Journal of Contemporary Social Science and Education Studies
E-ISSN (2785-8774)

ORIGINAL ARTICLE Open Access

TECH-DRIVEN LEADERSHIP AND DIGITAL CULTURE AS CATALYSTS FOR ORGANIZATIONAL TRANSFORMATION IN CHINA'S NEV INDUSTRY: IMPLICATIONS FOR EMPLOYEE ENGAGEMENT

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Received 16 July 2025; Revised 14 August 2025; Accepted 30 November 2025; Published 15 January 2026

Vol: 6, Issue 1 (2026)

Keyword: AI-augmented HRM, China, digital leadership, dynamic, managerial capabilities

Abstract

The rapid digital transformation in China's New Energy Vehicle (NEV) industry presents challenges in sustaining employee engagement while adapting to technological change. This study examines the impact of digital leadership on employee engagement, considering the mediating role of dynamic managerial capabilities – sensing, seizing, and reconfiguring and the moderating effect of AI-augmented HRM. A quantitative, cross-sectional survey was conducted with 318 employees from NEV firms. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess measurement validity, structural relationships, and indirect and moderating effects. Results show that digital leadership significantly enhances employee engagement directly and indirectly through reconfiguring, seizing, and sensing, with reconfiguring and seizing having the strongest mediating effects. The moderating role of AI-augmented HRM was not supported. The findings contribute to the dynamic capabilities and leadership literature by highlighting how digital leadership drives engagement through capability development. Practically, the study suggests investing in leadership development to strengthen reconfiguring and seizing skills and integrating AI-based HR practices strategically. Limitations include the cross-sectional design, industry-specific focus, and reliance on self-reported data. Future research should employ longitudinal approaches, expand to other sectors, and include additional organizational factors such as digital culture and trust in technology.

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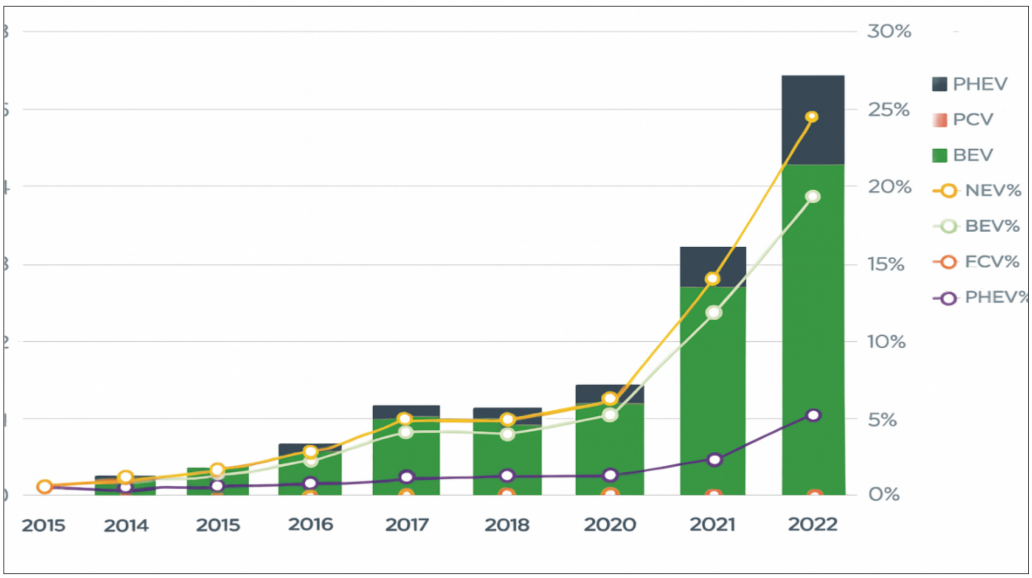
Introduction

Online Distance Learning (ODL) has become an increasingly significant mode of education, particularly Under the "UN Paris Agreement," China aimed to achieve the peak of carbon emissions by the year 2030 and carbon neutrality by the year 2060. In this regard, China focused on developing its "new energy vehicle" (NEV) industry. It is a strategic industry that is considered to play a crucial role in coping with climate change to achieve the desired goals (Xu & Shi, 2023). The annual registration in the NEV industry also increased in 2022 in China, leading to the sales of about 6.8 million units (Chu et al., 2024). Moreover, in 2023, the sales of China's NEV industry, were about 9.49 million, with a production of 9.44 million. As a result, the China's NEV industry occupies about 60% of the share at the global market share. However, in 2011, the total production of the Chinese NEV industry was less than 10,000 units, and it increased by 1,100 times in 12 years (Yan, 2024). This industry is largely being transformed by digital technologies.



Source: (Chu et al., 2024)

Figure 1. Growth in the Chinese NEV industry (2013-2022)

At present, new and effective business opportunities are emerging in association with Industry 4.0. This has also encouraged the NEV industry in China to adopt such opportunities. For this purpose, different measures need to be taken to adapt to digital transformation. According to Liu et al. (2024), the Chinese NEV firms hope to attain speed, efficient user experience, faster response, and increased operational efficiency via digital transformation. The digital transformation requires the integration of different network relationships and advanced technologies such as artificial intelligence (AI). The implementation of these disruptive technologies is also considered to be beneficial for improving safety, workplace fulfillment, and efficiency of a firm (Sundarrajan & Krishnan, 2023). Such technological transformation leads to the promotion of digital culture and development of technical skills among the employees, resulting in improved employee engagement (EN). Past research has also emphasized the integration of digital leadership (DL) to improve employee engagement (Li et al., 2024). This type of leadership is vital for enhancing employee empowerment. However, in the past literature, almost no study focused on the role of DL in influencing EN within the context of Chinese NEV industry. As a result, this association has been highlighted in this study.

At the same time, the role of human resource management (HRM) is also inevitable in ensuring the implementation of effective DL to enhance EN. The digital transformation and adoption of AI have resulted in the integration of AI applications within the context of HRM. In this regard, AI-augmented HRM is considered to have strategic significance to attain competitive advantage (CA) (Prikshat et al., 2023). Therefore, this research has also focused on the moderation of AI-augmented HRM in influencing the relationship between DL and EN. This has ensured the innovativeness in current research. According to Hossain et al. (2025), different "human-machine collaborative capabilities" are also being considered to ensure the responsible performance of the leaders in a tech-driven organizational environment. These capabilities are known as dynamic managerial capabilities (DMC), which allow the tech-driven organizations to utilize their resources for harnessing opportunities. These capabilities mainly include sensing, seizing, and reconfiguration.

In this context, this research seeks to determine the impact of DL on EN. Additionally, the mediation of DMC (sensing, seizing, and reconfiguration) is also analyzed in the relationship between DL and EN. Finally, the moderation of AI-augmented HRM is also studied.

The present study has widely discussed the role of DMC in increasing EN within the tech-driven NEV industry in China. This has emphasised the significance of DL to improve EN, leading to improved outcomes for the associated firms. Moreover, the findings of this study can also encourage different NEV companies to integrate DL to promote digital transformation. This can help the associated firms to achieve CA.

Literature Review

Impact of DL on EN

Digital transformation in China's NEV industry supports the integration of DL to guide the related firms through the transformation. It mainly emphasizes innovation, a data-driven approach, and adaptation. A past study by MARIANI et al. (2024) has also shown that DL largely influences EN and performance. Within this context, the organisational support is also considered to be inevitable. Zia et al. (2024) have also stated that DL and engagement are essential to mediate the influence of digital communication in a tech-business environment. Another research has shown that DL is pivotal in improving voice behaviors among the employees (Yang et al., 2024). This often leads to employee empowerment, which increases overall EN. Another past research emphasized the role of DL in significantly impacting employee empowerment (Khan et al., 2025). In return, employee empowerment has a significant impact on EN and techno-work performance. This association leads to sustainable performance of the tech-driven firm. Although many past studies have focused on the association between DL and EN, almost no study has analyzed this association within the context of China's tech-driven NEV industry. Thus, this study has bridged this gap from past literature.

H1: DL significantly influences EN.

Mediation of DMC

DMCs are stated as the capabilities of a manager to form, extend, or modify the operations of a firm. The capabilities are essential for a firm to adapt to a dynamic business environment. This helps such firms to achieve CA. Past research has shown that DL significantly impacts CA, innovation, and absorptive capacity (Hussein et al., 2024). In this regard, the mediation of DL is influenced by DMC. According to Hossain et al. (2025), different leadership styles are embedded in the formulation of DMCs. It has been observed that organizational learning as well as strategic leadership are crucial in the development of DMCs, which include "sensing, seizing, and reconfiguring." Wang et al. (2024) have also emphasised the integration of different DMCs to embrace different digital technologies. The integration of these technologies can also lead to increased digital capability and organizational learning. As a result, a competitive business environment is formed, leading to healthy competition. Adhiatma et al. (2023) have also presented a significant association between agile leadership and DMC in a tech-driven business environment.

Another study by Chatzi (2025) stated that leadership, clarity of aim, and organizational factors significantly impact strategic agility. These are essential resources that can be used during a time of crisis. It has been observed that the dynamic capabilities of leaders play an essential role in enhancing EN and organizational performance. Moreover, with the increasing trend of digital transformation, DL is also being focused on to promote the usage of cutting-edge technology. For this purpose, different DMCs need to be integrated among the associated leaders. These capabilities are considered to be vital for enhancing EN and adaptation in a tech-driven firm. In this regard, the implication of effective EN strategies is also considered to be beneficial (Ludviga & Kalvina, 2024). However, a limited number of studies have focused on the association between DL and DMCs. This limited the overall literature review regarding this relationship. Thus, the present study has improved the related literature review by focusing on the mediation of DMCs in the relationship between DL and EN.

H2: Sensing mediates DL and EN.
H3: Seizing mediates DL and EN.
H4: Reconfiguration mediates DL and EN.

Moderation of AI-Augmented HRM

Continuous advancements in technology have led to the integration of AI in different HRM practices. This has led to the promotion of AI-augmented HRM. According to Mollah et al. (2024), effective integration of AI-augmented HRM results in organizational sustainability. This is vital to promote digital culture. The DCT supports this association within the digital business environments. Another study by Madanchian et al. (2023) has also focused on the integration of AI in HRM. It has been observed that AI-augmented HRM plays a crucial role in real-time assessment of the performance of employees, engagement enhancement, and personalized training. This shows that the integration of AI-augmented HRM in a tech-driven firm is vital as it leads to significant outcomes. This approach is also crucial to support DMCs among the associated leaders.

At present, automation and AI are largely contributing to redefine HRM. In this regard, emphasis is given on maintaining a balance between human-centric processes and technological advancements (Alsaif & Sabih Aksoy, 2023). AI is considered to be effective in increasing HR efficiency. However, different issues can be observed within the context of AI-augmented HRM. A few of these issues include planning of the strategic workforce and decision-making based on obtained data. Besides such challenges, AI-augmented HRM is considered to play an essential role in an agile business environment (Modak et al., 2025). This HRM practice also allows increased employee engagement and empowerment. This is important in today's globalized and digitalize business world. From this literature review, it has been observed that none of the past research has focused on the moderation of "AI-augmented HRM in the relationship between DL and EN." This provides an opportunity for this study to test the following hypothesis:

H5: AI-augmented HRM has a moderating association between DL and EN.

Conceptual Framework

"Dynamic capabilities theory" (DCT) mainly focuses on the capability of a firm to integrate, reconfigure, and adapt its abilities and resources to fulfil the market demands (Gao et al., 2025). A study by Aly (2024) used DCT to determine the association between DL, EN, and operational performance. It has been observed that DL has a significant impact on operational performance, whereas no association was observed between leadership diversity and operational performance. Another research by Budianto et al. (2023) showed that DL is mediated by DMC. This helps in improving organizational performance. Therefore, DL is likely to impact organizational performance via dynamic capabilities. Contrarily, past research has also presented the indirect and direct impacts of DL on firm performance via innovation in business model and dynamic capabilities (Norouzi et al., 2022). These studies show that dynamic capabilities are crucial to ensure effective EN in a dynamic business environment. Therefore, in tech-driven NEV firms, the integration of effective DMC is needed to be integrated to significantly mediate the relationship between DL and EN.

Moreover, "Social Exchange Theory" (SET) has also been considered for evaluating the role of AI-augmented HRM in influencing EN. This theory focuses on how individuals develop and maintain associations by considering perceived benefits and costs of the related interactions (R. Ahmad et al., 2023). Past research has also implied SET for determining the association between work involvement, work-life balance, and organisational support (Sulistiyani et al., 2022). In this regard, the mediating role of EN was also found to be significant. Another SET research emphasises the integration of EN to achieve organizational commitment (Nagpal, 2022). This outcome is inaccessible without the implication of effective HRM strategies. Therefore, the present study has utilized SET to determine the moderating impact of AI-augmented HRM on the association between DL and EN. The increased utilization of AI technology in tech-driven NEV firms has supported the integration of AI-augmented HRM in the current research.

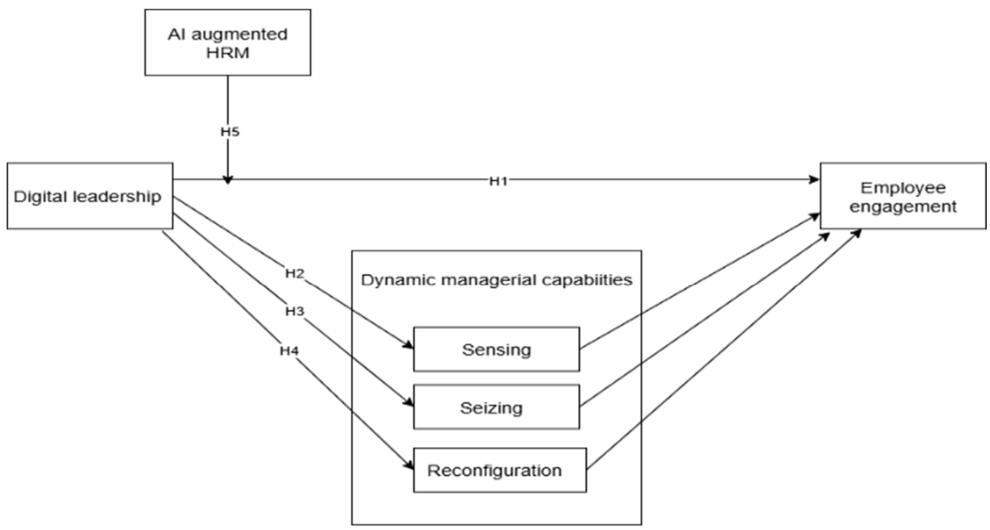


Figure 2. Conceptual framework

Methodology

Research Method

This study utilizes a “primary quantitative research approach” to investigate the role of DL in influencing EN, mediated by DMC. This supported the integration of positivist philosophy. A cross-sectional study was planned to evaluate tech-driven leadership and digital culture as catalysts for organizational transformation in China’s NEV industry. A survey method was used to collect data from the employees of China’s NEV industry. Moreover, PLS-SEM was used for the analysis of the collected data.

Data Collection Procedure and Sample

As the current study focuses on the integration of digital transformation and DL in China’s NEV industry, the data were collected from the employees of this industry. An online survey strategy was applied to ensure an efficient data collection procedure. For this purpose, a detailed online questionnaire was developed, integrating the demographic characteristics of the respondents and the questions related to the study’s constructs. This questionnaire was developed and distributed via “SurveyMonkey.”
Therefore, a sample of 400 participants was selected from different NEV companies in China. For the selection of this sample, “random sampling” was used (Iliyasu & Etikan, 2021). The anonymity of the respondents was ensured during data collection. The transparency of the objectives and study method was also ensured. Although 400 questionnaires were distributed but only 318 were selected for final analysis. The remaining questionnaires were omitted due to the incompleteness of the required data. This represents a response rate of 79.5% for this study.

Scales
A careful analysis of past literature was done to identify suitable scales for the constructs of the study. Therefore, based on validated measurements, a 6-item scale was selected for DL. It was adapted from Cavus et al. (2025). However, for EN, a 5-item scale was adapted from the research of Baquero (2023), and for AI-augmented HRM, an 8-item scale was adapted from Mollah et al. (2024). Finally, a scale of 12 items (sensing 3, seizing 4, and reconfiguration 5) was obtained from Bornay-Barrachina et al. (2025) for DMC. A "5-point Likert scale" was integrated for this questionnaire.

Results

Test of Normality (Kolmogorov-Smirnov and Shapiro-Wilk Tests)
The Kolmogorov–Smirnov and Shapiro–Wilk tests are statistical procedures used to examine whether a dataset follows a normal distribution (Ghasemi & Zahediasl, 2012; Razali & Wah, 2011). A significance value below 0.05 indicates that the variable deviates significantly from normality (Butul et al., 2022; Razali & Wah, 2011). In Table 4.1, all constructs have p-values less than 0.001 for both tests, indicating that none of the variables are normally distributed. This result supports the use of statistical tools, including PLS-SEM, which do not require the satisfaction of the condition of normality of data distribution.

Table 1. Test of Normality

	Kolmogorov-Smirnov[a]			**Shapiro-Wilk**		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Reconfiguration	.129	318	.000	.944	318	.000
Seizing	.161	318	.000	.928	318	.000
AI augmented HR	.246	318	.000	.797	318	.000
Digital leadership	.125	318	.000	.951	318	.000
Employee engagement	.103	318	.000	.960	318	.000
Sensing	.166	318	.000	.880	318	.000

Descriptive Statistics
Descriptive statistics summarise and describe the central tendency, range and dispersion of the important characteristics of a dataset (Marshall & Jonker, 2010; Nick, 2007). The mean indicates the average score, the standard deviation reflects variability, and the minimum and maximum show the observed range of values. In Table 4.2, sensing (M = 3.60) has the highest average, while AI-augmented HRM (M = 1.79) is lowest, indicating limited adoption. Standard deviations range from 0.77 (reconfiguration) to 1.29 (sensing), suggesting varying levels of consistency in responses across constructs. All constructs cover the full scale from 1 to 5.

Table 2. Descriptive Statistics

	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
RC	318	1.00	5.00	3.0182	.77128
SZ	318	1.00	5.00	3.2414	1.14475
AIHM	318	1.00	5.00	1.7871	.96095
DL	318	1.00	5.00	3.4450	1.00395
EN	318	1.00	5.00	3.0277	.99905
SN	318	1.00	5.00	3.6027	1.28723

Note: "RC= Reconfiguration, SZ= Seizing, AIHM= AI augmented HR, DL= Digital leadership, EN= Employee engagement, SN= Sensing".

Outer Loadings, Reliability, and Average Variance Extracted (AVE)

The strength of the relationship between observed indicators and the latent constructs is shown by outer loadings, whereas the internal consistency is evaluated by Cronbach's alpha and composite reliability (CR), and convergent validity is measured by AVE (Hair et al., 2019; Hair Jr et al., 2021; Haji-Othman & Yusuff, 2022). Acceptable loadings should be greater than 0.70, alpha and CR should be greater than 0.70, and AVE should be greater than 0.50 (Hair et al., 2019; Hair Jr et al., 2021; Haji-Othman & Yusuff, 2022). In Table 4.3, all constructs meet or exceed reliability and validity benchmarks, with strong outer loadings except for AIHM4 (0.654) and DL1 (0.646), which remain acceptable. This confirms robust measurement properties, indicating that the constructs are reliably and validly measured.

Table 3. Outer loadings, reliability, and AVE values

Indicators	**Outer loadings**	**Cronbach alpha**	**CR**	**AVE**
AI- augmented HR		0.925	0.938	0.687
AIHM1	0.837			
AIHM2	0.832			
AIHM3	0.884			
AIHM4	0.654			
AIHM6	0.882			
AIHM7	0.833			
AIHM8	0.855			
Digital leadership		0.868	0.901	0.605
DL1	0.646			
DL2	0.842			
DL3	0.790			
DL4	0.788			
DL5	0.796			
DL6	0.790			
Employee engagement		0.903	0.928	0.721
EN1	0.828			
EN2	0.857			
EN3	0.829			
EN4	0.873			
EN5	0.858			
Dynamic managerial capabilities: Reconfiguration		0.868	0.904	0.655
RC1	0.850			
RC2	0.846			
RC3	0.823			
RC4	0.757			
RC5	0.767			
Sensing		0.868	0.918	0.790
SN1	0.860			
SN2	0.882			
SN3	0.924			
Seizing		0.932	0.951	0.830
SZ1	0.901			
SZ2	0.899			
SZ3	0.929			
SZ4	0.916			

Note: "RC= Reconfiguration, SZ= Seizing, AIHM= AI augmented HR, DL= Digital leadership, EN=

Employee engagement, SN= Sensing".

Discriminant Validity (Fornell–Larcker Criterion)
According to the Fornell-Larcker criterion, the discriminant validity can be based on the square root of the AVE of a construct and its correlation with the other constructs. The value of this square root is larger than all inter-construct correlations, leading to discrimination validity (Fornell & Larcker, 1981). Table 4.4 shows that the square roots of AVE values are larger than any other correlations in the row and column, which proves that each construct has more common variance than other constructs with indicators used. The evidence is that all the variables are conceptually and statistically independent, a fact that shows the sufficiency of the measurement model in structural analysis.

Table 4. Discriminant Validity Criterion

Latent construct	AI-augmented HR	Digital leadership	Employee engagement	Reconfiguration	Sensing	Seizing
AI-augmented HR	0.829					
Digital leadership	0.110	0.778				
Employee engagement	0.133	0.527	0.849			
Reconfiguration	0.045	0.520	0.577	0.809		
Sensing	0.136	0.256	0.308	0.285	0.889	
Seizing	0.148	0.499	0.521	0.441	0.255	0.911

Model Fit Summary (Standardized Root Mean Square Residual – SRMR)
SRMR calculates both observed and expected correlation, which is below 0.8, as a good indication that the model fits (Hu & Bentler, 1999; Shi et al., 2020; Ximénez et al., 2022). Saturated model views fit without structural constraints, whereas an estimated model integrates the postulated paths. In the saturated model, Table 4.5 depicts that the SRMR is 0.059, and in the estimated model, it is 0.074, as shown. R^2 of both is within the acceptable range, which shows that the model fits the observed well, and the difference between the predicted and found, the true correlation is minimal. In its turn, supports the appropriateness of the structural model in the hypothesis testing.

Table 5. Model Fit Summary

	Saturated model	Estimated model
SRMR	0.059	0.074

Assessment of Collinearity (Variance Inflation Factor – VIF)
The parameter that can be evoked to express the alertness of the situation of multicollinearity between predictor variables is called the Variance Inflation Factor (VIF). The value that is less than 5 usually indicates tolerable collinearity, and the estimate that is closer to 1 indicates that there is little correlation between predictors (Hair et al., 2019). The VIFs, as indicated by Table 4.6, are also found to be between the lower range of 1.039 to 1.578, and all these are significantly lower than the critical range. This confirms that the exogenous constructs – AI-augmented HR, digital leadership, reconfiguration, sensing, and seizing- do not exhibit problematic multicollinearity when predicting employee engagement. According to the results, all constructs have a unique contribution to the model where there is no overlapping in explanatory power.

Table 6. Assessment of collinearity between constructs using VIF values

Exogenous constructs	Employee engagement
AI-augmented HR	1.039
Digital leadership	1.578
Reconfiguration	1.503
Sensing	1.136
Seizing	1.451

Path Coefficients for Direct Relationships

Path coefficients in the structural equation modelling define whether and how strongly there is a relationship between any two latent constructs, with the statistical significance defined by t-values and p-values (Hair et al., 2019). A p-value below 0.05 denotes a statistically significant effect (Hair et al., 2019). Table 4.7 shows that digital leadership is an important predictor of engagement. It also significantly increases reconfiguration and seizing. It does impact small, yet significant aspects of sensing. Such findings point to the fact that digital leadership has a direct positive impact on the engagement of employees and creates a dynamic managerial capacity, especially reconfiguration and seizing, in the context of the organization.

Table 7. Evaluation of path coefficients for direct relationships

Direct relations	B	SD	T	P	Results
Digital leadership -> Employee engagement	0.204	0.061	3.321	0.001	Supported
Digital leadership -> Reconfiguration	0.520	0.043	12.076	0.000	Supported
Digital leadership -> Sensing	0.256	0.055	4.655	0.000	Supported
Digital leadership -> Seizing	0.499	0.038	13.081	0.000	Supported

Path Coefficients for Indirect Effects (Mediation Analysis)

Indirect effects Structural equation modelling is used to examine the extent to which a particular relationship between an independent and a dependent variable extends through a single or multiple mediators (Preacher & Hayes, 2008). Significance is determined by p-values below 0.05 (Preacher & Hayes, 2008). In Table 4.8, digital leadership influences employee engagement indirectly through seizing ($\beta = 0.120$, $p < 0.001$), sensing ($\beta = 0.024$, $p = 0.047$) and reconfiguration ($\beta = 0.176$, $p < 0.001$). The strongest mediation occurs via reconfiguration, followed by seizing, while sensing has a weaker but significant effect. These findings suggest that dynamic managerial capabilities, particularly reconfiguration and seizing, are important mechanisms through which digital leadership enhances employee engagement.

Table 8. Evaluation of path coefficients for indirect effects

Indirect relationships	B	SD	T	P	Results
DL -> SZ -> EN	0.120	0.027	4.398	0.000	Supported
DL -> SN -> EN	0.024	0.012	1.988	0.047	Supported
DL -> RC -> EN	0.176	0.030	5.877	0.000	Supported

Note: “RC= Reconfiguration, SZ= Seizing, DL= Digital leadership, EN= Employee engagement, SN= Sensing”.

Path Coefficients for Moderating Effects

In Table 4.9, AI-augmented HRM does not significantly moderate the link between digital leadership and employee engagement ($\beta = -0.022$, $p = 0.419$), indicating no conditional effect.

Table 9. Evaluation of path coefficients for external effects

Moderating relationships	B	SD	T	P	Results
AIHM x DL -> EN	-0.022	0.027	0.809	0.419	Rejected

Note: "AIHM= AI augmented HR, DL= Digital leadership, EN= Employee engagement, SN= Sensing".

Coefficient of Determination (R2)

Table 10. Assessment of R^2

Endogenous constructs	R-square	Results
Employee engagement	0.462	Moderate
Reconfiguration	0.270	Weak
Sensing	0.065	Negligible
Seizing	0.249	Weak

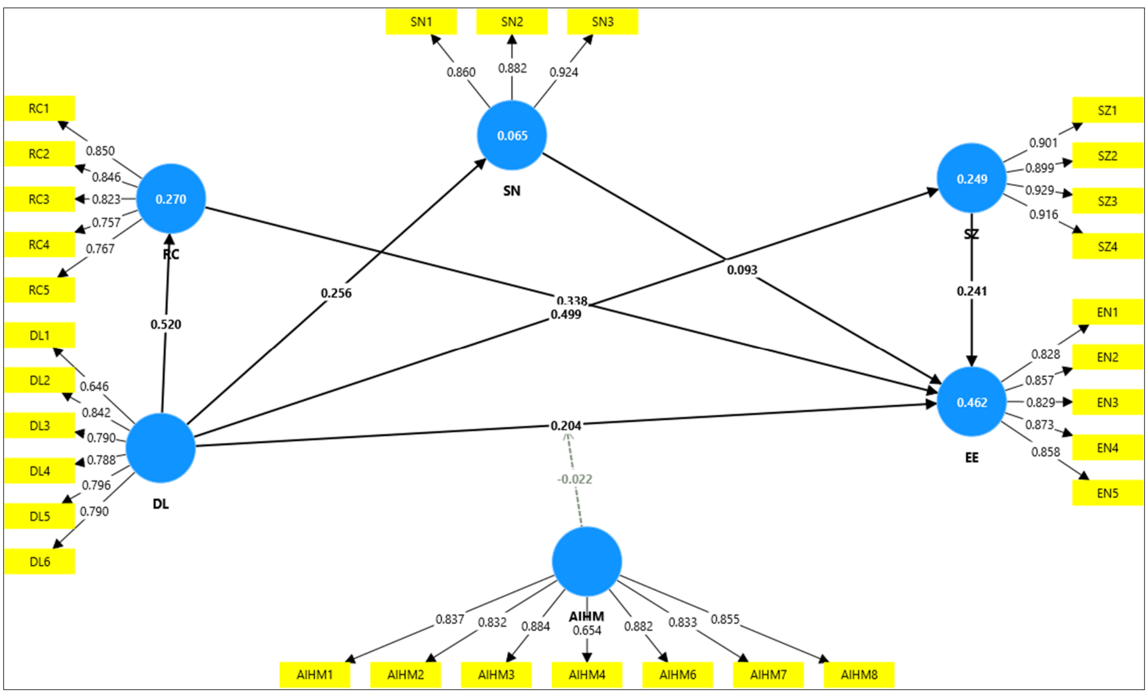


Figure 2. Path Model

The amount of variance in a dependent variable accounted by its predictors, as given by R^2 is 0.25, 0.50, and 0.75, which is weak, moderate, and large explanatory power (Hair et al., 2019). In Table 4.10, employee engagement shows moderate explanatory power (0.462), reconfiguration and seizing show weak power (0.270 and 0.249) and sensing has negligible explanatory power (0.065).

Discussion of Findings

This section discusses the results of each hypothesis tested in the study, reporting whether the hypothesis was supported, the statistical findings, and their alignment with relevant literature.

H1 proposed that digital leadership has a positive effect on employee engagement. This relationship was supported by the results (B = 0.204, p = 0.001), which revealed that digital leaders who integrate innovative ideas and are efficient in their communication in technological workplace settings display a strong impact on the engagement and involvement of the employees. This finding aligns with Aly (2024), who found that digital leadership fosters employee engagement in dynamic contexts by creating a culture of adaptability. In a similar way, Riski and Rino (2024) noted that digital leaders increase the sense of purpose and motivation among employees. H2 postulated that digital leadership positively influenced the sensing capability. This was also supported (β = 0.256, $p < 0.001$), meaning digitally oriented leaders enlarge the capacity of the organisation in recognising emerging opportunities and threats in the market. Tech (2019) and Hussein et al. (2024) made a similar conclusion when they found out that digital leadership facilitates environmental scanning and market intelligence. Hossain et al. (2025) further indicated that digital leaders facilitate data-driven sensing activities, which enhance the responsiveness to change in the environment. This paper establishes the fact that digital leadership plays a significant role in promoting proactive opportunity identification.

The H3 was that digital leadership has a positive influence on seizing capability. The association was highly confirmed (β = 0.499, $p < 0.001$). Leaders who implement the digital tools and strategies are more effective in the mobilization of resources and actions to capture identified opportunities (D'angelo et al., 2024). Razzak et al. (2025) have discovered that digital leaders enhance strategic agility, which means that they can respond to opportunities quickly. Moreover, Chukwunweike and Aro (2024) noted that leaders who are highly digitally savvy reduce decision-making time and allow strategic implementation to occur in an agile manner. These results yield the significance of digital leadership in sensing to executing. H4 stated that digital leadership influences reconfiguring capability positively. The hypothesis was to hold true in the strongest way (beta = 0.520, $p < 0.001$), which implies that the digitally competent leaders are unsurpassed in the process of realignment of processes, structures and resources in the context of technological change. Beth (2024) discovered that digital leadership increases organizational agility through the ability to reconfigure resources. In their study, Craig and Zhao (2021) indicated that these leaders help to transform by re-engineering the processes and reallocating the resources. This helps to conclude that reconfiguring capability is one of the most significant results of digital leadership.

According to the mediation analysis, seizing mediated the correlation between digital leadership and employee engagement at a significant scale (β = 0.120, $p < 0.001$). This implies that leaders have an indirect way of improving engagement through response to opportunities and mobilization of resources. Similar evidence was identified by Terhaar (2021) and Malik (2023), which demonstrates that the capabilities of seizing assist in the translation of leadership into positive employee outcomes. This affirms the essence of transitioning the identification of opportunities to action. The connection between digital leadership and engagement was also mediated by sensing, but the effect was minor (β = 0.024, $p = 0.047$). This implies that the mere detection of opportunities does not contribute to engagement as directly as acting on the detected opportunities. Similar results were reported by Engelmann (2024), who discovered that sensing capabilities have a rather minor impact on performance or engagement unless they are followed by efficient seizing and reconfiguring. The strongest mediation effect was portrayed by reconfiguring (β = 0.176, $p < 0.001$). This shows that leaders are very instrumental in enhancing engagement through reorganization of organizational resources and processes to align with the change conditions. Engelmann (2024) pointed to reconfiguring as a key process of transforming digital leadership into favourable organizational and employee performance.

The moderation analysis revealed that AI-augmented HRM did not significantly influence the relationship between digital leadership and employee engagement (β = -0.022, $p = 0.419$). This indicates that the presence or absence of AI-based HR practices did not change the strength of the leadership–engagement link in the studied NEV industry context. This result partially contradicts recent studies such as Do et al. (2025), which found that AI-enabled HR systems can enhance leadership-driven employee outcomes when employees perceive them as transparent and supportive. The discrepancy may be explained by the relatively early stage of AI-HRM adoption in China's NEV sector, where systems may not yet be mature, fully integrated or trusted by employees. Without sufficient cultural acceptance and alignment with leadership practices, AI-HRM's potential to enhance engagement remains unrealized.

The findings of this study collectively highlight the central role of digital leadership in directly and indirectly enhancing employee engagement in the NEV industry in China. Direct effects demonstrate that digital leaders inspire and involve employees, while indirect effects through dynamic managerial capabilities, especially reconfiguration and seizing, underscore the importance of adaptive resource management in driving engagement. The non-significant moderating effect of AI-augmented HRM indicates that technological HR tools alone are insufficient without strong integration and employee acceptance.

Theoretical, Practical, and Managerial Implications

Theoretical Implications - The study has contributed to the field of knowledge about digital leadership, dynamic managerial capabilities, and engagement of the employees, because the research has proven and provided direct effects, as well as the indirect ones. The findings favour the dynamic capabilities theory (Gao et al., 2025; Teece et al., 1997), it indicates that digital leadership matters in the sense that reconfiguring, seizing, and sensing are considerably enhanced, which in turn leads to engagement. The more powerful mediating effect of reconfiguring and seizing affirms the conclusion that these capabilities have a more decisive role in the outcomes of employees than sensing. The absence of the moderating effect of AI-augmented HRM further indicates that the technological systems might need more profound cultural and procedural integration to have a meaningful impact on engagement.

Practical Implications - The results have relevant managerial insights to organizations in the technology-intensive fields primarily in the NEV sector. It is necessary to develop leadership programs that would enable leaders to develop effective reconfiguring and seizing skills, since they best convert digital leadership into increased employee engagement. The relatively weaker effect of sensing implies that merely identifying digital opportunities is insufficient without the ability to execute and realign resources. Although AI-augmented HRM did not act as a significant moderator, this should not deter investment; rather, it highlights the need to embed such systems within broader leadership and HR strategies to maximize their potential benefits.

Managerial Implications - For managers, the study underscores the need to adopt a digital leadership style that combines strategic vision with the ability to act decisively. Leaders should work towards fostering organizational flexibility, enabling rapid reallocation of resources, and promoting cross-functional collaboration to strengthen reconfiguring capabilities, as emphasized by (T. Ahmad et al., 2023; Vasudevan & Kumar, 2024). They should also enhance seizing capabilities through data-informed, agile decision-making. Finally, integrating AI-augmented HRM into everyday leadership practices is crucial to creating a coherent environment where technology supports, rather than operates separately from, leadership-driven engagement strategies. This alignment is key for sustaining engagement in rapidly evolving digital landscapes.

Limitations and Future Research Directions

This study has several limitations that should be addressed in future research. To begin with, the data were gathered in a cross-sectional manner, and thus it is not possible to conclude the causality between the variables of interest (Maier et al., 2023; Van der Stede, 2014), i.e., between digital leadership and dynamic managerial capabilities, and employee engagement. These relationships may change over time, and longitudinal designs may be more suitable to capture these changes. Furthermore, the research was narrowed to the NEV industry in China, and this can reduce the applicability of the results to other industries or cultures. The external validity might be better accomplished by conducting the research in institutes other than the one used and in other states outside the country. Also, AI-augmented HRM was analyzed as a moderator, and the impact of entirely different organizational variables, such as digital culture or employee trust in technology, was not discussed, but also has been observed to corrode technology adoption and engagement. Future research might have more detailed images by adding these variables. Finally, the self-report measures in use introduce a predisposed likelihood of common method bias, despite the implementation of statistics in the control. The application of multi-source or objective data on performance as recommended by Podsakoff et al. (2012), would lend credibility to the results as these would contribute to measurement robustness.

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Editor: Ramlan Mustapha, Universiti Teknologi MARA, Malaysia
Publisher: CLM Publishing Resources Malaysia

Data Availability Statement: All relevant data are within the manuscript and its Supporting Information files.