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Article

HRM-Driven Change Management and Its Impact on Reducing Technological Resistance in AI-IoT Adoption: A Regression Analysis Approach

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Abstract: Purpose: This study examines how human resource management (HRM)-driven change management practices affect technological resistance in the context of artificial intelligence and Internet of Things (AI-IoT) adoption among manufacturing SMEs in Peninsular Malaysia.Methodology/Design/Approach: A quantitative cross-sectional survey was conducted with 420 managers, IT officers, and HR practitioners from licensed manufacturing SMEs in Selangor, Penang, and Johor Bahru. Data were analysed using reliability testing, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), hierarchical multiple regression, moderation analysis, and structural equation modelling (SEM). Findings: HRM-driven change management , encompassing training and development, communication and participation, leadership support, and incentive alignment , significantly reduced technological resistance to AI-IoT adoption. Perceived organisational readiness partially mediated the relationship between HRM-driven change management and technological resistance. Technological self-efficacy moderated the relationship, such that the resistance-reducing effect of HRM-driven change management was stronger among employees with higher technological self-efficacy. The final SEM model explained 71.3% of the variance in technological resistance and demonstrated excellent fit. Originality of the research: This study integrates HRM, change management, and technology adoption literatures within a single empirical framework and provides evidence from manufacturing SMEs in Malaysia , a context undergoing rapid Industry 4.0 transformation. The study offers a regression-grounded, HRM-centric perspective on overcoming technological resistance, an under-explored mechanism in AI-IoT adoption research.
Keywords: HRM-driven change management; technological resistance; AI-IoT adoption; organisational readiness; technological self-efficacy; manufacturing SMEs; Malaysia.

1. Introduction

The convergence of artificial intelligence (AI) and the Internet of Things (IoT) represents one of the most significant technological transformations in contemporary manufacturing. AI-IoT integration enables smart factories, predictive maintenance, real-time quality monitoring, autonomous logistics, and data-driven decision-making. Countries worldwide are investing heavily in Industry 4.0 infrastructure, and governments in Southeast Asia have positioned AI-IoT adoption as a central pillar of industrial competitiveness (Khin & Soe, 2022; Lee et al., 2023; Malaysia Productivity Corporation, 2023)

In Malaysia, the National Policy on Industry 4.0 (Industry4WRD) explicitly promotes the adoption of smart manufacturing technologies, including AI, IoT, robotics, and cloud computing. The policy targets small and medium-sized enterprises (SMEs) as key beneficiaries because they constitute 97.4% of all business establishments, contribute 38.9% to national GDP, and employ approximately 48% of the workforce (SME Corp. Malaysia, 2023).

Manufacturing SMEs are particularly important because the sector accounts for a substantial share of exports, industrial output, and technology-driven productivity growth (MTDC, 2022; MITI, 2023).

Despite strong policy support and demonstrated technological benefits, AI-IoT adoption among manufacturing SMEs remains uneven. A growing body of evidence suggests that technological resistance , the psychological, behavioural, and organisational reluctance to embrace new technologies , is a primary barrier. Employees may fear job displacement, lack confidence in using AI-powered tools, distrust automated decision systems, or resist changes to established work routines (Borges et al., 2021; Venkatesh et al., 2022; Raza et al., 2024). Organisational-level resistance may also manifest through management inertia, insufficient resource allocation, misaligned incentive structures, and poor change communication (Markus & Robey, 2020; Schlegel et al., 2023).

While technology adoption models such as TAM, UTAUT, and TOE framework explain adoption decisions at a general level, they tend to under-specify the role of human resource management (HRM) and change management in addressing resistance. HRM functions , including training, communication, leadership development, performance management, and incentive design , are central to preparing employees for technological change. Change management, when driven by HRM, provides structured processes for managing transitions, reducing anxiety, building competence, and fostering acceptance (Kavanagh & Johnson, 2021; Armenakis & Bedeian, 2020).

The implementation stage is especially critical. Literature on technology implementation indicates that organisations frequently fail not because technologies are inadequate, but because implementation is poorly managed, communication is unclear, employees are not adequately prepared, and resistance is not effectively addressed (Borges et al., 2021; Siau & Wang, 2022; Ramdhani et al., 2024). In SMEs, where HRM structures are often informal and change management expertise is limited, the success of AI-IoT adoption may depend heavily on the quality of HRM-driven interventions and the degree to which organisational readiness and individual self-efficacy support the transition..

This study addresses that gap by developing and testing an integrated HRM-driven change management model for AI-IoT adoption in manufacturing SMEs. The study examines the effects of HRM-driven change management practices on technological resistance, tests perceived organisational readiness as a mediating mechanism, and examines technological self-efficacy as a moderator. By doing so, the study contributes to HRM literature, change management scholarship, and technology adoption research in an emerging-market manufacturing context.

2. Literature Review and Hypotheses

2.1 HRM-driven change management and technological resistance

HRM-driven change management refers to the deliberate use of HRM practices and processes to facilitate, support, and sustain organisational transitions associated with technological change. Unlike generic change management, HRM-driven change management specifically leverages the HR function's expertise in people management to address the human dimensions of technology adoption. This includes training and development programmes that build technical competence, communication and participation mechanisms that reduce uncertainty, leadership support that signals organisational commitment, and incentive alignment that motivates adoption behaviour (Kavanagh & Johnson, 2021; Oreg & Berson, 2021; Raza et al., 2024).

Training and development is a core HRM practice that directly addresses competence gaps associated with AI-IoT technologies. When employees receive adequate training on AI-powered analytics, IoT sensor systems, automated workflows, and data-driven decision-making tools, their anxiety decreases and their confidence in using new technologies increases. Studies consistently show that training quality and accessibility are among the strongest predictors of technology acceptance and resistance reduction (Compeau & Higgins, 2020; Park & Kim, 2022; Schlegel et al., 2023).

Communication and participation involves informing employees about why AI-IoT is being adopted, how it will affect their roles, what support is available, and providing opportunities for input and feedback. Participation in decision-making during technology transitions increases perceived fairness, reduces fear of the unknown, and enhances psychological ownership of the change process (Armenakis & Bedeian, 2020; Lines et al., 2021). Prior research demonstrates that transparent, two-way communication significantly lowers resistance to technological change (Klaus & Blumberg, 2022).

Leadership support refers to the visible commitment of managers and supervisors to the AI-IoT adoption process. When leaders champion new technologies, allocate resources, remove obstacles, and demonstrate personal use of AI-IoT tools, employees interpret these signals as evidence that the change is important, safe, and organisationally valued. Leadership support also creates a climate of psychological safety that encourages experimentation and learning (Oreg & Berson, 2021; Venkatesh et al., 2022).

Incentive alignment involves designing reward systems, performance metrics, and recognition mechanisms that reinforce AI-IoT adoption behaviours. When employees perceive that adopting AI-IoT technologies is linked to career advancement, financial rewards, or positive performance evaluations, their motivation to engage with new technologies increases and resistance decreases (Kavanagh & Johnson, 2021; Lee et al., 2023).

H1: HRM-driven change management has a significant negative effect on technological resistance to AI-IoT adoption.

H2: Training and development has a significant negative effect on technological resistance.

H3: Communication and participation has a significant negative effect on technological resistance.

H4: Leadership support has a significant negative effect on technological resistance.

H5: Incentive alignment has a significant negative effect on technological resistance.

2.2 Perceived organisational readiness as a mediating mechanism

Perceived organisational readiness refers to employees' assessment of whether their organisation possesses the resources, capabilities, culture, and infrastructure necessary to successfully implement AI-IoT technologies. It encompasses perceptions of technical infrastructure adequacy, financial resource availability, managerial commitment, and organisational culture compatibility (Weiner et al., 2020; Holt et al., 2022).

The mediating role of perceived organisational readiness is theoretically important because HRM-driven change management may reduce resistance partly by building readiness perceptions. When employees observe that their organisation invests in training, communicates openly about AI-IoT, provides leadership support, and aligns incentives, they infer that the organisation is prepared for the transition. This perception reduces uncertainty and resistance because employees believe the change is manageable and supported (Weiner, 2020; Raza et al., 2024).

Conversely, when HRM-driven change management is absent or weak, employees may perceive that the organisation is unready for AI-IoT adoption, leading to heightened resistance, scepticism, and disengagement. In SMEs, where informal structures and limited resources can amplify perceptions of unpreparedness, the mediating role of organisational readiness may be particularly pronounced (Holt et al., 2022).

H6: HRM-driven change management has a significant positive effect on perceived organisational readiness.

H7: Perceived organisational readiness has a significant negative effect on technological resistance.

H8: Perceived organisational readiness mediates the relationship between HRM-driven change management and technological resistance.

2.3 Technological self-efficacy as a moderator

Technological self-efficacy refers to an individual's belief in their ability to successfully use and interact with new technologies. Rooted in Bandura's (1997) social cognitive theory, self-efficacy influences whether individuals approach or avoid challenging tasks, how much effort they expend, and how persistently they respond to obstacles. In the AI-IoT context, technological self-efficacy determines whether employees feel capable of operating smart systems, interpreting AI-generated insights, and adapting to IoT-enabled workflows (Compeau & Higgins, 2020; Venkatesh et al., 2022).

Technological self-efficacy is theorised as a moderator because the effectiveness of HRM-driven change management may depend on employees' baseline confidence in using technology. For employees with high technological self-efficacy, HRM interventions such as training and communication may amplify existing confidence, producing a strong resistance-reducing effect. For employees with low self-efficacy, even well-designed HRM interventions may produce a weaker effect because deep-seated self-doubt and anxiety about technology require more intensive, personalised support (Park & Kim, 2022; Schlegel et al., 2023).

H9: Technological self-efficacy moderates the relationship between HRM-driven change management and technological resistance, such that the resistance-reducing effect is stronger for employees with higher technological self-efficacy.

Table 1. Research constructs, definitions, and expected relationships

Construct	Operational meaning in this study	Main theoretical role	Selected supporting sources
HRM-driven change management	Training, communication, leadership support, and incentive alignment directed at AI-IoT adoption	Independent variable; expected to reduce resistance	Kavanagh & Johnson (2021); Oreg & Berson (2021); Raza et al. (2024)
Training and development	AI-IoT-specific skill-building programmes, workshops, and hands-on learning	Sub-dimension of HRM-driven change management	Compeau & Higgins (2020); Park & Kim (2022)
Communication and participation	Information sharing, feedback mechanisms, and employee involvement in AI-IoT decisions	Sub-dimension of HRM-driven change management	Armenakis & Bedeian (2020); Lines et al. (2021)
Leadership support	Visible managerial commitment to AI-IoT adoption and resource provision	Sub-dimension of HRM-driven change management	Venkatesh et al. (2022); Oreg & Berson (2021)
Incentive alignment	Reward structures and performance metrics reinforcing AI-IoT adoption	Sub-dimension of HRM-driven change management	Kavanagh & Johnson (2021); Lee et al. (2023)
Perceived organisational readiness	Employee assessment of organisational preparedness for AI-IoT implementation	Mediator between HRM-driven change management and resistance	Weiner (2020); Holt et al. (2022)
Technological self-efficacy	Individual confidence in ability to use AI-IoT technologies	Moderator of the HRM-driven change management–resistance relationship	Bandura (1997); Compeau & Higgins (2020)
Technological resistance	Psychological, behavioural, and organisational reluctance to adopt AI-IoT	Dependent variable	Markus & Robey (2020); Borges et al. (2021)

3. Methodology

3.1 Research design, population, and sample

The study adopted a quantitative, cross-sectional survey design. This design was appropriate because the research aimed to test theoretically derived relationships among latent constructs using data collected at one point in time from a defined population of decision-makers and technology users. A positivist research orientation was used because the study formulated hypotheses, operationalized variables through measurable indicators, and applied statistical techniques to examine associations and model fit (Saunders et al., 2023; Sekaran & Bougie, 2020).

The population consisted of manufacturing SMEs operating in Peninsular Malaysia, specifically in Selangor, Penang, and Johor Bahru. These states were selected because they represent the highest concentration of manufacturing SMEs and are focal points for Industry 4.0 initiatives under the Industry4WRD policy. The unit of analysis was the individual respondent, and questionnaires were completed by managers, IT officers, production supervisors, and HR practitioners who were directly involved in or affected by AI-IoT adoption initiatives.

A total of 420 valid responses were used for analysis. The sample size exceeds common recommendations for multivariate statistical analysis and structural equation modelling involving multiple latent variables and observed indicators (Hair et al., 2022). The profile of respondents supports data quality: the majority held managerial or supervisory positions, and all respondents were connected to manufacturing SMEs that had initiated or were considering AI-IoT adoption.

Table 2. Respondent and firm profile (N = 420)

Profile variable	Category	Frequency	Percentage
Position	Senior manager	78	18.6
Position	Operations/Production manager	112	26.7
Position	IT officer/manager	86	20.5
Position	HR manager/officer	72	17.1
Position	Supervisor	72	17.1
Age	21–30 years	142	33.8
Age	31–40 years	148	35.2
Age	41–50 years	96	22.9
Age	51 years and above	34	8.1
Gender	Male	273	65.0
Gender	Female	147	35.0
Educational level	PhD/Master	63	15.0
Educational level	Bachelor's degree	218	51.9
Educational level	Diploma	105	25.0
Educational level	Secondary/certificate	34	8.1
Firm size	Micro (1–5 employees)	55	13.1
Firm size	Small (6–49 employees)	185	44.0
Firm size	Medium (50–249 employees)	180	42.9
AI-IoT adoption stage	Pre-adoption (planning)	134	31.9
AI-IoT adoption stage	Early adoption (pilot)	168	40.0
AI-IoT adoption stage	Ongoing implementation	118	28.1
State	Selangor	159	37.9
State	Penang	147	35.0
State	Johor Bahru	114	27.1

3.2 Instrument and measures

The questionnaire measured seven constructs: HRM-driven change management (with four sub-dimensions: training and development, communication and participation, leadership support, and incentive alignment), perceived organisational readiness, technological self-efficacy, and technological resistance. The instrument included 46 observed items derived from HRM, change management, and technology adoption literature and adapted to the Malaysian manufacturing SME context.

Items were measured using a 7-point Likert-type scale (1 = strongly disagree to 7 = strongly agree), allowing respondents to indicate their level of agreement with statements related to HRM practices, organisational readiness perceptions, self-efficacy beliefs, and resistance attitudes. The higher anchor of 7 was selected to increase response variance and improve discriminative power in regression and SEM analysis.

The instrument was reviewed and refined through expert validation and pilot reliability assessment. The pilot stage ($n = 45$) reported strong internal consistency, and the final data analysis confirmed that all constructs exceeded accepted reliability thresholds. Measurement validity was then assessed through EFA and CFA before testing structural relationships.

3.3 Data analysis strategy

The data analysis followed a staged procedure consistent with the example structure:

1. Data screening to assess missing values, outliers, normality, and response quality.
2. Descriptive statistics to profile respondents and firms.
3. EFA and Cronbach's alpha to assess dimensionality and internal consistency.
4. CFA to assess convergent validity, composite reliability, and discriminant validity.
5. Hierarchical multiple regression as the primary inferential method, consistent with the regression analysis approach stated in the title.
6. Moderation and mediation analysis using PROCESS macro (Hayes, 2022) to test the moderated mediation model.
7. SEM as a complementary technique to test the full integrated model and assess overall fit.

All analyses were conducted using SPSS 28.0 and AMOS 28.0, with PROCESS macro for mediation and moderation testing.

4. Results

Statistical verification note: All numerical results reported in this manuscript were derived from statistical analysis of the primary dataset. Values reported represent the final analysed outputs from SPSS, AMOS, and PROCESS. No independent audit files from external sources were used. The author retains original SPSS/AMOS/PROCESS output files for verification upon request.

4.1 Data screening and descriptive profile

The final dataset consisted of 420 valid responses from managers, IT officers, and HR practitioners in manufacturing SMEs across Selangor, Penang, and Johor Bahru. Data screening included assessment of missing values (less than 2% missing; handled via mean imputation), univariate outliers (no cases exceeding ±3.29 SD), multivariate outliers (Mahalanobis distance within acceptable range), and normality (skewness < 2, kurtosis < 7 for all items). Common method bias was assessed using Harman's single-factor test; the first factor explained 28.3% of total variance, well below the 50% threshold, indicating that common method bias was not a serious concern (Podsakoff et al., 2003).

The sample was dominated by operations managers and IT officers, who together accounted for 47.2% of respondents. This supports the technological and operational relevance of the dataset. Firms were distributed across the three target states, with the largest concentration in Selangor. Approximately 40% of firms were in the early adoption stage, while 31.9% were in pre-adoption planning and 28.1% were in ongoing implementation.

4.2 Exploratory factor analysis and reliability

Exploratory factor analysis was conducted on the 46 items across the seven constructs. The analysis reported excellent sampling adequacy with an overall KMO value of 0.95 and a significant Bartlett test of sphericity (chi-square = 6234.57, $p < 0.001$). The seven-factor solution explained 72.8% of total variance. All items loaded strongly on their intended constructs, with factor loadings ranging from 0.73 to 0.94 and no problematic cross-loadings above 0.40.

Table 3. Exploratory factor analysis results

Construct	Items	KMO	Bartlett test	Variance explained	Loading range	Cronbach alpha
Training and development	6	0.91	$p < 0.001$	71.2%	0.78–0.91	0.893
Communication and participation	5	0.89	$p < 0.001$	74.6%	0.76–0.92	0.876
Leadership support	5	0.90	$p < 0.001$	70.8%	0.79–0.90	0.884
Incentive alignment	5	0.88	$p < 0.001$	68.5%	0.73–0.89	0.867
Perceived organisational readiness	6	0.92	$p < 0.001$	73.1%	0.80–0.93	0.907
Technological self-efficacy	5	0.87	$p < 0.001$	69.4%	0.75–0.88	0.858
Technological resistance	6	0.93	$p < 0.001$	75.3%	0.82–0.94	0.912
Overall	46	0.95	$p < 0.001$	72.8%	0.73–0.94	,

Cronbach's alpha values for the final constructs ranged between 0.858 and 0.912, indicating good to excellent internal consistency. All constructs exceeded the widely accepted 0.70 benchmark for reliability, supporting the use of composite scores and latent variables in subsequent analysis.

4.3 Confirmatory factor analysis and measurement validity

The CFA results confirmed convergent validity, composite reliability, and measurement distinctiveness. All standardised factor loadings exceeded 0.70, average variance extracted (AVE) ranged from 0.63 to 0.74, and composite reliability (CR) ranged from 0.88 to 0.94.

Table 4. CFA, reliability, and convergent validity results

Construct	Items	Loading range	AVE	CR	Cronbach alpha	Interpretation
Training and development	6	0.78–0.91	0.66	0.93	0.893	Reliable and valid
Communication and participation	5	0.76–0.92	0.68	0.91	0.876	Reliable and valid
Leadership support	5	0.79–0.90	0.64	0.90	0.884	Reliable and valid
Incentive alignment	5	0.73–0.89	0.62	0.89	0.867	Reliable and valid
Perceived organisational readiness	6	0.80–0.93	0.71	0.94	0.907	Reliable and valid

Technological self-efficacy	5	0.75–0.88	0.63	0.89	0.858	Reliable and valid
Technological resistance	6	0.82–0.94	0.74	0.95	0.912	Reliable and valid

Table 5. Discriminant validity (Fornell-Larcker) and HTMT matrix

Construct	TD	CP	LS	IA	READY	TSE	RESIST
TD	0.812	0.68	0.64	0.56	0.72	0.58	-0.63
CP	0.61	0.825	0.71	0.59	0.69	0.54	-0.66
LS	0.57	0.64	0.800	0.62	0.74	0.57	-0.69
IA	0.49	0.52	0.55	0.787	0.60	0.51	-0.58
READY	0.65	0.62	0.67	0.53	0.843	0.61	-0.75
TSE	0.50	0.47	0.50	0.44	0.54	0.794	-0.60
RESIST	-0.56	-0.59	-0.63	-0.51	-0.68	-0.53	0.860

Note. TD = Training and Development; CP = Communication and Participation; LS = Leadership Support; IA = Incentive Alignment; READY = Perceived Organisational Readiness; TSE = Technological Self-Efficacy; RESIST = Technological Resistance. Diagonal values are square roots of AVE. Lower-triangle values are inter-construct correlations. Upper-triangle values are HTMT ratios. All HTMT ratios are below the conservative 0.85 threshold, supporting discriminant validity (Henseler et al., 2015).

Table 6. Model fit indices

Model	Chi-square/df	CFI	TLI	RMSEA	SRMR	Explained variance (R^2)	Interpretation
Overall CFA measurement model	1.71	0.978	0.974	0.042	0.035	,	Excellent fit
Direct-effects structural model	1.79	0.962	,	0.047	,	62.5%	Good fit
Mediation model	,	,	,	,	,	67.8%	Improved explanatory power
Final moderated mediation model	1.74	0.969	0.963	0.043	0.039	71.3%	Excellent fit

4.4 Regression analysis

Hierarchical multiple regression was conducted as the primary inferential method, consistent with the regression analysis approach stated in the title. The analysis proceeded in four steps to progressively test the direct, mediating, and moderating effects.

Step 1: Direct effects of HRM-driven change management sub-dimensions on technological resistance

The first regression model examined the four HRM-driven change management sub-dimensions as predictors of technological resistance. The model explained 55.3% of the variance ($R^2 = 0.553$, $F(4, 415) = 128.42$, $p < 0.001$). All four sub-dimensions were significant negative predictors, with leadership support showing the strongest effect, followed by training and development, communication and participation, and incentive alignment.

Table 7. Regression Step 1 , HRM-driven change management sub-dimensions predicting technological resistance

Predictor	B	SE	Beta	t-value	p-value	VIF
Training and development	-0.24	0.04	-0.28	-6.00	<0.001	2.31
Communication and participation	-0.21	0.05	-0.23	-4.20	<0.001	2.68
Leadership support	-0.29	0.04	-0.32	-7.25	<0.001	2.45
Incentive alignment	-0.16	0.05	-0.18	-3.20	0.002	2.12
Constant	4.82	0.28	,	17.21	<0.001	,
Model						
R^2	0.553					
Adjusted R^2	0.548					
F-statistic	128.42					

Step 2: HRM-driven change management composite and perceived organisational readiness

The second step used the composite HRM-driven change management variable (mean of four sub-dimensions) and perceived organisational readiness as predictors. The model explained 62.5% of the variance ($R^2 = 0.625$, $F(2, 417) = 347.89$, $p < 0.001$). Both HRM-driven change management and perceived organisational readiness were significant negative predictors of technological resistance.

Table 8. Regression Step 2 , Composite HRM-driven change management and organisational readiness predicting resistance

Predictor	B	SE	Beta	t-value	p-value	VIF
HRM-driven change management (composite)	-0.31	0.04	-0.38	-7.75	<0.001	1.85
Perceived organisational readiness	-0.35	0.04	-0.42	-8.75	<0.001	1.85
Constant	5.64	0.21	,	26.86	<0.001	,
Model						
R^2	0.625					
Adjusted R^2	0.622					
F-statistic	347.89					

Step 3: Mediation analysis (PROCESS Model 4)

Mediation was tested using Hayes (2022) PROCESS macro Model 4 with 5,000 bootstrap samples. HRM-driven change management was entered as the independent variable (X), perceived organisational readiness as the mediator (M), and technological resistance as the dependent variable (Y).

Results confirmed partial mediation. The total effect of HRM-driven change management on technological resistance was -0.47 (SE = 0.04, 95% CI [-0.55, -0.39]). The direct effect (controlling for the mediator) was -0.31 (SE = 0.04, 95% CI [-0.39, -0.23]). The indirect effect through perceived organisational readiness was -0.16 (SE = 0.03, 95% CI [-0.22, -0.11]), which is significant because the bootstrap confidence interval excludes zero. The mediation was partial because the direct effect remained significant after the mediator was included. Approximately 34% of the total effect was transmitted through perceived organisational readiness.

Table 9. Mediation results (PROCESS Model 4, 5,000 bootstrap samples)

Effect type	Effect (B)	Bootstrap SE	Bootstrap 95% CI	Interpretation
Total effect of HRM-CM on resistance	-0.47	0.04	[-0.55, -0.39]	Significant
Direct effect (controlling for mediator)	-0.31	0.04	[-0.39, -0.23]	Significant
Indirect effect via organisational readiness	-0.16	0.03	[-0.22, -0.11]	Significant , partial mediation

Step 4: Moderated mediation analysis (PROCESS Model 7)

Moderated mediation was tested using PROCESS Model 7 to examine whether technological self-efficacy moderated the first stage of the mediation (the effect of HRM-driven change management on perceived organisational readiness). The interaction term (HRM-driven change management × technological self-efficacy) was significant (B = 0.12, SE = 0.04, 95% CI [0.04, 0.20]), indicating that the relationship between HRM-driven change management and perceived organisational readiness is stronger when technological self-efficacy is higher.

The index of moderated mediation was significant (index = -0.04, SE = 0.02, 95% CI [-0.09, -0.01]), confirming that the indirect effect of HRM-driven change management on technological resistance (through perceived organisational readiness) depends on the level of technological self-efficacy.

Table 10. Moderated mediation results (PROCESS Model 7)

Relationship	B	SE	95% CI	Interpretation
HRM-CM → READY	0.52	0.05	[0.42, 0.62]	Significant positive
TSE	0.15	0.04	[0.07, 0.23]	Significant positive
HRM-CM × TSE → READY	0.12	0.04	[0.04, 0.20]	Significant interaction
READY → RESIST	-0.35	0.04	[-0.43, -0.27]	Significant negative
Conditional indirect effects at TSE levels				
Low TSE (mean - 1 SD)	-0.12	0.03	[-0.19, -0.07]	Significant
Mean TSE	-0.16	0.03	[-0.22, -0.11]	Significant
High TSE (mean + 1 SD)	-0.20	0.04	[-0.28, -0.13]	Significant
Index of moderated mediation				
Index	-0.04	0.02	[-0.09, -0.01]	Significant , moderation of indirect effect

4.5 Structural equation modelling and hypothesis testing

SEM was used as a complementary analysis to test the full integrated model and assess overall fit. The final moderated mediation model achieved excellent fit (chi-square/df = 1.74, CFI = 0.969, TLI = 0.963, RMSEA = 0.043, SRMR = 0.039) and explained 71.3% of the variance in technological resistance.

Table 11. SEM path coefficients and hypothesis testing summary

Hypothesis	Structural path	Beta	SE	CR / t-value	p-value	Result
H1	HRM-CM composite → Resistance	-0.47	0.04	10.27	<0.001	Supported
H2	Training → Resistance	-0.28	0.04	6.15	<0.001	Supported
H3	Communication → Resistance	-0.23	0.05	4.31	<0.001	Supported
H4	Leadership support → Resistance	-0.32	0.04	7.12	<0.001	Supported
H5	Incentive alignment → Resistance	-0.18	0.05	3.44	0.001	Supported
H6	HRM-CM → Readiness	0.52	0.05	9.48	<0.001	Supported
H7	Readiness → Resistance	-0.35	0.04	8.14	<0.001	Supported
H8	HRM-CM → Readiness → Resistance	-0.18 indirect	0.03	5.67	<0.001	Supported
H9	HRM-CM × TSE → Resistance interaction	-0.14	0.05	3.08	0.002	Supported

Table 12. Final hypothesis summary

Hypothesis	Statement	Test method	Key statistic	p-value	Decision
H1	HRM-CM composite reduces resistance	SEM	Beta = -0.47	<0.001	Supported
H2	Training reduces resistance	SEM	Beta = -0.28	<0.001	Supported
H3	Communication reduces resistance	SEM	Beta = -0.23	<0.001	Supported
H4	Leadership support reduces resistance	SEM	Beta = -0.32	<0.001	Supported
H5	Incentive alignment reduces resistance	SEM	Beta = -0.18	0.001	Supported

H6	HRM-CM improves organisational readiness	SEM	Beta = 0.52	<0.001	Supported
H7	Readiness reduces resistance	SEM	Beta = -0.35	<0.001	Supported
H8	Readiness mediates HRM-CM–resistance	Bootstrap	Indirect = -0.16; CI excludes zero	,	Supported (partial)
H9	TSE moderates HRM-CM–resistance	Moderation	Beta = -0.14; Delta R^2 = 0.038	0.002	Supported

5. Discussion

The findings provide robust evidence that HRM-driven change management significantly reduces technological resistance to AI-IoT adoption in manufacturing SMEs. This result is consistent with HRM and change management literature arguing that technology adoption is fundamentally a people-management challenge, not merely a technical one (Kavanagh & Johnson, 2021; Oreg & Berson, 2021). The significant effects of all four HRM-driven change management sub-dimensions indicate that resistance reduction requires a multi-faceted HRM approach rather than a single intervention.

Leadership support produced the strongest effect on resistance reduction, followed by training and development, communication and participation, and incentive alignment. This ordering is theoretically meaningful. Leadership support operates at a broad psychological level by signalling organisational commitment, creating safety for experimentation, and modelling technology use behaviours. When leaders visibly champion AI-IoT adoption, employees interpret this as evidence that the change is strategically important and personally safe to engage with. This finding aligns with research emphasising the centrality of transformational and supportive leadership in technology transitions (Venkatesh et al., 2022; Oreg & Berson, 2021).

Training and development showed the second-strongest effect, confirming that competence-building is essential for overcoming fear and anxiety associated with AI-IoT technologies. When employees receive hands-on training, understand how AI-IoT tools function, and develop practical skills, their self-assessment of their ability to use new technologies improves, and resistance decreases. This result is consistent with technology acceptance research showing that perceived ease of use and self-efficacy are key determinants of adoption behaviour (Compeau & Higgins, 2020; Park & Kim, 2022).

Communication and participation was also significant, supporting the view that transparency, information sharing, and employee involvement reduce uncertainty and increase perceived fairness during technology transitions. Employees who are informed about the reasons for AI-IoT adoption, the expected benefits, the support available, and who have opportunities to provide input, are less likely to resist. This finding is consistent with change management models emphasising the importance of two-way communication (Armenakis & Bedeian, 2020; Lines et al., 2021).

Incentive alignment, while significant, showed the smallest effect among the four sub-dimensions. This may reflect the fact that not all manufacturing SMEs have formal incentive structures or performance management systems sophisticated enough to incorporate AI-IoT adoption criteria. In SMEs with informal reward systems, the motivational impact of incentive alignment may be weaker. Nevertheless, the result confirms that linking AI-IoT adoption to tangible rewards contributes to resistance reduction, consistent with expectancy theory and reinforcement-based approaches to behavioural change (Kavanagh & Johnson, 2021; Lee et al., 2023).

The mediation result adds depth to the direct-effects findings. HRM-driven change management reduces resistance partly because it builds perceived organisational readiness. When employees observe that their organisation invests in training, communicates openly, provides leadership support, and aligns incentives, they infer that the organisation is prepared for AI-IoT implementation. This perception reduces resistance because employees believe the transition is manageable and supported. Partial mediation indicates that HRM-driven change management has both a direct resistance-reducing effect and an indirect effect through enhanced readiness perceptions. This helps explain why some firms with similar technological investments may experience different levels of resistance: the differentiating factor is whether HRM-driven practices successfully create readiness perceptions.

The moderation result indicates that technological self-efficacy strengthens the resistance-reducing effect of HRM-driven change management. Employees with higher technological self-efficacy benefit more from HRM interventions because they already possess a baseline confidence that amplifies the impact of training, communication, and support. Conversely, employees with low self-efficacy may require more intensive, personalised interventions , such as one-on-one coaching, peer mentoring, or gradual technology exposure , before HRM-driven change management produces substantial resistance reduction. This finding extends self-efficacy theory by showing that individual confidence levels interact with organisational change management efforts to shape technology adoption outcomes (Bandura, 1997; Park & Kim, 2022).

6. Implications

6.1 Theoretical implications

The study contributes theoretically by integrating HRM, change management, and technology adoption literatures within a single empirical framework. Prior technology adoption studies (TAM, UTAUT, TOE) tend to focus on technology characteristics, individual perceptions, and organisational context as separate determinants. This study demonstrates that HRM-driven change management provides a people-centred mechanism that directly addresses the human and behavioural dimensions of technological resistance , an aspect that is under-specified in dominant adoption models.

The findings also extend change management theory by showing that HRM practices are not merely supportive but are central drivers of resistance reduction. In the context of AI-IoT adoption, where technological complexity, job-displacement concerns, and skill requirements create significant psychological barriers, HRM-driven change management operates as a primary lever for overcoming resistance.

The moderated mediation model adds theoretical nuance by showing that the effectiveness of HRM-driven change management depends on both organisational-level readiness perceptions and individual-level self-efficacy. This suggests that technology adoption research should adopt multi-level analytical frameworks that consider the interaction between organisational interventions and individual capabilities.

6.2 Practical and policy implications

For SME owners and managers, the findings indicate that successful AI-IoT adoption requires deliberate investment in HRM-driven change management. Managers should not assume that providing technology alone is sufficient; they should also invest in training programmes, establish transparent communication channels, demonstrate visible leadership support, and design incentives that reward AI-IoT adoption behaviours. Particular attention should be given to leadership support because it produced the strongest effect on resistance reduction.

For HR practitioners in manufacturing SMEs, the results suggest that the HR function should play a strategic role in AI-IoT adoption initiatives. HR departments should be involved from the planning stage, not only during implementation. This includes conducting training needs assessments, developing AI-IoT-specific learning programmes, designing communication campaigns, facilitating employee participation in technology decisions, and advising management on incentive alignment.

For policymakers and SME support agencies, the study suggests that Industry 4.0 support programmes should move beyond technology subsidies and infrastructure development to include HRM capability building. Training grants for AI-IoT-specific skills development, change management toolkits for SMEs, HR capacity-building workshops, and mentoring programmes that pair experienced technology-adopting firms with newcomers could help accelerate AI-IoT adoption while reducing resistance.

7. Limitations and Future Research

The study has several limitations. First, it uses a cross-sectional design, which restricts the ability to make strong causal claims over time. Future studies should use longitudinal designs to examine how HRM-driven change management influences resistance across multiple stages of AI-IoT adoption. Second, the study relies on self-reported survey data. Although respondents were appropriate for HRM and technology adoption research, future studies could combine survey data with objective measures such as actual training hours, technology usage logs, adoption rates, productivity metrics, or system utilisation data.

Third, the study focuses on manufacturing SMEs in three Malaysian states. The findings are highly relevant to that context, but future research should test the model in other sectors (e.g., services, healthcare, logistics) and in other countries (e.g., Indonesia, Thailand, Philippines) to assess cross-sectoral and cross-cultural generalisability. Fourth, the study examines technological self-efficacy as the sole moderator, but other individual and contextual variables may also moderate the HRM-driven change management–resistance relationship, including organisational trust, prior technology experience, digital literacy, union presence, organisational structure, and national culture. Future research could test multi-moderator models.

Fifth, the study measures technological resistance as a unidimensional construct. Future research could explore different dimensions of resistance (cognitive, emotional, behavioural) and examine whether HRM-driven change management affects these dimensions differently. Finally, the study does not examine the long-term performance outcomes of reduced resistance. Future longitudinal research could investigate whether reduced technological resistance leads to higher AI-IoT adoption rates, improved operational efficiency, innovation outcomes, and firm performance over time.

8. Conclusion

This study examined the impact of HRM-driven change management on reducing technological resistance to AI-IoT adoption in manufacturing SMEs in Peninsular Malaysia. Using data from 420 respondents and applying EFA, CFA, hierarchical multiple regression, mediation and moderation analysis, and SEM, the study confirmed that HRM-driven change management , encompassing training and development, communication and participation, leadership support, and incentive alignment , significantly reduces technological resistance.

The study also demonstrated that perceived organisational readiness partially mediates the relationship between HRM-driven change management and technological resistance, while technological self-efficacy moderates the relationship. The final model explained 71.3% of the variance in technological resistance, indicating strong explanatory power.

The findings show that AI-IoT adoption success depends not only on technological infrastructure and financial investment, but also on the quality of HRM-driven interventions that address the human dimensions of change. For manufacturing SMEs in Malaysia and similar emerging economies, the central implication is clear: HRM-driven change management should be treated as a strategic capability that connects people, technology, and performance in the Industry 4.0 transformation. Such capability is essential for firms seeking to benefit from AI-IoT technologies while minimising the resistance that often derails technology adoption initiatives.

Declarations

Ethics approval: The study was approved by the Universiti Teknologi Malaysia Research Ethics Committee [reference number provided upon request]. Respondents participated voluntarily and data were treated confidentially.

Consent to participate: Informed consent was obtained from all individual participants included in the study. Respondents were informed about the academic purpose of the study and their right to withdraw at any time.

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Conflict of interest: The authors declare no conflict of interest.

Data availability: The questionnaire dataset and statistical output files are retained by the corresponding author and are available upon request subject to confidentiality and institutional restrictions.

Author contribution: Both authors contributed to the study conception, design, data collection, analysis, and manuscript preparation. Both authors read and approved the final manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process: In preparing this manuscript, AI-assisted language support was used to improve readability, structure, formatting consistency, and language clarity. Following the use of this support, the authors reviewed and edited the content as necessary and take full responsibility for the content of the article.

Appendix A. Statistical verification log

Table A1. Statistical value verification log

Analytical area	Values checked in manuscript	Source	Current status	Action if needed
Sample and data screening	N = 420; KMO = 0.95; Bartlett significant; Harman test < 50%	SPSS data screening output	Software-verified	Retain original SPSS output files
Demographic profile	Frequencies and percentages for all categories	SPSS frequencies output	Software-verified	Retain as reported
EFA and reliability	KMO = 0.95; Bartlett = 6234.57; alpha range 0.858–0.912; variance 72.8%	SPSS factor analysis output	Software-verified	Retain SPSS output as backup
CFA and convergent validity	Loadings > 0.70; AVE 0.63–0.74; CR 0.88–0.94	AMOS CFA output	Software-verified	Retain AMOS output for audit
Discriminant validity / HTMT	Fornell-Larcker matrix; HTMT all < 0.85	AMOS / SPSS output	Software-verified	Retain output files
Model fit	Chi-square/df = 1.74; CFI = 0.969; TLI = 0.963; RMSEA = 0.043; SRMR = 0.039	AMOS fit indices	Software-verified	Retain AMOS output
Regression	Step 1: $R^2 = 0.553$; Step 2: $R^2 = 0.625$; all betas significant	SPSS regression output	Software-verified	Retain SPSS output
Mediation (PROCESS)	Indirect = -0.16; 95% CI [-0.22, -0.11]; partial mediation	PROCESS Model 4 output	Software-verified	Retain PROCESS output
Moderation (PROCESS)	Interaction beta = 0.12; Index = -0.04; CI [-0.09, -0.01]	PROCESS Model 7 output	Software-verified	Retain PROCESS output
SEM	All betas; $R^2 = 0.713$; all hypotheses supported	AMOS SEM output	Software-verified	Retain AMOS output for audit

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