on the result indicates that this TPB is relevant and the factors tested such as attitude, subjective norms and perceived behavioural control have significant influnce on the behavioural intention of depositors to choose Islamic bank services. Based on this result, it is suggested that Islamic bank operators should focus on these three factors in order to attract new customers who are looking for banking services. Educating the society on “Why Islamic Bank?” and the benefit of Islamic bank services which can enhance more new depositors to choose Islamic bank services. This can be done through awarenss campaign about the types of products offered by Islamic banks, the values of Islamic banking system compare to conventional banking system and etc. Furthermore, this result also can assist the Islamic banks operator to sustain their existing customer by focuses on these 3 aspects. Various steps can be taken by the Islamic bank operators, such as continous learning process about Islamic banks products and motivating the existing customer to sustain with the Islamic banks services using appropriate tools of marketing. Besides the above implications for the practitioners, the findings of the study have significant implications for the body of knowledge. In fact, this study shows that the theory of planned behaviour (TPB) has expanded into different area of study which is Islamic bank services, particulary focus on behavioural intention Islamic bank depositors' to choose Islamic banks services.

Future researchers are recommended to examine the determinants influencing the behavioural intention of depositors to choose Islamic bank services in other countries. Meanwhile, future research can examine using other techniques of analysis and theories that measure behavioural intention of individuals.

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Influence Leadership in Human Resource Management on Employee Motivation and Satisfaction

Mohd Anuar Arshad*
Universiti Sains Malaysia, Malaysia
Email: anuar_arshad@usm.my

Nur Syuhada binti Abdul Kadir, Kisnita A/P Charm Nan, Hafizatul Najwa binti Mohamed Johari, Nurhanisah binti Md Hanafiah, Dania Batrisha binti Yusri
Universiti Sains Malaysia, Malaysia

**Corresponding Author*

Abstract

This research paper was written to identify the relationship between influence of leadership in human resource management on employee motivation and satisfaction. To make this research paper complete in flying colors, the researcher has used one of the research methods which is through the qualitative research method by collecting secondary data sourced from existing journal articles rather than using primary data. Through the study that has been conducted, it has been found that leadership in human resource management significantly showed satisfactory results on employee motivation and satisfaction. In addition, there are also studies that take employee motivation as a mediator between leadership in human resource and have been found that the result showed a positive effect towards employee satisfaction. Through these findings collected, it can be concluded that leadership in an organization can influence employee motivation and satisfaction in many terms such as performance and behavior.

Keywords: leadership in human resource management, employee motivation and satisfaction.

Introduction

Leadership in Human Resource Management (HRM) functions to guide and inspire employees on achieving organizational goals. It is not just overseeing tasks, but it is about producing a supportive environment in which can help employees to contribute their best in terms of employee well-being. Despite directly overarching goals and driving sustainable success, leadership in HRM also plays a vital role in all organization's management which is important to ensure the motivation and satisfaction among employees align with the organizational goals. Hence, leadership styles like transformational and participative have been expertised broadly which offered a significant impact on morale, commitment and productivity.

Based on the study, leadership style plays as the main factors that can help businesses to overcome hardness as long as the style is appropriate for the qualifications. So, HRM needs to know that leadership style is varied and know how the effectiveness can lead an organisation to handle in practice. As past studies have shown the effect of transformational leadership in carrying employee satisfaction and employee motivation in some industries. That's why understanding how leadership within the HR function can drive motivation and job satisfaction is therefore essential for enhancing employee performance and organizational success.

Problem Statement

Previous studies have shown many types of leadership styles in HRM that can be used in organisation. However, there is still a gap in understanding the function of leadership in HRM, especially in influencing employee motivation and satisfaction. Therefore, through this study, we will look in more detail on how leadership in HRM can give impact and influence employee motivation and satisfaction in an organization.

Research Objectives

- To identify the relationship between leadership and employee motivation in HRM.
- To identify the relationship between leadership and employee satisfaction in HRM.
- To identify the influence of leadership in HRM between employee motivation and satisfaction.

Significance of the study

The study already set clear interests from various angles especially in terms of practicality in the organization. Practically, this research helps to provide awareness to organizations under human resource in the effectiveness of leadership on employee motivation and satisfaction. As a result, this research is able to expand knowledge about the complex relationship that exists in the context of higher education between transformational leadership, employee job satisfaction, and work motivation. Through this study, every organization needs to continue to strive to create an atmosphere that supports organizational success and employee well-being while dealing with the complexity of organizational leadership. Finally, this research is conducted as a support within the organization while at the same time being able to build a more committed, productive and satisfied workforce through strategic leadership in HRM.

Theoretical Framework

This theoretical framework aims to explore how leadership within the field of human resource management (HRM) influences employee motivation and satisfaction. There are several theories that are relevant to this relationship. The framework will be developed by looking at the leadership theories, motivation theories, and job satisfaction models. All of these theories will provide conceptual grounding for understanding how leadership can drive positive employee outcomes. This framework is based on three main theories which is Transformational Leadership Theory, Herzberg's Two-Factor Theory of Motivation, and the Job Characteristics Model.

Transformational Leadership Theory

According to Burns, transformational leadership is a leadership approach that elevates followers' attitudes, beliefs, and behaviors, motivating them to exceed their current performance and achievement levels through the inspiration provided by the leader (Anderson, 2017). Over the past three decades, it has remained a central focus in leadership studies, recognized for its potential to engage followers in ways that broaden and enhance their interests (Kotamena, Senjaya, & Prasetya, 2020; Ladkin & Bridges Patrick, 2022). This leadership style is acknowledged as a leadership style that heightens organizational members' awareness of the importance of working toward shared goals (Kotamena, Senjaya, and Prasetya, 2020). Transformational leadership has been shown to positively influence a variety of important outcomes beyond just performance (Deng, Gulseren, Isola, Grocutt, & Turner, 2022). These include organizational citizenship behaviors, extra effort, employee engagement, trust in the manager, stronger leader- member exchange relationships (Hoch et al., 2018), psychological empowerment, identification with the leader (Koh, Lee, and Joshi, 2019), follower motivation (Judge and Piccolo, 2004), and many other factors that benefit both employees and the organization (Deng, Gulseren, Isola, Grocutt, & Turner, 2022). Anderson (2022) also stated that in business organizations, transformational leadership has been shown to positively impact employee job performance, commitment, and satisfaction.

Bernard Bass explains that transformational leaders demonstrate four key behaviors in their daily interactions with staff or subordinates: idealized influence, inspirational motivation, intellectual stimulation and individualized consideration (Anderson, 2022).

Firstly, idealized influence involves leaders embodying a strong commitment to the vision and mission while inspiring others by providing a clear sense of purpose (Anderson, 2022). Employees will likely build greater trust and commitment when leaders act with integrity and uphold ethical standards. Secondly, inspirational motivation refers to the leader's ability to craft an attractive vision that followers are eager to pursue, while simultaneously setting high expectations, maintaining optimism, and establishing goals that inspire followers (Ladkin & Bridges Patrick, 2022). Leaders can enhance employees' sense of purpose and intrinsic motivation by clearly communicating organizational goals and connecting them to individual roles. Next, intellectual stimulation is the leader's capacity to challenge existing assumptions, encourage open disagreement, and motivate followers to explore their curiosity (Ladkin & Bridges Patrick, 2022). When employees are encouraged to think independently and participate in decision-making, their engagement and personal growth are significantly enhanced. Last but not least, individualized consideration means that leaders provide coaching, mentoring, and feedback tailored to the specific needs of each individual (Anderson,2022). Providing personalized support helps employees feel appreciated and deepens their emotional bond with the organization, leading to higher overall satisfaction.

Herzberg's Two-Factor Theory of Motivation

Many theoretical frameworks explore job satisfaction through the context of motivation (Kian et al., 2014; Alrawahi, Sellgren, Alwahaibi, Altouby, and Brommels, 2020). Alrawahi, Sellgren, Alwahaibi, Altouby, and Brommels (2020) stated that Herzberg's theory has served as a tool for examining employee job satisfaction (Lundberg et al., 2009). Abdulkhamidova (2021) cited that Hertzberg's two-factor theory explains that individual employees have two categories of needs which are the motivators and hygiene factors (Ibrahim et al., 2023). These two categories of factors can eventually influence employee attitudes and behaviors in a different way. Motivators are intrinsic elements that can help to enhance job satisfaction and drive motivation, meanwhile hygiene factors are extrinsic and can help to avoid dissatisfaction, even though they do not inherently boost motivation.

According to Alshmemri, Shahwan-Akl, & Maude (2017) Herzberg's theory states that motivation factors, or motivators, are inherent to the job itself and foster positive job attitudes by fulfilling the'need for growth or self-actualisation' (Herzberg, 1966). Bhatt, Chitranshi, & Mehta (2022) stated that effective motivators will lead to high levels of satisfaction by addressing employees' psychological needs and impacting them on an intrinsic level. There are several motivational factors including recognition, growth opportunities, authority and the work itself. First and foremost, positive recognition occurs when employees are rewarded or praised for achieving specific goals or delivering some high-quality work (Alshmemri, Shahwan-Akl, & Maude, 2017). Furthermore, growth opportunities refer to promotions and development opportunities that an organization can offer to its employees (Bhatt, Chitranshi, & Mehta, 2022). Next, authority can refer to the extent of decision-making, which the employee can make (Bhatt, Chitranshi, & Mehta, 2022). Lastly, the nature of job tasks and assignments can significantly influence employees whether in a positive or negative way. Factors such as whether the work is too simple or too challenging, engaging or boring, can affect employee overall job satisfaction or dissatisfaction (Alshmemri, Shahwan-Akl, & Maude, 2017).

On the contrary, hygiene factors are influenced by the external aspects of an employee's job environment (Bevins, 2018). There are several hygiene factors including salary, company policies and administration, working conditions and interpersonal relations. Salary refers to various forms of workplace compensation, including wage or salary increases, as well as unfulfilled expectations regarding pay raises or reductions (Alshmemri, Shahwan-Akl, & Maude, 2017). Company policies and administration involves the presence of clear or unclear company organization and management policies and guidelines, which can positively or negatively impact the employee (Alshmemri, Shahwan-Akl, & Maude, 2017). Next, working conditons relate to the physical work environment and the quality of available facilities. Working conditions may include elements such as workload, workspace, ventilation, equipment, temperature, and safety. A positive environment compared to a poor one will contribute to employee satisfaction (Alshmemri, Shahwan-Akl, & Maude, 2017). Last but not least, interpersonal relations refer to relationships with supervisors, peers, and subordinates. Any conflict within these workplace relationships can lead to stress (Bhatt, Chitranshi, & Mehta, 2022).

In short, Herzberg's theory emphasizes that leaders need to effectively manage both motivators and hygiene factors to ensure a satisfied and productive workforce. Therefore, this requires HRM strategies that will not only just minimize dissatisfaction but also actively promote motivation through intrinsic rewards.

Job Characteristics Model of Job Satisfaction

According to Hackman and Oldham (1976), the Job Characteristics Theory proposes that core dimensions of a job significantly influence employees' work outcomes (Guo, Peng, & Zhu, 2022). This theory, which explains the impact of job enrichment and job expansion initiatives, is one of the foundational frameworks in organizational psychology addressing both motivation and job satisfaction (Meriç & Erdem, 2020). When tasks are repetitive and monotonous, employees have limited opportunities to develop a wide range of skills, which can lead to dissatisfaction (Kamani, 2020). In contrast, employees engaged in job rotation where they perform different tasks are more likely to experience increased happiness and satisfaction compared to those assigned to the same routine work daily (Syukrina Alini Mat Ali, 2014; Kamani, 2020).

A job in general has five basic characteristics which are skill variety, task identity, task significance, autonomy and feedback according to the job characteristics theory (Hackman & Oldham, 1975; 1976; Meriç & Erdem, 2020). The first characteristic, skill variety, refers to the degree to which a job encompasses a variety of tasks that require the employee to apply a range of skills and competencies (J. Richard Hackman, 1976; Kamani, 2020). Engaging in varied tasks, along with increased independence and responsibility, can significantly enhance an individual's inner motivation (Kamani,2020). The second characteristic which is task identity refers to the extent to which a job involves completing a whole and identifiable piece of work (Brian T. Loher, 1985; Kamani, 2020). Kamani (2020) stated that finishing an entire process tends to be more fulfilling than handling only a small portion, as it allows the worker to feel a sense of pride in the final result. The third characteristic which is task significance refers to the extent to which a job impacts the lives of others (Meriç & Erdem, 2020). Meriç & Erdem (2020) stated that when an employee believes their work has meaningful effects on others, the perceived importance of the job increases.

Next, the fourth characteristic which is autonomy refers to the degree of freedom employees have to set their own work rules and carry out their tasks independently without instruction from others (Meriç & Erdem, 2020). Autonomy helps foster a sense of responsibility within the employee (Meriç & Erdem, 2020). Lastly, feedback refers to the extent to which employees receive clear and direct information about the outcomes of their work (Meriç & Erdem, 2020). Regular feedback supports learning and improvement, reinforcing satisfaction. The feedback of an employee's performance can positively influence an employee's future work (Kamani,2020). In summary, Hackman and Oldham's Job Characteristics Theory offers a comprehensive framework for understanding specific job dimensions which is skill variety, task identity, task significance, autonomy, and feedback. These things play a vital role in shaping employee motivation and satisfaction.

Conceptual Integration

The combination of Transformational Leadership Theory, Herzberg's Two-Factor Theory, and the Job Characteristics Model provide a comprehensive understanding of how leadership in HRM affects employee motivation and satisfaction. Transformational leaders inspire and support their employees. This thing matches well with the internal motivators in Herzberg's theory. In addition, how leaders design jobs and communicate with workers affects key parts of a job, as explained by Hackman and Oldham, which leads to higher job satisfaction and engagement.

In this framework, leadership plays a big role in shaping HRM practices. These practices then will affect employee motivation and satisfaction. For example, a transformational leader might create a program to recognize good work (a motivator), make sure pay is fair (a hygiene factor), and design jobs that give employees freedom and feedback (job characteristics). All of these can help employees feel more motivated and happier at work. This combined idea shows how good leadership in HRM can lead to better outcomes for employees.

Conclusion

In conclusion, this study's theoretical framework uses three well-known theories in order to understand how leadership in HRM affects employee motivation and satisfaction. Transformational Leadership Theory provides insight about how leaders can inspire and develop employees. Herzberg's Two-Factor Theory explains what motivates employees and what workplace conditions affect their behavior. The Job Characteristics Model illustrates how the job design can impact satisfaction and engagement. Hence, these three theories work together to give a clear and comprehensive understanding of how leadership in HRM can shape employee attitudes and behaviors that will eventually help the organization to reach its goals.

Methodology

The purpose of this study is to examine the influence of leadership in human resource management on employee motivation and satisfaction. To conduct this study successfully, the researchers employed a qualitative research approach by utilizing secondary data sourced obtained from existing journal articles rather than collecting primary data.

A comprehensive search was conducted across reputable academic platforms such as Google Scholar and JSTOR by using keywords such as leadership style, motivation, employee performance, and job satisfaction. The study was limited to journal articles published between 2010 to 2025 to ensure that the analysis reflects contemporary trends and research developments. This ensures that the findings are grounded in existing academic knowledge and aligned with the objectives of the research.

The inclusion criteria for article selection required that each article must focus on leadership within a human resource context and must examine outcomes related specifically to employee motivation and satisfaction. Only articles that directly addressed these elements were considered for review. The selected articles were slightly focused on recurring concepts such as leadership styles, human resource management or strategies, and motivational theories.

Thematic content analysis was used to analyse the selected articles to identify and interpret recurring patterns or themes related to the influence of leadership on employee motivation and satisfaction. This analytic approach enables the researchers to receive a deep understanding from diverse studies and organize them into coherent thematic categories. As a result, the study developed a clearer understanding of how various leadership styles in human resource management contribute to employee outcomes, offering valuable insights into the dynamic relationship between leadership practices and employee motivation and satisfaction within organizational settings.

Discussion

Transformational Leadership Theory

Transformational leadership theory is a leadership approach that focuses on how leaders can inspire and motivate followers or employees to exceed their own self-interest for the sake of the organization and to achieve higher levels of performance and personal growth (Bernard M. Bass, 1980). This leadership style strongly contributed to higher levels of employee motivation and satisfaction. In research conducted by Tracey and Hinkin, 1998, transformational leadership is a process that motivates employees by appealing to their higher ideals and moral values. It helps in shaping organizational culture, guiding employees' behaviors, and influencing employees' satisfaction. They can inspire and motivate followers or other subordinates whether in the same or different positions in organization setting to strive for organizational goals, fostering a sense of shared vision and purpose.

Effective communication in transformational leadership style

One of the core ways transformational leadership influences employees' motivation and satisfaction is through their effective communication. Transformational leadership always communicates a clear and compelling vision for the future. When leaders articulate to followers with attractive but achievable visions of the future, followers become clear about their vision and they can see how their work contributes to something meaningful. This clear vision also helps them to understand how their daily tasks contribute to broader organizational goals. With this effort, followers feel their work is meaningful, purposeful, goal-oriented, and connected to a larger mission, which directly supports their intrinsic motivation. As a result, the alignment between a leader's vision and employees' role helps followers to foster their sense of value and significance which can increase their self-confidence and engagement (Dubinsky et al, 1995), as employees feel both empowered and inspired in their job.

Individual recognition and trust in transformational leadership

Besides, transformational leadership also influences employees' motivation and satisfaction as it is strongly related to individual recognition and trust or often described as individualised consideration. It refers to the leader's awareness and appreciation for followers' uniqueness as well as their needs and consideration (Kathrin Rothfelder, Michael C Ottenbacher et al, 2012). Individual consideration occurs when leaders show they care about their employees, and thus, that they can be trusted (Bass, 1985; Hugo Asencio and Edin Mujkic, 2016). In this case, leaders will genuinely treat employees as unique individuals with their own strengths, not merely as subordinates or workers. This shows that the leaders are genuinely care about employees' well-being which leads employees to feel more emotionally connected to their work and organization. Moreover, this personalized attention where the leaders communicate respect and appreciation through their employees will make employees feel valued, appreciated, and respected.

Additionally, the authorities in decision-making provided by leaders to employees can explain the amount of trust leaders have in them. Once the employees feel trusted, their intrinsic motivation will increase as they become driven by a sense of purpose and belonging rather than working solely for rewards. In turn, this kind of feeling could be their emotional support. Generally, employees with more trust in outcomes under the current decision-makers are likely to be satisfied with the organization as a whole (James W. Driscoll, 1978; Kath Junberg, 2017). As a result, they are more likely to feel emotionally connected to leaders who recognise and trust them which cultivates a supportive climate that directly translates into job satisfaction (Hugo Asencio, and Edin Mujkic, 2016). Employees become more enjoy with their work and display the highest discretionary behaviors such as they tend to be more committed, engaged, and feel comfortable with their workplace setting. In short, recognition and trust given by transformational leaders could influence employees' emotional support which can increase motivation and lead to both individual and organisation satisfaction.

Transformational leaders as role models

Transformational leadership also plays a crucial role as a mediator in the relationship between traits and effectiveness (Jakub Prochazka, Martin Vaculik, 2018). The traits mentioned above are also known as "OCEAN" contained with openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Transformational leaders often score higher in OCEAN compared to other leadership styles. Leaders with transformational leadership skills are strongly associated with positive behaviors such as charismatic role modeling (Bass 1985; Sebastian C. Schuh and Peng Tian 2013). They influence their followers by role modeling or "walking the talk" rather than convincing communication. They often use enthusiasm and optimism to motivate followers to strive toward the shared goals. These traits explain that leaders are always working hard to achieve goals and high in responsibilities, self-disciplined. They will keep deadlines and promises as they have a clear vision of their future. They furthermore sacrifice their personal needs for the benefit of the group or organisation (Kathrin Rothfelder, Mishael C Ottenbacher et al, 2012). These positive behaviors have a powerful impact on employees as they will increase employees' attraction, respect, and admiration towards the leaders (Yussen and Levy, 1975; Michael E. Brown and Linda K. Trevino, 2014) and view them as their role models.

Generally, individuals tend to translate their respect towards their role model into their intrinsic and extrinsic motivation (Robert J. Vallerand, 2000) which can enhance followers' spirit. To illustrate, when employees feel that their leaders genuinely inspire them and serve as authentic role models, they are more likely to see their workplace as meaningful and they try to be part of something greater. This sense of inspiration fosters personal and professional growth as employees feel that they are growing greater which enhances their positive emotions toward their job. In turn, they become more committed which reports higher levels of job fulfillment, and more likely to embrace and work toward the organisation's vision.

Herzberg's Two-Factor Theory

Influence of leadership on motivators

Leadership styles play a vital role in ensuring employees' motivation. Motivators here include aspects such as recognition, achievement appraisal as well as advancement. According to multiple studies, leaders who empower their employees', recognize their contributions can create a positive working environment where employees feel valued and motivated.

To illustrate, Bass (1985) emphasizes that transformational leaders can foster intrinsic motivation by aligning employees' goals with organization's goals. Moreover, according to Deci and Ryan's Self-Determination theory, Herzberg's theory indicates that employees' internal motivation will increase if they are often given autonomy and meaningful tasks which makes them feel valued. On the other hand, employees that feel valued are more likely to increase their job satisfaction. In detail, human resource practices highlight the importance of leaders who coach, mentor, and provide opportunities for career advancement as a means to increase job satisfaction.

Influence of leadership on hygiene factors

Hygiene factors include salary, company policies, supervision, as well as interpersonal relations and working conditions. These factors particularly do not inherently motivate employees when present, but may cause employees' dissatisfaction when absent. Leadership styles play a critical role in managing and improving these factors to maintain a stable and satisfied workforce.

These hygiene factors can be enhanced by leaders' behaviors such as leaders ensure fair treatment among employees, apply open communication, and create a supportive work environment. Leaders who are responsive to employees' concern, provide transparent or clear communication, and resolve conflicts efficiently can help in minimizing employees' dissatisfaction.

Studies indicate that transactional leadership is the most accurate leadership style that drives the hygiene factor successfully. This is because transactional leaders always emphasize structure, rules, and rewards and ensuring that employees' basic needs are met which is effective in managing hygiene factors. Moreover, employees' satisfaction can also increase when they achieve recognition from leaders, creating a more stable and productive work environment.

Job Characteristics Model

The Job Characteristics Model (JCM) offers a valuable framework for understanding how leadership within Human Resource Management (HRM) influences employee motivation and satisfaction. According to the JCM, the design of jobs significantly affects employees' psychological states, which in turn impact their motivation and satisfaction (Fried & Ferris, 2014). HR leaders who apply this model strategically move beyond routine administrative roles and instead create work environments that fulfill employees' intrinsic psychological needs, leading to enhanced engagement and well-being (Bakker & Demerouti, 2017).

Aligning Work Design with Intrinsic Motivation

One of the fundamental insights of the JCM is its emphasis on intrinsic motivation, which arises when employees perceive their work as meaningful and have autonomy and feedback regarding their tasks (Morgeson & Humphrey, 2020). According to the model, having skill variety, task identity, task significance, autonomy and feedback in a job brings about essential psychological states that encourage self-motivation (Deci et al., 2017).

HR leaders play a pivotal role in embedding these characteristics into job roles. By redesigning jobs to increase autonomy or broaden the range of skills used, HR leadership helps employees feel a stronger connection and responsibility toward their work (Kim & Beehr, 2020). There is evidence for this: autonomy in particular has repeatedly been related to better creativity, commitment and motivation in people (Deci et al., 2017; Fried & Ferris, 2014). So, when HR leaders focus on creating meaningful work, they boost motivation that does not require much in the way of external motivators.

Enhancing Job Satisfaction through Strategic HR Practices

Apart from motivation, the Job Characteristics Model also points out that well-structured jobs raise the level of satisfaction in work, making employees generally more satisfied with their jobs and roles (Parker et al., 2019). Satisfaction increases when employees clearly understand their job responsibilities and how their contributions affect organizational outcomes (Van Wingerden et al., 2017).

Effective HR leadership fosters job satisfaction through strategic practices such as regular feedback, recognition, and transparent communication (Kim & Beehr, 2020). These initiatives ensure employees feel valued and perceive their roles as meaningful. Research confirms that such HR policies are closely aligned with the psychological needs outlined in the JCM and lead to higher levels of employee satisfaction and engagement (Van Wingerden et al., 2017). Therefore, HR leaders who emphasize these strategies create a positive work environment that supports employee contentment.

Integration of Theories: A Holistic View of Leadership in HRM

While each theory in this research which is Transformational Leadership, Herzberg's Two-Factor Theory, and the Job Characteristics Model always offers valuable insights on its own, their combined application reveals a more holistic and actionable framework for enhancing employee motivation and satisfaction in HRM.

Bridging Intrinsic and Extrinsic Motivation in HRM Leadership

An integrated HRM leadership approach that blends the Job Characteristics Model (JCM), Transformational Leadership Theory, and Herzberg's Two-Factor Theory provides a balanced strategy to mee employees' intrinsic and extrinsic motivational needs. Intrinsically, the JCM highlights the importance of autonomy, skill variety, task identity, and feedback in making jobs psychologically meaningful and engaging. When job roles are put together with these qualities, staff experience more purpose and responsibility which boosts their motivation. It also works by encouraging employees through united vision, personal recognition and mental challenges which supports the internal motivating forces.

However, intrinsic motivators alone cannot guarantee job satisfaction or commitment if basic extrinsic conditions are not met. Herzberg's Two-Factor Theory distinguishes between motivators (intrinsic) and hygiene factors (extrinsic), the latter of which include pay, job security, company policy, and working conditions. Proper hygiene measures do not necessarily motivate people, but not having them can result in great disappointment. In this regard, HRM leaders are responsible for ensuring equal compensation, clear policies and friendly conditions at the workplace. Eliminating discontent by paying attention to hygiene and raising employees' job satisfaction can help them have better careers at work.

As a result, HR leaders are able to motivate employees and ensure the company has a long-lasting foundation. Managers who mix job design, transformational habits and basic essentials make sure that workers are both inspired and remain secure and valued. Because of alignment, people remain involved at work, feel dedicated to the company and shape a positive culture. Research by Breevaart et al. (2014) supports this integration, emphasizing that leadership and job characteristics jointly predict employee motivation and performance. Ultimately, bridging intrinsic and extrinsic motivation through integrated HRM leadership enables organizations to cultivate a workforce that is both high-performing and deeply satisfied.

Enhancing Employee Engagement and Retention through Integrated Leadership

Employee engagement and retention are central goals of strategic HRM, and they are best achieved when leadership practices are aligned with comprehensive motivational frameworks. The integration of JCM, Transformational Leadership, and Herzberg's theory offers a multidimensional approach to enhancing engagement. By designing jobs that are meaningful, varied, and autonomous, HR leaders can stimulate employees' internal motivation and promote deep work involvement. Transformational leaders amplify this by building emotional commitment and fostering trust, encouraging employees to go beyond mere compliance to become invested contributors to organizational goals.

Retention, meanwhile, is closely linked to employees' overall satisfaction with both their work and workplace conditions. Herzberg's hygiene factors play a crucial role here, as issues such as inadequate pay, unclear job roles, or poor management practices often contribute to voluntary turnover. Leaders who proactively address these external factors while simultaneously enriching jobs and empowering employees are more likely to retain top talent. In this way, the integrated approach not only enhances daily engagement but also reduces the likelihood of burnout and dissatisfaction, leading to stronger organizational loyalty.

Furthermore, this integrated model contributes to organizational citizenship behaviors (OCBs), where employees voluntarily contribute to the well-being of their team and the organization beyond formal job duties. Wang et al. (2021) emphasize that when employees feel both intrinsically motivated and extrinsically supported, they are more likely to exhibit these behaviors. By doing this, the work environment improves, teamwork gets better and the company succeeds in the long run. Therefore, through the strategic integration of these three theories, HR leaders can enhance not just individual satisfaction and motivation, but also broader organizational outcomes such as engagement, retention, and cultural cohesion.

Implication

Practical Implications

a. Reinforcing the Interdisciplinary Role of Leadership Theories in HRM
It proves that HRM is closely connected to leadership theory. The study shows that successful HR practices rely on the understanding of transformational leadership, motivation and job design ideas. More research and study should be conducted in these mixed areas of study, mostly in areas like technology or healthcare that are quickly changing.

b. Embedding Dual-Focus Motivation Strategies in HR Practices
According to Herzberg, job satisfaction comes from both intrinsic elements as well as extrinsic hygiene factors. So, HR policies ought to make sure that employees are rewarded fairly, their safety is protected and they have chances to grow within the company. Firms that apply dual strategies are giving their staff a mix of bonuses, career help, and competitive ends and this led to higher retention and a keen sense of motivation, according to Bhatt et al. (2022).

c. Designing Meaningful Jobs, Not Just Tasks
Implementing changes following the Job Characteristics Model can do a lot to increase job satisfaction. High psychological engagement and interest in their work come from jobs providing autonomy, lots of types of tasks and significance (Guo et al., 2022; Meriç & Erdem, 2020). Companies have to return to how jobs are made and reconstruct them so that workers receive feedback and a chance to be involved in their work.

d. Aligning Organizational Policies With Employee Expectations
Nowadays, employees want more than the traditional package and hope companies put mental health, flexibility and ethics first. Having policies that help workers separate their work and home lives and making it easy to raise grievances, is connected to employees being happier (Ibrahim et al., 2023). If organizations do not adjust their rules to what's expected, their employees might become less engaged and quit.
e. Cultivating a Leadership Culture Across All Levels
Good leadership should be a value shared by all, not only middle or top-level managers. Promoting individuals who act on their own, cooperate with teams and accept responsibility at any point in an organization leads to more dedicated staff. Transformational leadership at each level helps build togetherness and responsibility, making the organization work effectively and respond to challenges easily.

Theoretical Implications

a. Advancing a Multidimensional View of Leadership in HRM Research
The research suggests that leadership effectiveness is most clearly understood by looking at it from different theoretical viewpoints. Transformational leadership provides the motivation and emotion, Herzberg's theory deals with satisfaction and dissatisfaction and the Job Characteristics Model includes the basic framework. This integration creates a more detailed way to see motivation among employees (Deng et al., 2022)

b. Highlighting the Interdependence Between Job Structure and Leadership
According to the study, the design of job roles affects the outcomes of leadership. Even those who are most well-known as motivational leaders may find it hard to engage workers if their jobs do not have meaning or independence. Research in the future should examine how job tasks and how managers act together impact employee effectiveness.

c. Encouraging Context-Specific Leadership Adaptation
The way leaders approach tasks should vary according to the situation. Transformational leadership leads to creative industries flourishing, whereas a more directive approach is better for running or handling a crisis. It is important for future studies to see how culture, generational differences and work sectors play a role in the success of different leadership styles.

d. Inspiring Future Studies on Leadership's Emotional Impact
Building trust, making sure employees feel emotionally safe and raising their self-esteem are areas of leadership that need more attention. This study agrees with Asencio & Mujkic (2016), who argued that getting individual support can help strengthen psychological bonds relating to job satisfaction. Researchers might focus on how using emotional leadership leads to strong loyalty and the ability to handle stressful situations in particular industries.

e. Bridging Leadership Theory With Ethical and Sustainable HRM
Ethical leadership, rooted in fairness, transparency, and employee dignity, is essential for long-term organizational sustainability. With rising interest in ESG (Environmental, Social, Governance) practices, leadership models must increasingly be evaluated based on their social and ethical impacts. This opens new avenues for leadership theory that incorporates values-based and sustainability-centered approaches.

Conclusion and Recommendation

The purpose of this study was to explore how leadership in Human Resource Management (HRM) contributes to employee satisfaction and motivation. Drawing on transformational leadership theory, Herzberg's two-factor theory, and the job characteristics model, the study was able to demonstrate that strong leadership is the key to engaging employees and organizational success. The managers who communicate an inspiring vision, recognize individual contributions and create purposeful work can potentially significantly increase the motivation and job satisfaction of employees. Integrating the three theories offered a complete framework that enhanced understanding of how leadership behavior, work design and motivational dynamics intertwine in HRM practices.

The findings suggested that transformational leaders are at the core of creating emotionally supportive and goal-focused work environments. Through individual role matching with organizational objectives, provision of autonomy, and providing positive feedback, leaders can enhance psychological engagement of employees. Furthermore, both intrinsic and extrinsic factors which terms used in Herzberg's model, recognized the importance of not only encouraging development and appreciation but also ensuring fair policies and a good working culture. All these aspects combined illustrated that HRM leadership is not just about guidance but more the development of structures and cultures where staff can thrive.

Limitations

Despite the depth of analysis, this study is not without limitations. One of the primary limitations is its reliance on secondary data. All its conclusions and insights were based on available journal articles and not personal contact with organizations or workers. This limits the empirical validity of the study and cannot be capable of capturing the rich, lived experiences of individuals within actual organizational settings.

Further, most of the articles studied were context-specific, often focusing on certain geographies or sectors. Therefore, the generalizability of the results may be confined because the same sectors and cultures have different HR and leadership issues to address. Finally, the absence of primary data collection meant ignoring critical variables such as demographics of the workers, cultural diversity or firm size.

Another limitation is the static nature of the theoretical framework.Leadership, motivation and job satisfaction are dynamic terms that evolve over time and under external pressures. The research did not examine the impact of technologies such as disruption, organizational change, or crises (e.g., the COVID-19 pandemic) on the dynamic of leadership motivation and satisfaction. Further, while emotional and ethical leadership was mentioned; these were not explicitly examined, and hence the research gap into the emotional and ethical dimensions of leadership in HRM continues.

Recommendations

To address these limitations and enhance the depth of understanding, several recommendations are proposed for future research:

a. Incorporate Primary Data Collection

Future studies must engage organizations directly in the form of focus groups, questionnaires, or interviews. Through this, researchers would have access to the real-time experiences of the employees and leaders, thus a stronger empirical foundation to validate the theoretical principles under discussion.

b. Conduct Industry-Specific Studies
The effectiveness of leadership will vary across industries. Studies on industries like healthcare, education, or technology can reveal how various styles of leadership influence motivation and job satisfaction under industry-specific contexts to facilitate more targeted HRM actions.

c. Conduct Longitudinal Research
Long-term studies can assess how changes in leadership impact over time. This would determine whether or not leadership behaviors translate into long-term motivation and satisfaction or if they must be revised as organizational and employee needs change.

d. Bridge Leadership Theory with Sustainable HRM
With more emphasis placed upon corporate responsibility, leadership models must be expanded to incorporate ethics, societal and environmental sustainability. Researching the method by which leaders promote sustainable actions while not diminishing employee morale is an area worth pursuing in future research.

In conclusion, while this study provides a strong theoretical foundation for understanding the relationship between leadership in HRM and employee outcomes, its scope is limited by the absence of empirical data and contextual diversity. Future research that addresses these limitations will not only enrich academic knowledge but also offer practical insights for building motivated, satisfied, and high-performing workforces in an evolving organizational landscape.

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Economic and Non-Economic Satisfaction, Commitment and Compliance Among Franchisees: An Empirical Evidence

Hazril Izwar Ibrahim*
Universiti Sains Malaysia, Malaysia
Email: hazrilizwar@usm.my

Siti Noorjannah binti Abd Halim
Universiti Sains Malaysia, Malaysia
Email: sitinoorjannah@uum.edu.my

Abdul Hadi Zulkafli
Universiti Sains Malaysia, Malaysia
Email: hadi_zml@usm.my

**Corresponding Author*

Abstract

Franchising is a key driver of economic activity. This study explores compliance issues between franchisees and franchisors from the franchisee's point of view. It aims to provide a framework to understand how economic and non-economic satisfaction, along with commitment, influence compliance in a franchise partnership. The research highlights the importance of both economic and non-economic satisfaction for franchisees, as these factors encourage compliance and can lead to a more successful business. Based on an analysis of 193 responses, the findings show that economic satisfaction and commitment are strong predictors of compliance. The study also reveals that the link between commitment and compliance is stronger when there is low environmental uncertainty.

Keywords: Economic, Non- Economic, Commitment, Compliance, Franchise.

Introduction

Franchising is a business expansion strategy where an organization grants a franchisee the right to use its intellectual property, brand name, and products for a set period. This legal and economic partnership is defined by a franchise agreement, which outlines the rules the franchisee must follow. The relationship can become more complex in an international setting due to intercultural differences. Despite its popularity as a business expansion option, franchising is often challenged by conflicts and compliance issues between the franchisor and the franchisee. This study specifically aims to investigate these compliance-related issues, focusing on how the franchisor-franchisee relationship impacts the franchisee's compliance with the franchisor's rules.

Literature Review

Economic Satisfaction

Economic satisfaction is defined as a “channel member’s evaluation” that focused on the economic outcomes flow from the sales volume, margins, and discounts (Geyskens & Steenkamp, 2006). In fact, economic satisfaction is a kind of satisfaction that is involved with incentives and benefits including financial performance and sales (Ferro et. al, 2016). According to Soto et. al (2024), economic satisfaction functions as a critical antecedent in the development and consolidation of durable exchange relationships. Hence, a successful business performance comes from an economic satisfaction that can help both parties to generate revenue and help the franchisor in securing greater profits in the long run (Rauyruen, Miller, & Barrett, 2007). By generating bigger profit, the franchisor and franchisee develop a good relationship that can be long lasting and adding value to their business (Walter, Muller, Helfert & Ritter, 2003). Hence, economic satisfaction is important to boost franchisees’ behaviour and motivation especially in their relationship with their principal.

Non-Economic Satisfaction

Non-economic satisfaction is synonymous with social economics and is associated with intangible attributes of business relationship between two parties (Geyskens & Steenkamp, 2000). This type of satisfaction is a positive and affective response towards psychological aspects including happiness and enjoyment that might be experienced by the one or both parties in their relationship (Sanzo, Santos, Vazquez, & Alvarez, 2003). For instance, a review of the literature show that most studies measure satisfaction by looking at the social economic aspects of franchise business relationship (Goaill et al., 2017). According to Rutherford (2012), the result of non-economic satisfaction will provide a different perspective compared to economic satisfaction because the cultural factors have a way of influencing the dynamics of business relationships including relationship-related factors that may be more valued than others. Furthermore, non-economic satisfaction is a robust predictor of continuity intentions, cooperation and relationship commitment (Soto, Suárez & Bayón, 2024). Conversely, economic satisfaction is easier to reflect the franchising partnership because it only depends on revenue and profit orientation (Christine & Douglas, 1991).

Commitment

Commitment between franchisor and franchisee is a foundational element influencing the long-term success and sustainability of franchise systems. In the context of franchising, commitment refers to the mutual willingness of both parties to invest in and maintain the relationship over time, beyond contractual obligations (Gilliland & Bello, 2002). This relational commitment fosters cooperation, reduces opportunistic behaviors, and enhances system-wide performance (Mendoza-Abarca & Gras, 2020). The franchisor's commitment is often demonstrated through continuous support, training, and brand development, whereas the franchisee reciprocates by adhering to system standards and promoting brand integrity (Dant, Weaven, & Baker, 2011). Studies have shown that perceived fairness, trust, and open communication significantly strengthen this commitment (Nyadzayo, Matanda, & Ewing, 2015). Furthermore, relationship-specific investments, such as localized marketing and operational adaptations indicate a deeper level of commitment that contributes to mutual dependency and reduces the likelihood of defection (Heide & John, 1988). A high level of bilateral commitment not only stabilizes the franchise network but also serves as a buffer against environmental uncertainties and market fluctuations. Therefore, understanding and managing commitment dynamics is critical for franchisors aiming to build resilient franchise relationships and achieve strategic objectives.

Compliance

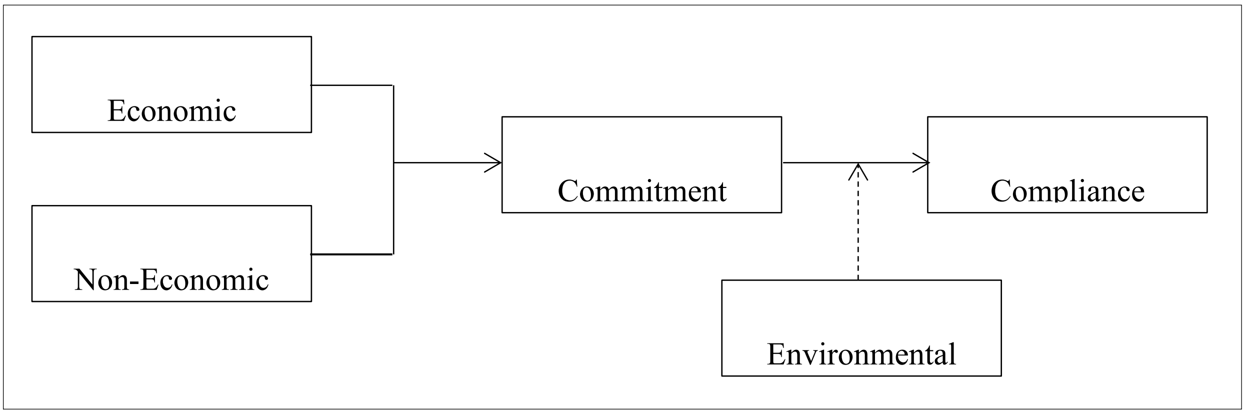
In franchising today, the challenge for franchisor is to build a stronger foundation for the franchise system to gain compliance from the franchisee (Wang & Yang, 2013). Through franchisee's compliance, franchisors can achieve a base level of performance and satisfy customer's needs and expectations (Davies et al., 2011). Due to this, franchisee's compliance is an important factor to gain competitive advantage in the franchise industry because it is the degree to which a franchisee adheres to franchisor directives, policies, and procedures, regardless of the reason for uniformity and conformity (McDonnell et al., 2009). Compliance refers to the concept of cooperation among individuals that occur when two or more parties establish a relationship between them. According to McFarland, Challagalla and Shervani (2005), compliance is one party's adoption of the behaviours desired by another party. In order to establish compliance, both parties need a specific agreement between them that can help to strengthen the relationship (Davies et al, 2011). Furthermore, the success of a franchise system requires uniform product and service standards from both franchisor and franchisee to make it profitable (Kaufmann & Eroglu, 1999).

Environmental Uncertainty

Environmental uncertainty in business refers to the unpredictability of external conditions that influence organizational decision-making and performance. It encompasses fluctuations in market dynamics, regulatory changes, technological advancements, and socio-political instability (Milliken, 1987). High levels of environmental uncertainty challenge firms by limiting their ability to accurately forecast future trends, thereby increasing the complexity of strategic planning (Duncan, 1972). According to Lawrence and Lorsch (1967), organizations operating in highly uncertain environments must adopt more flexible structures and adaptive strategies to maintain competitiveness. Moreover, uncertainty intensifies the need for robust information processing capabilities and dynamic capabilities that allow firms to sense and respond rapidly to environmental shifts (Teece, Pisano, & Shuen, 1997). Failure to effectively manage environmental uncertainty can result in strategic misalignment, resource misallocation, and reduced organizational performance. Consequently, understanding and mitigating environmental uncertainty is essential for sustaining long-term business resilience and adaptability in volatile market conditions.

Research Framework

The research framework for this study as below:



Due to the significant influences of economic satisfaction and has been defined differently by different scholars depending on the type of franchise's industry involved (Yousef, 1999). In economic satisfaction, if the franchisee is unable to generate profit, it will result in dissatisfaction between the parties involved (Ferro et al., 2016). Furthermore, this economic satisfaction can influence the commitment within franchisor and franchisee relationship that will influence the stability in the franchise relationship (Niazi & Hassan, 2016)

Conceptually, commitment is related to a continuing relationship which is built on the foundation of economic satisfaction, with the objective to strengthen the franchise relationship (Mpinganjira et al., 2017). According to Wright and Grace (2011), the decision to commit to a relationship is influenced by the economic efficiency of past interaction because a partner's ability to deliver superior benefits will be highly valued. Several recent studies in franchise contexts find that economic satisfaction significantly predicts commitment-related outcomes Ferro-Soto et al. (2024). In franchise research, measures of franchisee satisfaction that capture economic outcomes (profitability, margin, pricing support) are positively associated with franchisees' willingness to remain and identify with the franchisor (i.e., commitment).Thus, past study found that economic satisfaction does have a positive effect on commitment in business relationship. In line with these findings, it is hypothesized that:

Hypothesis 1*: There is a significant and positive relationship between economic satisfaction and commitment in the franchise relationship.*

Non-economic Satisfaction and Commitment

Non-economic satisfaction is known as a social outcome in terms of sense of appreciation in a business relationship, which excludes monetary transaction (Geyskens et al., 1999). For instance, non-economic aspects exhibit how both parties are happy or enjoy working together as a team (Ferro et al., 2016). Additionally, Rutherford, Anaza, and Phillips (2012), found that non-economic satisfaction are significant precursors of commitment , while Nyaga et al. (2010) found that commitment is influenced by both economic and non-economic satisfaction. Ferro-Soto et al. (2024) highlight that non-economic satisfaction is interlocked with commitment by encouraging cooperation and continuity intentions. In franchise contexts, Lee (2023) finds that franchisor social support enhances franchisees'relational satisfaction, which in turn strengthens their psychological attachment and behavioral intentions to remain loyal. These results underscore the importance of relational satisfaction in sustaining long-term commitment beyond purely financial benefits. Thus, it would be the best if both franchisor and franchisee try to gain non-economic satisfaction in their relationship other than just focusing on economic satisfaction.

Hypothesis 2*: There is a significant and positive relationship between non-economic satisfaction and commitment in the franchise relationship.*

Commitment and Compliance

Franchisee's compliance is the level to which a franchisee adheres to franchisor's directives, policies, and procedures (Dickey et al., 2008). According to Davies et al. (2011), franchisee's compliance is a consequence of the franchisee's motivation and commitment to comply with their franchisor's requirements. Related to this, franchisee's compliance is also the consequence of franchisee's commitment towards their franchisor (Lee , 2017). Therefore, absence of commitment in franchising relationship will affect compliance in a franchise relationship (Davies et al., 2011). The role of commitment in a franchise system is very important as the lack of commitment especially as it was found to increase non-compliance (Dickey et al., 2008). Compliance means the franchisee does not opportunistically try to "go around" franchisor's directives and it could be compulsory through an explicit contract, or it could be managed through commitment and cooperation (Rajiv, 2009). Studies of franchising find that greater franchisee commitment/attachment leads to more cooperative, brand-protecting behaviours which are conceptually very close to compliance (Nyadzayo, Matanda & Ewing, 2015 and Suttidharm, 2024). Thus, obtaining compliance in franchise relationship is the most important goal in the franchise business strategy (Davies et al., 2011).

Hypothesis 3*: There is a significant and positive relationship between commitment and compliance in the franchise relationship.*

Commitment as a Mediator

Commitment has been assessed as a mediator in previous studies (Lee, 2017). However, little attention has been paid to the mediating role of commitment between economic and non-economic satisfaction and compliance in the franchise industry in Malaysia. Researchers have hypothesized that commitment may function as a mediator between economic and non-economic satisfaction and compliance for specific reasons. Kaur and Soch (2018) states that it allows for attaining a wider perspective regarding the influence of relational quality and commitment on franchisee's compliance towards their franchisor.

In the field of relationship quality, compliance has been frequently studied and is a common phenomenon (Cheng, 2014). A study conducted by Lee and Lee (2017), states that there is a positive mediating relationship of commitment between knowledge sharing and compliance. It is supported by Hackel (2014) which supports the mediating role of commitment impacts on compliance. Studies in franchise and channel relationships show mediation chains where satisfaction increases trust and commitment, which then drive cooperation/behavioral outcomes (Makartiningrum, Pramudita & Yudi, 2022). Thus, commitment as a mediator between satisfaction (economic and non-economic) and compliance is supported in the recent literature. In other words, commitment will mediate the relationship between relationship quality and compliance in franchisee-franchisor relationship. Thus, based on the argument above, this study predicts that the mediating role of commitment between economic and non-economic satisfaction and compliance, as shown below.

Hypothesis 4*: Commitment will mediate the relationship between economic satisfaction and compliance.*
Hypothesis 5*: Commitment will mediate the relationship between non-economic satisfaction and compliance.*

Environmental Uncertainty as a Moderator between Commitment and Compliance

The moderating impact of environmental uncertainty on business relationship have received little attention in previous research despite the importance of this variable given its effect on the franchise relationship (Elbanna & Gherib, 2012). Franchisee may not comply with their franchisors due to environmental uncertainty causing franchisee resorting to use substitute raw material due to religious issues, and economic crisis (Fynes et al., 2004). Thus, the context of this moderator will strengthen or weaken the relationship between commitment and compliance between both parties.

It should be made clear that the reason for testing the moderating effect in relationship between commitment and compliance in particular is based on the fact that, although franchisee can comply with their franchisor in their business relationship but when changes in franchise business environment occurs, it will either strengthen or weaken the relationship (Zhang & Lv, 2015). Tong (2021) also highlights that environmental uncertainty changes how commitment translate into compliance behaviours. According to Wang et al. (2013), when there is high level of environmental uncertainty, the organization faces rapid change and complex challenges. Therefore, it is essential to look at the impact of the moderator in the business relationship.

Hypothesis 6*: The impact of commitment on compliance is higher with lower levels of environmental uncertainty than with higher levels of environmental uncertainty.*

Methods

Sample Profile

This research is designed as a quantitative approach that utilizes a quantitative research method to examine the relationship between dependent and independent variables. This study is a correlational study which has two or more variables from the same group of participants and determines relationship between variables. This current study adopted a cross-sectional survey research and the data is collected at just one-point of a period of time. Thus, self-administered questionnaire survey is used as a technique for data collection which the sample or respondent have to answer the questions.

This study used non-probability sampling where the elements do not have an acknowledged or predetermined chance of being selected as subjects. Purposive sampling is used in this study because the franchisee is the only ones who can respond to the survey, or they can conform to the criteria set by the researcher. The sample for this study is individual franchisee in Malaysia who registers under the Registrar of Franchise, Ministry of Domestic Trade and Consumer Affairs (MDTCA). Then, the unit of analysis in this study is the individual which refers to the franchisee as an individual unit. For instance, this study used G*Power to determine the minimum sample size. Thus, the results indicated that a minimum sample size of 98 respondents for this study which considered large enough for organizational study. Hence, the minimum sample size required for this study is 98 respondents. The current study uses PLS-SEM to obtain the statistical results.

Measures

This section discusses the items and scales of measurement in detail. The items in the questionnaires sought to assess the economic satisfaction, non-economic satisfaction, commitment, compliance and environmental uncertainty. The independent variable for this study consists of economic satisfaction and non-economic while the dependent variable consists of compliance. Next, the proposed mediating variable in this study is commitment while environmental uncertainty is proposed as moderator variable in this study. All the variables are measured by the 5 Likert-type scales (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree). Table 3.1 summarized the measurements items used in this study.

Table 1.1 Summary of Measurements for the Study

No	Variable	Source of scale	Reliability
1	Economic Satisfaction	Santos et al. (2003) Geyskens et al. (1999)	0.870
2	Non-economic Satisfaction	Andaleed (1995) Dwyer and Oh (1987)	0.710 0.779
7	Commitment	Dant et al. (2013)	0.989
8	Compliance	Davies et al. (2011) Dickey et al. (2008)	0.750 0.789
9	Environmental Uncertainty	Duncan (1972) and Bourgeois et al. (1978)	0.880

Results

The target respondents in this study were the franchisees (outlet owners) who are actively and vigorously involved in the daily management of franchise outlets in Malaysia. A total of 193 usable questionnaires were returned which accounted for the 48.2 per cent response rate. According to Hayes (2000), 20 per cent to 30 per cent is reasonable and, in this case, the response rate of 48.2 per cent is acceptable and sufficient for data analysis because it is more than 30 per cent response rate. Furthermore, the sample size from 30 up to 500 is sufficient for most research for multivariate study such as multiple regression analysis . Hence, the samples of 193 are considered sufficient.

Demography of the Sample

The descriptive analysis demonstrates the franchisee's profile with 1 screening question and 11 demographic categories on the questionnaires. The first question was a screening question which only included franchisee's status as a respondent for this study. The majority of the samples are male with 62.7 per cent and followed by female with 37.3 per cent. Next, there are 96 respondents (49.7%) are from Malay ethnicity, followed by 62 respondents (32.1%) from Chinese ethnicity, 32 respondents (16.6%) from Indian ethnicity and 3 respondents (1.6%) from other ethnicity. In term of academic qualification, most of the respondents hold a SPM (high school) certificate (31.6%), followed by Diploma certificate (31.1%), bachelor's degree (25.9%), master's degree (8.3%) and STPM (A-level) (3.1%).

Next, out of 193 total responses, 133 respondents (68.9%) are from private limited companies, 21 respondents (10.9%) are sole proprietors, 20 respondents (10.4%) are in partnership firms while 19 respondents (9.8%) are registered as business cooperatives. The majority of respondents are in single unit agreement with franchisor with a percentage of 72 per cent (139 respondents), followed by multi-unit agreement with percentage of 19.2 per cent (37 respondents) and 8.8 per cent (17 respondents) are in other types of agreement with their franchisor. In term of which agency, they are registered with, there are 83 respondents (43%) registered under Ministry of Domestic Trade, Cooperatives and Consumerism (MDTCC), 51 respondents (26.4%) registered under Malaysian Franchise Association (MFA), 44 respondents (22.8%) are registered under others agencies and 15 respondents (7.8%) are registered under both MDTCC and MFA in the same time.

There are various sectors involved in franchise industry and majority of respondents are involved in food and beverage sector with 45.6 per cent (88 respondents), followed by nursery and education sector with 17.1 per cent (33 respondents), 13 per cent (25 respondents were from clothing and accessories sector, 11. 9 per cent (23 respondents) from services and maintenance sector, 8.8 per cent (17 respondents) from convenience shop, 2.1 per cent (4 respondents) from others sector, 1.6 per cent (3 respondents) from information technology, telecommunication and electrical sector and lastly there were no respondent from health and beauty sector. Based on the demographic profile, 61.7 per cent of respondents had more than 1 year and less than 5 years operating their business in franchise industry, followed by 21.8 per cent respondents with more than 5 years and less than 10 years business operation, 16.6 per cent less than 1 year operation and none of the respondent has operated their business more than 10 years.

Table 1.2 Demographic profile of the franchisees

Franchisee's Profile	**Categories**	**Frequency**	**Percent**
Are you the owner (franchisee) to the franchise outlet?	Yes	193	100.0
	No	0	0.000
Type of business registration	Cooperatives	19	9.8
	Partnership	20	10.4
	Sole Proprietor	21	10.9
	Private Limited Company	133	68.9
Type of agreement with the franchisor	Single Unit	139	72.0
	Multi-Unit	37	19.2
	Others	17	8.8
Membership	Malaysian Franchise Association (MFA)	51	26.4
	Ministry of Domestic Trade, Cooperatives and Consumerism (MDTCC)	83	43.0
	Others	44	22.8
	MFA & MDTCC	15	7.8
Sectors	Health & Beauty	0	0
	Food & Beverage	88	45.6
	Nursery & Education	33	17.1
	Clothing & Accessories	25	13.0
	Services & Maintenance	23	11.9

Franchisee's Profile	Categories	Frequency	Percent
	Convenience Shop	17	8.8
	Information technology, Telecommunication & Electrical	3	1.6
	Others	4	2.1
Length of business operation	Less than 1 year	32	16.6
	More than 1 year and less than 5 years	119	61.7
	More than 5 years and less than 10 years	42	21.8
	More than 10 years	0	0
Number of outlets	1-5 outlets	144	74.6
	6-10 outlets	31	16.1
	11-15 outlets	12	6.2
	16-20 outlets	3	1.6
	More than 20 outlets	3	1.6
Numbers of staff	1-5 persons	95	49.2
	6-10 persons	95	49.2
	11-15 persons	3	1.6
	16-20 persons	0	0
	More than 20 persons	0	0
Average initial investment	Below RM 100,000	158	81.9
	RM 100,000 – RM 299,999	35	18.1
	RM 300,000 – RM 499,999	0	0
	RM 500,000 – RM 699,999	0	0
	More than RM 700,000	0	0
Gender	Male	121	62.7
	Female	72	37.3
Ethnicity	Malay	96	49.7
	Chinese	32	16.6
	Indian	62	32.1
	Others	3	1.6
Education	PhD	0	0
	Master	16	8.3
	Degree	50	25.9
	Diploma	60	31.1
	STPM / Foundation	6	3.1
	SPM	61	31.6

In term of outlets number, there are 144 respondents (74.6%) having outlet in range between of 1 to 5 outlets, followed by 31 respondents (16.1%) having outlet in range between of 6 to 10 outlets, then 12 respondents (6.2%) having outlet in range between 11 to 15 outlets, and there are 3 respondents (1.6%) having outlet in range between 16 to 20 outlets. Besides that, there are 95 respondents employing between 1 to 5 employees per outlet and similarly, another 95 respondents employed 6 to 10 employees per outlets and followed by 3 respondents stating that they employ 11 to 15 employees in their outlets. Next, there was several average initial investment of the franchise outlet such as 158 respondents (81.9%) invested below RM 100,000 and followed by 35 respondents (18.1%) who invested in range of more than RM 100,000 and less than RM 300,000.

Descriptive Analysis

The descriptive analysis consists of mean, standard deviation and normality tests. Respondents in this research were asked to indicate their perceptions regarding each statement in the questionnaire by using a 5-point Likert scale (1= strongly disagree to 5= strongly agree). As shown in Table 1.3 the mean scores for all variables involved ranges from 3.744 to 4.541, these scores are above the mid-point of 2.50. Hence, in the context of franchise industry in Malaysia, these scores indicate that the respondents generally held positive perceptions regarding the respective variables that are being tested in this study. In addition, Table 1.3 also indicated the scores of standard deviation for the respective variables are in the range between 0.410 and 0.641.

In this study, normality is assessed by using skewness and kurtosis values for each variable. As shown in Table 1.3, the skewness and kurtosis are between +4 and -4, which demonstrates the datasets are within the acceptable range as mentioned by Tabachnick and Fidell (2007). Thus, the findings indicated that the normality assumptions data of this study were not violated. Hence, the use of PLS-SEM as the statistical analysis method for further data analysis was supported. Thus, the findings indicated that the data of this study are acceptable.

Table 1.3 Descriptive Statistics for the Variables

Variable	Means	Standard Deviation	Skewness	Kurtosis
Economic Satisfaction	4.442	0.636	-1.276	2.071
Non-economic Satisfaction	4.541	0.410	-1.059	0.583
Commitment	4.435	0.571	-0.707	-0.172
Environmental Uncertainty	3.744	0.641	-0.819	0.320
Compliance	4.320	0.608	-0.595	-0.472

Data Analysis and Result

This study utilized the Partial Least Squares (PLS) analysis using the SmartPLS 3.0 software). This is second-generation multivariate technique which permits to assess both the measurement and structural models. For instance, the measurement model is used to measure the reliability and validity, while the structural model is used to test the hypotheses relationship. Hence, to test the significance of the path coefficients and the loadings of a bootstrapping method (5000 resamples) was used. Thus, the next section will explain on both measurement and structural model.

Structural Model

The structural model represents the relationship between latent variables hypothesized in the research model. In this study, path co-efficients of the structural model was measured and bootstrap analysis was carried out to assess the statistical significance of the path coefficients. The economic satisfaction (β= 0.191, p< 0.01) was found to have a positive and significant relationships with commitment, while the non-economic satisfaction (β= 0.062, p> 0.10) was not found to be significantly related to commitment. Hence, H1 was supported while H2 was not supported. The structural path of commitment (β= 0.227, p< 0.01) was found to have a positive significant relationship with compliance. Hence, H3 was supported in this study.

Next, for hypothesis H4, the bootstrapping analysis showed that the indirect effect β= 0.043 was significant with a t-value of 2.045 ($p<0.05$) (two-tailed). Besides the indirect effect of 0.043, 95% Boot CI: [LL= 0.061, UL= 0.315] did not straddle a zero value in between, indicating that a mediating effect of commitment on the relationship between economic satisfaction and compliance existed and supported.

In terms of non-economic satisfaction's hypothesis H5, the bootstrapping analysis showed that the indirect effect β= 0.014 was not significant with a t-value of 0.629 ($p>0.10$) (two-tailed). Besides, the indirect effect of 0.014, 95% Boot CI; [LL=-0.133, UL= 0.233] did straddle a zero value in between, indicating that a mediating effect of commitment on the relationship of non-economic satisfaction and compliance was not supported.

Lastly, hypothesis H6 tested the moderating effects in the framework. Table 1.4 shows the path coefficients, standard errors, and the results of the hypothesis testing between the commitment and compliance through the environmental uncertainty. This interaction term was found significant (β= -0.100, t= 1.677). To explain the nature of this interaction, the effect of commitment on the compliance at high or low levels of environmental uncertainty was plotted (See figure 2). This figure elucidated that the positive relationship between commitment and compliance was found to be weaker at low level of environmental uncertainty. However, H6 actual hypothesis was investigated that the high level of environmental uncertainty weakens the positive relationship between commitment and compliance. Hence, based on the statistical results H6 was not supported.

Table 1.4 Hypothesis Testing for Moderating Effects

H	Relationship	Path Coefficients (Beta)	Std. Error	t-value	P-value	Effect Size (f 2)
H 6	CMT*EU -> COMP	-0.100	0.060	1.677	0.047	0.131 (small effect)

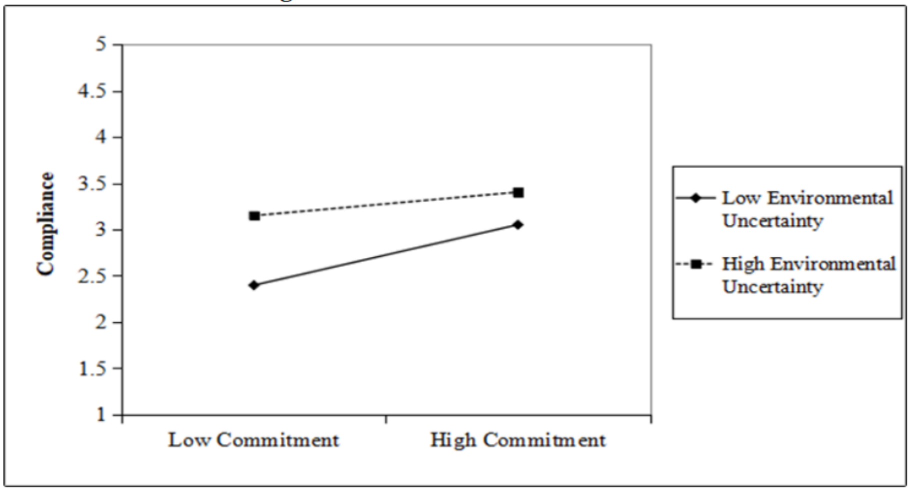


Figure 2: Interaction of Variables

Discussions and Contributions

The outcome of the analysis indicated that economic satisfaction has a positive and significant relationship with commitment (β= 0.191, $p<0.01$). This implies that the economic satisfaction as an important concept and providing evidence that the franchisee can be committed to their franchisor based on economic satisfaction. Moreover, the finding is similar with the results discovered by Mpinganjira et al. (2017), proving that economic satisfaction can boost franchisee's motivation to be committed the franchisor. Furthermore, economic satisfaction is also critical for franchisee as franchisee has to pay royalty to the franchisor as stated in the franchise agreement (Goaill et al., 2017). Thus, economic satisfaction becomes an important criterion to achieve commitment between franchisor and franchisee in the franchise relationship.

In the current study, the result showed that non-economic satisfaction did not have a significant relationship with commitment. The current result is the opposite of the results from an earlier study by Kalargyrou et al. (2018) which found that non-economic satisfaction is a form of social interaction between the principal and the agent. The reason for the non-significant relationship in the present study is possibly due to low social interaction in franchise industry as it is considered not important to establish commitment between franchisor and franchisee as parties are more concerned with the outcome of their investment rather than fraternising with each other. However, the franchisee probably has difficulties to achieve non-economic satisfaction due to time constrain, thus disregarding social needs that they have to accomplish compared to the more objective profit orientation and thus, non-economic satisfaction is not a necessity in the franchise's- franchisor's relationship.

The result of the findings suggests that commitment from the franchisee can lead to a better compliance with the franchisor. Franchisee will be fully committed to the franchisor in order to gain positive perception from the franchisor. Furthermore, this indicates that franchisees are willing to contribute to a long-term relationship with the franchisors' business model. For instance, when a franchisee is fully committed to the relationship with the franchisor, they are more than willing to comply with the franchisor's terms and conditions. It is because commitment is the key for a long-lasting relationship between two parties. They believe that their contribution in the long-term relationship can provide a more positive outcome for the business environment.

The result of this study discovered that commitment significantly and positively mediated the relationship between economic satisfaction and compliance ($\beta = 0.043$, $p<0.05$). The franchisee recognizes commitment as mediator that bridges the relationship between economic satisfaction and compliance. Understandably this indicates that, when a franchisee gains more profit (economic satisfaction), they are more committed to the franchisor (Harif, Azhar,Hoe & Zainal Abidin, 2011). This implies that achieving profit will encourage franchisee to be more commitment and this leads to compliance with the franchisor (Sanzo et al., 2003).

The indirect relationship between non-economic satisfaction and compliance has been found to be non-significant. Therefore, commitment did not mediate the relationship between non-economic satisfaction and compliance in franchise partnership. This implies that despite non-economic satisfaction of franchisee toward franchisor, the level of compliance does not increase. Consequently, this can be related with the current demographic result where most of the respondents are just starting their business. It is 61.7 per cent of respondents who run their franchise business with more than 1 year and less than 5 years' experience. Thus, in the early stage of business operation, the franchisees would be focused on the economic satisfaction rather than non-economic satisfaction. This is supported by Mpinganjira and Mysen (2014), which the position of economic satisfaction and non-economic satisfaction should be separated due to different necessity. In addition, the position of economic satisfaction is earlier than non-economic satisfaction in the nomological network (Shaikh, 2018).

The finding of this study revealed that the effect of environmental uncertainty on the relationship between commitment and compliance was significant, but the hypothesis H14 was not supported due to the direction of the relationship was positive; opposite of what had been hypothesized. The proposed hypotheses stated that the relationship between commitment and compliance will be stronger when then the environmental uncertainty become weak but the result from this study indicated vice versa from the proposed hypotheses. Thus, the hypothesis was not supported even though the relationship was significant. As conclusion, to enhance the compliance between franchisee and franchisor, franchisee must be committed to the franchisor especially during the uncertainty in their franchise business. Furthermore, result from this study also indicated that the relationship between commitment and compliance would be better in the occurrence of environmental uncertainty. Therefore, the franchisee does not have to worry in the event of uncertainty in the business environment because their will get support from the franchisor due to the compliance to business model agreed between both parties.

From this research, there are several contributions in terms of theory could be drawn for the benefit of those in the academic and research field. The research provides invaluable insight and improved understanding on the management of talent resources in the context of Malaysian franchise business industry. In fact, this study integrates economic satisfaction and non-economic satisfaction with mediating role of commitment in examining the compliance from franchisee's perception towards their franchisor. Hence, the research intends to discover new findings and contributions in different areas of economic and non-economic satisfaction by having commitment as the mediator. Furthermore, it also integrated environmental uncertainty as moderating roles to strength the relationship between commitment and compliance. Thus, franchisee should be ready to face any issues arise in their partnership with the franchisor because the quality that have naturally have by the franchisor cannot be control by the franchisee.

Aside from theoretical contributions, the findings from this research have provided valuable suggestions to practitioners in Malaysia's franchise industry. Specifically, it provides better appreciation on the importance of economic and non-economic satisfaction in attracting, developing and retaining the good relationship between franchisee and franchisor in their franchise relationship. Based on the result, the franchisor can take note on the non-significant relationship in direct relationship by as indicated by non-economic satisfaction and commitment. Ultimately, franchisee will comply and stay with the business if there is a good profit generated from their business relationship. The economic satisfaction is the main concern in the franchise relationship because without profit to be gained, the probability of compliance between the franchisee and franchisor would be low.

This study provided a clearer picture on the nature of the relationship between franchisee and franchisor and as indicated the results, economic satisfaction is the mainstay of the business relationship in the franchise business model. Thus, the profit come first in generating a good relationship and then will follow with other criteria based on the situation for each of the franchisee. As such, the franchisor shall give high priority to franchisee relationship management apart from other contract management and other operation related issues. Hence, the franchisee always looks on the economic satisfaction first rather than non-economic satisfaction because the main objective for a business is profit generation.

Conclusion

The proposed research framework was able to provide several imperative findings based on the analysis of the responses obtained from the survey instrument distributed among franchisees in Malaysia's franchise business sector. The analysis was carried out by using both SPSS and PLS methods for descriptive statistic and to test the direct and indirect effects between the variables. Thus, the results from PLS modelling are used to validate the proposed hypotheses. Furthermore, the results provided evidence for commitment to be significant as a mediator between economic satisfaction and compliance. Whereas, commitment was not significant as a mediator in the relationship between non-economic performance and compliance. Based on the proposed hypotheses on the relationship between commitment and compliance, it was hypothesised to be stronger in the presence of a weak environmental uncertainty. However, the outcome signifies that, environmental uncertainty did not moderate the relationship between commitment and compliance even though the direct relationship between commitment and compliance was significant. Thus, the hypotheses were not supported as the direction was negative and contradictory to the proposed hypothesis. As a conclusion, the current study highlighted the significance of economic satisfaction in predicting commitment as it leads to compliance from the franchisee to the franchisor.

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AI-Driven Financial Fraud Detection in the Five Highest-Risk Areas of BCA'S 2019–2024 Financial Statements

Girang Permata Gusti*
Universiti Sains Malaysia, Malaysia
Email: girangpermatagusti@student.usm.my

Alswar Ali Hassan D, Al Zoubi Hussein Nahar Mahmoud, Salimin
Universiti Sains Malaysia, Malaysia
**Corresponding Author*

Abstract

This research investigates the application of AI-driven financial fraud detection in the five highest-risk areas of PT Bank Central Asia Tbk (BCA)'s financial statements from 2019 to 2024, which include consumer loans, financing loans, cash & giro at Bank Indonesia, securities for trading, and estimated losses on commitments and contingencies. Using a quantitative descriptive approach with secondary data from BCA's audited annual reports, this study analyzes trends, anomalies, and potential fraud indicators that could impact the bank's profitability and liquidity. The findings reveal that these five areas handle large monetary values, are prone to earnings manipulation, hidden defaults, and liquidity irregularities, and therefore represent the core focus for fraud risk assessment. By conceptually applying AI techniques such as anomaly detection, predictive analytics, and machine learning for pattern recognition, the study demonstrates how AI can enhance early fraud detection and strengthen financial reporting integrity. The research underscores the importance of adopting technology-based fraud monitoring systems in modern banking and recommends future studies to implement real-time AI models with transaction-level data for more comprehensive and proactive fraud prevention.

Keywords: AI-Driven Fraud Detection, Financial Statement Analysis, Banking Sector, Predictive Analytics, Risk Management.

Introduction

Financial fraud has become one of the most critical challenges for the banking sector in the digital era. Banks process an enormous volume of transactions daily, creating opportunities for anomalies, misstatements, and concealed fraudulent activities to occur. PT Bank Central Asia Tbk (BCA), as one of Indonesia's largest banks by assets and customer base, is particularly exposed to such risks. While conventional audits and regulatory supervision remain essential, the increasing complexity of financial transactions requires more advanced and intelligent detection methods.

Artificial Intelligence (AI) provides a transformative approach to financial fraud detection. AI- powered systems can process large datasets in real-time, detect unusual transaction patterns, and identify early indications of fraud much faster than traditional manual audits. By leveraging AI, banks can enhance the accuracy and speed of fraud detection, reducing the likelihood of losses caused by concealed or late-discovered fraudulent activities.

In the case of BCA, analysis of its 2019–2024 financial statements highlight five areas that consistently carry the highest risk of fraud: consumer loans, financing loans, cash and giro at Bank Indonesia, securities for trading, and estimated losses on commitments and contingencies. These areas involve large sums of money and complex transactions that are often difficult to monitor manually, making them susceptible to manipulation or exploitation by internal and external parties.

AI-driven financial fraud detection offers an integrated solution to these challenges. Through anomaly detection, predictive analytics, and machine learning models, AI can identify irregularities in real-time and flag suspicious patterns across these high-risk areas. This approach allows the bank to detect and address potential fraud proactively, strengthening the reliability of its financial reporting and reducing the risk of financial loss.

AI-driven financial fraud detection leverages artificial intelligence to identify suspicious patterns and anomalies in financial data faster and more accurately than traditional auditing methods, and tools like ChatGPT can play a supportive role by analyzing multi-year financial statements, detecting inconsistencies, highlighting unusual fluctuations, and summarizing high-risk areas such as sudden loan spikes, unexpected drops in cash balances, or volatile loss provisions. While ChatGPT does not directly access transaction-level banking systems, it can assist in data analysis, anomaly detection, and generating clear fraud risk explanations or reports for auditors and management. It functions best as a complementary analytical tool, guiding investigators toward areas of concern and automating complex narrative insights, while real-time detection and final fraud confirmation still rely on AI models specialized in anomaly detection, predictive analytics, and machine learning trained with transactional banking data. Integrating ChatGPT for insight generation with transactional AI tools creates a comprehensive and proactive fraud detection framework that enhances financial reporting integrity and supports risk management in the banking sector.

Fraud is a widespread crime that not only causes financial losses but also has emotional, psychological, and even physical impacts on its victims. The rapid development of online communication technologies provides new opportunities for fraudsters, who increasingly use advanced methods such as Generative AI and deepfakes in phishing campaigns. While these risks grow, the application of AI, especially Natural Language Processing (NLP), in detecting and analyzing patterns of online fraud is still relatively underexplored. A systematic literature review shows that AI and NLP have been applied in various fraud categories, using different text-based data sources and models, evaluated with performance metrics to measure their effectiveness (Papasavva et al., 2025). Connecting to this study, the same principles can be applied to identify anomalies and irregularities in the five highest-risk areas. By leveraging AI models that are capable of analyzing large and complex financial data, BCA can strengthen its ability to detect suspicious activities, reduce fraud risk, and improve the reliability of its financial reporting.

Chen (2025) highlights the transformative role of ChatGPT in the financial sector, particularly in areas such as customer service, financial planning, risk management, portfolio analysis, insurance, and fraud prevention, where it can deliver efficient automated solutions. The research stresses that successful implementation requires careful management of conversational AI, including defining business needs, identifying application areas, developing accurate data models, safeguarding privacy and security, ensuring human oversight, and creating evaluation systems. However, challenges such as data reliability, privacy risks, model bias, and compliance issues remain significant. Connecting to this research, ChatGPT's potential can be extended to enhance fraud risk monitoring and early detection systems, particularly in high-risk accounts such as consumer loans, financing loans, cash and giro at Bank Indonesia, securities for trading, and estimated losses on commitments and contingencies. By addressing both technological opportunities and regulatory challenges, ChatGPT can serve as a valuable tool for BCA to strengthen fraud prevention strategies and safeguard financial integrity.

Financial fraud is the intentional act of deception or misrepresentation in financial activities aimed at gaining unlawful benefits or causing financial harm to others. It typically involves manipulating financial statements, misusing assets, or falsifying transactions to mislead stakeholders such as investors, regulators, or the public. Examples include accounting fraud like inflating profits or hiding losses, asset misappropriation such as cash embezzlement, loan fraud through fictitious lending or under-reported defaults, and securities fraud like insider trading or market manipulation. In the banking sector, financial fraud is especially critical because it targets high-value accounts and complex transactions, making early detection essential to protect the institution's financial integrity and stakeholder trust.

This study focuses on the application of AI-driven fraud detection within the five highest-risk areas of BCA's 2019–2024 financial statements. By analyzing potential vulnerabilities and exploring the use of AI technologies for early detection, this research aims to contribute to modern banking practices that enhance risk management and improve the integrity of financial information.

Research Method

This study employs a quantitative descriptive research method to analyze the potential for financial fraud within PT Bank Central Asia Tbk (BCA) by applying an AI-driven detection framework. The research focuses on five financial statement areas identified as having the highest fraud risk between 2019 and 2024: consumer loans, financing loans, cash & giro at Bank Indonesia, securities for trading, and estimated losses on commitments and contingencies.

Quantitative analysis is used to detect abnormal trends, potential earnings manipulation, and other indicators that may suggest fraudulent activity.

The research relies entirely on secondary data obtained from BCA's audited annual reports and financial statements for 2019–2024, which are publicly available through the official BCA website and the Indonesia Stock Exchange (IDX). Data extracted include figures related to the five high-risk areas and supporting financial performance indicators such as total assets, net profit, and comprehensive income. These data are compiled and tabulated to allow year-to-year comparisons, enabling the identification of significant fluctuations and anomalies that may indicate fraud risks.

Table 1. Financial data of PT Bank Central Asia Tbk (BCA) from 2019 to 2024

Category	**2019 (IDRMillion)**	**2020 (IDRMillion)**	**2021 (IDRMillion)**	**2022 (IDRMillion)**	**2023 (IDRMillion)**	**2024 (IDRMillion)**
Total Assets	918,982,318	1,174,737,789	1,228,346,444	1,316,174,314	1,408,107,016	1,449,901,328
Total Liabilities	740,067,127	855,537,979	1,019,773,736	1,081,704,554	1,157,565,545	1,177,400,038
Temporary Syirkah Funds	4,779,028	5,317,688	5,271,988	6,440,375	7,893,872	9,063,133
Total Equity	174,136,163	184,759,781	203,300,720	228,029,385	242,647,599	263,260,641
Total Liabilities + Syirkah + Equity	918,982,318	1,174,737,789	1,228,346,444	1,316,174,314	1,408,107,016	1,449,901,328
Total Operating Income (Interest + Syariah)	64,354,024	70,345,634	75,623,511	81,651,688	87,016,517	92,746,456
Operating Expense (Interest + Syariah)	60,210,126	65,008,792	69,484,510	71,605,050	71,458,965	72,532,200
Net Interest Income	4,143,898	5,336,842	6,139,001	10,046,638	15,557,552	20,214,256
Other Operating Income	17,840,211	18,923,765	19,693,382	21,615,796	20,069,733	21,900,973
Other Operating Expense	30,142,345	30,476,331	31,046,622	30,419,422	28,054,289	30,054,289
Profit Before Tax	28,174,121	35,789,865	43,270,271	50,467,683	60,317,660	68,211,670
Net Profit	23,581,944	28,654,332	31,440,159	40,755,572	48,658,095	54,861,274
Comprehensive Income	24,009,355	29,081,217	31,867,065	37,432,854	47,551,886	54,506,320

Source: BCA (2025)

The financial data of PT Bank Central Asia Tbk (BCA) from 2019 to 2024 shows a consistent upward trend in total assets, liabilities, and equity, reflecting the bank's strong growth and financial stability. Total assets increased from IDR 918,982,318 million in 2019 to IDR 1,449,901,328 million in 2024, with a notable jump in 2020, likely due to increased deposits and asset expansion during the pandemic. Total liabilities followed a similar path, rising from IDR 740,067,127 million to IDR 1,177,400,038 million, while temporary syirkah funds and total equity also grew steadily, indicating strong capital accumulation. These growth trends suggest a robust balance sheet, but the significant jumps in 2020 and 2021 warrant closer analysis for potential anomalies that could indicate misstatements or aggressive accounting practices.

From an income perspective, operating income and expenses show stable growth, while net interest income demonstrates a sharper rise, particularly from 2022 to 2024. Total operating income increased from IDR 64,354,024 million in 2019 to IDR 92,746,456 million in 2024, reflecting expansion in lending and financing activities. Operating expenses remained relatively stable, and the modest reduction in 2023 could signal either cost efficiency or delayed expense recognition.

Meanwhile, net interest income surged from IDR 4,143,898 million to IDR 20,214,256 million, raising the need for AI-driven anomaly detection to ensure that revenue growth aligns with actual loan performance and is not driven by manipulated interest recognition or unreported defaults.

Profitability indicators also reflect strong and accelerating growth, with net profit rising from IDR 23,581,944 million in 2019 to IDR 54,861,274 million in 2024. Profit before tax and comprehensive income followed similar trends, with the most significant increases occurring between 2021 and 2022. While this growth indicates excellent financial performance, it also heightens the importance of fraud risk monitoring, especially in high-risk areas like loan portfolios, cash transactions, securities, and loss provisions. Applying AI-driven financial fraud detection using anomaly detection, predictive analytics, and pattern recognition would allow BCA to identify irregularities in real-time, providing early warnings for potential fraud and strengthening the integrity of financial reporting.

Table 2. Highest fraud risk in BCA’s 2019–2024 financial statements

Financial Area	**2019 (IDR Million)**	**2020 (IDR Million)**	**2021 (IDR Million)**	**2022 (IDR Million)**	**2023 (IDR Million)**	**2024 (IDR Million)**
Consumer Loans	7,065,234	7,605,934	7,855,976	8,215,827	8,713,450	9,435,564
Financing Loans	149,428	100,299	7,270,945	8,127,116	7,733,008	8,376,496
Cash & Giro at Bank Indonesia	162,991,763	186,940,351	114,722,219	141,265,051	114,722,219	65,157,326
Securities for Trading	8,407,700	9,544,700	9,007,201	9,744,378	10,383,524	10,001,769
Estimated Losses on Commitments & Contingencies	1,330,469	1,537,371	2,239,171	3,439,318	3,371,646	2,975,147

Source: BCA (2025)

These five areas—Consumer Loans, Financing Loans, Cash & Giro at Bank Indonesia, Securities for Trading, and Estimated Losses on Commitments & Contingencies—were chosen because they represent the highest fraud risk in BCA’s 2019–2024 financial statements due to their large monetary values, reliance on management judgment, and vulnerability to manipulation. Consumer and financing loans are prone to fictitious lending, collectibility manipulation, and under-reported defaults, while cash and giro balances are highly liquid and susceptible to embezzlement or unrecorded transactions, especially with the sharp 2024 decline signaling a potential anomaly.

Securities for trading can be used for insider trading, false mark-to-market, or round-tripping to create artificial profits, and estimated losses are easily exploited for earnings management through under-provisioning or delayed recognition of losses. Because these areas are difficult to monitor with traditional audits, they are ideal for AI-driven fraud detection using anomaly detection, predictive analytics, and pattern recognition to identify irregularities early and enhance financial reporting integrity.

Consumer Loans represent one of the most critical areas in financial fraud detection because of their size and continuous growth. From IDR 7,065,234 million in 2019 to IDR 9,435,564 million in 2024, the increase reflects BCA's consistent expansion in the retail lending segment. This area is highly susceptible to fictitious loans, where loans are recorded under non-existent borrowers, and collectability manipulation, where non-performing loans are restructured to appear current. Even though the growth appears stable, subtle irregularities can indicate earnings management or hidden credit risk. AI-driven anomaly detection can identify abnormal repayment patterns and delayed recognition of non-performing loans, offering early fraud signals before they affect profitability.

Financing Loans show a dramatic change, rising sharply from IDR 100,299 million in 2020 to IDR 7,270,945 million in 2021, and then reaching IDR 8,376,496 million in 2024. This sudden surge raises concerns about potential misreporting and over-aggressive credit expansion. Common fraud risks include under-reporting of defaults, overvaluation of collateral, and duplicate loans using the same asset. The rapid growth could indicate hidden credit issues, especially if loan approvals were accelerated without proper risk assessment. Predictive analytics powered by AI is essential in this area, as it can model default probabilities, identify irregular lending trends, and detect deviations from historical credit performance, which manual audits might overlook.

Cash & Giro at Bank Indonesia is another high-risk area due to its high liquidity and vulnerability to misappropriation. The balances were extremely high in 2019 - 2020 (IDR 162 - 186 trillion) but declined sharply to IDR 65,157,326 million in 2024. Such a significant drop is a red flag for potential cash-related fraud, such as embezzlement, unrecorded withdrawals, or fictitious inter-branch transfers. Because cash transactions are highly liquid and difficult to trace manually, this account requires continuous monitoring. AI pattern recognition can analyze cash flow movements in real- time, detect unusual large withdrawals, repetitive transactions, or missing entries that may indicate internal fraud.

Table 3. The most significant areas for potential financial fraud in BCA's 2019–2024

Financial Area	2019–2024 Value (IDR Million)	Why It's Prone to Fraud	Simple Fraud Examples	Insight	AI Detection Method
Consumer Loans	7,065,234 → 9,435,564	Retail loans are large and spread across many borrowers, making them easier to manipulate.	Fictitious loans recorded under fake borrowers. Extended default to appear current. Loan amount mark-up to inflate portfolio.	Steady growth suggests retail lending expansion but risk of earnings manipulation if loan quality is disguised.	Anomaly detection in payment patterns: monitor unusual delays and detect hidden non-performing loans.
Financing Loans	149,428 → 8,376,496	Sudden loan growth (especially from 2021) can hide credit problems.	Under-reporting of defaults. Overvaluing collateral. Duplicate loans using the same asset.	Sharp growth indicates rapid expansion vulnerable to misreporting.	Predictive analytics for credit risk: model default probability and alert deviations from normal patterns.
Cash & Giro at Bank Indonesia	162,991,763 → 65,157,326	Large, highly liquid funds can be misappropriated without quick detection.	Cash embezzlement by staff. Unrecorded deposits or withdrawals. Fictitious inter-branch transfers.	Significant drop in 2024 is a red flag for liquidity anomalies.	Pattern recognition for abnormal cash flows: detect unusual withdrawals and repetitive, high-value transactions.
Securities for Trading	8,407,700 → 10,001,769	Securities are vulnerable to market manipulation and insider trading.	Insider trading for personal gain. False mark-to-market to boost profit. Round-tripping with related parties.	Stable value requires market monitoring since fraud may not appear in raw numbers.	Machine learning for market behavior monitoring: detect abnormal trading patterns and price deviations.
Estimated Losses on Commitments & Contingencies	1,330,469 → 2,975,147	Loss provisions are estimates, making them easy to manipulate for earnings management.	Under-provisioning to inflate profit. Delayed recognition of losses. Reverse provisioning booked as income.	2022 spike and 2024 drop suggest potential earnings manipulation.	Predictive modeling for asset impairment: compare expected vs. reported provisions and flag inconsistencies.

Source: BCA (2025)

Securities for Trading remained relatively stable, ranging from IDR 8,407,700 million in 2019 to IDR 10,001,769 million in 2024, peaking in 2023. Despite this stability, securities are highly prone to market-related fraud such as insider trading, false mark-to-market valuation, and round-tripping transactions designed to create artificial profits. These fraudulent activities are often invisible in the nominal figures of the financial statements, making traditional audits less effective. By applying machine learning for market behavior monitoring, AI can track trading patterns, compare them to market benchmarks, and detect unusual activities that suggest manipulation or unauthorized trading.

Estimated Losses on Commitments & Contingencies is the final critical area, showing a rise from IDR 1,330,469 million in 2019 to a peak of IDR 3,439,318 million in 2022, before declining to IDR 2,975,147 million in 2024. This account is particularly vulnerable to earnings management, as loss provisions are estimates and can be manipulated by management. Fraud may occur through under- provisioning to inflate profit, delayed recognition of losses, or reversing provisions without valid justification. The fluctuation pattern suggests the potential for profit smoothing, which is a classic sign of hidden financial risk. AI-based predictive modeling can compare expected provisions based on historical trends and credit risk models to reported figures, automatically flagging inconsistencies for investigation.

The Consumer Loans segment represents one of the most significant areas for potential financial fraud in BCA's 2019–2024 financial statements. The value of consumer loans grew steadily from IDR 7,065,234 million in 2019 to IDR 9,435,564 million in 2024, reflecting the bank's expanding retail lending portfolio. This area is prone to fraud because retail loans are spread across many borrowers, making manipulation easier without immediate detection. Common fraudulent activities include fictitious loans under fake borrowers, extended defaults to make non-performing loans appear current, and loan mark-ups to inflate the portfolio's size. While the growth appears stable, these subtle risks can lead to earnings manipulation if loan quality is misrepresented. AI-driven anomaly detection can monitor unusual delays in repayment and identify hidden non-performing loans, providing an early warning of potential fraud.

The Financing Loans account experienced dramatic changes, rising from just IDR 149,428 million in 2019 to IDR 8,376,496 million in 2024, with a particularly sharp jump starting in 2021. Such rapid growth raises fraud risk because sudden loan expansions may conceal credit problems or be used to misreport financial performance. Typical frauds include under-reporting of defaults to inflate profits, overvaluation of collateral to secure more loans, and duplicate loans using the same asset as collateral. The spike indicates vulnerability to misreporting or aggressive lending practices that may not follow prudent risk management. AI-powered predictive analytics is particularly useful in this area, as it can model default probabilities and alert deviations from normal historical lending patterns.

Cash & Giro at Bank Indonesia is another critical high-risk area because of its liquidity and susceptibility to misappropriation. The account showed extremely high balances in 2019–2020 (over IDR 162 trillion) but dropped significantly to IDR 65,157,326 million in 2024, which is a red flag for potential cash-related fraud. This account is vulnerable to cash embezzlement by internal staff, unrecorded deposits or withdrawals, and fictitious inter-branch transfers that can mask missing funds. Because large cash movements can be hidden in complex banking operations, this area requires real-time monitoring. AI-based pattern recognition can detect abnormal withdrawals, repetitive high-value transactions, or unusual cash flow patterns that deviate from historical norms, helping to uncover fraud before it causes significant financial loss.

The Securities for Trading account remained relatively stable between IDR 8,407,700 million in 2019 and IDR 10,001,769 million in 2024, peaking in 2023. Despite its stability, this area is highly prone to market manipulation and insider trading, which often cannot be seen directly from nominal figures in the financial statements. Common fraudulent practices include insider trading for personal gain, false mark-to-market valuations to inflate profit, and round-tripping transactions with related parties to create artificial revenue. Stability in reported amounts does not eliminate fraud risk; instead, it highlights the need for AI-driven market behavior monitoring. By tracking unusual trading patterns and price deviations, machine learning can reveal suspicious activities that would otherwise go unnoticed in conventional audits.

Finally, Estimated Losses on Commitments & Contingencies is inherently risky because it involves management estimates, making it an area vulnerable to earnings manipulation. This account increased from IDR 1,330,469 million in 2019 to IDR 3,439,318 million in 2022, before declining to IDR 2,975,147 million in 2024. Such fluctuations suggest potential profit smoothing strategies, where management manipulates provisions to stabilize reported earnings. Typical frauds include under-provisioning to inflate profit, delaying recognition of losses, and reversing provisions as income without proper justification. These practices are difficult to detect manually but can be identified using AI-based predictive modeling, which compares expected provisions derived from historical data and credit risk patterns to reported figures. Any significant inconsistency can trigger further investigation, reducing the likelihood of undetected fraud.

Conclusion

This study highlights that five financial statement areas—consumer loans, financing loans, cash & giro at Bank Indonesia, securities for trading, and estimated losses on commitments & contingencies—represent the highest fraud risk in BCA's 2019–2024 financial statements. The analysis shows that these accounts handle large monetary values, are prone to manipulation, and can significantly impact profitability and liquidity if fraud occurs. By integrating AI-driven financial fraud detection techniques, including anomaly detection, predictive analytics, and machine learning for pattern recognition, banks can proactively identify unusual patterns, detect potential fraud early, and enhance the reliability of financial reporting. The findings emphasize the importance of leveraging technology-based risk management to strengthen internal controls and reduce the limitations of traditional auditing methods.

This study is limited to secondary financial data from 2019–2024 and focuses solely on one bank (BCA), which may restrict the generalizability of the findings across the entire banking sector. Additionally, the research provides a conceptual framework for AI-driven fraud detection without implementing real-time AI models due to data confidentiality constraints. Future studies should expand the sample to multiple banks to provide comparative insights and apply real AI models using transaction-level or customer-level data to enhance fraud prediction accuracy. Furthermore, future research could integrate behavioral analytics and real-time monitoring systems, allowing for dynamic fraud detection and prevention that aligns with the evolving complexity of digital banking transactions.

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Artificial Intelligence and Ethical Leadership: Mapping Governance Challenges and Strategies (2015–2025)

Oskar Vitriano*
Universitas Indonesia, Indonesia
Email: ovitriano@gmail.com

Kiki Pranowo
Planning Division in Secretary of Directorate General of Agricultural Infrastructure and Facilities of The Ministry of Agriculture
Email: kiki_pranowo@yahoo.com

**Corresponding Author*

Abstract

This paper presents a Systematic Literature Review (SLR) guided by PRISMA 2020 to examine how ethical leadership is enacted in the adoption of artificial intelligence (AI) across sectors and regions from 2015 to 2025. A total of 147 peer-reviewed articles retrieved from Scopus were analyzed through transparent screening and thematic coding. The review identifies four recurring barriers: governance and normative gaps, model opacity and fairness concerns, fragile data-governance foundations, and weak organizational oversight. In response, seven governance strategies are proposed: ethics-by-design, proportional risk and impact assessment, defined human oversight, continuous audit and monitoring, vendor guardrails, capacity building, and contextual adaptation to local settings. Descriptive findings reveal that 98.6% of studies were published between 2016 and 2025, with a 2025 peak, and contributions concentrated in North America and Asia-Pacific yet scattered across more than 130 journals. Theoretically, this study extends ethical leadership into the sociotechnical domain; practically, it offers a framework to operationalize ethical AI governance.

Keywords: artificial intelligence; ethical leadership; PRISMA; SLR

Introduction

Artificial Intelligence (AI) has rapidly evolved into one of the most transformative forces of the 21st century. Its integration into organizational decision-making has redefined how governments, businesses, and non-profits operate. From predictive policing in the United States to AI-based medical diagnostics in South Korea and automated welfare allocation in the United Kingdom, the applications of AI have expanded across diverse domains (Dwivedi et al., 2021; Eubanks, 2018). These innovations promise efficiency, precision, and scalability, yet they also surface profound ethical dilemmas regarding fairness, accountability, and transparency

(Mittelstadt, 2019). AI's dual character as both an enabler of efficiency and a potential amplifier of injustice that places leadership at the center of ethical deliberation.

In developed economies, regulatory frameworks have begun to address these challenges. The European Union's AI Act (2024) and the U.S. National Institute of Standards and Technology (NIST) AI Risk Management Framework (2023) provide structured approaches to mitigate harm while promoting innovation (Fjeld et al., 2020; OECD, 2022). These frameworks emphasize transparency, human oversight, and risk-based governance. Conversely, developing countries such as Indonesia, Kenya, and Bangladesh face unique challenges, including inadequate digital infrastructure, limited AI literacy, and a dependence on imported technologies from global vendors (Mhlanga, 2023; Rana et al., 2024). This disparity underscores the global imbalance in AI governance and raises concerns about digital dependency and ethical asymmetry.

At the heart of these challenges lies the question of leadership. Ethical leadership in a framework traditionally rooted in moral philosophy and organizational behavior that provides a valuable lens for examining how values and conscience shape technology adoption (Brown & Treviño, 2006; Dignum, 2019). Unlike purely technical approaches such as fairness-by-design or privacy-by-design, ethical leadership emphasizes the human agency of leaders who must balance innovation with justice, efficiency with equity, and progress with responsibility. Leaders are therefore not only decision-makers but also moral agents who influence how AI systems impact human dignity and social trust (Birkstedt et al., 2023; Uddin, 2023; Zuiderwijk et al., 2021).

Despite the growing scholarly interest in AI ethics, there remains a significant research gap at the intersection of AI governance and leadership studies. The majority of AI ethics research focuses on principles and technical safeguards fairness, explainability, bias mitigation, and privacy without examining the role of leadership in operationalizing these values (Jobin et al., 2019; Leslie, 2019). Conversely, leadership literature tends to analyze personal virtues, moral reasoning, and organizational culture, with limited attention to the digital and algorithmic dimensions of governance. Bridging these two domains is essential to ensure that ethical leadership evolves in step with technological advancement.

This gap is particularly evident in contexts where governance capacity is weak. In countries with underdeveloped regulatory structures, AI adoption risks perpetuating systemic biases or introducing new forms of digital inequality (Misuraca & Viscusi, 2020). Meanwhile, in advanced economies, debates increasingly focus on how to operationalize high-level principles into verifiable practices such as algorithmic audits, model documentation, and impact assessments (E. A. Hassan & El-Ashry, 2024; Lee & Mitson, 2025; Oladele et al., 2024). The divergence between high-capacity and low-capacity ecosystems highlights the necessity of localized, context-sensitive strategies for ethical leadership in AI.

In response to these challenges, this paper presents a systematic literature review (SLR) guided by the PRISMA 2020 methodology. By analyzing 147 peer-reviewed articles published between 2015 and 2025, this review synthesizes the barriers to AI-based ethical leadership and the governance strategies proposed to overcome them. Specifically, the study seeks to answer two guiding research questions:

1. What are the main barriers to implementing AI-based ethical leadership across different sectors and national contexts?
2. What governance strategies are most effective in ensuring ethical and responsible AI adoption?

By systematically mapping global scholarship, this article contributes to both theory and practice. Theoretically, it extends ethical leadership into the sociotechnical domain, bridging organizational behavior with algorithmic governance. Practically, it offers policymakers, practitioners, and organizational leaders a structured framework to translate ethical principles into auditable routines, thereby ensuring that AI adoption supports both innovation and human dignity.

Methodology

This study employs a Systematic Literature Review (SLR) guided by the PRISMA 2020 framework (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure validity, transparency, and reproducibility in identifying, screening, and synthesizing scholarly literature (Page et al., 2021). PRISMA is widely adopted in interdisciplinary research, including management, computer science, and public policy, as it reduces selection bias and enhances clarity in reporting findings (McKenzie et al., 2019; Moher et al., 2009). This is particularly relevant when examining complex, multi-dimensional topics such as artificial intelligence (AI), ethics, and leadership (Dwivedi et al., 2021; Jobin et al., 2019).

The Scopus database was chosen as the primary data source due to its broad coverage of high-quality journals across technology, leadership, governance, and social sciences (Falagas et al., 2008). The search period spanned January 2015 to June 2025 to capture a decade of literature during which AI adoption and ethical leadership emerged as a pressing research concern (Dignum, 2019; Mittelstadt, 2019). Keywords included "Artificial Intelligence" AND "ethical leadership," yielding an initial 150 records.

Duplicates were removed, leaving 147 unique articles. Screening was conducted in two stages— title/abstract review followed by full-text assessment based on inclusion criteria: (1) peer-reviewed journal articles, (2) written in English, (3) explicitly discussing AI in relation to ethical leadership or governance, and (4) organizational context (public, private, or non-profit). Exclusion criteria included conference proceedings, editorials, non-peer-reviewed articles, and purely technical AI studies without ethical or leadership implications (Snyder, 2019; Tranfield et al., 2003). To enhance objectivity, two independent reviewers evaluated the articles, with disagreements resolved through discussion. Inter-rater reliability was measured using Cohen's Kappa, which is a widely recognized measure for agreement in systematic reviews (McHugh, 2012). For analysis, a combination of qualitative thematic coding was used (Saldaña, 2021).

The process was documented in a PRISMA 2020 flow diagram, showing the four stages of identification (n=150), screening (n=147), eligibility assessment, and final inclusion (n=147). This systematic approach ensures rigor, minimizes bias, and supports reproducibility, thereby reinforcing both the internal validity and external generalizability of the findings (Page et al., 2021).

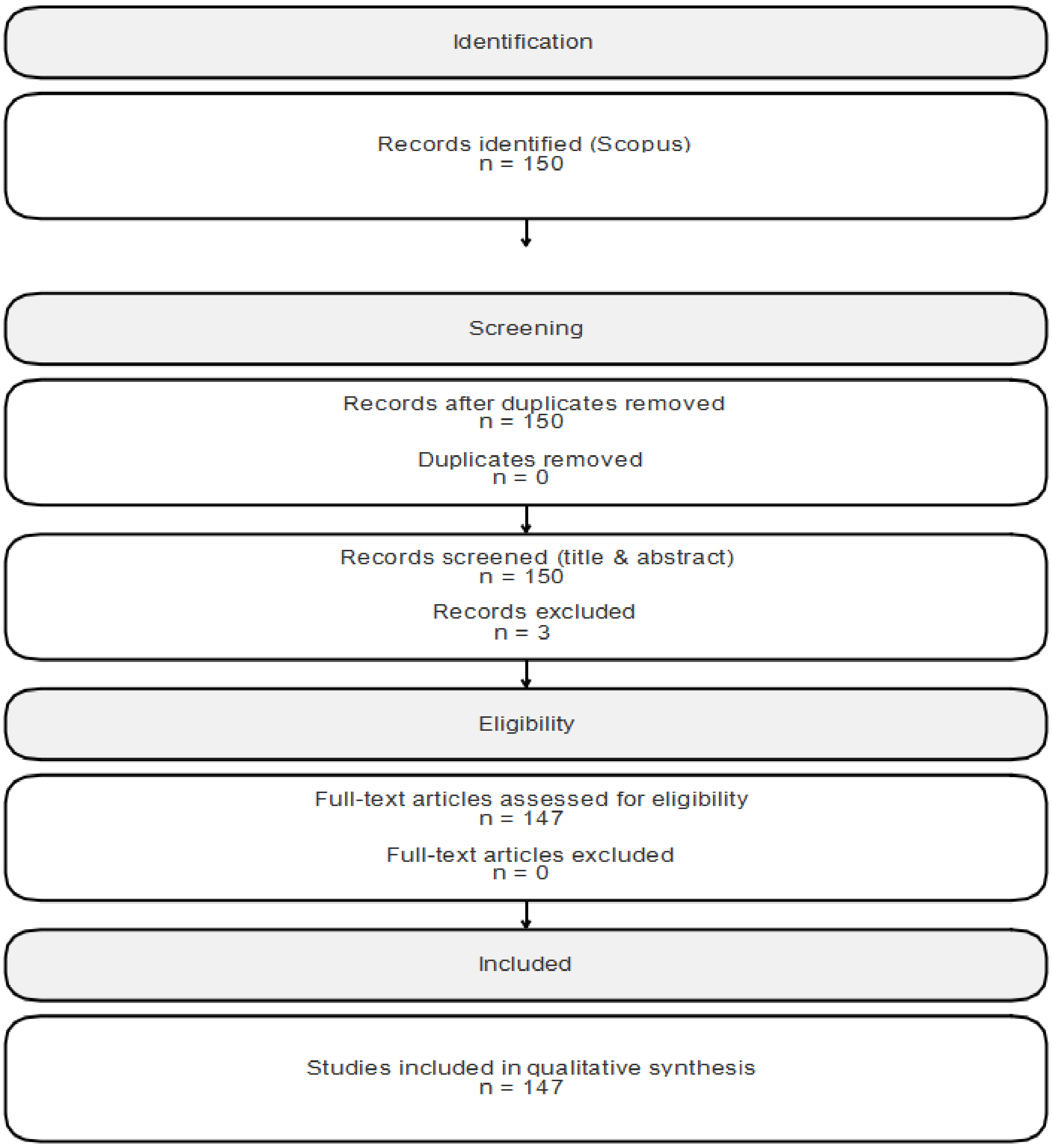

Figure 1. PRIMA 2020 Flow Diagram

Discussion

Over the last decade, publication activity accelerates sharply toward the end of the period. Articles from 2016–2025 account for 145 of 147 records (98.6%), with effective coverage from 2017 to 2025. The productivity peak occurs in 2025 with 79 articles, indicating not only sustained growth but a consolidation of AI-and-ethical-leadership as a front-line topic. This matters for the synthesis because the evidence base is markedly current, aligning with present policy debates and organizational practice.

Across 147 entries, the corpus spans 132 unique journals, with 91.7% represented by a single publication that highlighting a pronounced long-tail distribution. The most frequent outlet is Journal of Leadership Studies (4), followed by Administrative Sciences (3) and Cogent Education (3). A second tier of outlets contributed two articles each, including International Journal of Basic and Applied Sciences, Information (Switzerland), Development and Learning in Organizations, Humanities and Social Sciences Communications, Journal of Managerial Psychology, Business Ethics and Leadership, and Healthcare Management Forum. Altogether, the top 10 journals account for 24 papers (≈16.5%), while the remainder is dispersed across leadership/management, education, health, computing/HCI, and policy/law journals. This wide dispersion underscores the inherently sociotechnical character of the field and emphasizes the importance of bridging technical approaches with governance and leadership perspectives. The distribution of articles across journals is illustrated in Figure 2 below.

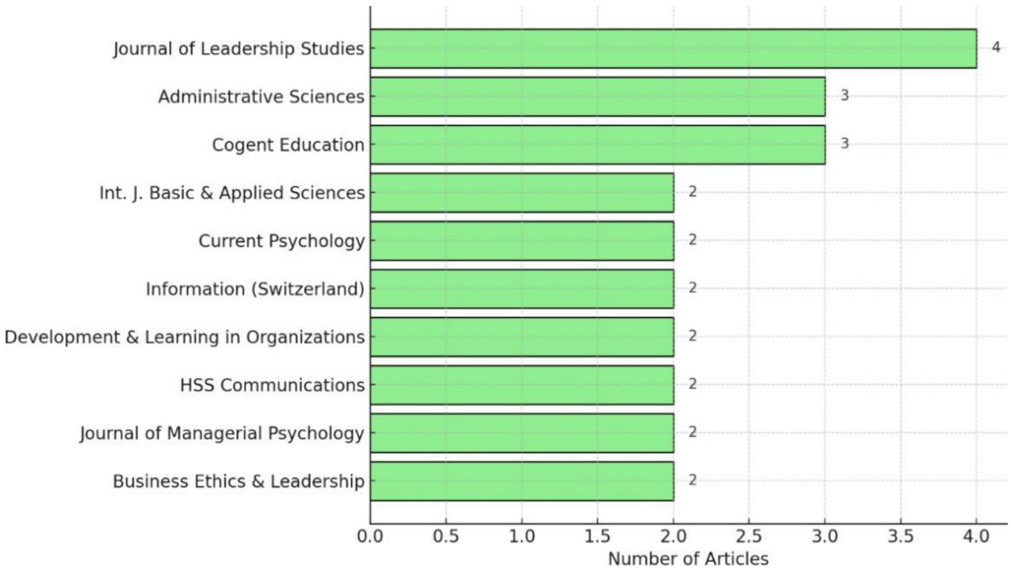

Figure 2. Distribution of Articles

The year-by-year concentration in the latter half of the decade suggests two dynamics. First, governance of AI and ethical leadership has shifted from normative statements to operational needs, which coincides with more studies on audit, reporting, and human oversight in real deployments. Second, the dominance of 2025 outputs implies that recent contributions bring more mature frameworks and tooling such as model cards, data cards, and structured post-deployment monitoring so the review captures methods that organizations can implement now rather than concepts that are merely aspirational.

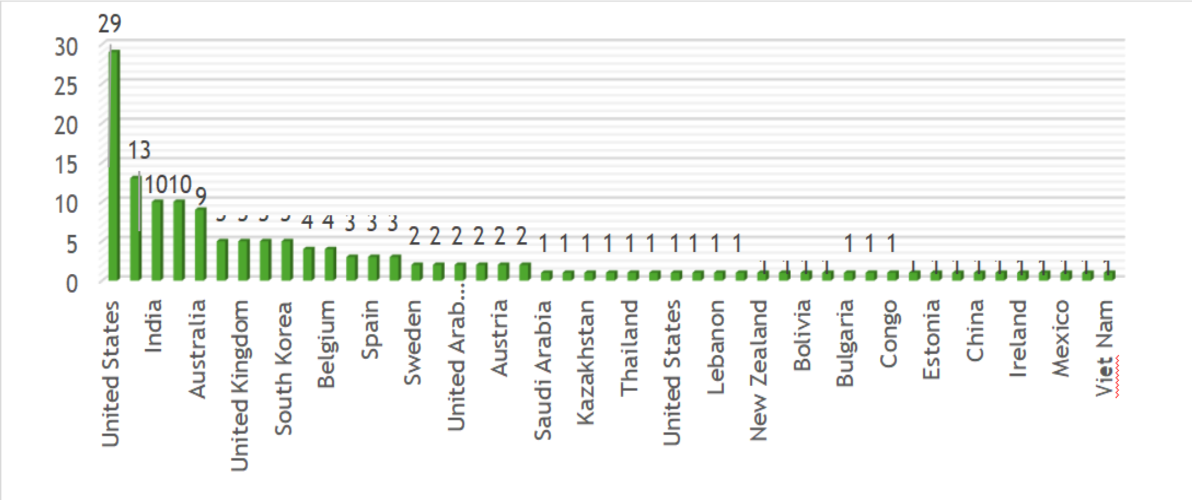

Figure 3. Country of Origin

In Figure 3. by country of origin (assigning one country per paper), knowledge production is led by the United States with 29 of 147 articles (19.7%), followed by Canada (13; 8.8%), India (10; 6.8%), China (10; 6.8%), and Australia (9; 6.1%). A second tier comprises Turkey (5; 3.4%), the United Kingdom (5; 3.4%), Germany (5; 3.4%), and South Korea (5; 3.4%), with Malaysia (4; 2.7%) close behind. Together, the top five countries account for ~48.2% of the corpus, and the top ten for ~64.5%, indicating a North American lead alongside expanding contributions from large Asia–Pacific economies.

Because this view attributes each paper to a single country, it does not capture cross-border collaboration; counts sum to 100% by construction and will differ from the earlier multi-country coverage where the UK appeared stronger. Even with this stricter assignment, the presence of India and China among the top contributors signals growing activity in major non-Western ecosystems that are rapidly adopting AI. In turn, the US-led profile helps explain why themes such as auditability, transparency reporting, and independent assurance feature prominently in the literature, while the visibility of Canada and Australia aligns with public-sector AI guidance and risk frameworks maturing in those settings.

Looking at the journal landscape, output is broad with a few anchor venues. Journal of Leadership Studies appears most frequently with 4 articles, followed by Administrative Sciences (3) and Cogent Education (3), then International Journal of Basic and Applied Sciences (2) and Current Psychology (2). This spread indicates that ethical leadership and AI governance are not confined to core technology journals; the conversation spans leadership, public policy, education, and psychology. That interdisciplinary footprint matches the sociotechnical nature of the topic: effectiveness depends on methods, regulation, and organizational behavior working together.

The intersection of temporal trends, country profiles, and outlet choices carries practical implications. The recent surge enriches evidence on operationalizing ethics ethics-by-design, risk and impact gates, explicit human intervention points, and stronger audit and reporting routines. Dominant contributions from high- capacity countries offer patterns that can be adapted elsewhere, while the sizeable multi-country share cautions that transfer requires adjustment to local capacity and norms. Completing SJR quartiles for all titles will help decision-makers weigh not only the substance of findings but also the standing of the outlets publishing them.

Overall, the past decade’s panorama reveals a corpus that is highly current, globally networked, and multidisciplinary. Its strengths are temporal relevance and contextual breadth; its main limitation is incomplete outlet-quality metadata. Filling the SJR fields will let you draw sharper links between outlet quality and the types of governance strategies endorsed turning your narrative into one that is data-rich and methodologically robust in connecting evidence, context, and publication quality.

This discussion addresses research question 1: identifying the principal barriers to implementing AI-based ethical leadership across sectors and countries. From the 147 PRISMA-selected articles, a consistent pattern emerges a wide gap between high-level principles and auditable operating practices. Organizations frequently invoke transparency, fairness, and accountability, yet those values are not reliably translated into procedures such as decision traceability, risk reporting, and clear assignment of responsibility (Ariffin et al., 2025; E. A. Hassan & El-Ashry, 2024; Lin et al., 2024; Marcinkevage & Kumar, 2025; Nord & Schleier, 2025; Sullivan et al., 2024).

At the technical layer, model opacity is the most persistent obstacle. When systems function as black boxes, explanations tend to be post hoc and superficial, limiting the ability of leaders to justify or remediate outcomes. Although interpretability, transparency, fairness, and bias are discussed in the literature, they occupy a smaller share of attention than broader ethical talk. In practical terms, that imbalance weakens accountability and delays corrective action in settings such as recruitment, risk scoring, and the distribution of social benefits (Berger-Estilita et al., 2025; Ghasemaghaei & Kordzadeh, 2024; Gisselbaek et al., 2025; Kulkarni et al., 2024; Lee & Mitson, 2025; Murire, 2024).

Privacy and data governance pose a quieter but foundational barrier. Principles like purpose limitation, data minimization, and robust provenance tracking rarely become everyday routines. Many organizations have not yet linked privacy impact assessments to technical documentation such as model cards and data cards, which makes upstream bias hard to spot early and to manage systematically (Boikanyo, 2025; Karakose et al., 2023; Mansour et al., 2025; Polat et al., 2025; Tabaghdehi & Ayaz, 2025; Vinodh, Subramani, Neeraja, et al., 2025; Wang et al., 2025).

Institutional capacity further amplifies these challenges. Leaders' algorithmic literacy, the availability of data-stewardship roles, and the ability to balance accuracy, fairness, and explainability remain uneven. In developing contexts, immature digital infrastructure and dependence on global platforms narrow the room to negotiate procurement terms that protect audit rights and transparency, leaving organizations exposed to ethical and operational blind spots (Ariffin et al., 2025; Gisselbaek et al., 2025; Marcinkevage & Kumar, 2025; Orfanidis, 2025; Yam et al., 2025).

Control mechanisms are not yet normalized. Human-in-the-loop checkpoints, independent audits, periodic bias tests, and incident reporting are the exception rather than the rule. Procurement contracts often omit enforceable clauses on technical documentation and access, effectively shifting ethical control from the organization to vendors. Effective governance, however, requires clearly defined human intervention points across the system life cycle, together with verifiable reporting and assurance (Jenkins & Khanna, 2025; Kim et al., 2024; Marcinkevage & Kumar, 2025; Masaeid et al., 2025; Nair et al., 2024; Zárate-Torres et al., 2025).

Sectoral and country differences sharpen these barriers. Public-sector studies foreground citizen accountability but confront oversight resource constraints. Health care emphasizes clinical risk management yet struggles with explainability in high-stakes decisions. Education debates equity of access and assessment but lacks mature audit toolchains. Finance appears less frequently despite its high stakes. In advanced economies, debates gravitate toward audits and transparency reporting; in developing countries, realistic priorities are to strengthen basic data governance and leaders' algorithmic literacy (M. Hassan et al., 2025; Lin et al., 2024; Marcinkevage & Kumar, 2025; Nord & Schleier, 2025; Orfanidis, 2025; Shabbir et al., 2024; Sullivan et al., 2024; Yam et al., 2025).

Taken together, the barriers paint a consistent picture. Ethical leadership in the AI era cannot rely on a moral compass alone; it demands sociotechnical and institutional competence to turn values into working procedures. In practice, this means reading and managing model risk, designing explicit human intervention points, strengthening data governance, institutionalizing verifiable audits, and negotiating procurement terms that secure organizational audit rights and transparency (Gisselbaek et al., 2025; M. Hassan et al., 2025; Lin et al., 2024; Marcinkevage & Kumar, 2025; Murire, 2024; Nord & Schleier, 2025; Shabbir et al., 2024; Sullivan et al., 2024).

Table 1. Issues and Discussion

No	Issue	Discussion	References
1	Normative and governance ambiguity	Ethical principles (transparency, fairness, accountability) often remain soft law; traceability, risk reporting, sanctions, and clear accountability roles are not yet institutionalized across units.	(Ariffin et al., 2025; M. Hassan et al., 2025; Lin et al., 2024; Marcinkevage & Kumar, 2025; Nord & Schleier, 2025; Sullivan et al., 2024)
2	Model opacity and limited explainability	Models behave like black boxes; explanations tend to be post hoc and shallow, weakening practical accountability. Corrections arrive late in recruitment, risk scoring, or social service delivery contexts.	(Berger-Estilita et al., 2025; Ghasemaghaei & Kordzadeh, 2024; Gisselbaek et al., 2025; Kulkarni et al., 2024; Lee & Mitson, 2025; Murire, 2024)
3	Fragile privacy and data governance	Purpose limitation, data minimization, and data lineage rarely become routine practice; privacy impact assessments are not connected to technical artefacts (model/data cards), making upstream bias hard to detect early.	(Boikanyo, 2025; Polat et al., 2025; Tabaghdehi & Ayaz, 2025; Vinodh, Subramani, Abirami, et al., 2025; Wang et al., 2025)
4	Institutional capacity and algorithmic literacy gaps	Leaders and teams lack socioâ€‘technical competence to weigh tradeâ€‘offs among accuracy, fairness, and explainability; in developing countries, constraints include immature infrastructure and platform dependence.	(Ariffin et al., 2025; Gisselbaek et al., 2025; Marcinkevage & Kumar, 2025; Orfanidis, 2025; Sullivan et al., 2024; Yam et al., 2025)
5	Weak control mechanisms (HITL, audit, bias testing)	Human in the a loop is rarely defined; internal/external audits and periodic bias testing are not standard; incident reporting is inconsistent.	(Jenkins & Khanna, 2025; Kim et al., 2024; Marcinkevage & Kumar, 2025; Masaeid et al., 2025; Zárate-Torres et al., 2025)
6	Vendor lockin and weak procurement clauses	Contracts often omit technical documentation duties, audit rights, or incident reporting standards; ethical control drifts to vendors, reducing organizational transparency.	(M. Hassan et al., 2025; Orfanidis, 2025; Sullivan et al., 2024; Yam et al., 2025)
7	Cross sector and cross country variation	Public sector stresses due process; health focuses on clinical safety; education on equitable access; finance is underrepresented. Advanced economies emphasize audits/reporting; developing contexts focus on data governance and leadership literacy.	(M. Hassan et al., 2025; Lin et al., 2024; Nord & Schleier, 2025; Shabbir et al., 2024; Yam et al., 2025)

This section addresses research question 2 by outlining governance strategies that make ethical leadership in AI operational rather than merely declarative. The synthesis of 147 articles indicates that effective practice emerges when organizations connect high-level values to concrete, auditable routines across the lifecycle: design choices grounded in ethics, proportionate risk and impact assessment, defined human oversight, continuous monitoring and audit, vendor and procurement guardrails, capacity building, and local contextualization. Taken together, these elements convert ethical intentions into durable organizational capabilities (M. Hassan et al., 2025; Marcinkevage & Kumar, 2025; Sullivan et al., 2024).

A first pillar is ethics-by-design integrated into the data and model pipeline. This means documenting datasets and features, articulating use constraints, embedding fairness and privacy criteria in acceptance tests, and selecting model families that enable sufficient explainability for the decision context. Model and data cards, pre-deployment bias tests, and clear interpretability targets keep leaders' ethical commitments aligned with technical work products, so that "explainability" is not an afterthought but a design constraint. Organizations that treat documentation and evidence generation as non-optional artefacts report better traceability and faster remediation when issues arise (Ghasemaghaei & Kordzadeh, 2024; Kim et al., 2024; Lee & Mitson, 2025; Lin et al., 2024; Marcinkevage & Kumar, 2025).

Second, risk and impact assessment needs to be proportionate, repeatable, and tied to gates. Rather than a one-off checklist, assessments are triggered when the context changes new data sources, new populations, or material model drift. Red-teaming and scenario stress-tests expose failure modes before deployment; thresholded risk ratings then decide whether to proceed, add mitigations, or escalate for independent review. Where this discipline is used, leaders gain a defensible basis for trade-offs between accuracy, fairness, and explainability under real constraints of time and cost (Jenkins & Khanna, 2025; Kulkarni et al., 2024; Nair et al., 2024; Nord & Schleier, 2025; Zárate-Torres et al., 2025).

Third, human oversight works when it is specific, not symbolic. Organizations should map exactly where humans can intervene, what evidence they receive, how escalation works, and which outcomes can be reversed. Logging the rationale for overriding model outputs both protects affected individuals and accumulates organizational learning that feeds into the next training cycle. Studies show that clearly defined oversight points reduce harm in high-stakes settings and rebuild trust in decisions that cannot yet be fully automated (Ariffin et al., 2025; Berger-Estilita et al., 2025; Gisselbaek et al., 2025; Murire, 2024).

Fourth, auditability and monitoring must be normalized. Internal and independent audits verify data lineage, fairness metrics, and performance stability across subgroups; post-deployment monitoring detects drift and re-checks bias at agreed intervals; incident reporting makes adverse outcomes visible and correctable. Dashboards that surface key indicators to governance committees, plus third-party assurance when risk is high, translate accountability from policy statements into observable practice (M. Hassan et al., 2025; Kim et al., 2024; Marcinkevage & Kumar, 2025; Nair et al., 2024; Sullivan et al., 2024; Zárate-Torres et al., 2025).

Table 2. Strategy, Purpose/Outcome and Core Actions

No.	Strategy	Purpose/Outcome	Core Actions	References
1	Ethics-by- Design (data & model pipeline)	Translate values into design constraints so fairness, privacy, and explainability are built-in, not added later.	Document datasets/features; define use constraints; embed fairness/privacy criteria in acceptance tests; choose explainable model families; run pre-deployment bias tests; set interpretability targets.	(Ghasemaghaei & Kordzadeh, 2024; Kim et al., 2024; Lee & Mitson, 2025; Lin et al., 2024; Marcinkevage & Kumar, 2025)
2	Risk & Impact Assessment (proportionate, repeatable, gated)	Make go/no-go decisions defensible and evidence-based under real constraints of time and cost.	Conduct AIA/DPIA; red-team & stress-test scenarios; assign thresholded risk ratings; define mitigation plans; escalate high-risk to independent review.	(Jenkins & Khanna, 2025; Kulkarni et al., 2024; Nair et al., 2024; Nord & Schleier, 2025; Zárate-Torres et al., 2025)
3	Human Oversight (specific, not symbolic)	Protect individuals and build trust by ensuring reversible decisions with clear escalation paths.	Map intervention points; define evidence shown to reviewers; set escalation paths; log rationales for overrides; feed overrides back to training loop.	(Ariffin et al., 2025; Berger-Estilita et al., 2025; Gisselbaek et al., 2025; Murire, 2024)
4	Auditability & Continuous Monitoring	Institutionalize accountability through verifiable checks and transparent reporting.	Internal & independent audits; monitor drift and bias at set intervals; implement incident reporting; create governance dashboards; seek third-party assurance for high-risk systems.	(M. Hassan et al., 2025; Kim et al., 2025; Marcinkevage & Kumar, 2025; Nair et al., 2024; Sullivan et al.,2024; Zárate-Torres et al., 2025)
5	Procurement & Vendor Governance	Prevent ethical control from drifting to vendors by encoding obligations in contracts.	Mandate technical documentation; require bias/safety test evidence; secure audit rights; define incident reporting timelines; ensure data portability & exit ramps; include SLAs for ethical incidents.	(M. Hassan et al., 2025; Marcinkevage & Kumar, 2025; Orfanidis, 2025; Sullivan et al., 2024; Yam et al., 2025)
6	Capacity Building & Culture	Shift from compliance-after- the-fact to assurance-by- design through skills and shared habits.	Executive AI literacy; data stewardship roles; privacy engineering training; communities of practice; templates for documentation; quarterly bias reviews.	(Boikanyo, 2025; Mansour et al., 2025; Polat et al., 2025; Tabaghdehi & Ayaz, 2025; Vinodh, Subramani, Neeraja, et al., 2025; Wang et al., 2025)
7	Localization & Sector- Specific Playbooks	Adapt global principles to legal, cultural, and risk profiles of specific sectors and jurisdictions.	Map sector risks; define sector-specific metrics & thresholds; align with local law; co-design with stakeholders; phase adoption based on capacity.	(Lin et al., 2024; Nord & Schleier, 2025; Orfanidis, 2025; Shabbir et al., 2024; Yam et al., 2025)

Fifth, procurement and vendor governance should encode ethics as contract terms, not aspirations. Clauses that mandate technical documentation, bias and safety test evidence, audit rights, incident reporting timelines, data portability, and exit ramps prevent ethical control from drifting to vendors. Service-level agreements for ethical incidents, not only uptime, make remediation time a formal obligation. This is especially critical for public agencies and resource-constrained organizations that rely on external platforms (M. Hassan et al., 2025; Marcinkevage & Kumar, 2025; Orfanidis, 2025; Sullivan et al., 2024; Yam et al., 2025).

Sixth, capacity building underpins everything else. Leaders need algorithmic literacy to read risk indicators and challenge trade-offs; teams need data-steward roles, privacy engineering skills, and habits of documenting decisions. Communities of practice, targeted training, and coaching for governance committees help shift culture from “compliance after the fact” to “assurance by design.” Studies highlight that even lightweight investments a shared template for model cards, a quarterly bias review, a short course for executives that produce outsized returns in clarity and accountability (Boikanyo, 2025; Mansour et al., 2025; Polat et al., 2025; Tabaghdehi & Ayaz, 2025; Vinodh, Subramani, Abirami, et al., 2025; Wang et al., 2025)

Finally, strategies are contextual. Public services prioritize fairness, explainability, and due process; health care focuses on clinical safety and traceability; education emphasizes equitable access and assessment integrity; finance requires robust stress-testing and traceable credit decisions. In advanced economies the emphasis is compliance-plus audits, reporting, and independent assurance whereas in developing contexts the pragmatic path is to strengthen data governance foundations, secure minimum vendor transparency, and build leaders’ algorithmic stewardship before attempting complex automation. Localizing global principles into sector-specific playbooks makes adoption feasible without diluting ethical intent (Lin et al., 2024; Nord & Schleier, 2025; Orfanidis, 2025; Shabbir et al., 2024; Yam et al., 2025).

Taken together, the corpus suggests that the most effective governance is not a single tool but a layered system: ethics-by-design, risk and impact gates, targeted human oversight, auditable monitoring, enforceable vendor terms, capability building, and localization. When leaders orchestrate these layers, ethical leadership becomes a set of repeatable decisions backed by evidence, not a promise. This directly answers RQ2 by specifying how organizations can move from values to verifiable practice across sectors and jurisdictions (Lin et al., 2024; Marcinkevage & Kumar, 2025; Yam et al., 2025; Zárate-Torres et al., 2025).

Conclusions and Recommendation

This review concludes that the central challenge of ethical leadership in AI is not a shortage of principles, but the difficulty of turning principled intent into auditable, everyday practice. Across the corpus, organizations frequently affirm transparency, fairness, and accountability; yet these ideals too often fail to appear in the artefacts that actually govern people’s lives decision logs, risk registers, escalation pathways, and post-incident learning loops. When that normative operational gap persists, automated decisions affecting hiring, welfare eligibility, credit access, education, or clinical triage become hard to explain, hard to contest, and slow to correct. Ethical leadership, in other words, acquires meaning only when values are bound to procedures that can be checked and improved.

A second finding is that technical opacity amplifies this gap. Where models behave like black boxes, leaders are pushed toward post hoc narratives that soothe rather than diagnose. Explanations arrive after harm is felt, fairness is evaluated as a late-stage add-on, and stakeholders especially those already vulnerable carry the cost of uncertainty. Human-centred leadership requires the opposite orientation: clear interpretability targets set in advance, evidence of subgroup performance disclosed routinely, and the humility to pause or reverse an automated decision when the evidence is weak or the stakes for the individual are high.

Third, privacy and data governance remain fragile foundations in many settings. Without purposeful data collection, disciplined minimization, traceable lineage, and quality checks, upstream bias and drift are difficult to spot, and downstream remedies become guesswork. These weaknesses are not abstract; they shape whether a patient's history is misclassified, whether a student's potential is underestimated, or whether a family's benefit is delayed. Ethical stewardship therefore begins with the mundane discipline of data: what is collected, why, how it is protected, and how long it is kept.

Institutional capacity and context also matter. Leaders differ in their fluency with algorithmic trade-offs; roles such as model steward, privacy engineer, and AI risk owner are unevenly defined; and contractual leverage over vendors varies widely across jurisdictions. In higher-capacity ecosystems, the agenda naturally shifts toward deeper audits, transparency reporting, and independent assurance. In resource- constrained contexts, the humane and realistic path is to prioritize data foundations, secure minimum transparency from providers, build executive literacy, and deliberately defer automation until ethical and technical preconditions are met.

In response to these barriers, the literature points to a layered, life-cycle approach that makes ethics operational. Ethics-by-design draws values into the data and model pipeline through documentation, use constraints, pre-deployment bias tests, and explicit interpretability targets. Proportionate risk and impact assessments function as gates that trigger on meaningful change new data sources, new populations, or evidence of drift so go/no-go decisions are defensible under real constraints of time and cost. Human oversight becomes protective when it is specific: mapping the points where people can intervene, defining what evidence reviewers see, and ensuring that harmful outcomes can be reversed with a recorded rationale that feeds the next training cycle.

Continuous monitoring and audit institutionalize accountability. Scheduled drift detection, periodic subgroup checks, and incident reporting tied to remediation deadlines convert policy into practice that can be observed and verified. Because many capabilities are procured, contracts must encode ethics as obligations rather than aspirations: documentation duties, test-evidence packets, audit and log access, incident service levels, data portability, and credible exit ramps. For opaque systems, behavioral transparency through standardized test-suite results and update-linked assurance letters is essential to protect the public interest.

Finally, durable progress rests on people and place. Executive AI literacy equips leaders to navigate the real trade-offs among accuracy, fairness, and explainability; defined stewardship roles keep responsibility visible; and communities of practice help organizations learn from near-misses as well as failures. Localization then adapts global principles to sectoral risk profiles and to the legal and cultural fabrics of public services, health, education, and finance. Throughout, a concise set of governance indicators subgroup performance gaps, explanation satisfaction, override and reversal rates, time-to-mitigation, audit pass rates, coverage of model/data cards, vendor audit rights, incident frequency and resolution time, and user-trust signals keeps improvement grounded in evidence rather than rhetoric.

Taken together, these conclusions foreground a simple human truth: people experience AI not as principles, but as processes. Ethical leadership therefore lives in the discipline of design choices, risk gates, human judgment, and verifiable routines structures that make dignity, equity, and accountability felt in everyday decisions. This is neither a purely technical program nor a purely moral one. It is a sociotechnical craft that organizations can begin to build now, incrementally, with clear safeguards for those most affected and with the humility to change course when evidence demands it.

Ethical leadership should make ethics-by-design the default rather than an afterthought. Before any deployment, organizations ought to require complete model and data documentation, define use constraints, set explicit targets for explainability that fit the decision context, and establish fairness thresholds that are proportionate to potential harm. Pre-deployment bias testing and lightweight red-teaming should be treated as routine evidence-generation, not exceptional scrutiny. This reframes "ethics" from aspiration to design constraint and gives leaders verifiable artefacts that can be audited.

Decision making should be gated by proportionate risk and impact assessment. Algorithmic Impact Assessments and privacy impact assessments need to be repeatable, triggered by material change (new data sources, new populations, observed drift), and tied to clear go/no-go criteria. High-risk systems warrant independent review and, where feasible, third-party assurance prior to launch or major revision. These practices do not eliminate difficult trade-offs, but they make those trade-offs legible and defensible in terms of individual dignity, equity, and due process.

Human oversight must be specific and reversible. Leaders should map the exact points at which people can pause, modify, or overturn automated outputs, specify what evidence reviewers see, and define escalation paths, timelines, and responsibilities. Every override should include a documented rationale that feeds back into model improvement and training data curation. An accessible appeals pathway for affected individuals is essential to restore agency and rebuild trust when uncertainty is high or stakes are personal.

Accountability becomes durable only when monitoring, audit, and incident response are normalized. Post-deployment governance should include scheduled drift detection, periodic subgroup performance checks, and an incident taxonomy with tight internal reporting clocks and remediation deadlines. Governance dashboards that surface key indicators to oversight committees, together with targeted external assurance for high-risk systems, shift organizational culture from crisis response to quality management.

Because many AI capabilities are procured, procurement and vendor governance must encode ethics as contractual obligations. Contracts should mandate documentation duties, test-evidence packets, audit and log access, incident service levels, data portability, and credible exit ramps. For opaque or proprietary tools, leaders should insist on behavioural transparency disclosed results from standardized test suites and update- linked assurance letters so that ethical control does not silently migrate to vendors.

All of these controls rest on sound data governance. Ethical stewardship begins with purpose limitation and minimization, traceable data lineage, and quality checks for training and inference data alike. Rules for sensitive attributes, lawful bases and consent, retention periods, and the use of synthetic data should be explicit and enforceable. Without disciplined data practice, higher-order safeguards cannot reliably protect individuals from bias, drift, or misuse.

Sustained progress requires capacity and culture. Executives need AI literacy that focuses on real trade- offs among accuracy, fairness, and explainability; organizations should formalize roles such as AI risk owner, model steward, and privacy engineer; and communities of practice should be convened on a regular cadence so that near-misses and incidents translate into organizational learning rather than isolated fixes. Framing ethical leadership as a sociotechnical competence—rather than a moral stance alone—helps these investments endure.

Finally, localization and measurement make the program practical. Global principles should be adapted into sector-specific playbooks that align with local law, risk profiles, and cultural expectations in public services, health, education, and finance, ideally co-designed with affected communities. Progress should be tracked with a compact set of governance indicators such as subgroup performance gaps, explanation satisfaction, override and reversal rates, time-to-mitigation after alerts, audit pass rates, coverage of model/data cards, the share of contracts with audit rights, incident frequency and resolution time, and user- trust signals—so that improvement is steered by evidence rather than rhetoric. As an on-ramp, a time-boxed 90-day plan can demonstrate feasibility: establish the governance forum and templates; apply them to one high-impact and one low-risk system; run first bias tests, drift monitors, and an incident drill; then complete a mini-audit with fixes and fold lessons into a reusable playbook.

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Accounting and Ethical Leadership in the Age of AI: Insights from Malaysian Practitioners Toward Industry 5.0

Kenny Wei Jie Quah*
Universiti Sains Malaysia, Malaysia
Email: kennyquah@usm.my

**Corresponding Author*

Abstract

This study investigates how accounting and ethical leadership are enacted in the age of artificial intelligence (AI), situating the inquiry within the human-cent red ethos of Industry 5.0. Using a qualitative case study design, data were drawn from a series of practitioner talks in Malaysia that foregrounded ethics and AI in professional practice. Participants represented diverse sectors, including audit, taxation, corporate accounting, financial technology, public sector accounting, and management consulting, and shared experiences of AI adoption in workflows such as risk assessment, compliance modelling, financial forecasting, process automation, and governance. Thematic analysis identified three interrelated dimensions: navigating the ethical boundaries of AI, repositioning leadership in human–machine collaboration, and sustaining professionalism through moral anchoring. Together, these dimensions reflect the contours of responsible leadership, integrating ethical reflexivity, moral agency, and human-cent red stewardship in AI-mediated decision-making. The findings underscore that effective leadership requires proactive ethical stewardship that embeds empathy, fairness, and accountability into digital transformation.

Introduction

The proliferation of artificial intelligence (AI) across business functions has reshaped the accounting profession, prompting new expectations for efficiency, accuracy, and data-driven decision-making (Alruwaili & Mgammal, 2025; Kokina et al., 2025). As organizations pursue automation strategies to enhance competitiveness, accounting practitioners are increasingly working alongside intelligent systems that not only process transactions but also generate predictive insights and flag anomalies in real time (Al-Omush et al., 2025; Zhang et al., 2023). While the integration of AI into accounting workflows promises substantial benefits, it also raises profound ethical questions regarding transparency, accountability, and the preservation of professional judgment (Cheong, 2024; Mökander & Floridi, 2021).

These concerns are particularly salient in the context of the Fifth Industrial Revolution (IR5.0), a paradigm that emphasizes the reintegration of human values, ethics, and empathy into increasingly digital and automated environments (Martini et al., 2024). Unlike its predecessor IR4.0, which was cent red on digital transformation, IR5.0 shifts focus toward the coexistence of human and machine intelligence, with ethical leadership positioned as a critical enabler of sustainable and responsible innovation (Huy & Phuc, 2024). For accounting professionals, this evolution underscores a renewed responsibility (i.e., to harness AI in ways that augment, rather than diminish, ethical judgment and professional integrity) (Goto, 2021).

Recent studies have highlighted the dual-edged nature of AI in accounting enhancing audit quality and fraud detection while simultaneously posing risks related to algorithmic bias, overreliance, and erosion of accountability (Fülöp et al., 2023; Murikah et al., 2024; Schiff et al., 2024). In Malaysia, the discourse around AI adoption is further complicated by regulatory reform, growing stakeholder expectations, and cultural emphasis on ethical conduct in corporate governance. However, little empirical research has explored how accounting practitioners in Malaysia navigate the ethical tensions emerging from AI implementation within their work environments.

This paper presents a qualitative case study based on a series of talks with accounting practitioners in Malaysia. Guided by the lens of Responsible Leadership and aligned with the human-cent red ethos of Industry 5.0, the study investigates how accounting and ethical leadership are enacted in the age of AI. To pursue this aim, the analysis is structured around three interrelated research questions: (1) How do accountants cultivate and exercise ethical reflexivity when navigating AI-integrated workflows? (2) How do they negotiate the tensions between institutional imperatives and personal moral agency under automation-driven pressures? and (3) How are leadership practices adapted to preserve empathy, fairness, and other human-cent red values in AI-mediated decision-making? These questions are informed by the thematic convergence observed in the talks, which highlighted the moral, professional, and organizational work required to sustain the legitimacy of the accounting profession in an era of intelligent systems.

By exploring these questions, the paper contributes to emerging conversations on ethical governance in digital accounting, offering insights into how professionals can “keep the heart” in an age where machines increasingly mediate accounting work.

Literature Review

AI in Accounting Practice

The accounting profession is undergoing rapid transformation as AI technologies become embedded in core financial processes such as transaction processing, auditing, and decision support (Alruwaili & Mgammal, 2025; Kokina et al., 2025). AI systems, including machine learning algorithms and natural language processing tools, now support high-volume data analysis, fraud detection, and predictive modelling (Zhang et al., 2023). These developments have sparked renewed interest in the evolving competencies and roles of accounting professionals, particularly as firms shift from routine bookkeeping to strategic advisory functions (Goto, 2021; Khan et al., 2025).

However, the integration of AI is not without ethical and governance implications. Concerns have emerged regarding algorithmic opacity, data privacy, and the overreliance on automated systems in making judgment-sensitive decisions (Cheong, 2024; Murikah et al., 2024). These issues are particularly salient in accounting, where the trustworthiness of financial information is central to stakeholder confidence. The literature highlights the need for ethical safeguards to mitigate the risks posed by AI, especially in contexts where accountability may become diffused between human and machine agents (Fülöp et al., 2023; Mökander & Floridi, 2021).

Ethical Leadership in Technology-Driven Environments

Ethical leadership is defined by the promotion of integrity, fairness, and accountability through actions that model and reinforce ethical standards (Huy & Phuc, 2024). In the context of accounting, ethical leadership plays a vital role in shaping the moral climate of organizations and ensuring that professional standards are upheld despite environmental pressures (Khan et al., 2025). The adoption of AI introduces new ethical challenges, including those related to surveillance, decision autonomy, and stakeholder equity, thereby requiring leaders to recalibrate their ethical responsibilities (Cheong, 2024).

Recent scholarship indicates that AI in accounting not only alters technical workflows but reshapes the ethical landscape in which leadership operates. Leaders must increasingly navigate the ethical boundaries of AI, determining not only what the technology can accomplish but what it should be permitted to do, especially when algorithmic outputs challenge principles of fairness, transparency, or professional independence (Goto, 2021; Zhang et al., 2023). In parallel, the shift toward algorithm-assisted decision-making necessitates repositioning leadership within human–machine collaboration. Rather than leading purely human teams, accounting leaders now manage socio-technical arrangements, balancing efficiency gains with the preservation of human judgment in domains where moral accountability cannot be delegated.

Another related imperative is sustaining professionalism and moral anchoring in environments driven by technological imperatives (Mökander & Floridi, 2021; Schiff et al., 2024). This requires resisting pressures to priorities speed, scale, or profit at the expense of the profession's public-interest mandate. In accounting, such moral anchoring underpins the trust that stakeholders place in financial information, trust that rests not only on technical accuracy but on the assurance that practitioners' decisions remain guided by enduring ethical values, or what some describe as the "human heart" of the profession.

These evolving demands on ethical leadership, which involve balancing technological capability with moral restraint, integrating human–machine collaboration with the preservation of human judgment, and sustaining innovation without compromising core values, form the conceptual bridge to the emerging discourse on IR5.0. Whereas IR4.0 foregrounds the ethical recalibration required in AI-driven contexts, IR5.0 advances a broader paradigm that embeds human-centric principles into digital transformation, positioning technology as a complement to, rather than a substitute for, human ethical agency.

IR5.0 and the Human-Centric Turn in Digital Transformation

IR5.0 has recently emerged in policy and academic discourse as a response to the mechanistic and efficiency-focused nature of IR4.0. Where IR4.0 emphasized automation and real-time connectivity, IR5.0 centers on human-centric innovation, ethical technology, and emotional intelligence (Martini et al., 2024). Within this framework, technology is not seen as a substitute for human labor but as a complement that enables more meaningful, creative, and ethical work (Al-Omush et al., 2025).

In the accounting domain, IR5.0 has particular relevance given the profession's reliance on trust, judgment, and social accountability. The literature suggests that embedding human values within technological systems is key to ensuring that digital transformation remains aligned with societal and ethical expectations (Huy & Phuc, 2024; Goto, 2021). Accounting scholars have thus called for more research into how practitioners retain their ethical agency amid algorithmic augmentation and institutional digitalization (Martini et al., 2024; Zhang et al., 2023).

Despite the growing body of literature on AI in accounting and the ethical implications of digital transformation, there remains limited empirical research on how practitioners themselves perceive and respond to these challenges, particularly within emerging economies such as Malaysia. Most existing studies (as highlighted above) are conceptual, technical, or conducted in highly developed regulatory contexts. Moreover, the intersection between ethical leadership, AI, and IR5.0's human-centric vision remains underexplored. This paper addresses these gaps by investigating the lived experiences of accounting practitioners navigating ethical tensions in AI-augmented workplaces in Malaysia.

Responsible Leadership as an Integrative Lens

Responsible Leadership (Maak & Pless, 2006; Pless, 2007) offers a comprehensive framework for examining the intersection of ethics, technology, and professional practice. Unlike traditional leadership models that emphasize hierarchical authority or transactional efficiency, responsible leadership situates leaders within a web of stakeholder relationships and calls for decisions grounded in ethics, accountability, and human dignity. It emphasizes the dual responsibility of leaders to meet organizational objectives while safeguarding broader societal values.

In the context of this paper (i.e., AI adoption), responsible leadership provides an effective lens for understanding how accountants negotiate emerging ethical and professional challenges. First, it underscores the importance of ethical reflexivity, where leaders critically examine the implications of AI-assisted decisions to preserve professional judgment and accountability. Second, it addresses the tension between institutional imperatives and personal moral agency, framing accountants as mediators who must reconcile efficiency-driven demands with enduring professional and ethical obligations. Finally, responsible leadership emphasizes human-cent red stewardship, where leaders ensure that empathy, fairness, and dignity are preserved in AI-mediated workflows, thereby positioning technology as a complement rather than a substitute for human values.

By framing ethical reflexivity, moral anchoring, and human-cent red leadership as interconnected dimensions of responsible leadership, this study aligns with the emerging vision of IR5.0, which prioritizes human-centric principles in digital transformation. Responsible leadership thus provides not only a theoretical anchor but also a practical guide for rethinking leadership in AI-integrated accounting contexts.

Methodology

This study adopts a qualitative case study design, drawing on insights from a series of professional talks delivered by experienced accounting practitioners in Malaysia. While the case study approach is often associated with in-depth examinations of single organizations, it can also encompass multi-perspective engagements that illuminate a shared phenomenon within its real-world context (Yin, 2015, 2017). In this instance, the talks functioned as the primary source of empirical material, providing situated reflections on practice and allowing for the co-construction of meaning through collective narratives.

The talks involved six senior practitioners representing diverse sectors: audit, taxation, corporate accounting, financial technology, public sector accounting, and management consulting. These individuals were purposefully selected for their direct professional experience with AI adoption in accounting workflows, spanning applications such as risk assessment, compliance modelling, financial forecasting, process automation, public expenditure monitoring, and governance strategy. Selection criteria also emphasized their ability to articulate ethical and leadership considerations in technology-mediated decision-making. This purposeful sampling ensured diversity of expertise while maintaining strong relevance to the study's focus on ethical leadership in AI adoption.

The talks were organized to balance structured thematic coverage with openness to emergent issues. A guiding protocol, informed by the literature on ethical leadership, AI governance, and IR5.0 workplace transformation, was used to frame the sessions while allowing speakers to explore topics in their own terms. This approach aligns with Mason's (2017) recognition that collective qualitative forums can surface not only individual perspectives but also the negotiation of shared norms and contested meanings.

Table 1. Participants Overview

Participant ID	Sector / Specialization
P1	Audit
P2	Taxation
P3	Corporate Accounting
P4	Financial Technology
P5	Public Sector Accounting
P6	Management Consulting

Each talk lasted approximately 90 minutes and was conducted in a setting designed to foster openness, where practitioners engaged candidly and reflexively with both their own experiences and those of their peers. Audio recordings were transcribed verbatim, and all identifying details were replaced with pseudonyms to preserve confidentiality. Ethical clearance was not required, as no personal or sensitive corporate data were disclosed; where organizational contexts were mentioned, these were either generalized or pre-approved for academic disclosure.

Data analysis followed a thematic coding process inspired by Braun and Clarke's (2006) reflexive thematic analysis framework. Initial codes were generated inductively from the transcripts, then iteratively refined against theoretical constructs from the ethical leadership and AI ethics literature. This allowed for both data-driven discovery of emergent themes and alignment with established conceptual frameworks. The interactive and discursive nature of the talks was treated as an analytical asset, offering insight into how practitioners shared experiences, articulated ethical challenges, negotiated tensions, and constructively critiqued prevailing institutional logics. To strengthen credibility, methodological triangulation was employed by cross-referencing emergent insights with field notes, relevant policy documents, and extant literature, ensuring that interpretations were both contextually grounded and theoretically robust.

Findings

Across the talks, discussion moved beyond discrete operational concerns toward a collective interrogation of AI's ethical, organizational, and professional implications. The exchanges were not linear question–answer sequences but iterative, reflexive engagements in which participants questioned assumptions, extended arguments, and situated their practices in relation to others. Although sectoral contexts differed, the conversations progressively coalesced around three thematic domains: (1) navigating the ethical boundaries of AI, (2) sustaining professionalism and moral anchoring, and (3) repositioning leadership within human–machine collaboration. This thematic convergence reflects the central problematic of this study (i.e., how accounting and ethical leadership are enacted in the age of AI) while underscoring the salience of Responsible Leadership as a guiding framework for safeguarding the human values that underpin the profession's legitimacy.

Navigating the Ethical Boundaries of AI

The discussions first converged on issues surrounding the ethical implications of AI integration in accounting practice. Practitioners reflected on how these technologies reshape the boundaries of professional responsibility, often raising concerns about transparency in decision-making, diminished human autonomy, and the diffusion of accountability.

Reframing Responsibility in Algorithmic Decisions

Across interviews, a recurring concern was the ambiguity surrounding responsibility when AI systems produce errors or unintended outcomes. Practitioners described discomfort with the blurring lines of accountability in hybrid human-AI systems, especially when outcomes affect clients or regulatory compliance.

"If the system makes a wrong forecast, who’s to blame? The developer? The user? We rely on it, but we’re also expected to double-check everything. It’s confusing."(P3)

This discomfort reflects a broader ethical tension in delegating decision-making authority to AI tools while retaining human oversight. Some participants acknowledged the efficiency gains but remained cautious about over-reliance on systems they do not fully understand.

"We’re responsible for the outcome, but we didn’t create how the AI thinks (i.e., the AI algorithm). It’s hard to explain to management when something goes wrong." (P1)

These narratives suggest a need to revisit traditional notions of professional accountability in light of algorithmic mediation. As decision-making becomes increasingly automated, ethical leadership entails developing clearer guidelines for distributed responsibility among developers, users, and organizational leaders.

The Invisible Hand of Bias

Participants voiced significant concerns regarding the presence of hidden biases within AI-generated insights. While algorithms are often perceived as objective, practitioners acknowledged that biased training data or flawed logic in system design can result in skewed outcomes. This creates challenges in detecting, interpreting, and responding to AI recommendations, particularly when outputs appear authoritative but subtly reinforce existing inequalities or erroneous assumptions.

A participant shared:

“Sometimes the system flags something, but when we dig deeper, it’s not really an issue. It’s hard to argue with it because it’s coded that way, we’re not sure where the logic came from.” (P2)

Another echoed similar concerns:

"There's a tendency to over-trust the system. But we forget that what goes into the system matters. If biased data feeds it, then biased results come out." (P4)

These reflections suggest that practitioners face difficulty in scrutinizing AI outputs, especially when the decision-making process is opaque. This invisibility of bias (i.e., both in data and algorithmic reasoning) poses a risk to ethical judgement and professional skepticism.

Ethics in Design vs. Ethics in Practice

Following the AI algorithm and possible bias, a recurring tension emerged between the ethical principles embedded during AI system development and the practical realities of their deployment. While many systems are designed with ethical safeguards or fairness parameters, these intentions are often diluted by organizational priorities, time constraints, or limited user understanding.

One participant remarked:

"The vendor told us it's an ethical system, they've thought about bias, privacy, everything. But when we use it, we still need to make trade-offs. It's not always clean-cut." (P4)

Another noted:

"Ethics at the development stage is one thing. But once it hits the ground, users need to make quick decisions. The practice is messier." (P6)

These perspectives highlight the gap between ethical design and ethical execution. While AI tools may be built with ethical considerations in mind, real-world use introduces complexities that challenge the consistent application of those principles. Practitioners are often left to navigate these grey areas without clear guidance or support.

Professionalism and Moral Anchoring in the Age of AI

This theme captures how accounting practitioners mobilize their professional identity, ethical frameworks, and personal convictions to maintain ethical conduct in AI-augmented work environments. As automation and algorithmic systems reshape traditional roles, participants reveal a heightened awareness of their ethical responsibilities. Rather than relinquishing judgment to machines, they actively seek to preserve the moral foundations of their profession. This theme shows how professional codes, informal norms, and individual values are invoked to navigate ethically ambiguous or technically opaque decisions.

Ethical Reflexivity and Professional Identity

Participants describe frequent engagement in ethical reflexivity (i.e., critically examining their decisions in light of both professional standards and personal beliefs). Several participants recounted episodes where AI-generated outputs challenged their moral intuitions or conflicted with human-cent red priorities, prompting deliberate reflection on "what should be done" versus "what can be done." This process of self-questioning, often undertaken in isolation, was framed as essential to sustaining their integrity in a changing technological landscape.

For instance, a participant shared how they overrode a data-driven recommendation that would have resulted in staff layoffs, stating:

"Just because the system showed an efficiency gain doesn't mean I should ignore the human cost. That's not what I stand for." (P3)

This expression of thoughts was not merely about adhering to formal codes but also about preserving a coherent sense of professional identity. Several participants saw their role as stewards of accountability, interpreting their responsibilities as extending beyond technical correctness to include fairness, transparency, and care for affected stakeholders.

In this context, ethical reflexivity served as a mechanism of resistance against what some described as a "cold logic" of efficiency embedded in AI systems. The professional identity became a moral anchor, enabling practitioners to assert agency in AI-mediated environments and uphold their values even when organizational or technological pressures pointed elsewhere.

Institutional Ethics vs. Individual Moral Agency

Participants frequently described a palpable tension between organizational expectations such as cost reduction, efficiency, and rapid innovation and their own commitments to ethical responsibility.

"Our leadership pushes for faster implementation to meet quarterly targets, but I pause, asking, does it compromise fairness or due diligence?" (P2)

This dynamic reflects a conflict between operational imperatives and personal judgment. Leaders often find themselves acting as ethical bulwarks in the face of conflicting priorities.

"The board wants quick numbers but I want accuracy. If you just run with the AI suggestion without thinking, you might get some results not following your context. Leading to misjudgment" (P3)

These narratives underscore a crucial point: while institutional ethics can shape system design and governance, true moral accountability often rests with individuals. Practitioners asserted that when AI-driven approaches collide with human-cent red decision criteria, their moral autonomy becomes the decisive factor.

Keeping the Heart in AI Leadership

Amid technological change, practitioners emphasized a proactive commitment to human values such as empathy, fairness, integrity as essential components of ethical leadership.

"AI might optimize the process, but without empathy, the system fails the people relying on it. For example, when we automate client risk assessments, we still make space to listen to their unique circumstances. We consciously keep the 'heart' in every decision." (P6)

One participant described deliberate efforts to preserve compassion, ensuring AI serves human needs rather than eclipsing them.

"When designing new AI workflows, we always ask: how does this impact people? Even if it's fast and accurate, if it undermines trust or empathy, it's not worth it." (P5)

These acts of moral intentionality even small gestures were seen as vital in reinforcing the ethical integrity of AI-augmented processes. They illustrate leadership grounded not in algorithmic efficiency, but in preserving the human elements at the core of professional responsibility.

Repositioning Leadership in Human–Machine Collaboration

Building on the ethical concerns and moral anchoring surrounding AI, the discussion turned to how leadership itself is being reshaped in environments where machines increasingly handle routine accounting tasks. Rather than ceding authority to automated systems, leaders are repositioning themselves as mediators who integrate machine logic with human values. Their role is less about technical supervision and more about ensuring that workflows preserve empathy, ethical reasoning, and professional judgment as defining features of organizational practice. This reframing underscores leadership not as displaced by technology but as reconstituted through its responsible alignment with human priorities.

Leading with Human Values in Digital Workflows

A recurring narrative across the different talks are the deliberate effort by leaders to keep human values at the heart of efficiency-driven, automated workflows. Participants described this as a form of "ethical anchoring" a continuous reminder that decisions, even when facilitated by AI, should remain grounded in compassion, fairness, and contextual understanding.

"AI improves our speed, but doesn't challenge us to slow down and think about impacts. Good leadership means asking, is the system's recommendation just expedient or is it fair?" (P4)

Participants spoke of consciously embedding pause-points in AI workflows, moments intended for reflection. These deliberate interruptions create space for ethical judgment.

"We (the participant and his team) built a checkpoint after automated flagging. Staff must ask: Could this misclassify or dehumanize a decision? That human check balances the machine's speed." (P6)

Several participants reflected on how leading with human values often involves visible modeling of discretion stepping in when AI recommendations go against organizational or ethical norms.

"When the analytics tool suggested cost cuts that would hurt our team morale, I vetoed it even though it was within the parameters. That sends a message: human welfare still matters." (P3)

In these ways, leadership becomes less about following AI-directed paths and more about ensuring that automation serves the profession rather than the reverse. For the participants, leaders are positioned as stewards of ethical balance, responsible for preventing AI from eclipsing human-centered decision-making and for safeguarding the values that underpin professional legitimacy.

Mediating Between Machine Logic and Moral Judgment

Across the participants highlighted a growing leadership responsibility to reconcile the logic of AI systems with the moral complexity of accounting decisions. AI may offer precise outputs, but leaders noted that such outputs often lack the ethical elements that needed in professional judgment. Rather than accepting algorithmic decisions at face value, leaders are increasingly stepping into a mediation role balancing data-driven recommendations against contextual, ethical, and stakeholder-sensitive considerations.

"There are times when the system flags a client as risky, but we know the client. Their history, intent, it doesn't always fit the pattern. That's where our judgment comes in." (P1)

This mediating role often involves questioning the assumptions underlying algorithmic outputs. Participants described situations where following AI-generated insights blindly could lead to ethically questionable outcomes, particularly in client assessments, hiring decisions, and risk categorization.

"I see my role as translating the numbers. The AI sees patterns, but I have to interpret those patterns through the lens of our values and what's right for the people involved." (P5)

According to the quotes above, participants noted that leaders also carried the moral weight of choosing not to follow AI-generated advice, particularly when decisions affected people or long-standing client relationships. Such moments of moral resistance served as a critical counterbalance to what one participant described as "the cold precision of the machine."

Building Trust in Augmented Decision-Making

With AI increasingly shaping high-stakes decisions, participants emphasized that trust (i.e., both in the systems and in the leaders who use them) has become more fragile and more important. Participants spoke of the challenges in explaining how decisions are made when they are partially guided by AI logic, especially when the underlying algorithms are opaque.

"When we rely on AI, we also inherit its black box. That makes it harder to explain to clients or even team members why a decision was made and that erodes trust." (P3)

To counter this, participants described investing time in humanizing AI systems clarifying their role as tools, not arbiters. Transparency, they noted, was key to preserving trust, particularly in client-facing roles where accountability must be clearly communicated.

"We told the team: the AI flags, but we decide. That simple distinction helps restore confidence. People need to know that judgment hasn't been outsourced." (P5)

Some participants also highlighted symbolic acts of trust-building such as publicly overriding AI decisions when they conflicted with fairness or professional standards. These acts were seen as reaffirmations of leadership accountability in an automated context.

"I remember rejecting an AI-led recommendation because it disadvantaged a junior staff unfairly. It mattered that I did it openly because trust, once lost, is hard to rebuild." (P1)

In these accounts, ethical leadership in AI environments is not just about controlling technology but also about managing perception, transparency, and moral clarity in augmented decision-making.

Discussion

This study highlights the enduring role of ethical leadership in mediating the integration of AI technologies within the accounting profession. The themes that emerged, namely ethical reflexivity, institutional–ethical tension, the preservation of empathy in leadership, and leadership responsibility, were grounded in the framework of Responsible Leadership. From this perspective, leadership responsibility is not limited to supervising technical adoption but extends to safeguarding professional integrity, ensuring accountability in AI-mediated decisions, and embedding human values such as fairness, empathy, and transparency into digital transformation processes. These findings resonate with and extend current scholarship on AI ethics, professional values, and human-centered leadership in the digital era.

Ethical Reflexivity and Professional Identity

The findings underscore that ethical reflexivity—defined as the capacity to critically evaluate one's moral stance in the face of evolving professional challenges—is central to how practitioners navigate AI-infused environments. Participants consistently highlighted the need for continuous self-awareness and moral deliberation when facing ethically ambiguous situations, such as algorithmic opacity, bias in AI models, or tensions between automation efficiency and human-centered values (Cheong, 2024; Murikah et al., 2024). Rather than treating ethics as a checklist or compliance exercise, participants framed decision-making as an internalized, evolving process shaped by personal values and professional norms. This reflects calls in the literature for ethics to be adaptive, context-sensitive, and grounded in critical reflection (Hosseini Tabaghdehi & Ayaz, 2025; Mökander & Floridi, 2021).

Professional identity emerged as a key anchor in this process. Participants, whether from auditing, corporate accounting, or financial technology, invoked norms such as due care, objectivity, and public interest as intrinsic commitments rather than merely formal obligations (Goto, 2021; Huy & Phuc, 2024). This suggests that professional identity is built not only on technical competence but also on moral values cultivated through practice, mentorship, and peer discourse (Khan et al., 2025).

These insights point to the limitations of generic AI ethics frameworks that emphasize abstract principles or procedural audits. Instead, they align with arguments that ethical capacity must be actively developed through reflective practice, collaborative dialogue, and leadership support. Participants emphasized that AI does not simply introduce new technical issues but reconfigures moral landscapes, reshaping what it means to act responsibly in the profession. Fostering ethical reflexivity, therefore, is not only crucial for mitigating harm but also for sustaining the moral authority and legitimacy of accounting and finance professionals in an era of intelligent systems.

Navigating Institutional Pressures and Moral Agency

A central tension emerging from our case study is the interplay between institutional imperatives such as automation speed, operational efficiency, and cost minimization and practitioners' moral agency. These pressures reflect broader structural forces in the digital economy, where AI adoption is often driven by business rationales that prioritize outcomes over ethical deliberation (Alruwaili & Mgammal, 2025; Kokina et al., 2025).

Practitioners in our study expressed awareness of these dynamics and a sense of ethical responsibility that extends beyond compliance protocols. While organizations have introduced ethics frameworks and AI governance policies, these mechanisms often remain procedural or risk-oriented, offering limited scope for discretionary moral judgment. Several participants described situations where institutional goals conflicted with personal values such as when AI systems lacked explainability or posed risks of unfair outcomes highlighting the limits of formal codes without moral empowerment.

Opacity and probabilistic logic in AI systems can undermine accountability, leaving practitioners disempowered even when they perceive ethical concerns (Cheong, 2024; Schiff et al., 2024). In such contexts, fostering moral resilience becomes critical to safeguarding ethical standards in AI-integrated workflows (Goto, 2021; Martini et al., 2024). Our findings align with calls for organizations to move beyond regulatory adherence toward fostering climates that enable open dialogue, reflective judgment, and value-based reasoning. This involves creating channels for dissent, supporting professional discretion, and embedding ethics into strategic deliberations, ensuring practitioners remain active moral agents even in highly automated environments.

Human-Centered Leadership in AI Contexts

A key insight from the case study concerns the reconfiguration of leadership practices in response to AI integration. As algorithmic systems increasingly influence decision-making in accounting workflows, leadership is not being replaced but redefined. Participants described a shift toward roles requiring mediation between machine outputs and human values, underscoring a persistent need for empathy, discretion, and relational sensitivity in digital environments. This reorientation reflects the broader logic of Industry 5.0, which emphasizes aligning technological advancement with human-centric goals such as well-being, inclusivity, and sustainability (Martini et al., 2024).

Rather than deferring to the authority of AI systems, leaders are called to actively interpret, contextualize, and, when necessary, override algorithmic recommendations. Several participants highlighted the importance of "ethical checkpoints" within automated workflows (i.e., deliberate pauses where human judgment takes precedence over computational efficiency). These moments of reflection are not merely procedural but acts of leadership that safeguard fairness, transparency, and trust. In contexts where AI outputs may lack nuance or embed hidden bias, such interventions are essential to uphold professional ethics. This emphasis on relational leadership aligns with research highlighting the role of professional identity and moral responsibility in technology-mediated environments (see Goto, 2021; Huy & Phuc, 2024). Leaders who foster open dialogue, care, and moral responsibility can counterbalance the impersonal logic of automation, while vision-driven engagement inspires trust and prioritizes the collective good (i.e., attributes especially salient in rapidly changing technological contexts).

Moreover, our findings suggest that human-centered leadership is vital not only for internal organizational cohesion but also for sustaining external trust. Participants noted that clients and stakeholders increasingly question AI-driven decisions, particularly when transparency is lacking. Leaders thus act as ethical intermediaries, translating machine outputs into accountable actions and ensuring that decisions remain clear and justifiable. In sum, the emergence of AI elevates rather than diminishes the role of leadership. As machines assume more analytical and operational functions, human leaders become critical stewards of ethical meaning-making. By keeping empathy, fairness, and professional integrity at the forefront, human-centered leadership ensures AI serves the public interest rather than displacing it.

Conclusion

This study contributes to the emerging discourse on how accounting and ethical leadership are enacted in the age of AI. By anchoring our findings within the lens of IR5.0 and sociotechnical perspectives, we highlight how the ethical contours of leadership are being reshaped not displaced by automation and algorithmic decision-making. Far from being rendered obsolete, relational competencies such as empathy, fairness, and trust gain renewed importance in AI-augmented workplaces. Leaders are increasingly called upon to serve as moral anchors, ensuring that technological advancements do not erode the social fabric of organizational life.

The empirical insights point to a pragmatic yet principled approach to AI integration, wherein human judgment remains central. Accounting practitioners describe deliberate pauses before implementing AI recommendations, emphasize inclusive consultations, and uphold transparency in decision-making processes as such practices that reflect a conscious effort to preserve human dignity and ethical accountability. These findings resonate with evolving models of leadership, particularly servant and transformational styles, that foreground care and responsibility as vital to sustaining trust in an increasingly digitized profession. Practically, these findings suggest that organizations must move beyond compliance-oriented ethics frameworks and invest in the cultivation of emotionally intelligent leadership. Training programs, codes of conduct, and AI governance protocols must be reframed to acknowledge and embed relational ethics as a strategic priority. This is particularly pertinent for accounting firms and regulatory bodies seeking to maintain public trust while enhancing operational efficiency through AI.

Future research should expand the inquiry into diverse cultural and institutional contexts, comparing how different governance models mediate the human-AI ethical interface. Longitudinal studies could further examine how ethical leadership practices evolve over time in response to advances in AI capabilities. Additionally, interdisciplinary research bridging accounting, information systems, and organizational ethics can help develop robust models that capture the complexity of human-centered leadership in AI-enabled environments. In an era where algorithms increasingly shape organizational choices, the imperative to “keep the heart” in leadership is not merely aspirational, it should be strategic, necessary, and urgent. This study affirms that ethical leadership in the age of AI must be guided as much by human values as by technological fluency.

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The Influence Of Artificial Intelligence (AI) On Employee Performance And Work Engagement Moderated By Change Leadership Among Generation Z In The Workplace

Ita Wipiana
Universitas Indonesia, Indonesia

Muthia Pramesti, Shahnaz Natasya Arina*
Universitas Indonesia, Indonesia
Email: shahnaz.natasya@ui.ac.id

**Corresponding Author*

Abstract

This research aims to examine the influence of artificial intelligence (AI) on employee performance and work engagement among Gen Z workers. The investigation was conducted by analysing the role of the moderating variable of change leadership on the influence of AI on employee performance and work engagement. A quantitative approach was used with partial least square structural equation model (PLS-SEM) data analyis method using SmartPLS 4. The sampling method used was purposive sampling with the criteria: Gen Z workers, work in the Jabodetabek area, have worked for at least 1 year, have a direct supervisor, and used AI for work-related tasks. A total of 186 respondents who met the criteria were collected. The study results show that AI has a positive and significant effect on employee performance and work engagement. Change leadership positively moderates the influence of AI on work engagement. However, change leadership negatively moderates the influence of AI on employee performance. The contribution of this study is to fill the research gap in the development of human resource management theory in the context of AI technology usage and organizational effectiveness, particularly for generation Z workers. As a managerial implication, organizations need to quickly to adapt to the development of AI technology, especially in terms of management decision making and solving operational and strategic problems.

Keywords: artificial intelligence, employee performance, work engagement, change leadership, Gen Z.

Introduction

One of the important roles in an organization that can determine the effectiveness of a company's operations is human resources (HR). Human resources are an important, crucial, and asset for improving the performance of a company, considering that employees with high knowledge, experience, and skills will contribute to increasing the company's value (Batarlien ė et al., 2017). In the present time, with the numerous innovations and changes occurring on a massive and fundamental scale, companies need the ability to develop and retain employees with the best talents as important assets of the company. Therefore, employee performance also plays a crucial role amidst the wave of technology adoption.

According to Na-Nan et al. (2018), employee performance is demonstrated by employees' behaviour regarding the desired outcome in terms of quality, quantity, or working time. In addition, employee performance is determined by the work and work behaviour required to complete tasks and responsibilities within a certain timeframe (Kasmir, 2016). In the era of digitalization and disruption, companies need to add aspects to improve employee performance, such as implementing technology in the workplace. The results of a survey conducted by PwC (2018) explain that 73% of employees who participated in this survey agree that technology can help them create higher quality work than before.

Besides employee performance, another equally important factor during times of disruption and digitalization is employee work engagement. Work engagement is a psychological condition where employees have the ambition to contribute and play a role in the success of the company, and the ambition to remain a member of the company where they work (Schaufeli, 2013). Work engagement plays an important role in maintaining the stability and productivity of the company. A recent study by Gallup (2023) reported that only 34% of employees are engaged in their work. The figure has decreased compared to the percentage in the previous year. However, the percentage of workers who feel engaged with their jobs is only 13% worldwide, and in Southeast Asia, it is only 12% (Crabtree, 2013).

Companies need to start adopting and implementing technology in their business processes. One of the technologies created in the era of innovation and technology today is Artificial Intelligence (AI). AI according to Luhana et al. (2023) is the use of computers to form intelligent behaviour that can disregard human intervention. The development and use of AI have become increasingly massive in recent years, including businesses that have adopted it to remain competitive. In the study by Belhadi et al. (2024), it is revealed that AI is increasingly becoming an important intangible resource for more productive business advancement. In line with Fatemi (2019), whose research states that 83% of companies claim that the use of AI in business has become a top priority in their operations. AI is a driver of business competitive advantage because AI is a valuable, unusual, unique, and invaluable resource (Chaudhuri et al., 2021).

In Indonesia itself, a study conducted by Microsoft-IDC (2019) stated that 14% of companies have adopted AI technology. Nevertheless, many employees have adopted AI in their work. The reason is that there are still differences in perspective between management and employees regarding AI, and many of them are still sceptical about adopting the technology. Nevertheless, many employees have adopted AI in their work. However, until now, AI remains the most fantastic IT application, an innovation that has undergone unparalleled improvements over the past few years (Dwivedi et al., 2020). Work Trend Index (2024), employees who understand the digital world and use AI in their work have reached a figure of 92%. In the same report, it is mentioned that employees want AI to be present and used in their work.

AI capabilities include language translation, learning, speech recognition, computer vision, and planning (BalRam & Verma, 2023). The presence of AI influences the human resources of an organization, including employee performance and engagement. Luhana et al. (2023) revealed that several studies have shown AI can enhance worker productivity by automating tasks and eliminating repetitive manual tasks performed daily. Additionally, AI can assist workers in data analysis and decision-making, enabling them to make more accurate and efficient decisions (Wang et al., 2022). AI allows workers to be more creative and innovative in their jobs, as AI can provide feedback on ideas that can help them develop and refine innovative solutions (Luhana et al., 2023).

Furthermore, Hou et al. (2023) in their study mentioned that AI can provide workers with more flexibility because tools that have adapted AI can manage workloads more effectively, allowing workers to work more efficiently. Then, AI also has the potential to enhance employee engagement by providing valuable insights related to employee performance and facilitating feedback regarding their work (Luhana et al., 2023).

Currently, workers who openly show interest and engagement in their jobs are Generation Z (Gen Z) workers, who have now entered the workforce and are entering the labor market. This is in line with the research by Rzemieniak & Wawer (2021), which states that Gen Z shows a positive attitude, demonstrates interest and engagement, and tends to have high mobility. Nezich (2024) states that Gen Z is quickly becoming a dominant force in the workforce. Internet facilities and supporting technology in the workplace are one of the factors considered by Gen Z (Hendratmoko & Mutiarawati, 2024).

In the TalentTMS report (2024), it is mentioned that nearly half (47%) of Gen Z workers prefer to rely on AI to guide them in the workplace rather than their managers. The same report found that 46% of Gen Z employees prefer to ask AI about their work rather than their colleagues or managers. It was also mentioned that 68% of Gen Z workers feel that AI helps them in their workflow and daily tasks. Thus, the implementation of AI in business processes requires organizational support so that its use can be maximized overall.

Therefore, employees need a leader who is capable of leading, guiding, and implementing effective change. Successful change leadership can help subordinates understand the necessary changes and be enthusiastic about the opportunities brought by the changes, both for themselves personally and for the organization (Caulfield & Senger, 2017). Both top management and mid-level management need to initiate the urgency of the changes related to the implementation of AI in the company. The official implementation of AI that can be used by employees in their work. From that presentation, the author is interested in further studying the impact of AI on employee performance and work engagement among workers in Jabodetabek, and the moderating effect of change leadership considering that implementing change is not easy.

This research is a replication study of the previous research conducted by Wijayati et al. (2022), on workers in the service and banking sectors in East Java. The research results reveal that AI has an influence on employee performance and work engagement with AI in the form of virtual programs, not in the form of robots. The findings of this study indicate that AI, with its various technologies, offers a range of options, benefits, and services to enhance employee performance. Therefore, this research aims to examine the influence of AI on employee performance and work engagement among Gen Z workers. Gen Z, with more advanced technological knowledge than previous generations, is starting to dominate the workforce. The research was conducted in a different area from previous studies, namely the metropolitan area of Jabodetabek, which has more adequate facilities and well-integrated technology implementation.

Theoretical Review

Artificial Intelligence (AI)

AI is the use of technological devices aimed at reproducing human cognitive abilities to achieve its goals independently, considering potential obstacles that may be encountered (Benko and L ányi, 2009; Haenlein and Kaplan, 2019; McCorduck et al., 2020). Another definition of AI according to Luhana et al. (2023) is the use of computers to form intelligent behavior that can disregard human intervention. Rai et al. (2019) in Collins et al. (2021) mention that AI is defined as the ability of machines to perform cognitive functions associated with human thought, such as perception, reasoning, learning, interaction with the environment, problem solving, decision making, and even creativity. In line with the research by Hanlein & Kaplan (2019), which states that AI is the system's ability to interpret data, learn from data, and utilize learning to achieve specific goals and tasks using flexible configurations. Referring to the research by Begum Siddiqui et al. (2023), it is stated that AI can help organizations improve performance. Then, according to Eubanks (2018), it is stated that with several applications, AI can enhance workers' abilities to perform tasks with the help of extended intelligence.

Employee Performance

According to Na-Nan et al. (2018), it is shown through employee behaviour regarding the desired distribution of results in terms of quality, quantity, or working time. Kasmir (2016) mentions that employee performance is determined through the work and work behaviour required to complete tasks and responsibilities within a certain timeframe. According to Peterson and Plowman (1953), work quality includes the achievement of criteria and standards set for procurement, production, quality inspection, and delivery of goods and services. Artha and Kumar in Mahfouz et al. (2021) define employee performance as the ability of workers to perform their tasks effectively and competently to achieve the best results. Referring to Mathis and Jackson (2002), there are three factors that influence employee performance, namely (1) the individual's ability to perform the job; (2) the level of effort exerted; and (3) organizational supportSimilarly, employee performance will decline if any of those factors are lacking. Managing employee performance is a challenge for companies, because employee performance is an important aspect and a key element in the effectiveness of a company to operate in the business world (Soomro & Shah, 2019).

Work Engagement

Work engagement is a condition that is the opposite of burnout, where workers with engagement will exhibit feelings of energy and have effective relationships with all work activities, enabling them to adequately meet all job demands (Schaufeli, Bakker, & Salanova, 2006). Schaufeli et al. (2002) in their research state that work engagement is a condition of positive and satisfied thoughts related to work, referring to the dimensions of vigor, dedication, and absorption as measures of work engagement. Furthermore, Schaufeli et al. (2002) revealed that vigor can be seen through the level of strength and mental resilience of workers while working, the workers' desire to exert effort in their jobs, and their persistence in overcoming difficulties. Schaufeli, Salanova, Roma & Bakker (2011) state that there are two ways to measure work engagement, namely using the student method and the worker method. According to Salanova et al. (2001), workers have a total of 24 indicator question items, consisting of 9 items for the vigor dimension, 8 items for the dedication dimension, and 7 items for the absorption dimension. The total UWES-9 score can be used as a measurement of work engagement where each dimension is represented by 3 question items (Schaufeli et al., 2006). Bindl & Parker (2010) state that engaged workers more often experience positive emotions. Cropanzano & Wright (2001) state that happy workers tend to be sensitive to opportunities in the workplace, more open and willing to help other workers, and more confident and optimistic.

Change Leadership

Change leadership is developing a vision for the future, creating strategies to realize that vision, and mobilizing the energy of all members of the organization to achieve the same goals (Hooper and Potter, 2000). According to Gill (2002), change leadership is defined as the ability of a leader, both cognitively and rationally (cognitive intelligence), the need for meaning in people's work and lives (spiritual intelligence), emotions or feelings (emotional intelligence), and will or behaviour (behavioural skills) to achieve organizational goals. Holten et al. (2020) state that change leadership represents the behaviour of informing, communicating, engaging, and supporting employees during change. Furthermore, Kotter (2011) explains the significant difference between what is currently known as "change management" and "change leadership." Change leadership is more connected with large-scale changes. Change management tends to be related to small-scale changes when those changes are running smoothly. Therefore, leaders must make more leaps in a shorter time (Kotter, 2011).

Generation Z

Hung et al. (2017) define a generation as a group of individuals who belong to the same age group and have gone through or will go through the same life experiences that shape their personalities. The division of generational groups according to Pew's Research Center is as follows: Silent Generation (born 1928 to 1945), Baby Boomers (born 1946 to 1964), Generation X (born 1965 to 1980), Generation Y (born 1981 to 1996), Generation Z (born 1997 to 2012), and Generation Alpha (born 2013 to present) (Dimock, 2019). People who belong to Gen Z are also known as "digital natives" who are highly qualified, experienced in using technology, innovative, and highly creative (Duffet, 2017; Plé, 2019; Priporas et al., 2017). Gen Z tends to prefer working individually rather than in groups. Nevertheless, Gen Z shows a positive attitude, demonstrates interest and engagement, and tends to have high mobility (Rzemieniak & Wawer, 2021Gen Z highly values opportunities to actively engage in organizational projects that align with their values. However, meeting these specific needs will be a challenge for managers or leaders, as they usually come from different generations with different behaviours and may be less prepared to face the unique characteristics and expectations of younger workers (Jung et al., 2023; Schroth, 2019).

Hypothesis Development

The Influence of Artificial Intelligence on Employee Performance

Based on several previous research findings, it has been revealed that AI has an influence on employee performance (Wijayati et al., 2022; Luhana et al., 2023; Malik, 2024; Prentice et al., 2023). Wijayati et al. (2022) in their research mention that the use of AI technology referred to is in the form of programs and virtual processes. According to Luhana et al. (2023), AI refers to the use of computers to simulate intelligent behaviour with minimal human intervention. Malik (2024) states that in his research, he offers a new approach in presenting cost-effect techniques by illustrating how AI tools and applications can be used to improve employee service and employee performance. Tong et al. (2021) in their research state that AI data analysis can improve the quality of feedback, which in turn will enhance worker productivity. According to Pretince et al. (2023), AI-powered tools and applications can be utilized to enhance employee service and job performance. Based on several research findings, the hypothesis regarding the relationship between AI and employee performance is as follows:

H1: *AI has a positive influence on employee performance*

The Influence of Artificial Intelligence on Work Engagement

Several previous studies have revealed that AI has an influence on work engagement (Wijayati et al., 2022; Luhana et al., 2023; Malik, 2024; Rožman et al., 2022; Prentice et al., 2023). According to Wijayati et al. (2022), the main benefits of AI innovation are trade, distribution, communication, marketing, and advertising. Digital technology has a positive impact on employee work engagement in the banking and services sector in East Java. Malik (2024) revealed that the most effective method for increasing employee engagement is by providing organizational support through effective leadership. Luhana, Memon & Khan (2023) state that AI has the potential to enhance employee engagement through its ability to offer valuable insights and facilitate feedback related to work. According to Rožman et al. (2022), employee training and development supported by AI have a positive effect on performance and work engagement in companies in Slovenia. By using AI as machine learning, employee engagement is 18% better than using traditional methods, which reduces the time required for learning by 65%. According to Prentice et al. (2023), providing adequate organizational support and appropriate leadership are key strategies in enhancing employee engagement. Based on several research findings, the hypothesis regarding the relationship between AI and work engagement is as follows:

H2: *AI has a positive impact on work engagement*

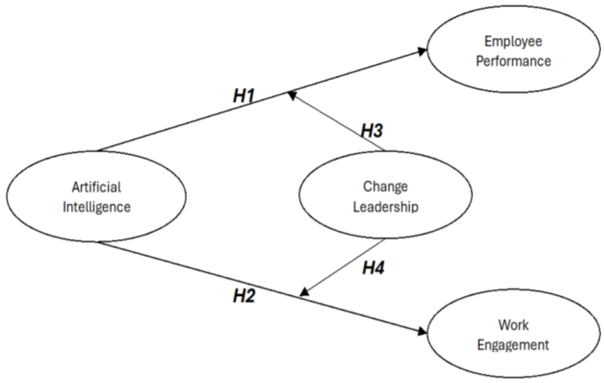
The Moderating Effect of Change Leadership on the Relationship between AI and Employee Performance and Work Engagement

Wijayati et al. (2022) that change leadership has a moderating effect on the relationship between AI and employee performance and AI and work engagement in the banking and services sector in East Java, Indonesia. Visionary and development-oriented change leadership can enhance the influence of AI on employee performance and work engagement. Malik (2024) revealed that the most effective method for increasing employee engagement is by providing organizational support through effective leadership. According to Peifer et al. (2022), leaders and leadership play a very important role in the success of AI implementation and usage. Hughes et al. (2019) state that AI management systems can encourage workers to be engaged in their jobs, as evidenced by direction, monitoring, and rewards. Employee engagement is positively related to the time spent by leaders on internal online platforms, the code of ethics of internal online networks, and the presence of an open organizational culture (Korzynski, 2015). Based on several research findings, the hypothesis of the moderating effect on the relationship between AI and employee performance and work engagement is as follows:

H3: *Change leadership positively moderates the relationship between AI and employee performance.*

H4: *Change leadership positively moderates the influence between AI and work engagement.*

The model used in this study is a replication of the research model conducted by Wijayati et al. (2022). Based on the variables used in the research by Wijayati et al. (2022), this study establishes 1) AI as the independent variable, 2) Employee Performance and Work Engagement as the dependent variables, and 3) Change Leadership as the moderating variable.



Research Method

This research uses Google Forms filled out by respondents online as a data collection instrument. The respondents are Gen Z workers in the Jabodetabek area, limited by the following criteria: (1) they are Gen Z workers (born between 1997 and 2012); (2) they work in the Jabodetabek area; (3) they have worked for at least 1 year in their current company; (4) they have a direct supervisor; (5) they have used AI in their work. The minimum sample size according to Malhotra (2006) is 5 times the number of indicators, which is 5 x 30 indicators with a total sample of 150. During the data collection period, a total of 252 respondents were gathered, with 66 data not meeting the criteria, leaving 186 respondents whose data could be processed.

Table 4.1 Respondent Demographics

Profile	Classification	Number of Respondents (person)	Percentation
Age	17 s.d. 21 years old	30	16,1%
	21 s.d. 25 years old	56	30,1%
	25 s.d. 27 years old	100	53,8%
Level of Education	SMA/SMK	25	13,4%
	Diploma I/II/III	55	29,6%
	Diploma IV/ S1	105	56,5%
	S2	1	0,5%
	S3	-	-
Duration of Work	1 s.d. 2 tahun	79	42,5%
	3 s.d. 5 tahun	65	34,9%
	>5 tahun	43	22,6%

Job Title	Staff	158	85%
	Supervisor	20	10,7
	Manager	8	4,3%
	Top Level	-	-

The data analysis methods used are descriptive analysis and structural equation modelling (SEM). This research uses the embedded two-stage approach referring to Sarstedt et al. (2019), starting with the first stage by storing the scores of all constructs into the model and adding new variables to the dataset. The second stage involves using the construct scores as indicators in the measurement model for the higher-order construct.

The reflective measurement model refers to Hair et al (2022) and can use "reliability indicators, internal consistency (Cronbach's alpha, composite reliability, RhoC, reliability coefficient RhoA, Convergent validity (Average Variance Extracted), Discriminant Validity (HTMT)". The Structural Model is analysed according to Hair et al (2022) using "Collinearity VIF, Significance and relevance of the structural model relationship (path coefficients), explanatory power (coefficients of determination; R2), Predictive power (PLSpredict procedure, model comparisons)".

Research Results

Measurement Test Results

Hair et al. (2022) state that the standard outer loading value is 0.708 or above. However, it is also stated that indicator values in the range of 0.4 to 0.7 can be considered for retention. In the first stage of measurement, the outer loading of each variable and dimension of the research was measured.

In the AI variable, 2 out of 7 indicators have outer loading values below 0.7, but still above 0.4, so they can be considered for the next testing process. The AI variable has a Cronbach's alpha value of 0.855 and an RhoC value of 0.890. Next, the AVE value of 0.537 can be considered reliable. The highest outer loading value on the AI variable is found in the AI3 indicator, which states that Gen Z workers in Jabodetabek feel assisted by AI in making job-related decisions.

Then, in the employee performance variable, the indicator EP7 has an outer loading value below 0.7. This can be considered for the next stage of testing because it is still above 0.4. In addition, the Cronbach's alpha value exceeds the minimum threshold of 0.7, which is 0.898, and the AVE value is 0.623. The outer loading value of the employee performance variable is found in the indicator EP6, which reflects that Gen Z workers in Jabodetabek complete their tasks within a reasonable timeframe using AI.

In the work engagement variable, the vigor dimension, the highest outer loading value is found in the WE1 indicator. This reflects that Gen Z workers in Jabodetabek feel full of energy at their workplace. Then, in the dedication dimension, the highest outer loading value is found in the WE6 indicator, which shows that Gen Z workers in Jabodetabek feel proud of the work they do. Next, in the work engagement variable under the absorption dimension, the WE9 indicator has the highest outer loading value, indicating that Gen Z workers feel absorbed in their work when they are working. Next, in the change leadership variable, the highest outer loading value is found in the CL3 indicator. This indicates that Gen Z workers in Jabodetabek feel that their leaders/supervisors clearly explain to the workers in the unit why the change is necessary.

Table 5.1 Recapitulation of the First Stage Measurements

Variable	Dimension	Outer Loading	Cronbach's Alpha	CR	AVE	Explanation
Artificial Intelligence	-	0.673-0.807	0.855	0.890	0.537	Valid and reliable
Employee Performance	-	0.684-0.852	0.898	0.920	0.623	Valid and reliable
Work Engagement	Vigor	0.866-0.907	0.863	0.916	0.785	Valid and reliable
	Dedication	0.872-0.893	0.859	0.914	0.780	Valid and reliable
	Absorbtion	0.795-0.810	0.732	0.843	0.642	Valid and reliable
Change Leadership	-	0.760-0.843	0.910	0.928	0.649	Valid and reliable

The second stage of outer loading measurement produced values with insignificant differences for each variable, and all indicators passed the minimum standards of validity and reliability. In the work engagement variable, the second stage measurement results show the highest value of the work engagement variable in the vigor dimension, specifically on indicator WE6, which explains that Gen Z workers in Jabodetabek feel proud of the work they do.

Table 5.2 Recapitulation of the First Stage Measurement

Variabel	Outer Loading	Cronbach's Alpha	CR	AVE	Keterangan
Artificial Intelligence	0.673-0.807	0.855	0.890	0.537	Valid and reliable
Employee Performance	0.684-0.852	0.898	0.920	0.623	Valid and reliable
Work Engagement	0.805-0.906	0. 854	0.912	0.7776	Valid and reliable
Change Leadership	0.759-0.843	0.910	0.928	0.649	Valid and reliable

Furthermore, in the measurement of internal consistency reliability analysis of all indicators, both in the first and second measurement phases, the results are above the minimum standard reliability threshold, thus it can be stated that each measurement indicator is reliable. The reliability standard according to Hair et al. (2022) states that the Cronbach's Alpha value must be between 0.7 and 0.9. Meanwhile, the RhoC value should be in the range of 0.6 to 0.95. This measurement explains reliability based on the inter-correlation of indicators within the variable being studied.

In the analysis of convergent validity, it is conducted to measure the extent to which a measurement item positively correlates with an alternative measure of the same variable/dimension. The measurement was conducted using average variance extracted (AVE) above 0.5. According to the measurement results, almost all AVE values of each indicator exceed the minimum threshold of 0.5.

The results of the discriminant validity analysis explain the differences between one variable and other variables, in other words, that a variable is unique and can represent a phenomenon without being represented by other variables in the model. The measurement indicator uses the heterotrait-monotrait ratio (HTMT) value with a maximum value limit of 0.9. The HTMT assessment is conducted through the first and second stages. It can be stated that all variables and dimensions are valid (HTMT<0.9) and successfully highlight a phenomenon that cannot be represented by other variables in the model. Based on the feasibility of the test results, it determines the continuation of testing in the second stage.

Next, in the second stage, we test the Discriminant Validity among the four variables, namely AI, employee performance, work engagement, and change leadership. The test results can be seen in Table 5.3.

Table 5.3 Results of the Second Stage Discriminant Validity Test

	Artificial Intelligence	Change Leadership	Employee Performance
Artificial Intelligence			
Change Leadership	0.504		
Employee Performance	0.854	0.521	
Work Engagement	0.588	0.715	0.544

In table 5.3, it can be stated that all variables in the model are valid (HTMT<0.9) and successfully represent a phenomenon that cannot be replaced by other variables in the model. In other words, these results can confirm the feasibility as a prerequisite for proceeding to the next stage of structural testing.

Results of Structural Model Analysis

The assessment of the variance inflation factor (VIF) explains whether there is multicollinearity among the measurement indicators within a variable. According to Hair et al. (2022), the VIF value threshold below 5, with the note that below 3 indicates that the multicollinearity is quite low or can be ignored.

Table 5.4 Results of the Collinearity Test (VIF)

	Employee Performance	Work Engagement
Artificial Intelligence	1.253**	1.253**
Change Leadership	1.289**	1.289**
Note: *: VIF < 5 **: VIF < 3		

Based on Table 5.4, it shows that the overall test results of the variables do not indicate any issues of collinearity among the indicators/items being measured. It is stated that both the AI variable, employee performance, work engagement, and change leadership have VIF values below 3. This indicates that the issue of collinearity is quite low and can be ignored.

The results of the Path Coefficient analysis for direct influence were conducted through hypothesis testing by analysing the bootstrapping results in the second stage of testing, with path coefficient values or p-values below 0.05 to indicate that both relationships are significant. In addition, t-values were tested for significance above 1.64 for a one-tailed test.

Table 5.5 Results of the Direct Effect Patch Model Test

Pengaruh	Path Coefficient	t values	p values	95% Confidence Intervals	Keterangan
AI → EP	0.685	12.755	0.000	(0.593-0.770)	Data supports H1
AI → WE	0.268	3.835	0.000	(0.154-0.383)	Data supports H2
Catatan: AI: Artificial Intelligence EP: Employee Performance WE: Work Engagement					

The results of this study indicate that the overall path model testing results are significant (t values > 1.65, p values < 0.05) or support both hypotheses (H1 and H2). From these results, the most significant relationship is between AI and employee performance ($\beta = 0.685$, t value = 12.755). Meanwhile, the relationship with the lowest significance is the relationship between AI and work engagement ($\beta = 0.268$, t value = 3.835). The overall results of this testing indicate that all relationships have a direct influence and possess a level of stability and significance in a positive direction, making this research worthy of implementation both theoretically and practically.

Table 5.6 Results of the Indirect Effect Test Patch Model

Pengaruh	Path Coefficient	t values	p values	95% Confidence Intervals	Keterangan
CL x AI → EP	-0.096	2.123	0.017	((-0.171) – (-0.022))	Data does not support H3
CL x AI → WE	0.108	1.737	0.041	(0.013-0.217)	Data supports H4
Catatan: AI: Artificial Intelligence EP: Employee Performance WE: Work Engagement CL: Change Leadership					

In testing the indirect effect (moderation), it can be observed through the measurement of the indirect effect in the path model being tested. The results from Table 5.6 above can explain that the indirect effect (moderation) on the path model of this research is significant (t values > 1.65, p values < 0.05). However, the influence of AI on employee performance with change leadership moderation is negative. Thus, the hypothesis of the moderating effect of change leadership on the relationship between AI and employee performance is not supported. Meanwhile, the hypothesis of the moderating effect of change leadership on the relationship between AI and work engagement is supported.

Results of Interpretation Analysis

The results of the hypothesis testing prove that AI has a positive influence on employee performance. The results of the tests are consistent with several previous studies that examined the relationship between AI and employee performance (Wijayati et al., 2022; Luhana et al., 2023; Prentice et al., 2023). Wijayati et al. (2022) in their research mentioned that AI and its technologies offer a variety of options, benefits, and services that can enhance employee performance. This is in line with the research conducted by Prentince et al. (2023), which states that when workers lack the appropriate personal competencies for performance, management can invest in AI technology to improve employee performance. Furthermore, Luhana et al. (2023) mention that AI can collaborate with humans in enhancing work and enabling workers to complete tasks more effectively and efficiently.

The results of the hypothesis testing prove that AI has a positive influence on work engagement. The results are consistent with several previous studies that examined the relationship between AI and work engagement (Wijayati et al., 2022; Rožman et al., 2022; Prentice et al., 2023). The research conducted by Wijayati et al. (2022) states that digital technology has a positive impact on work engagement in the banking and service sectors in East Java, Indonesia. According to Rožman et al. (2022), employee training and development supported by AI have a positive effect on performance and work engagement in companies in Slovenia. This is in line with Malik's (2024) research, which states that performance management benefits from AI's ability to analyze, automate, and provide relevant insights, as it can conduct fair evaluations, make data-driven decisions, and implement continuous improvements. According to Prentince et al. (2023), the significant relationship between AI, job engagement, and performance in their research demonstrates how technology can be used to enhance employee engagement and performance.

The results of the third hypothesis test prove that there is a different finding, namely that the hypothesis test results show that change leadership has a negative moderating effect on the relationship between AI and employee performance. The result is different from the findings of Wijayati et al. (2022), which revealed that change leadership positively moderates the relationship between AI and employee performance. However, on the other hand, the study by Gusti et al. (2024) also did not find any moderating role of change leadership on the relationship between AI and employee productivity. Productivity can be used as a benchmark for employee performance in the company (Mulyana, 2010 in Fitriana, 2022) and the increase in productivity is directly proportional to the improvement in performance (Andriani et al., 2023).

Conclusion and Suggestions

Based on the data processing results and hypothesis testing, it is concluded that Artificial Intelligence has a positive impact on employee performance and work engagement among Gen Z workers. The change in leadership does not play a moderating role in the influence of artificial intelligence on employee performance. However, change leadership plays a moderating role in the influence of artificial intelligence on work engagement.

Research limitations

There are some drawbacks faced by authors during the research which can be improved on further research. The scope of research is limited around Jabodetabek area, not specifically focus on selected industry sector, only included Generation Z workers and left the other generations behind, and not using in-depth interview since using questionnaires for quantitative research approach.

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Harnessing AI for Ethical Leadership: Preserving Human-Centered Values in the Age of Intelligent Machines

Xuesongzi Feng
Universiti Sains Malaysia, Malaysia
Email: fengxuesongzi@student.usm.my

Hasliza Abdul Halim*
Universiti Sains Malaysia, Malaysia
Email: haslizahalim@usm.my

**Corresponding Author*

Abstract

The integration of artificial intelligence (AI) into organizational decision-making is transforming the landscape of leadership. While AI offers unprecedented opportunities for efficiency, precision, and data-driven insight, it also raises profound ethical challenges. This paper examines how leaders can harness AI responsibly while preserving human empathy, moral reasoning, and social accountability as the "heart" of leadership. Drawing on theories of ethical leadership, AI governance frameworks, and emerging case studies, the paper argues for a hybrid leadership model that embeds AI within a values-driven decision-making process and the recommendations are provided for integrating AI ethics principles into leadership training, organizational governance, and stakeholder engagement.

Keywords: Artificial Intelligence; Ethical Leadership; AI Governance; Human-Centered Decision-Making; Organizational Ethics.

Introduction

The rapid adoption of artificial intelligence (AI) technologies has significantly transformed leadership practices across diverse sectors. In healthcare, predictive analytics enhance diagnostic accuracy and treatment planning; in finance, automated decision-making accelerates risk assessment and fraud detection (McAfee, 2018). These advancements promise substantial gains in efficiency, scalability, and innovation, enabling leaders to respond swiftly to complex challenges (West, 2018).

However, alongside these benefits arise profound ethical risks. Algorithmic bias can perpetuate or exacerbate social inequities (Jain, 2017), opaque decision-making processes can erode accountability (Doshi-Velez & Kim, 2017), and excessive reliance on automation may diminish the moral agency and empathy required for responsible leadership (Jobin, Ienca, &

Vayena, 2019). These risks are compounded by the global and cross-sector reach of AI systems, which makes ethical oversight more complex, The central challenge for contemporary leaders is to integrate AI in ways that uphold ethical principles, safeguard stakeholder trust, and maintain the uniquely human capacities of empathy, moral reasoning, and relational integrity (Brown & Treviño, 2006). Ethical leadership in the AI era requires more than technical competence; it demands a values-driven approach that aligns technological capabilities with societal well-being.

This paper examines how ethical leadership can navigate these tensions, drawing on leadership theory, AI ethics frameworks, and real-world case studies. It proposes practical strategies for embedding ethical considerations into AI governance and offers recommendations for sustaining human-centered leadership in an increasingly machine-mediated world.

Literature Review

The literature on ethical leadership and artificial intelligence (AI) in organizational contexts spans multiple disciplines, including business ethics, computer science, organizational psychology, and public policy. This review synthesizes current scholarship to clarify how ethical leadership theories intersect with AI governance frameworks and practical applications in leadership contexts, it is organized into three thematic areas: ethical leadership, AI applications in leadership, and AI ethics principles.

Ethical Leadership

Ethical leadership has been widely defined as “the demonstration of normatively appropriate conduct through personal actions and interpersonal relationships” and the promotion of such conduct among followers (Brown & Treviño, 2006). This definition encompasses two core dimensions: the moral person (leaders’ personal integrity, honesty, and fairness) and the moral manager (leaders’ proactive role in promoting ethical conduct in organizations) (Treviño et al., 2000).

The literature emphasizes that ethical leadership is inherently relational; it involves trust-building, role modeling, and fostering a shared ethical climate (Ilyas et al., 2020). Ethical leaders are expected to navigate competing stakeholder interests, balancing profitability with social responsibility (Maak & Pless, 2006) and their role includes ensuring procedural justice, engaging in transparent communication, and making decisions guided by societal values rather than short-term gains (Kalshoven et al., 2011).

In the digital era, the scope of ethical leadership has expanded to include digital ethics that the moral obligations associated with emerging technologies (Metcalf et al., 2019), it is said that leaders must now interpret and apply ethical principles in contexts involving algorithmic decision-making, data privacy, and cybersecurity (Martin, 2019). This extension of ethical leadership theory recognizes that leadership responsibilities increasingly extend into technical domains that were previously outside traditional managerial expertise.

Notably, there is growing scholarly interest in technomoral leadership, a concept that integrates traditional moral philosophy with technological governance (Vallor, 2016). Technomoral leaders are those capable of understanding both the capabilities and the limitations of AI, while actively embedding human-centered values in technological systems and this skillset is becoming a core requirement for leaders in AI-enabled organizations.

Artificial Intelligence in Leadership

AI in leadership is not confined to automating routine processes; rather, it is increasingly deployed as a strategic tool that influences decision-making, talent management, and organizational culture (Doshi-Velez & Kim, 2017; Wilson & Daugherty, 2018) and common applications include:

Decision-Support Systems: AI can synthesize large datasets into actionable insights, allowing leaders to anticipate market trends, optimize supply chains, and improve public service delivery (Shrestha et al., 2019).

Algorithmic Hiring: AI-powered recruitment tools can screen resumes, predict candidate performance, and reduce manual workload for human resource departments (Raghavan et al., 2020).

Sentiment Analysis: AI tools can analyze employee feedback or customer reviews to assess organizational climate and brand reputation in real time (Cambria et al., 2017).

Strategic Forecasting: Predictive analytics allow leaders to model economic scenarios, assess risk, and develop contingency plans (Hemphill, 2019).

While these applications promise efficiency and scalability, the literature consistently warns of associated risks. Algorithmic bias that the embedding of societal prejudices into machine learning models can result in discriminatory outcomes, especially in hiring and lending decisions (O'Neil, 2016), opacity in complex AI models, often referred to as the "black box" problem, undermines explainability and makes accountability difficult (Doshi-Velez & Kim, 2017).

Scholars also highlight the over-reliance dilemma that the risk that leaders may defer too heavily to algorithmic recommendations, leading to the erosion of human moral agency (Mittelstadt et al., 2016). This is particularly concerning in high-stakes contexts such as criminal justice, healthcare, and financial regulation, where AI errors can have severe human consequences.

In response, recent studies advocate for human-AI collaboration rather than replacement, where AI augments human decision-making while preserving space for moral reasoning and contextual judgment (Dellermann et al., 2019). This approach aligns closely with ethical leadership theory, which prioritizes moral accountability and empathy qualities that AI currently cannot replicate.

AI Ethics Principles

AI ethics has emerged as a distinct field of study, synthesizing perspectives from philosophy, computer science, law, and policy. Across global frameworks, there is substantial convergence on key principles such as fairness, accountability, transparency, and explainability (FATE) (Jobin et al., 2019).

The OECD Principles on AI (OECD, 2019) outline five values-based principles: (1) AI should benefit people and the planet by driving inclusive growth and sustainable development; (2) AI systems should respect the rule of law, human rights, and democratic values; (3) AI should be transparent and explainable; (4) AI systems should be robust, secure, and safe; and (5) organizations should be accountable for AI outcomes. Similarly, the EU Artificial Intelligence Act proposes a risk-based regulatory framework, imposing stricter requirements on high-risk AI systems used in critical sectors such as healthcare, law enforcement, and education (European Union, 2025). The Act emphasizes data governance, transparency obligations, and human oversight.

Philosophical contributions to AI ethics, such as Floridi and Cowls' (2019) unified framework expand these ideas into five overarching principles: beneficence (promoting well-being), non-maleficence (avoiding harm), autonomy (respecting human decision-making), justice (ensuring fairness), and explicability (providing transparency and understanding), these principles parallel many of the normative expectations in ethical leadership theory.

A critical insight from the literature is that alignment between AI ethics principles and organizational leadership values is not automatic (Daugherty & Wilson, 2018). Ethical leadership requires proactive governance structures to translate abstract principles into enforceable organizational policies. Without such mechanisms, AI ethics risks being reduced to "ethics washing," where organizations publicize principles without changing practices (Hagendorff, 2020).

Intersection of Ethical Leadership and AI Ethics

The integration of ethical leadership theory with AI ethics principles reveals complementary strengths, it is said that ethical leadership offers a human-centered governance lens, focusing on integrity, fairness, and stakeholder engagement. AI ethics provides technical and procedural guidance for ensuring that AI systems themselves operate in alignment with societal values.

Scholars have argued that ethical leadership is critical for operationalizing AI ethics because principles such as fairness and transparency require organizational champions who can bridge the gap between technical design and stakeholder expectations (Morley et al., 2020), leaders must mediate between engineers, policymakers, and affected communities, ensuring that AI deployment reflects collective values rather than narrow commercial objectives.

This intersection also raises new challenges. Ethical leadership traditionally assumes that leaders have direct control over decision processes, but AI systems often operate autonomously or in opaque ways. This necessitates new leadership competencies in algorithmic literacy that the ability to understand, question, and guide AI systems effectively (Long & Magerko, 2020).

Ultimately, the literature supports a hybrid leadership model in which ethical leaders integrate AI capabilities while embedding human values at every stage from design and deployment to monitoring and adaptation. Such a model is not merely reactive but anticipatory, aiming to foresee ethical risks before they materialize.

Theoretical Framework

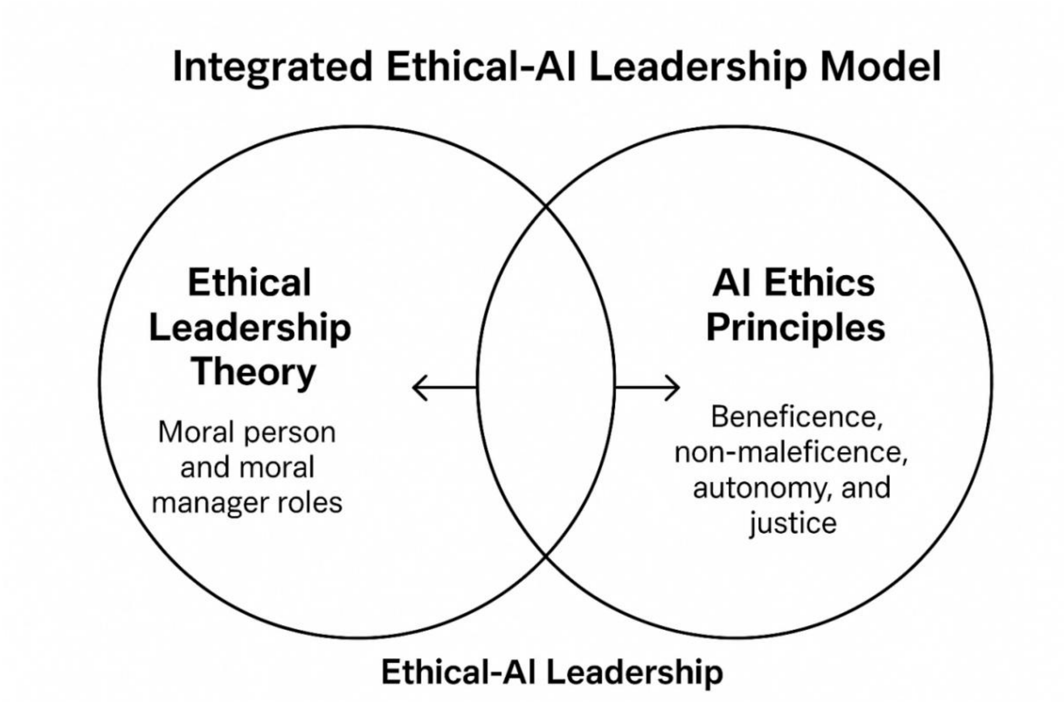
This paper employs an Integrated Ethical-AI Leadership Model that synthesizes Ethical Leadership Theory (Brown & Treviño, 2006) and AI Ethics Principles (Floridi & Cowls, 2019). Ethical Leadership Theory is grounded in two core roles: the moral person, who demonstrates personal integrity, fairness, and empathy in interpersonal relationships, and the moral manager, who actively promotes ethical conduct through policies, explicit communication, and consistent role modeling. These roles collectively emphasize that leaders must embody and advocate for ethical norms, ensuring that decisions and behaviors align with shared organizational and societal values.

The AI Ethics Principles framework offers a complementary perspective, emphasizing four guiding imperatives: beneficence (promoting individual and collective well-being), non-maleficence (avoiding harm to people and the environment), autonomy (respecting and enabling human agency in decision-making), and justice (ensuring fairness, equity, and inclusivity in the design and deployment of AI systems). These principles have been reflected in international guidelines such as the OECD Principles on AI (OECD, 2019) and UNESCO's Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021).

By integrating these two frameworks, the model positions leaders as ethical mediators between the technical potential of AI and the moral imperatives of human-centered governance. This mediation role involves more than applying static ethical codes, it requires interpreting AI-generated insights through the lens of societal values, managing trade-offs between efficiency and fairness, and fostering accountability in contexts where decision-making processes may be opaque due to algorithmic complexity.

Operationalizing this model demands design oversight to ensure that AI systems are developed with embedded ethical safeguards, algorithmic literacy so that leaders can critically evaluate AI's outputs and limitations, and participatory governance that engages diverse stakeholders in AI-related decisions. Furthermore, given AI's rapid evolution and the dynamic nature of its societal impacts, the model underscores the necessity of continuous monitoring and adaptation. Leaders must remain vigilant in updating governance strategies, refining ethical guidelines, and responding proactively to emergent risks.

In essence, the Integrated Ethical-AI Leadership Model recognizes that technology does not inherently produce ethical or unethical outcomes; rather, it is the leader's informed, values driven engagement with AI that determines whether its use advances fairness, accountability, and human dignity.



Discussion

The integration of AI into leadership presents a complex landscape of opportunities and challenges. While AI offers powerful tools for improving decision-making, inclusivity, and organizational ethics, it also introduces new risks that require deliberate, values-driven governance. This section examines the potential benefits (4.1), persistent challenges (4.2), and strategies for balancing technological capabilities with human-centered leadership (4.3).

Opportunities

Bias Reduction

One of the most frequently cited advantages of AI is its potential to reduce certain human cognitive biases in decision-making (Lee, 2018). Human judgments are often influenced by heuristics, stereotypes, and emotional states (Kahneman, 2011). Properly designed and trained AI systems can, in theory, apply decision criteria more consistently. For example, AI-based recruitment tools can anonymize resumes to prevent hiring managers from being influenced by gendered or ethnic cues (Bogen & Rieke, 2018). In financial lending, AI models that incorporate diverse datasets can be calibrated to reduce discriminatory practices in credit scoring (Hurley & Adebayo, 2017).

However, scholars caution that bias reduction through AI is contingent upon careful data curation and model testing (Mehrabi et al., 2021). Ethical leadership plays a key role here, as leaders must ensure that technical teams have the mandate and resources to audit datasets and algorithms for bias before deployment.

Data-Driven Ethics

AI enables leaders to move beyond intuition and anecdotal evidence toward data-driven ethics, where decisions are informed by quantifiable social and environmental metrics (West, 2018). For instance, real-time monitoring of supply chain emissions can help organizations identify and mitigate environmental harm more quickly (George et al., 2022). In corporate social responsibility, AI tools can analyze stakeholder sentiment from social media and public forums, enabling leaders to respond proactively to ethical concerns (Li et al., 2020).

The availability of these analytics supports evidence-based ethical decision-making (George et al., 2022), where leaders use empirical data to evaluate the social impact of policies, programs, and investments. Importantly, data-driven ethics does not replace moral judgment but enhances it with broader situational awareness (Vallor, 2016).

Enhanced Inclusivity

AI-powered translation, speech-to-text, and accessibility tools can broaden participation in organizational decision-making. For global companies, AI-enabled simultaneous translation allows diverse stakeholders to engage in real time across language barriers (Lewis-Kraus, 2021). In education and training, AI-based accessibility tools, such as automated captioning for the hearing impaired that ensure that learning resources are available to all employees (Choudhary & Bansal, 2022).

This inclusivity aligns with ethical leadership's commitment to fairness and equal opportunity (Brown & Treviño, 2006). By removing communication and access barriers, leaders can draw on a wider range of perspectives, improving both the quality and legitimacy of decisions (Zerilli et al., 2018)

Challenges

Algorithmic Bias

Despite AI's potential to mitigate bias, poorly designed systems can encode and even amplify existing inequities (O'Neil, 2016). Algorithmic bias can arise from skewed training data, flawed feature selection, or the replication of historical prejudices embedded in datasets (Barocas & Selbst, 2016). The high-profile case of a technology company's recruitment AI that downgraded resumes containing the word "women's" underscores the risks of uncritical adoption (Dastin, 2018).

Ethical leaders must therefore move beyond vendor assurances to implement independent audits and impact assessments and this involves questioning not only the technical integrity of AI tools but also their alignment with organizational values and social responsibility mandates (Raji et al., 2020).

Opacity

Many AI systems, particularly those based on deep learning, operate as "black boxes," producing outputs that are difficult to explain even to their developers (Lipton, 2018). This opacity undermines accountability, as stakeholders may not understand or be able to challenge the rationale behind AI-driven decisions (Doshi-Velez & Kim, 2017).

For leaders, opacity poses a governance challenge: How can they uphold transparency and trust if they cannot explain how an AI system reached its conclusion? Explainable AI (XAI) research is advancing methods for making model behavior interpretable, but its adoption remains uneven (Gunning & Aha, 2019). Ethical leadership requires prioritizing XAI solutions in procurement and development, even when they involve trade-offs in predictive accuracy.

Over-Reliance on Automation

AI's predictive accuracy and efficiency can tempt organizations into over-reliance, where human oversight is reduced to a rubber-stamping function (Mittelstadt et al., 2016). This "automation complacency" risks eroding the moral agency of leaders and employees, especially in high-stakes contexts such as healthcare diagnoses or parole decisions (Green & Chen, 2019).

Ethical leaders must resist this tendency by maintaining human-in-the-loop systems, where humans retain final decision authority and can override AI recommendations when necessary (Rahwan et al., 2019). Over-reliance is not merely a technical issue but a cultural one, requiring leaders to reinforce norms of critical thinking and accountability (Raji et al., 2020)

Balancing Heart and Machine

Ethical leadership in the AI era demands a deliberate balance between leveraging AI's strengths and preserving human moral judgment. This balance can be operationalized through three interrelated commitments (Zerilli et al., 2018).

Moral Vigilance

Moral vigilance refers to the continuous evaluation of AI outcomes for ethical implications (Zerilli et al., 2019). Unlike traditional compliance checks, moral vigilance is proactive and anticipatory, seeking to identify potential harms before they occur. Leaders must establish mechanisms such as ethics review boards, ongoing algorithmic audits, and post-deployment monitoring to ensure that AI systems remain aligned with organizational values and societal norms (Morley et al., 2020).

Transparency

Transparency is both a technical and relational imperative (Lipton, 2018). Technically, it involves the use of explainable AI methods to make decision logic comprehensible (Gunning & Aha, 2019). Relationally, it requires leaders to communicate openly with stakeholders about how AI is used, what data it relies on, and what safeguards are in place (Ananny & Crawford, 2018). This openness builds trust and enables informed consent, especially in contexts where AI directly affects people's rights or opportunities.

Empathy-Driven Decision-Making

Empathy-driven decision-making involves integrating AI-derived insights with human values and lived experiences (Vallor, 2016). While AI can process vast datasets, it lacks the contextual sensitivity and moral imagination needed to fully appreciate the human impact of decisions (Tourky et al., 2020). Leaders must interpret AI outputs through an empathetic lens, considering how different options will affect diverse stakeholders, particularly marginalized groups (Zerilli et al., 2018). This approach ensures that efficiency gains do not come at the expense of human dignity or fairness.

Balancing heart and machine is not a one-time calibration but an ongoing process that evolves alongside AI capabilities and societal expectations. It requires leaders to cultivate algorithmic literacy, embed ethical considerations in strategic planning, and engage in cross-disciplinary dialogue with technologists, ethicists, and community representatives.

Case Examples

Case 1: AI in Healthcare Diagnostics

Artificial intelligence has become a transformative force in healthcare diagnostics, with notable applications in radiology, pathology, and genomics (Jiang et al., 2017). For example, AI-assisted diagnostic tools have achieved significant improvements in early detection rates for cancers such as breast cancer and lung cancer (McKinney et al., 2020). These systems use deep learning algorithms to analyze large volumes of imaging data, identifying subtle patterns that might be missed by human clinicians.

In one hospital network, the deployment of an AI mammography analysis system resulted in a measurable reduction in false negatives, thereby improving patient survival rates (Rodriguez-Ruiz et al., 2019). However, the ethical success of this implementation hinged on the leadership approach taken. Ethical leaders mandated that the AI system be introduced alongside clear protocols for informed patient consent, ensuring that patients understood how AI was involved in their care. Moreover, rigorous bias testing was conducted to confirm that diagnostic accuracy was consistent across demographic groups, addressing concerns about algorithmic disparities (Topol, 2019).

From an ethical leadership perspective, this case illustrates the principle of moral vigilance continuous oversight of AI outputs to ensure fairness and safety (Brown & Treviño, 2006), it also reflects the AI ethics principle of non-maleficence, as the system was actively monitored to prevent harm caused by misdiagnosis or unequal accuracy rates (Floridi & Cowls, 2019). The leadership team fostered a culture in which human clinicians retained the final authority in diagnosis, preserving human moral agency and ensuring that AI served as a support tool rather than a decision-maker. The outcome demonstrates how AI can enhance healthcare quality without eroding patient trust, provided that ethical leadership integrates transparency, fairness, and human oversight into implementation.

Case 2: Algorithmic Hiring in Technology Firms

In the technology sector, recruitment processes have increasingly adopted AI-powered screening tools to manage high volumes of applicants. While these tools can improve efficiency, they have also been shown to reproduce and even amplify existing biases when trained on historically biased hiring data (Raghavan et al., 2020).

One notable case involved a global technology firm that discovered gender disparities in its AI-powered resume screening tool, with female applicants being underrepresented in shortlists for technical positions. The leadership responded by commissioning an independent algorithmic audit, which confirmed that historical hiring data had biased the model toward male candidates. Rather than discarding AI entirely, the company adopted a human-AI hybrid model for recruitment.

This new approach combined AI's capacity for processing large datasets with human evaluators trained in structured, bias-aware recruitment methods (Bogen & Rieke, 2018). The AI was redesigned to prioritize skill-based criteria rather than proxies such as university attended or specific job titles from both of which had been found to disadvantage certain demographic groups. Human recruiters were tasked with final decision-making, ensuring contextual judgment and accountability (Topol, 2019).

Ethical leadership played a central role in this transformation. Leaders adopted a transparency-first approach, publicly acknowledging the bias issue and communicating the corrective measures to both internal teams and the public. This aligns with the AI ethics principle of justice, ensuring that recruitment systems promote fairness and inclusivity (Floridi & Cowls, 2019).

Furthermore, the company introduced periodic bias audits and stakeholder consultations to maintain moral vigilance over the system's performance. This practice also embodies the ethical leadership role of the moral manager, actively shaping organizational processes to align with shared ethical values (Brown & Treviño, 2006).

Within a year, internal diversity metrics indicated a measurable reduction in gender disparities in technical hiring. The case highlights that while AI can embed harmful patterns from historical data, ethical leadership can redirect its use toward equitable and transparent hiring processes (Rodriguez-Ruiz et al., 2019).

Cross-Case Analysis

Both cases demonstrate that AI's ethical impact is not predetermined by the technology itself but is shaped by leadership decisions during design, deployment, and monitoring (Jiang et al., 2017). In healthcare diagnostics, AI improved life-saving outcomes, but only because leaders enforced rigorous bias testing and preserved human oversight. In hiring, AI initially amplified systemic bias, but ethical leadership transformed it into a fairer process by integrating human judgment and revising algorithmic criteria.

Three cross-case themes emerge:

Human-AI Complementarity — In both scenarios, ethical leaders resisted full automation and retained human oversight. This hybrid approach acknowledges AI's strengths while mitigating risks associated with moral abdication (Rahwan et al., 2019).

Transparency as Trust-Building — Public and internal transparency was critical in sustaining trust. In healthcare, patients were informed about AI involvement; in hiring, the company openly addressed algorithmic bias. Transparency aligns with AI ethics frameworks such as the OECD Principles on AI (OECD, 2019), which stress explainability as a pillar of trustworthy AI.

Continuous Ethical Monitoring — Both cases implemented ongoing evaluation through bias audits in hiring and continuous diagnostic accuracy testing in healthcare that ensuring that ethical alignment is sustained over time.

These findings reinforce that ethical leadership is not a static trait but a set of active, ongoing practices. Leaders must act as mediators between AI's technical potential and the societal values it impacts, ensuring that innovations contribute to both performance goals and the public good.

Recommendations

The integration of Artificial Intelligence (AI) into organizational decision-making requires leadership approaches that preserve ethical standards, promote accountability, and maintain the human dimension in governance. Building on the Integrated Ethical-AI Leadership Model, the following recommendations address practical strategies to operationalize responsible AI leadership.

Embed AI Ethics in Leadership Training

Organizations must ensure that leadership development programs incorporate AI literacy and ethical reasoning as core competencies. Leaders should understand not only the technical aspects of AI, such as data structures, model training, and algorithmic limitations, but also the socio-ethical implications of AI use (Mökander & Floridi, 2021). Training should address topics such as fairness, transparency, accountability, and the mitigation of bias, aligning with international ethical guidelines like the OECD Principles on AI (OECD, 2019).

By embedding AI ethics into training, leaders become better equipped to evaluate AI-driven recommendations critically, detect potential ethical pitfalls, and communicate AI-related decisions with clarity to stakeholders. Furthermore, this enhances their ability to balance technological efficiency with human-centered values, thus reducing risks of over-reliance on automated systems (Rahwan, 2018).

Create AI Governance Committees

The complexity of AI systems necessitates cross-functional governance committees that oversee the development, deployment, and monitoring of AI applications within organizations. These committees should include representatives from technology, legal, compliance, human resources, ethics, and end-user groups to ensure diverse perspectives (Cath, 2018).

Such bodies can function as ethical oversight mechanisms, ensuring that AI implementation aligns with both corporate values and societal expectations. They can also provide structured frameworks for approving AI projects, monitoring performance, and assessing ethical risks. By institutionalizing governance, organizations can create an ongoing feedback loop that detects and addresses unintended consequences early, fostering public trust in AI-enabled operations (Jobin, Ienca, & Vayena, 2019).

Adopt Human-in-the-Loop Systems

Despite the sophistication of AI, certain domains, especially those involving high-stakes or morally sensitive decisions require human-in-the-loop (HITL) systems (Shneiderman, 2020). HITL approaches preserve human judgment by ensuring that AI outputs are reviewed, contextualized, and, when necessary, overridden by qualified decision-makers.

For instance, in healthcare diagnostics, an AI system may provide probabilistic predictions for disease detection, but final diagnoses should remain under the authority of licensed clinicians (Topol, 2019). In finance, automated credit scoring can be supplemented with manual review for borderline cases to ensure that applicants are not unfairly excluded due to algorithmic bias (O'Neil, 2016). By keeping humans actively engaged in decision-making, organizations reduce risks associated with automation bias and maintain moral accountability.

Mandate Algorithmic Impact Assessments

Before deploying AI systems, organizations should conduct Algorithmic Impact Assessments (AIA) to evaluate potential societal, ethical, and legal implications (Reisman, Schultz, Crawford, & Whittaker, 2018). These assessments should include:

Bias audits to identify and mitigate discriminatory patterns in training data and outputs. Transparency evaluations to determine the explainability of AI decision-making processes. Stakeholder analysis to understand how AI systems affect different demographic groups. Compliance checks with relevant regulations such as the EU AI Act (European Commission, 2021) or the General Data Protection Regulation (GDPR). AIAs can serve as formal checkpoints in the AI lifecycle, enabling leaders to address ethical concerns proactively. Moreover, making these assessments publicly available can enhance transparency and strengthen stakeholder trust.

Engage Stakeholders in AI Governance

Ethical AI governance benefits significantly from multi-stakeholder engagement. This involves consulting a wide range of voices employees, customers, affected communities, regulators, and civil society organizations to ensure that AI deployments reflect shared societal values (Bryson, 2018).

Engagement mechanisms may include participatory workshops, open comment periods, and advisory councils composed of external experts and community representatives. This inclusivity ensures that decisions are informed by diverse experiences and reduces the risk of overlooking vulnerable or marginalized groups (West, Whittaker, & Crawford, 2019). Furthermore, involving stakeholders in governance can prevent reputational harm by demonstrating a commitment to openness, accountability, and social responsibility.

Conclusion

Artificial Intelligence (AI) presents unprecedented opportunities for enhancing decision-making, operational efficiency, and strategic foresight in leadership contexts, its ability to process vast datasets, identify patterns, and generate actionable insights can significantly augment human capability. However, these benefits are accompanied by equally profound ethical challenges, including issues of bias, transparency, accountability, and societal impact (Jobin, Ienca, & Vayena, 2019). These challenges cannot be addressed solely through technological refinement; they require deliberate, values-driven leadership.

The essence of ethical leadership lies in balancing technological innovation with human-centered values. Leaders who approach AI governance with empathy, integrity, and accountability are better equipped to ensure that AI systems do not merely optimize for efficiency but also promote fairness and social well-being (Brown & Treviño, 2006). In this regard, ethical leadership functions as both a safeguard and a guide that ensuring that AI serves as a force for collective good rather than exacerbating inequality or eroding public trust.

A central insight is that the future of leadership will not be defined by a binary choice between human and machine decision-making. Instead, it will emerge from integration leveraging AI's computational strengths while preserving and enhancing distinctly human qualities such as moral reasoning, contextual judgment, and empathy (Rahwan, 2018). This approach aligns with the "human-in-the-loop" principle, where humans retain ultimate oversight and responsibility for critical decisions, thus maintaining ethical and legal accountability (Shneiderman, 2020).

To operationalize this integration, leaders must embed AI governance into the fabric of organizational culture. This includes establishing cross-functional governance structures, mandating algorithmic impact assessments, and engaging diverse stakeholders in decision-making processes. Such measures are not merely compliance mechanisms; they are strategic imperatives for building resilience, adaptability, and trust in an AI-enabled future (Cath, 2018).

Moreover, ethical AI leadership is not static. As technology evolves, so too must the ethical frameworks and governance models that guide its use. This requires leaders to adopt a mindset of continuous learning staying informed about advances in AI capabilities, evolving regulatory landscapes, and shifting societal expectations. The capacity to anticipate and adapt to emerging risks will be as critical as the ability to deploy AI effectively.

Ultimately, the integration of AI into leadership is an opportunity to elevate both human and machine potential. When implemented thoughtfully, AI can free leaders from routine decision-making, allowing them to focus on strategic vision, innovation, and relationship-building. At the same time, human oversight ensures that decisions remain grounded in ethical principles, cultural awareness, and social responsibility.

In conclusion, the transformative potential of AI in leadership will only be realized when technology and human values are developed in tandem. Leaders must navigate this intersection with foresight, courage, and compassion, ensuring that AI not only drives organizational success but also contributes to the broader public good. In doing so, they can help shape a future where technology amplifies humanity rather than diminishes it.

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Hedonic Motivation In Fintech Adoption: A Literature Review of Conflicting Evidence, Moderating and Mediating Factors, and Research Gaps

Lingeswary Ramachandran
Universiti Sains Malaysia, Malaysia
Email: lingeswaryram@usm.my

Ema Izati Zull Kepili*
Universiti Sains Malaysia, Malaysia
Email: emazull@usm.my

Nik Hadiyan Nik Azman
Universiti Sains Malaysia, Malaysia
Email: nikhadiyan@usm.my

**Corresponding Author*

Abstract

This paper reviews the role of hedonic motivation in the adoption of financial technologies, with a focus on emotionally engaging features such as gamification and personalization. While these elements can enhance user experience, their influence varies across cultural settings, platform types, and user demographics. Drawing on studies from mobile banking, e-wallets, and peer-to-peer lending, the review highlights both supportive and contradictory findings. It also examines how factors like trust and perceived risk mediate or moderate hedonic effects. The paper argues that emotional design in FinTech must be balanced with ethical considerations, especially in high-risk or investment-oriented platforms. By identifying key gaps in the literature, this review contributes to a more context-sensitive understanding of technology adoption and offers insights for leaders seeking to align AI-driven financial services with human values.

Keywords: financial technologies, hedonic motivation.

Introduction

The global rise of financial technology (FinTech) has transformed how individuals pay, borrow, save, and invest. Services such as mobile payments, peer-to-peer (P2P) lending, digital wallets, and crowdfunding offer speed and convenience, but also raise important questions about how technology influences human behavior. As artificial intelligence (AI) becomes increasingly embedded in FinTech platformsthrough personalization, automation, and predictive analytics understanding the emotional and ethical dimensions of user engagement becomes critical.

These factors are emerging within a wider shift in financial intermediation, where technology is redefining the role of traditional banks. Advances in artificial intelligence, blockchain, and mobile technologies enable fintech companies to deliver more personalized, efficient, and secure services (Alam et al., 2025). Such services not only boost consumer satisfaction but also improve operational efficiency and intensify competition in the financial sector (Luu et al., 2021).

This competitive pressure is a core part of the digital transformation of banking, shaped by new technologies and changing customer expectations. Fintech firms often use hybrid business models that combine financial expertise with the agility of technology companies. This raises the question of how they should be valued more like banks, or more like tech firms? Increasingly, evidence points to the latter, reflecting the innovative and technology-driven nature of fintech (Moro-Visconti & Cesaretti, 2023).

Still, innovation comes with challenges. Regulatory compliance, data privacy, and consumer protection remain central issues, as policymakers try to encourage progress without compromising safety (Luu et al., 2021). At the same time, adoption depends on human factors such as trust, perceived enjoyment, and emotional connection. One factor gaining attention is hedonic motivation the pleasure people feel when using a technology.

Hedonic motivation is especially relevant for consumer-facing fintech, where design, ease of use, and emotional engagement can make or break user adoption. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by Venkatesh et al. (2012) identifies hedonic motivation as a key driver of behavioral intention, marking a shift from purely functional models toward those that also account for the user's experience and emotions.

However, the evidence is mixed. In Malaysia, Osman, Razli, and Ing (2021) found that trust and government support encouraged fintech use, but perceived enjoyment had little effect suggesting that in some contexts, security and institutional backing matter more than fun or pleasure. By contrast, Pokharel and Khanal (2024) showed that enjoyment, alongside trust and ease of use, significantly boosted adoption among grocery shoppers using fintech, highlighting the role of emotional engagement in everyday retail transactions.

Other studies reinforce this emotional dimension. Mulya (2023) found that both hedonic and practical motivations improve financial management behavior among Gen Z mobile banking users. Similarly, a meta-analysis by Bommer, Milevoj, and Rana (2023) identified hedonic motivation as one of the strongest predictors of fintech adoption, alongside price value and performance expectations showing that even simple models with a few well-chosen variables can explain adoption behavior effectively.

Together, these findings suggest that hedonic motivation plays a vital role in fintech adoption. Its influence varies by demographic group, cultural setting, and platform type. Some studies show strong positive effects in mobile payment and e-wallet contexts, while others find little or no effect for investment platforms like P2P lending or sharia-compliant fintech. Factors such as age, culture, and religiosity may all help explain these differences.

Given these inconsistencies, this paper critically reviews the literature on hedonic motivation in fintech adoption. It examines research across different fintech services and global contexts to identify patterns, contradictions, and gaps. The goal is to support the development of more context-sensitive adoption models and provide insights for researchers, developers, and policymakers aiming to strengthen user engagement and experience.

Hedonic Motivation as a Determinant of FinTech Adoption

Hedonic motivation comes from consumer behavior theory and refers to the pleasure, enjoyment, or emotional satisfaction gained from an activity. In technology adoption, it measures how much fun, excitement, or personal reward a user experiences when engaging with a system. This concept has become increasingly important in digital environments, particularly in consumer-facing platforms where user experience is central to long-term engagement.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), developed by Venkatesh et al. (2012), formally recognized hedonic motivation as one of seven key predictors of behavioral intention. Building on the original UTAUT model (Venkatesh et al., 2003)which synthesized eight well-known adoption theories such as the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), and Innovation Diffusion Theory (IDT) UTAUT2 shifted the focus from workplace technologies to consumer technologies. It expanded the model to include emotional and experiential factors, such as hedonic motivation, price value, and habit, to better explain consumer behavior.

In UTAUT2, hedonic motivation is defined as the degree of pleasure derived from using a technology, with the expectation that higher enjoyment leads to a stronger intention to use. This idea echoes earlier extensions of TAM, where perceived enjoyment was found to influence technology acceptance (Davis et al., 1992), and aligns with Cognitive Evaluation Theory, which highlights intrinsic motivation doing something for the satisfaction it provides, not just for external rewards.

In fintech, hedonic motivation plays an increasingly visible role due to the rise of gamification, personalized interfaces, and interactive features in platforms like mobile banking apps, e-wallets, and investment tools. These platforms aim to make financial services not just efficient, but also engaging. Reward systems, visually rich dashboards, and social sharing features are deliberately designed to enhance user experience and build emotional attachment.

Gamification applying game-like elements to non-game contexts has become a popular strategy to increase user engagement (Prasetyaningrum, Purwanto, & Rochim, 2022). Many fintech applications now use gamified features to encourage interaction, boost financial literacy, and guide decision-making (Dulloo, 2024). By tailoring these features to specific demographic and psychological profiles, fintech firms can improve both engagement and satisfaction.

However, results have been mixed. Some studies show that gamification significantly boosts consumer engagement and system performance, while others point to issues like oversimplification or declining interest over time (Prasetyaningrum et al., 2022). In e-wallet contexts, gamification has even drawn criticism for blurring the line between responsible finance and game-like behavior. This concern has contributed to growing interest in decentralized finance (DeFi) platforms, which promise greater transparency and security through blockchain-based smart contracts (Yathiraju & Dash, 2023).

Despite these debates, the fusion of gamification and fintech continues to grow. Well-designed gamification strategies have been shown to strengthen both hedonic and utilitarian motivations, boosting loyalty and shaping better financial habits across different user groups (Dulloo, 2024). For fintech providers competing in a crowded market, emotionally engaging features can be a powerful way to build lasting customer relationships.

That said, hedonic motivation's role in fintech adoption is not universal. In high-stakes financial activities like investment or lending, many users still place greater importance on functional factors such as trust, security, and ease of use. This suggests that hedonic motivation should not be treated as a one-size-fits-all predictor, but rather as a context-dependent variable shaped by platform type, cultural norms, and user demographics.

Conflicting Evidences

The role of hedonic motivation in fintech adoption has been explored across various platforms and user groups, yielding a spectrum of findings. This section synthesizes the literature into three key themes: studies supporting hedonic motivation, studies showing contradictory or insignificant effects, and contextual factors that influence its impact.

Studies Supporting Hedonic Motivation

A growing body of research confirms that hedonic motivation plays a significant role in influencing users' intentions to adopt FinTech services, particularly in consumer-facing platforms where emotional engagement and user experience are central. This aligns with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which identifies hedonic motivation as a key construct influencing behavioral intention, especially in voluntary technology use.

Evidence from multiple contexts supports this relationship. In Malaysia, Salimon et al. (2017) found that enjoyment enhances satisfaction and loyalty in e-banking adoption, while Tun-Pin et al. (2019) showed that perceived enjoyment significantly affects the uptake of FinTech services, particularly among users who value intuitive and aesthetically appealing interfaces. Similar patterns are evident in mobile banking: Saprikis et al. (2022) reported hedonic motivation as a strong predictor of app adoption, and Srivastava et al. (2024) observed that Indian Gen Z users were especially influenced by gamification and visual appeal in digital payment platforms.

The influence of hedonic motivation has also been highlighted in studies conducted during the COVID-19 pandemic. Singh and Sharma (2023) found that Indian Gen X and Millennials adopted FinTech payment services not only out of necessity but also because of the pleasure and convenience associated with contactless transactions. Similarly, Edo et al. (2023) reported that Nigerian users embraced mobile payments for their enjoyable and seamless user experience during periods of physical restrictions.

These findings are consistent with earlier work in digital commerce. Yang (2010) identified hedonic motivation as a key driver of mobile purchasing in the United States, while Adirinekso (2021) extended this to Paylater services, where users valued the pleasure of deferred payments. Wong and Ong (2021) further emphasized that gamification and aesthetic design in FinTech applications enhance hedonic value, boosting both adoption and retention rates.

Meta-analytic evidence reinforces these conclusions. Bommer et al. (2023) identified hedonic motivation as one of the strongest predictors of FinTech use intention across cultures and platforms. In Nigeria, Akinwale and Kyari (2022) reported that hedonic factors strongly influenced attitudes toward FinTech, particularly among younger, tech-savvy users. Muzaldin et al. (2022) and Seng and Hee (2021) similarly found that joy and "gadget love" were important predictors of e-wallet adoption among younger demographics. The summary of the studies are listed in Table 1.0.

Collectively, these studies underline the strategic importance of designing FinTech platforms that deliver not only functional efficiency but also emotional satisfaction. Enjoyment, gamification, visual appeal, and interactive features consistently emerge as levers for enhancing user engagement, satisfaction, and loyalty. This effect is especially pronounced among younger cohorts, such as Gen Z and Millennials, who place high value on engaging and visually appealing interfaces.

Even in crisis contexts like the COVID-19 pandemic, hedonic motivation has encouraged adoption of contactless payment methods, showing its relevance in both routine and exceptional circumstances. These insights reinforce the theoretical foundations of UTAUT2, which position hedonic motivation as a core determinant of technology acceptance. As competition in the digital finance space intensifies, integrating emotionally engaging features will be critical not only to attract users but also to secure long-term adoption and market differentiation.

Table 1.0 Summary of Studies Supporting Hedonic Motivation in FinTech and Digital Payment Adoption

Author	Title	Findings	Country/Region
Salimon et al. (2017)	E-banking adoption in Malaysia	Hedonic motivation positively affects e-banking adoption, enhancing satisfaction and loyalty.	Malaysia
Tun-Pin et al. (2019)	FinTech service adoption in Malaysia	Perceived enjoyment significantly influenced FinTech adoption.	Malaysia
Saprikis et al. (2022)	Mobile banking app adoption	Hedonic motivation was a strong predictor of mobile banking app adoption.	Not specified
Srivastava et al. (2024)	Digital payment adoption among Gen Z	Gen Z users in India were driven by hedonic factors like gamification and visual appeal.	India
Singh & Sharma (2023)	FinTech payment services during COVID-19	Indian Gen X and Millennials adopted FinTech due to pleasure and convenience of contactless transactions.	India
Edo et al. (2023)	Mobile payment adoption during COVID-19	Hedonic motivation significantly influenced mobile payment adoption.	Nigeria
Bommer et al. (2023)	Meta-analysis of FinTech use intention	Hedonic motivation was one of the strongest predictors of FinTech use intention.	Not specified
Akinwale & Kyari (2022)	FinTech service adoption in Lagos State	Hedonic factors influenced attitudes toward FinTech services.	Nigeria
Yang (2010)	Mobile purchasing behavior in the U.S.	Hedonic motivation was a key driver for mobile purchasing.	United States
Adirinekso (2021)	Paylater service adoption	Users were motivated by the convenience and pleasure of deferred payments.	Not specified
Wong & Ong (2021)	Gamification and design in FinTech apps	Gamification and aesthetic design contribute to hedonic value, increasing adoption and retention.	Not specified
Muzaldin et al. (2022)	E-wallet adoption	Joy and gadget love were strong predictors of e-wallet adoption among younger users.	Not specified
Seng & Hee (2021)	E-wallet adoption	Hedonic motivation such as joy and gadget love influenced adoption.	Not specified

Studies Showing Insignificant or Negative Impact

Although hedonic motivation is a central construct in models such as UTAUT2, empirical evidence shows that it does not universally drive FinTech adoption—particularly in contexts where users prioritize functionality, trust, and risk management over emotional gratification. In such settings, practical considerations often outweigh the appeal of enjoyment or entertainment. For example, Penney et al. (2021) found no significant link between hedonic motivation and mobile money adoption in Ghana, with users focusing instead on reliability and transactional efficiency. Similarly, Amnas et al. (2023) reported that many users perceived FinTech platforms primarily as practical tools, reducing the influence of hedonic factors on behavioral intention. Summary of studies which shows insignificant or negative impact is in Table 2.0

In Bangladesh, Mahmud et al. (2022) conducted a nationwide study and concluded that hedonic motivation played an insignificant role in adoption decisions, with trust, security, and system stability taking precedence. Shahzad et al. (2022) reached similar conclusions in their study on financial portals, where hedonic elements were not significant predictors of usage intention. In Malaysia, Alsmadi et al. (2024) examined Islamic FinTech platforms and found no direct effect of hedonic motivation on behavioral intention—likely reflecting the ethical and religious orientation of such services, which emphasize compliance and trustworthiness over enjoyment.

Other studies highlight a similar trend in high-stakes financial services. Zhang and Kim (2020) showed that responsiveness, reliability, and perceived value had a stronger impact on customer satisfaction in mobile FinTech than hedonic elements. Broader research, including Mansyur and Ali (2022) and Kwateng et al. (2018), confirms that in investment-oriented, high-risk, or ethically sensitive platforms, users tend to place greater value on utilitarian benefits than on emotional engagement. Recent evidence from Malaysia further illustrates the important role of hedonic motivation in investment-oriented FinTech platforms. Ramachandran, Zull Kepili, and Nik Azman (2024) found that while hedonic motivation significantly influenced individual investors' intention to invest in P2P lending platforms, its effect was relatively weaker compared to performance expectancy and effort expectancy. This suggests that in high-stakes financial contexts, emotional gratification may be secondary to functional and experiential factors, reinforcing the context-dependent nature of hedonic motivation.

Together, these findings point to the importance of a context-sensitive approach in designing and marketing FinTech services. While hedonic motivation can be influential in certain consumer-focused applications, it may have limited relevance in environments where security, stability, and functional performance are the primary determinants of adoption.

Table 2.0 Summary of Studies Showing Insignificant, Weaker or Negative Impact of Hedonic Motivation in FinTech and Digital Payment Adoption

Author	Title	Findings	Country/Region
Penney et al. (2021)	Mobile money adoption in Ghana	No pertinent effect of hedonic motivation on mobile money adoption.	Ghana
Amnas et al. (2023)	FinTech use intention	Hedonic motivation was not significant; users viewed FinTech as practical.	Not specified
Mahmud et al. (2022)	FinTech adoption in Bangladesh	Hedonic motivation played an insignificant role in nationwide adoption.	Bangladesh
Shahzad et al. (2022)	Behavioral intention to use financial portal	Hedonic motivation was not a significant factor in FinTech adoption.	Not specified
Alsmadi et al. (2024)	Islamic FinTech in Malaysia	Hedonic motivation had no significant direct effect on behavioral intention.	Malaysia
Zhang & Kim (2020)	Customer satisfaction with mobile FinTech	Service characteristics were more influential than hedonic elements.	Not specified
Mansyur & Ali (2022)	Sharia-compliant FinTech adoption among Indonesian millennials	Hedonic motivation had no significant effect due to ethical and religious priorities.	Indonesia
Kwateng et al. (2018)	Mobile banking adoption	Users prioritized reliability and functionality over emotional satisfaction.	Not specified
Adnan (2014)	Online shopping behavior in Pakistan	Consumers preferred utilitarian benefits like ease of use and security over enjoyment.	Pakistan
Al-Edrus et al. (2023)	Crowdfunding platform adoption	Hedonic motivation was not a strong predictor due to financial and legal risks.	Not specified
Thusi & Maduku (2020)	FinTech services adoption	Poor customer support and limited promotions diminished hedonic motivation's impact.	Not specified

Therefore, in conclusion, the above studies presents a holistic picture of hedonic motivation in FinTech adoption. On one hand, studies across Malaysia, India, Nigeria, and the United States demonstrate that enjoyment, gamification, visual appeal, and other emotionally engaging features can enhance user satisfaction, loyalty, and behavioral intention particularly in consumer-facing, low-risk platforms such as e-wallets, mobile banking, and digital payments. These findings align with the UTAUT2 framework, which positions hedonic motivation as a core driver of technology acceptance in voluntary use contexts.

On the other hand, evidence from Ghana, Bangladesh, Malaysia, and Indonesia shows that hedonic motivation is not universally applicable. In contexts where users prioritize functionality, trust, and risk mitigation such as Islamic FinTech, investment-oriented platforms, or services with high perceived risk practical benefits like reliability, security, and ethical compliance outweigh enjoyment or aesthetic appeal. Here, hedonic motivation may be secondary or even irrelevant, with adoption decisions shaped primarily by utilitarian and cultural considerations.

Taken together, these findings suggest that the role of hedonic motivation in FinTech adoption is highly context-dependent. Its influence is strongest in platforms that emphasize user experience, convenience, and visual engagement, and weakest in those requiring high levels of trust, long-term commitment, or adherence to ethical and religious principles. For developers, designers, and marketers, this signifies the need for tailored strategies that integrate hedonic elements where they add value, while ensuring that functional, cultural, and security priorities remain central to the adoption experience.

Moderator and Mediator of Hedonic Motivation in FinTech Adoption

Hedonic motivation the enjoyment or pleasure derived from using financial technology is widely recognized as a driver of FinTech adoption. However, its influence is not universal. A synthesis of studies from 2021 to 2025 reveals that its impact is shaped by various moderators and mediators, which help explain the conflicting evidence across contexts.

Cultural orientation plays a significant moderating role. In collectivist or religious societies such as Indonesia, Malaysia, and Sub-Saharan Africa, utilitarian values often outweigh hedonic ones. Baharuddin et al. (2023) found that religiosity did not moderate the relationship between behavioral drivers and FinTech interest, suggesting that users in such contexts prioritize trust and responsibility over enjoyment. Similarly, Appiah & Agblewornu (2025) demonstrated that trust mediated the effects of perceived benefits and risks, indicating that emotional engagement is contingent on cultural norms and perceived safety.

The type of FinTech platform also moderates the relevance of hedonic motivation. Bommer et al. (2023), in a meta-analysis, identified hedonic motivation as a strong predictor of adoption for low-risk, high-frequency platforms like e-wallets and PayLater apps. In contrast, platforms involving investment or lending, such as P2P lending and crowdfunding, require higher levels of trust and risk assessment, which diminish the influence of enjoyment-based features. This aligns with findings from Appiah & Agblewornu (2025), where trust played a central mediating role in adoption decisions.

User demographics further moderate the effect of hedonic motivation. Singh et al. (2021) showed that age and internet experience influenced the transition from intention to actual use. Younger users were more responsive to gamified and visually engaging platforms, while older users focused on functionality and security. Bommer et al. (2023) also noted that demographic factors subtly influenced the strength of hedonic motivation across user segments.

Platform design and features can mediate the relationship between hedonic motivation and adoption. Haritha (2022) found that perceived trust mediated the impact of design features on behavioral intention, while Ismail & Rashidi (2025) showed that digital financial innovation mediated the link between entrepreneurial capabilities and FinTech adoption. These findings suggest that well-designed platforms with personalization, gamification, and social sharing can enhance emotional engagement, whereas poor design may neutralize hedonic effects.

Trust consistently emerges as a key mediator. Saadah & Setiawan (2023) found that trust mediated the effects of perceived benefits and risks on continued use of FinTech among SMEs. In high-risk financial contexts, users tend to suppress hedonic impulses in favor of risk mitigation and trust-building. This reinforces the notion that hedonic motivation is not a standalone driver but one that operates within a broader framework of perceived safety and reliability.

In conclusion, hedonic motivation is a context-sensitive construct whose impact on FinTech adoption is moderated by cultural orientation, platform type, and user demographics, and mediated by trust and platform design. These findings underscore the importance of tailoring FinTech strategies to specific user segments and service types, ensuring that emotional engagement is supported by trust, usability, and cultural relevance.

Research Gap

Despite the growing body of literature on hedonic motivation in FinTech adoption, several gaps remain:

Limited exploration of mediators and moderators: While some studies have examined trust, religiosity, and demographics as influencing factors, there is a lack of comprehensive models that systematically integrate these variables to explain when and how hedonic motivation matters.

Underrepresentation of platform-specific dynamics: Most studies treat FinTech as a homogeneous category, overlooking the differences between payment apps, investment platforms, and crowdfunding services. Future research should disaggregate FinTech types to better understand the role of hedonic motivation in each.

Cultural and regional diversity: Although some cross-cultural comparisons exist, there is a need for more studies in underrepresented regions, especially in Africa, Southeast Asia, and the Middle East, where cultural norms may significantly shape user behavior.

Longitudinal and behavioral data: Much of the existing research relies on self-reported intention rather than actual usage data. Longitudinal studies tracking user engagement over time could provide deeper insights into the sustainability of hedonic motivation.

Design and UX factors as mediators: While gamification and personalization are often mentioned, few studies empirically test how specific design features mediate the relationship between hedonic motivation and adoption. This presents an opportunity for interdisciplinary research combining behavioral science and UX design.

Addressing these gaps will contribute to a more nuanced and actionable understanding of hedonic motivation in FinTech adoption, enabling developers, marketers, and policymakers to craft more effective and inclusive financial technologies.

Conclusion

This paper shows that hedonic motivation plays a complex and context-dependent role in FinTech adoption. Although the UTAUT2 framework positions it as a core predictor of behavioral intention, empirical evidence reveals substantial variation across regions, platform types, and user demographics. In consumer-oriented applications such as mobile banking and e-wallets, hedonic motivation expressed through gamification, aesthetic design, and emotional gratification has been found to enhance engagement and adoption, particularly among younger users such as Gen Z and Millennials, who place high value on interactivity and visual appeal.

In contrast, hedonic motivation appears less influential in utilitarian or high-risk financial contexts, including investment platforms, Islamic FinTech, and services requiring long-term commitment. In these environments, users tend to prioritize trust, security, and compliance over enjoyment, reflecting a more functionally driven decision-making process. This divergence indicates that hedonic motivation is not a universal driver but operates within a broader framework shaped by cultural norms, platform characteristics, and user expectations.

Several moderating factors influence the strength of hedonic motivation. Cultural orientation, religiosity, and demographic variables such as age and internet experience can amplify or diminish its effect. For example, in collectivist societies, financial services may be viewed primarily as tools for responsibility and prudence rather than sources of enjoyment. Mediating factors, such as trust and platform design, also play a pivotal role in translating hedonic features into behavioral intention. Trust, in particular, consistently mediates the relationship between perceived benefits and adoption in high-risk or ethically sensitive settings.

Overall, these findings highlight the importance of designing FinTech platforms that strike a balance between emotional engagement and functional reliability. Gamification and personalization can enhance hedonic appeal, but they must be implemented in ways that reinforce, rather than undermine, trust and ethical expectations. The interplay between hedonic and utilitarian motivations suggests that FinTech adoption is best explained through context-aware models that integrate both emotional and rational drivers of user behavior.

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Strategic Enablers of Digital Business Model Innovation in SMEs

Noor Hazlina Ahmad, Hasliza Abdul Halim*
Tarnima Warda Andalib, T. Ramayah
Universiti Sains Malaysia, Malaysia

**Corresponding Author*

Abstract

Digital business model innovation (DBMI) has emerged as a strategic imperative for small and medium-sized enterprises (SMEs) operating in increasingly digitalized markets. Despite its growing importance, empirical understanding of the key organizational drivers of DBMI remains limited, particularly in emerging economies such as Malaysia. Grounded in Upper Echelons Theory, the Resource-Based View (RBV), and Dynamic Capabilities Theory, this study develops a research framework examining the influence of digital leadership, digital capability, and digital technology on DBMI. DBMI is conceptualized through four dimensions: value creation, value proposition, value delivery, and value capture. Drawing on qualitative insights and prior literature, this study highlights how leadership orientation, technological assets, and capability reconfiguration collectively shape SMEs' digital transformation trajectories. The findings contribute to the growing DBMI literature by offering an integrated theoretical perspective and practical implications for SMEs navigating digital transformation.

Keywords: digital business model innovation (DBMI), digital leadership, digital capability, digital technology, SMEs

Introduction

Digitalization exert great influence to the global marketplace, Rachinger et al. (2019) highlighted that organization innovating its business model digitally in order to exploit digital opportunities, produce new products and service at lower production cost, optimize existing production capacity and communicate effectively with stakeholders. According to Rantala, Ukko, Saunila, Puolakoski, & Rantanen (2019), digital sphere leads to intense competition due to its low entry barrier and capital investment.

In Malaysia context, SMEs service sector is the organizations with annual sales that not greater than RM20 million or not exceeding 75 full-time employees, meanwhile SMEs in manufacturing sector has sales turnover not greater than RM50 million or not exceeding 200 employees (SME Corporation Malaysia, 2020). In year 2016, 98.5% out of 920 624 businesses in Malaysia are SMEs and there are 89.2% of SMEs in service sector, 5.3% in manufacturing sector, 4.3% in construction sector, 1.1% in agriculture sector, 0.1% in mining and quarrying sector (Department of Statistics Malaysia, 2020). As compared to year 2017, SMEs contributed more to GDP and exports in year 2018, which is RM521.7 billion (38.3%) and total exports at RM171.9 billion (17.3%) (Department of Statistics Malaysia, 2019). SMEs play a vital role in driving economic growth of Malaysia and they are more flexible to make changes on existing business model. Due to the rapid changes in the marketplace, SMEs need reconfigure its business model digitally, reorganizing both internal and external resources in order to stay competitive (North et al., 2019).

Innovating digital business model changing the business structure, processes and value creation to customers, business partners (Martín-Peña et al., 2018). Digital technologies such as cloud computing, IoT, mobile broadband, and big data analytics can support business expansion and exploit opportunities in the digital environment (SME Corporation Malaysia, 2018). In the near future, local SMEs in manufacturing and service sectors planning to offer new products and services, improve online marketing, implement new business strategy (SME Corporation Malaysia, 2018). Hence, it is extremely important to determine the drivers of DBMI.

Digital development has significant impact on all organizations, in order to survive in the digital age, they need to transform its business model by using digital technologies to streamline business operations, improve efficiency at lower average cost (Martín-Peña et al., 2018; Verhoef & Bijmolt, 2019). Existing digital businesses can execute further innovation on its digital business model (Verhoef & Bijmolt, 2019). Nowadays, customers demand for digital solutions instead of traditional ones on music, travelling and others (Verhoef & Bijmolt, 2019). Organizations can deploy mobile technologies, digital channels and artificial intelligence (AI) to create value and better connections to serve customers, capture values from them (Verhoef & Bijmolt, 2019). For example, UBER incorporate an app to offer taxi rides and Booking.com using digital platform to escalate customer experiences and conveniences (Verhoef & Bijmolt, 2019). Therefore, SMEs in Malaysia could take advantage of digital resources and embark on DBMI to elevate its competitiveness in digital environment.

Problem statement

Despite increasing emphasis on digital transformation, the adoption of digital business model innovation (DBMI) among Malaysian SMEs remains at an early stage (New Straits Times, 2020). Although SMEs constitute 98.5% of businesses in Malaysia and significantly contribute to GDP and exports (Department of Statistics Malaysia, 2019, 2020), many continue to rely on traditional business practices with limited integration of advanced digital technologies. While some SMEs utilize social media platforms for marketing and communication, the adoption of more sophisticated digital solutions such as cloud computing, data analytics, Internet of Things (IoT), and integrated digital payment systems remains relatively low (SME Corporation Malaysia & Huawei Technologies, 2018).

This limited digital integration constrains SMEs' ability to redesign their value creation, value delivery, and value capture mechanisms in response to evolving digital market demands (Rachinger et al., 2019). In increasingly competitive digital environments characterized by low entry barriers and rapid technological change (Rantala et al., 2019), failure to innovate business models digitally may reduce firms' competitiveness and long-term sustainability.

Although prior research has examined digital technology adoption and innovation performance (Khin & Ho, 2019), there is insufficient empirical evidence explaining the organizational drivers that enable successful DBMI, particularly in emerging economy contexts such as Malaysia. Existing studies often focus on technological implementation in isolation, without integrating leadership orientation and organizational capabilities into a comprehensive explanatory framework.

From a theoretical standpoint, three interrelated organizational drivers warrant further investigation. First, digital leadership may shape strategic decision-making related to business model transformation, consistent with Upper Echelons Theory (Hambrick & Mason, 1984). Leaders' digital vision and competencies influence how firms perceive and exploit digital opportunities (Mihardjo et al., 2019). Second, digital capability—conceptualized as the firm's ability to deploy and reconfigure digital resources—represents a dynamic capability that supports organizational adaptation (Teece & Pisano, 1994; Khin & Ho, 2019). SMEs with insufficient digital capabilities may struggle to execute DBMI effectively (Martín-Peña et al., 2018). Third, digital technology constitutes a strategic resource that can enable business model transformation, as suggested by the Resource-Based View (Barney, 1991).

Despite the conceptual importance of these drivers, their combined influence on DBMI remains underexplored. Therefore, this study addresses this gap by developing an integrated framework that examines how digital leadership, digital capability, and digital technology collectively influence digital business model innovation among Malaysian SMEs.

Literature review

Evolution of business model

Business model was introduced in 1957 (Morabito, 2014), this term was applied in various studies in 1960 (Jones, 1960; Wikström & Ellonen, 2012) and widely investigated by researchers in 1990 (Faghih et al., 2018; Pucihar et al., 2019). The intense competition leads to the growing attention on business model innovation in 2000 (Foss & Saebi, 2016). In 21st century, digital business model innovation (DBMI) gained tremendous interest of SMEs in order to sustain in this digitalized environment.

Business model

Business model provide a guideline to SMEs on the approaches to use strategic resources to create, deliver and capture values; differentiated business model provide obstacles for competing organization to mimic it due to the time constraints to reorganize its internal resources and business operations (D. J. Teece, 2018). Value creation, value proposition, value capture and value delivery constitute a business model (Dasí et al., 2017; Faghih et al., 2018; Suhendra, 2017). Boojihawon & Ngoasong (2018) and Osterwalder & Pigneur (2010) explain that business model help to implement organization's strategy with new offerings, new business structure and practices. In order to develop a business model, firstly, SMEs need to evaluate the business model elements, follow by design different business models and choose the most profitable model, next execute the trial version of business model, and lastly, reexamine it and make changes when necessary in order to ensure the business model is compatible with market needs (Faghih et al., 2018; Osterwalder & Pigneur, 2010). SMEs can create agile business models to compete with competitors that have similar business size to achieve superior performance (Parnell et al., 2018).

Business model innovation

SMEs should not be using the same business models over a period of time. Due to the external changes, SMEs can innovate its business model based on the latest market trends and customer preferences. Business model innovation mean make significant changes on business model elements and the way to communicate with business partners, existing and new customers (Djaja & Arief, 2015; Bouwman, Nikou, Molina-Castillo, & de Reuver, 2018; Wahyono, 2018). Innovation on products and services, business structure and operations leads to the changes on value creation, value proposition, value caption and delivery of SMEs (Bouncken et al., 2019; Bouwman et al., 2018). Essentially, business model innovation can be carry out without the inclusion of technology, as example, "just-in-time" inventory management system that developed by Toyota to minimize inventory costs and wastage (Baden-Fuller & Haefliger, 2013). Parnell, Stone, & Aravopoulou (2018) argue that some media organization resist to adopt business model innovation because worry the newly business model will interrupt existing operations and leads to unpredictable outcome. Balan-Vnuk and Balan (2015) advocate that organization revolutionize its business model to achieve sustainability. This viewpoint is supported by Teece (2018), he highlighted that business model innovation which is compatible with the organization resources and serving the right customer segment can lead to business sustainability in the long term.

Digital business model innovation (DBMI)

Digital business model innovation refer to the organization employ digital technology to do remarkable changes on business elements (Remane et al., 2017; Veit et al., 2014). In smart waste management business, organization employ fill level sensors to organize the routes, emptying schedule, improve waste collection process (Aagaard et al., 2018).

To innovate digital business model, SMEs need to identify factors that can affect customer behavior, target at right customer segments when offer both digital, non-digital goods, seeking for potential partners that able to provide supporting services (Remane et al., 2017; Woerner, 2019). Collaboration of different parties in supply chain management, innovation activities and the integrated production resources further support the success implementation of DBMI (Martín-Peña et al., 2018). As example, Tokio Marine Holdings cooperate with Docomo to provide innovative and customized insurance package via mobile app (Bonnet & Westerman, 2015). Weill and Woerner (2013) delineate that LexisNexis collaborate with the experts to create unique content, explore customer hidden needs with the purpose to provide delightful customer experiences and using flexible platform to optimize DBMI. SMEs could revise existing offerings, digital capabilities and economic model by adopting DBMI to develop new capabilities and earn higher profit (Bonnet & Westerman, 2015; Faghih et al., 2018; Parida et al., 2019). This study incorporates four DBMI elements that include value creation, value proposition, value capture and value delivery.

Value creation

Value creation of DBMI is the ability of SMEs to use its core capabilities, digital technology, partnership, value-added processes to create values to stakeholders (Clauss et al., 2019; Still et al., 2017). Data mining, internet of things, cloud computing can be employed in value creation process to achieve internal gains (Frank et al., 2019). More predominately, qualitative research by Clauss et al. (2019) and Still et al. (2017) found that the changes on value creation innovation such as new capabilities, technology, business processes and partnerships resulting in higher value capture and proposition. Effective value creation processes demand the integration of reliable business partners (Dasí et al., 2017), new physical material, intellectual capital, human and finance resources (Ibarra et al., 2018). Innovation on value creation processes by Scandinavian fashion magazine include replace traditional method with blogger network to engage fashion bloggers in co-creation process of digital contents meanwhile Scandinavian newspaper (business daily) using discussion forum and blogs to have two-way open discussion with targeted customers pertaining customer service issues, product development, and digital content production (Wikström & Ellonen, 2012).

Value proposition

Value proposition refer to new product/ service portfolio and customer relations (Clauss et al., 2019; Still et al., 2017). In other words, SMEs emphasize on the products and service offerings, customer demanding needs, the price they willing to pay (Dasí et al., 2017). Panda (2019) extended these viewpoint and propose that value proposition tie with the offerings and good relationship with customers. For instance, LinkedIn connects employers and applicants, employers can post job vacancy, hunting for talents and applicants can upload their resumes; besides that, LinkedIn provide free, limited features to users, if users required for advanced features, they can purchase the exclusive version (Panda, 2019). Amazon using cloud computing platform to offer on-demand music and videos, it highly stress on convenient, fast shipping, lower price at virtual marketplace (Hänninen et al., 2018). Another study by Blaschke et al. (2017) and Boojihawon & Ngoasong (2018) assert that digital value proposition focus on on-demand service and personalized product, better understanding on customer preferences thru their purchase history, and proactive strategies. Generally, value proposition of DBMI immerse on customize online services, variety offering that have been extended the traditional value proposition that solely stress on product quality, features and price (Slywotzky & Morrison, 2001).

Value capture

Value capture of DBMI elements associated with the ability of SMEs to transform its value proposition into revenues at effective cost (Clauss et al., 2019; Still et al., 2017). Similarly, Boojihawon and Ngoasong (2018) explain value capture as the model to gain revenues and profits from particular customer segments. Value capture by SMEs refer to cost reduction and exploring the new revenues streams from dynamic pricing and pay-per-use (Ibarra et al., 2018). In automotive industry, value capture include investment in digital technologies and improve revenue structure thru digital products/services, whilst media industry is by collecting information on customer buying behaviors, next, using content platform to earn revenues (Rachinger et al., 2019). Digital services decrease the expenses for physical counters and adaptive pricing strategy able to boost up the revenues (Blaschke et al., 2017). Manufacturer of power system for defense aviation such as Rolls Royce using onboard sensors to practice “pay-per-use” principle as a new revenue model, customers (airlines) no need to buy aircraft engines but only pay for the hourly fee upon using the turbines; sensor able to record the hourly usage by customers and customers can make payment accordingly (Bleicher & Stanley, 2016; International Association of Controllers, 2017).

Value delivery

Value delivery refer to channel of delivery and market segments, LinkedIn target on mass market and deliver values to the customers via its digital channels, partner channels (Panda, 2019). Value delivery innovation include targeted on new customer segments and develop new distribution channels to deliver values to main customers and partners (Baber et al., 2019; Clauss et al., 2019; Rayna & Striukova, 2014; Still et al., 2017). Value delivery include the flexible ways to improve customer experiences, stimulate customer participation to support SMEs to penetrate international marketplace (Blaschke et al., 2017). Indeed, value delivery of DBMI elements diverse with conventional business model, Parida et al. (2019) highlighted that this element indicate the most efficient approaches to deliver the expected value globally thru delivery channels, online monitoring systems and excellent customer service. Cloud computing, big data and intelligence sensor can be used to deliver smart products and services to customers (Ibarra et al., 2018). New value delivery of Telenor is deliver e-sim to customers thru retailers and digital channels (Dasí et al., 2017).

Digital leadership

Drawing on the Upper Echelons theory developed by (Hambrick & Mason, 1984), leader with certain characteristic, capabilities and experiences in digital era able to identify external opportunities, threats, foresee future prospects, and these will definitely influence their organizational decisions. Therefore, digital leadership is important driver to embark DBMI in the organization (Hambrick, 2016; Herman & Smith, 2015; Leonardus W.W. Mihardjo et al., 2019; Wasono & Furinto, 2018).

Gurkan et al. (2019) assert that digital leadership is acknowledged as leadership 4.0 (leadership in Industry 4.0). Digital leadership is known as subset of IT roles with disruptive innovation, it is a fresh term, the ordinary term that apply widely is e-leadership, business information management or information technology (IT) governance (De Waal et al., 2016). Example of digital leaders such as chief information officer, chief marketing officer, chief digital officer (De Waal et al., 2016; Gurkan et al., 2019). When SMEs plan to transform existing business operation into digital ones, it demands a digital leader to employ digital technologies efficiently to solidify this transformation.

Digital leadership refer to the capability of digital leader to explore new digital opportunities and disrupt current business model by using digital technology and other resources (De Waal et al., 2016). Strong digital leadership is vital to drive innovation on business model, especially innovation on product and services in digital marketplace (Kreutzer et al., 2018; Leonardus W.W. Mihardjo et al., 2019).

Digital leadership play an important role in digital disruptive environment, where digital leader can develop DBMI, penetrate new market segments and coordinate digital transformation activities in the organization (Wasono & Furinto, 2018). In this disruptive era, co-creation strategy can mediates the relationship between digital leadership and business model innovation (Leonardus Wahyu Wasono Mihardjo & Sasmoko, 2019). They highlighted that digital leader using digital technology to collaborate with stakeholders in value creation activities, subsequently supporting the digital business model innovation.

Indeed, not all leaders eligible to be known as digital leaders, according to Gurkan et al., (2019), digital leaders must be able to use digital resources to facilitate DBMI, optimize business efficiency and growth, at the same time, they stimulate employees to become autonomous, come out with unique ideas and active participation in brainstorming session. Competencies of a digital leader include ability to manage digital technology for strategic advantage, governing risk and making digital technology related decisions, employ digital technology to create values and leverage organizational performance (De Waal et al., 2016; Valentine & Stewart, 2015). In the context of telecommunication industry at Indonesia, digital leadership can influence business model innovation directly (Leonardus W.W. Mihardjo et al., 2019). They explain that digital leader with global mindset, creative, risk-taking can provide direction and foster innovation activities, carry out organizational change and new ways of doing business in digital age.

Ultimately, Oberer and Erkollar (2018) posit that this leadership style is greatly emphasizing on innovation, team performance, cross-hierarchical and cooperative-oriented. Digital leaders have high proficiency in technology and concern on employee needs, they use digital resources efficiently, agile and actively embrace changes to adapt to the rapidly changing environment, solve complicated problems with distinctive solutions, delegate task according to employee competences, create flexible workplace and cooperative atmosphere (Oberer & Erkollar, 2018). According to El Sawy et al. (2016), digital leadership able to think differently on business models and strategy, integration of the enterprise platforms, mindsets and digital skill, organization's IT function, and organize flexible working environment. It can be postulated that digital leaders able to lead employees to reshape its existing value proposition, create and deliver new values to stakeholders, capture values from them, specifically, digital leaders are more likely to drive DBMI in SMEs, Malaysia in order to perform ahead than their competitors.

Digital Capability

Digital capabilities refer to capabilities of SMEs to manage digital technologies (Khin & Ho, 2019). Technological capability as organizational factor (Del Aguila-Obra & Padilla-Meléndez, 2006) associated with the organization's ability to employ different types of technologies (Afuah, 2002; Zhou & Wu, 2010). Zhou & Wu (2010) posit that technological capability has direct impact on innovation activities. Khin & Ho (2019) found that organization's digital capability can be improved by digital professionals who employ digital technologies to create new digital products to satisfy new needs of customers, in addition, SMEs need to have readiness to embrace new digital technologies and allocate resources to magnify digital capabilities thru training, outsourcing, joint ventures or strategic alliances with business partners.

Based on resource based view (RBV) theory, organization needs to coordinate its own resources efficiently such as digital capability to achieve competitive advantage in the long run (Barney, 1991; Miles, 2012; Wetering et al., 2018). By referring to the dynamic capabilities theory, digital capability could be known as dynamic capability of SMEs, where SMEs can reconfigure its digital capability to launch new offerings and expedite existing business processes (Khin & Ho, 2019; D. Teece & Pisano, 1994). To stay competitive, organization must generate new digital capabilities and leveraging existing digital resources to support the adoption of DBMI (Carcary et al., 2016; Wiesböck, 2019).

There are some barriers to manage digital capabilities, such as identify the methods to transform and evolve current capabilities, these could not be done if SMEs lack of digital talents, digital resources and flexibility (Wulf et al., 2017). Digital capability of hospitals are crucial in managing, transferring and accessing the clinical information, assist clinical related decision making and optimize operational efficiency (Wetering et al., 2018). In fact, internet organization (known as digital natives), has higher digital capabilities to execute digital activities and innovate digital business model than other organization (Vendrell-Herrero et al., 2018). SMEs with deficient digital capabilities not able to develop DBMI (Martín-Peña et al., 2018). Nonetheless, non-digital SMEs can adopt DBMI via integration or acquisition of digital native SMEs in order to share their digital capabilities (Vendrell-Herrero et al., 2018). Effective digital capability leads to efficient business operations, better customer experiences and agile business model (Westerman et al., 2012). It hints that digital assets can support implementation of DBMI (Bonnet & Westerman, 2015). SMEs with high digital capability, coupled with competitive business strategy leads to high revenue model (Bughin & Zeebroeck, 2017).

Information technology (IT) capabilities has direct relationship with digital business value (Riera & Iijima, 2019). On the other hand, Chae et al., (2018) found that when the role of IT is to "transform" to the new ways of doing business in airline, accounting, publishing, telecommunication industries, organization with superior IT capability did not achieve better performance than other organization with similar size, whereas when IT capability is use to promote "automation" in metals, utilities and transportation industries, organization with higher IT capability has same performance with organization in same business size. It justified that not every industries must possesses high IT capability to improve its value capture (Chae et al., 2018). Due to the nature of products or industries, it could be difficult to provide innovative digital solutions.

Digital capabilities which includes information management capability and adaptable IT infrastructure are essential in digital era as it allow organization to promptly response to the customers' new digital requirements (Levallet & Chan, 2018). They revealed that new IT infrastructure at affordable cost can be acquired by digital enterprise and small businesses, another essential point is regular assessment on organizations' digital capability are required, frequency to conduct this assessment depends on business size and the extent of macroeconomic changes. Digital capability can improve value creation, value delivery (Grover & Kohli, 2012) and value co-creation activities with customers (Lenka et al., 2017). The preliminary finding from Da Silva Freitas et al. (2017) claim that responsive and agile digital capability is the driver of digital business model. It reflected that the greater digital capability of SMEs, they have greater capability to execute DBMI.

Digital technology

Rapid advancement in digital technology leads to dramatic shift in the organizations, it motivates them to adopt DBMI, automate and digitalized business processes in digital landscape. Digital technology such as mobile devices, analytics, social media, enterprise software can expedite operational processes, new approach to manage business activities, support effective communication with partners and customers, amplify customer experiences, and make pervasive changes on business model (Fitzgerald et al., 2013; Li, 2018).

Based on resource based view (RBV) and dynamic capabilities theory, digital technology is the important asset for SMEs to constantly reorganize its business model and adopt DBMI to achieve long term success (Khin & Ho, 2019; Miles, 2012; D. J. Teece, 2018). SMEs should embrace digital technology at optimum level, for instance big data, cloud computing, artificial intelligence, cyber-physical systems, internet of things, augmented and virtual reality (Khin & Ho, 2019; Urbinati et al., 2018). Digital technology supports the organization to target new market segments and build closer relationship with customer at lower costs, customers can personalize the products based on their preferences and make payment according to the exclusivity level of the products (Li, 2018).

SMEs with digital mindset are responsive to technological changes and harness new digital technology to adopt DBMI, recognizing digital technology as a strong tool to accelerate innovation activities and provide distinctive digital offerings (Khin & Ho, 2019). As an example, in SMEs manufacturing context, collaborative robots (cobots) can work together with human to enhance SMEs productivity, reduce defect rate, implement value creation innovation and increase profits (Noordin, 2020).

Artificial intelligence (AI) technology has been applied extensively by the organizations. For example, Amazon Alexa to communicate with human virtually, autonomous car to identify obstacles and response accordingly, CEMEX Go, a digital system to deliver ready-mix concrete products to customers after they placed the orders; Emirates Airline adopt both real-time analytics and AI to disrupt its business model and diminish aircraft turnaround at Dubai International (DXB) airport (Zaki, 2019). These signify digital technology can impact DBMI components in order to deliver seamless services and delightful customer experiences.

Digital technology impacts the business operations, costs and revenue, support business expansion at the global stage (Leonardus W.Wasono Mihardjo et al., 2019). Lack of awareness on technological trends and employ inappropriate digital technology leads to poor performance and not able to offer innovative solution to satisfy customer digital needs (Khin & Ho, 2019). Digital technology add value to the main services offered by an organization, mobile app can be used to check the different coating, painting processes at oil painting exhibition (Li, 2018). Fashion retailer can employ webcam social shopper developed by Zugara, a virtual fitting room that allow customers to virtually preview their appearance with the chosen clothes; 3D printer can be used to produce customized fashion items like jewelry and accessories that ordered by customers; lastly is interactive mirror that can integrated with inventory and internet, it can capture customer image, and merge it with the clothes from certain articles that customer browses (Batista, 2013).

Digital technology has significant influence on DBMI dimensions such as value proposition, value creation, value delivery and value capture, in digital platform oriented businesses, automotive and creative industries (Bouncken et al., 2019; Hildebrandt et al., 2015; Li, 2018). Strutynska et al. (2019) manifested that social media, supply chain management (SCM), enterprise resource planning (ERP), telematics, supervisory control and data acquisition (SCADA) business process management (BPM), cloud computing, data mining can be used in value creation innovation. To improve value proposition, organization can employ digital system like product lifecycle management (PLM), product data management (PDM), digital sensors, chat bot, customer relationship management (CRM) (Strutynska et al., 2019). Google analytics, avatar digital persona, internet, email, mobile devices, e-commerce platform can be adopted to transform value delivery; meanwhile cost and revenue models can be magnified by using forecasting analytics system, stastistical system and analysis of big data (Strutynska et al., 2019). To sum up, digital technology is an enabler of DBMI and it can support the SMEs' efforts to offer idiosyncratic digital solutions.

To do the cross theme analysis based on the philosophical paradigms, researchers have taken a slight dig on the qualitative approach. Among the categorized philosophical paradigms the significant ones are ontology, epistemology, axiology, rhetorical structure, and methodology with research paradigms of positivism, post-positivism, constructivism, inter-pretivism, and the critical-ideological perspective (Andalib, 2018; Creswell, 2013). According to Andalib and Darun (2018), the parameters, those are found from qualitative coding and developed into the themes are the final stage of cross-checking and relativity analysis with the philosophical paradigms.

The following Table 1 discusses about the cross-themes analysis based on the philosophical paradigms.

Table 1: Cross- Theme Analysis

Themes	**Digital Business Model value addition**	**Philosophical Paradigm**	**Scholars' Ref**
Digital Leadership	innovation base, vision base, cost base, strategy base	Ontology, Interpretive Post-Positivism	Creswell, 2013; Andalib, Azizan and Abdul-Halim, 2020
Digital Capability	Innovation base, skillset base, performance base, motivational activities base	Ontology, Constructivism, Rhetorical, Axiology	Creswell, 2013; Andalib and Abdul-Halim, 2019
Digital Technology	Alignment base, infrastructure base, new technology system and application base , innovation base, cost base , competition with the stakeholders base	Constructivism, Epistemology and Methodology	Creswell, 2013; Auerbach and Silversten, 2003

Convergence of the characterized meaningful themes in the physical business scenario by implementing the virtual philosophical notion always becomes the difficult phase. The rapid infusion of innovative and new technological system, apps, networks need to create the inline adjustment with the existing technological capabilities, business models and designed customized frameworks. Nevertheless, value addition in certain themes usually extend the capabilities in a complex form and provides the opportunity to deal with initiation and revolutionary possibilities (Andalib, 2018).

The three themes are elaborated in the qual-data as driven from end-to-end coding processes, where the raw and flawed codes are transferred to the meaningful furnished themes to assist in building up the following research model (Andalib and Darun, 2018). According to Andalib and Abdul-Halim (2019), the leadership determinants are generated from this soft qual technique as well, nevertheless in this paper the scholars have validated the digital leadership theme from the empirical evidence besides justifying it with the FGD data. Also, the qual-FGD data has been thoroughly scrutinized while finalizing the theme Digital capability whereas the capability of the resources is not just machine oriented but also humane oriented (Auerbach and Silverstein, 2003; Andalib et. Al, 2019). Twenty participants had a roundtable discussion with the focus on generated themes. In the focused group discussion, the participants have focused and discussed about various themes and constructs whereas these following themes are 'digital leadership', 'digital capability' and 'digital technology' also have been noticed pretty meticulously. The following Table 2 reveals the FGD data regarding the acknowledged themes.

Table 2: Theme based FGD data analysis

Themes	**FGD participants' focus**	**Applicability on the model**
Digital Leadership	9 +	"weak integration"
Digital Capability	12 +	"strong integration"
Digital Technology	7 +	"weak integration"

Theoretical Gap

Although digital business model innovation (DBMI) has gained increasing scholarly attention, existing literature remains theoretically fragmented. Prior studies have largely examined digital transformation from isolated perspectives—focusing either on technological adoption (Khin & Ho, 2019), business model innovation outcomes (Foss & Saebi, 2016), or leadership roles in digital transformation (Mihardjo et al., 2019). However, limited research has systematically integrated leadership orientation, organizational capabilities, and technological resources within a unified theoretical framework to explain DBMI.

From a theoretical standpoint, three dominant perspectives appear relevant yet insufficiently integrated.

First, Upper Echelons Theory posits that organizational outcomes are shaped by top leaders' characteristics and cognitive orientations (Hambrick & Mason, 1984). While digital leadership has been examined in relation to innovation and transformation, its specific role in driving DBMI dimensions—namely value creation, value proposition, value delivery, and value capture—remains underexplored.

Second, the Resource-Based View (RBV) emphasizes firm-specific resources as sources of competitive advantage (Barney, 1991). Digital technologies can be conceptualized as strategic resources; however, RBV alone does not fully explain how such resources are mobilized and reconfigured to enable business model transformation.

Third, Dynamic Capabilities Theory explains how firms reconfigure internal and external competences to address rapidly changing environments (Teece & Pisano, 1994). Although digital capability may represent a dynamic capability enabling DBMI, empirical validation of this mechanism remains limited, particularly in SME contexts.

Importantly, existing DBMI research tends to examine these constructs independently rather than examining their complementary and interdependent effects. There is insufficient understanding of:

- How digital leadership shapes strategic intent toward DBMI,
- How digital capability enables the reconfiguration of resources,
- How digital technology provides the infrastructure supporting DBMI execution, and
- How these elements collectively influence the four core dimensions of DBMI.

Thus, the theoretical gap lies in the absence of an integrated multi-theoretical explanation linking leadership cognition (Upper Echelons), strategic resources (RBV), and reconfiguration mechanisms (Dynamic Capabilities) to digital business model innovation.

Research model

Based on prior literatures, this study provides a research model (Figure 1) that illustrate the influence of digital leadership, digital capability, digital technology on DBMI.

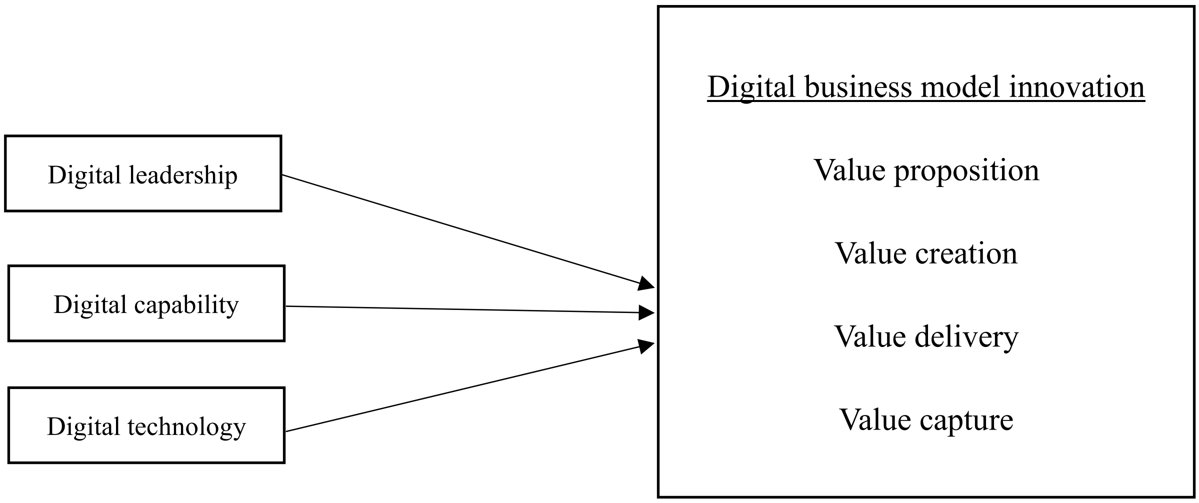

Figure 1: Research model

Hypotheses Development

This study proposes that digital leadership shapes the strategic orientation toward digital transformation, while digital technology provides the necessary infrastructural resources. However, these factors influence DBMI both directly and indirectly through digital capability, which represents the firm's dynamic ability to reconfigure digital resources. Thus, DBMI is conceptualized as the outcome of leadership cognition, resource availability, and capability orchestration.

Digital Leadership and DBMI

Drawing on Upper Echelons Theory (Hambrick & Mason, 1984), organizational outcomes reflect leaders' cognitive frames, experiences, and strategic orientations. Digital leaders possess digital vision, technological awareness, and innovation-driven mindsets that influence strategic decisions related to business model transformation. In digital environments, leaders play a critical role in initiating and legitimizing business model redesign, allocating resources, and fostering digital experimentation.

Prior research indicates that digital leadership positively influences innovation performance and digital transformation initiatives (Mihardjo et al., 2019; Kreutzer et al., 2018). Extending this logic, digital leaders are more likely to drive changes across value creation, value proposition, value delivery, and value capture mechanisms.

H1: Digital leadership positively influences digital business model innovation.

Digital Capability and DBMI

Digital capability reflects a firm's ability to effectively deploy, integrate, and reconfigure digital technologies. From a dynamic capabilities perspective, such capability enables firms to adapt business models in response to environmental changes.

Firms with higher digital capability can redesign processes, personalize offerings, enhance customer engagement, and develop new revenue models (Khin & Ho, 2019; Lenka et al., 2017).

H2: *Digital capability positively influences digital business model innovation.*

Digital Technology and DBMI

Digital technology enables firms to transform value creation and delivery mechanisms. It facilitates automation, data-driven decision-making, digital platforms, and new pricing models (Rachinger et al., 2019). Firms that leverage advanced digital technologies are more likely to innovate their business models.

H3: *Digital technology positively influences digital business model innovation.*

Research Methodology

Research Design

This study will adopt a quantitative, cross-sectional research design to empirically examine the relationships between digital leadership, digital technology, digital capability, and digital business model innovation (DBMI) among Malaysian SMEs. A survey method was employed as it enables systematic data collection from SMEs and is appropriate for testing theory-driven hypotheses using structural equation modeling (SEM).

The study is grounded in a positivist research paradigm, as it seeks to test theoretically derived hypotheses and examine causal relationships among constructs.

Population and Sampling

The target population comprises SMEs operating in Malaysia, as defined by SME Corporation Malaysia (2020). SMEs were selected because they represent the backbone of the Malaysian economy and face increasing pressure to digitally transform their business models.

The unit of analysis is the firm level, while the key informants are:

- Owners
- Managing directors
- CEOs
- Senior managers responsible for digital or strategic decisions

These respondents are appropriate because, consistent with Upper Echelons Theory, strategic decisions related to business model transformation are shaped by top management.

A purposive sampling technique was used to select SMEs that:

- Have been operating for at least three years, and
- Have adopted at least one form of digital technology in their business operations.

The minimum required sample size was determined using power analysis and SEM requirements. Following Hair et al. (2019), a minimum sample of 200 responses is considered adequate for structural equation modeling with reflective constructs.

Data Collection Procedure

Data will be collected through a structured questionnaire distributed via:

- Email invitations
- Online survey platforms
- SME networks and business associations

Prior to full data collection, a pilot test will be conducted with 30 SME managers to ensure clarity, reliability, and content validity of the instrument. Minor wording revisions were made based on feedback.

To minimize common method bias:

- Respondents were assured of confidentiality and anonymity
- Question order was randomized
- Harman's single-factor test was conducted post-data collection

Discussion and Conclusion

This paper develops a conceptual framework explaining digital business model innovation (DBMI) through the integration of digital leadership, digital capability, and digital technology. Positioned as a concept paper, this study does not empirically test relationships but instead advances theoretical understanding by synthesizing three complementary perspectives: Upper Echelons Theory, the Resource-Based View (RBV), and Dynamic Capabilities Theory.

The paper argues that DBMI is not merely driven by technological adoption but is a strategically orchestrated transformation process shaped by leadership cognition, organizational capability development, and technological resource deployment. Specifically, digital leadership is proposed as the strategic driver that shapes digital vision and transformation intent; digital technology represents the foundational resource base; and digital capability functions as the dynamic mechanism enabling the reconfiguration of business model elements—value creation, value proposition, value delivery, and value capture.

By integrating these theoretical lenses, this study addresses the fragmentation in existing DBMI literature and proposes a multi-level explanation of how SMEs can navigate digital transformation. The framework contributes to the growing discourse on digital transformation by positioning DBMI as a higher-order strategic outcome emerging from leadership–capability–technology alignment.

Thus, this concept paper extends prior research by offering a theoretically grounded and integrative model that can serve as a foundation for future empirical validation, particularly within SME contexts in emerging economies.

Theoretical Implications

This study makes three primary theoretical contributions:

First, it integrates three dominant theoretical perspectives—Upper Echelons Theory, RBV, and Dynamic Capabilities—into a unified framework explaining DBMI. This integration advances theoretical coherence in digital transformation research.

Second, it conceptualizes DBMI as a second-order construct comprising value creation, value proposition, value delivery, and value capture, providing clearer construct operationalization for future studies.

Third, it introduces digital capability as a potential mediating mechanism linking leadership and technology to business model innovation, offering a more nuanced explanation of transformation processes.

Practical Implications

From a managerial perspective, the framework suggests that SME digital transformation should not focus solely on acquiring new technologies. Instead, successful DBMI requires:

- Strong digital leadership with clear strategic direction
- Continuous development of digital capabilities
- Strategic alignment between technological investments and business model redesign

SME owners and policymakers should therefore prioritize leadership development programs and capability-building initiatives alongside digital infrastructure investments.

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Asian Academy of Management
School of Management
Universiti Sains Malaysia
11800 USM, Penang, Malaysia