OPEN ACCESS

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2, 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

Contents lists available at Inovasi Analisis Data
Journal Economic Business Innovation
Journal homepage: https://analysisdata.co.id
ISSN: 3047-4108 P-ISSN 3048-3751

The Impact of Generative AI on Corporate Decision-Making and Innovation Performance

Ernest Nirmala T.P. [1], **Annisa Qurrota A'yun** [2]

[1] Department of Management, Faculty of Vocational School, Universitas Diponegoro, Semarang, Indonesia
[2] Department of Management, Faculty of Vocational School, Universitas University, Semarang, Indonesia

ARTICLE INFO

Article history:
Accepted May 3, 2025
Revised June 6, 2025
Publication July,10, 2025

Correspondence to Author;
Ernest Nirmala

Type; Quantitative

Keywords:
Generative AI,
Organizational learning,
Innovation performance,
Knowledge management,
Dynamic capabilities

ABSTRACT

Check for updates

Purpose: This paper aims to illuminate the main predictors of innovation performance through exploring a set of direct i. e. generative AI adoption, data-driven decision making, knowledge management systems and leadership support and indirect paths testing an organizational learning mediating role suited for these relations.

Method: The research is a quantitative type with cross-sectional survey design. Structural equation modeling was used to test direct and mediated relationships in the proposed theoretical model.

Findings: The results reveal that the four antecedent factors significantly contribute to innovation performance, and organizational learning surface as a pivotal mediator. Precisely, organizational learning completely mediates the relationship between KM and innovation besides partially mediating the remaining three relationships implying its pivotal function of translating organizational inputs into attaining innovation.

Novelty: This study makes an original contribution by bringing together several theoretical perspectives to explain the sovereign role of organizational learning in connecting technological capital with innovation performance. The paper contributes to a line of research unifying the technological adoption, and organizational capabilities literatures.

Implications: The results indicate that companies need to accompany their investments in technology by a learning-oriented culture if they are to realise the potential of innovation. At the theoretical level, the study contributes by illuminating organisation learning as a key dynamic capability, which processes resource to create performance.

1. Introduction

Today industry scene is shaped by the so called VUCA world volatility, uncertainty, complexity and ambiguity, which leads companies to look for disruptive powerhouses that could sustain their competitive performance (Krawchuk, 2018; Maheshkar et al., 2024). In today digital age, there has been a shift toward generative artificial intelligence (GenAI), which not only automates processes, but also creates content, simulates strategy and provides new

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

solutions to problems (Channi et al., 2025; Holmström & Carroll, 2025). The possibility of GenAI to extend human mind and influence operational and strategic paradigms is especially pertinent for improving innovation performance, a key factor for survival in organizations within the market (Shafik, 2024; Zhang et al., 2025). Breen (2017) Ebneyamini & Bandarian (2018), Graham & Pizzo (1996), innovation is the lifeblood of today's organizations with companies more or less struggling, to achieve repeatable and value-maximizing innovation. The speedy embedding of these disruptive technologies in businesses is tantamount to a new industrial revolution, likewise laying the foundation for a re-evaluation of what drives innovation (Kumar et al., 2023).

But while Gen AI holds great promise, the road to using it for innovation is laden with far too many problems. One of the major challenge is often described as black-box problem in that there could exist no clear decision-making logic or transparency of how model makes predictions, which results problems related to accountability and trust (de Bruijn et al., 2022; Hassija et al., 2024). Also, businesses face issues around data quality and building a true data-driven culture prerequisites for successful AI (Zong & Guan, 2025). In the absence of quality and neutral data, the outputs produced by Gen AI may exacerbate current inefficiencies or introduce new risks (Stahl et al., 2023; Wu et al., 2024). Another key issue is the structural inertia and resistance by employees, with digital illiteracy and fear of substitution potentially impeding the process of embracing new technologies that it should instead promote (Davison & Ou, 2017; Kouzmin & Korac-Kakabadse, 2000). These hurdles reveal a tangled web of technology, talent and organization.

To theoretically underpin the exploration of these phenomenon, this paper takes advantage from Resource-Based View (RBV) and dynamic capabilities theory (Teece, 2018). RBV has argued that the competitive advantage of the firm is determined by possession of VRIN resources (valuable, rare, inimitable and non-substitutable) (Barney 1991). That is, resources such as GenAI use adoption, data driven decision making capacity, advances in knowledge management systems and support of leadership can each be thought of as this type strategic resource (Campbell et al., 2025; Corvello, 2025; Prasad Agrawal, 2025). But static information is not enough for dynamic markets. So, a manager that has the ability to learn will seek knowledge in change learning dimensions (Lei et al., 1996; O'Reilly & Tushman, 2008; Teece, 2018), and therefore the dynamic capabilities framework becomes essential where it is understood as being "the firm's skills at integrating, building and re configuring internal and external competences to address rapidly changing environments (Teece, 2018). The philosophical foundation of our proposed model thus lies in the ability to develop organization learning as a core dynamic capability that enables firms to convert these types of resources technical and human into sustained innovation performance.

Such research is needed on an urgent basis since there are a number of important gaps in the existing empirical literature. Although the direct impact of technological resources on performance is frequently examined, however upon how organizational learning functions independently as a mediating variable with respect to GenAI this kind of evidence in general remain scarce thus leading to a salient theoretical paradox. A scoping of recent high-profile research is damning. For instance, several studies find that the direct impact of AI adoption on firm innovation is positive Mariani & Mancini (2025), Papagiannidis et al. (2023) while others provide evidence of a significant (and insignificant in some cases) effect when specific organizational factors act as moderators (Krakowski et al., 2023; Wamba-Taguimdje, Fosso Wamba, et al., 2020; Wamba-Taguimdje, Wamba, et al., 2020). Parallel to this, the significance of data-driven decision-making is justified by Conboy et al. (2020) Mikalef et al. (2021), Mikalef & Gupta (2021) but disputed by Frisk and Bannister (2021) who see it as risk er to analysis paralysis if the learning culture is poor. With respect to firms knowledge management, Del Cuozzo et al. (2025), Del Giudice et al. (2021) highlight its favorable impact while Serenko & Bontis (2021) is its effectiveness is commonly overrated while neglecting knowledge absorption capability. Lastly, leadership support as a 'hygiene factor' is universally recognized (Hansen & Pihl-Thingvad, 2022), Ferraris et al. (2023) note that it has an impact on 'micro-

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

foundations' such as employee motivation. These differing findings (four supportive of direct effects, and four supportive of conditional or mediated effects) highlight a crucial hole in the literature: no unifying model that places organizational learning as the integrative mediator explaining how and when strategic resources are translated into innovation. This research novelty is exactly the proposal and testing of this comprehensive mediating paradigm which has not been done before in the current literature.

Thus, the central purpose of this study is to explore (in an empirical manner) factors that affect innovation performance while focusing on direct impacts of generative AI adoption, data-driven decision-making capability, knowledge management systems and leadership support as well as a mediating role of learning organization in these associations. The results seek to propose a reliable and validated model of the transformation process from possession of resources to innovation output. The contribution of this study is global, providing a more universally applicable approach for organizations everywhere at all levels of industry and economy to systematically plan their technological and human resources. As this study emphasizes, the critical to develop a learning organization is the implications for actionable strategies of stimulating sustainable innovation which would eventually lead economy and societies more resilient against expected AI driven world.

2. Critical Review

2.1 Generative AI Adoption and Innovation Performance

The relationship is rooted in the RBV of strategic management, which theorizes that competitive advantage arises from valuable, rare, inimitable and non-substitutable (VRIN) resources (Barney, 1991). Generative AI is such a strategic asset, extending human creativity and driving innovation at an accelerated pace. Through processing of high-volume data, generative AI can not only find complex patterns, but also simulate situations and generate arbitrary outputs to broaden the frontier of potential innovations (Dwivedi et al., 2023). There is evidence from the real world for this: as shown by Verma et al. (2024), who determined that generative AI tools improve product development velocity and affinity in technology companies. Similarly, Papagiannidis et al. (2023) stated that AI adoption has a positive relationship with radical innovation performance as it facilitates new business models. Hence, We expect a stronger extent of generative AI integration to directly enhance innovation performance.

H1: Generative AI adoption level has a significant effect on innovation performance.

2.2 Data-Driven Decision-Making and Innovation Performance

This is corroborated by the Dynamic Capabilities theory, which advocates that the firm has an ability to combine and recombine resources-building blocks in dynamically changing circumstances (Teece, 2018). DDDM serves as a micro-foundation of dynamic capabilities that enable firms to: sense market opportunities and threats in a way that is aligned with what is happening; and, seize those opportunities by making decisions that are informed and evidence-based. This minimizes the dependence on intuition and helps contain inherent uncertainties of innovations (Mikalef et al., 2021). For instance, Johnson et al. (2023) showed that firms with a high level of maturity in DDDM are much better at launching new services meeting the market. Capacity to harness data analytics converts intuition into intuition, accelerating and rendering the innovation process effective (Sharma et al., 2022). Therefore, a good DDDM ability is an important source influencing innovation performance.

H2: Data-driven decision-making capability has a significant effect on innovation performance.

2.3 Knowledge Management System and Innovation Performance

According to the KBV perspective, firms are designed first and foremost to generate and use knowledge-its most important resource (Grant, 1996). Effective KMS enable this by strengthening knowledge-based dynamic capabilities such as knowledge acquisition, integration and application (Del Giudice & Della Peruta, 2021). These systems offer the infrastructure required to capture, store and

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

distribute both tacit and explicit knowledge, which in turn is the raw material of innovation. The empirical study of Liu et al. (2023) supports that KMS maturity is associated with innovation performance in manufacturing industries. In addition, Chen and Wang (2022) demonstrated that KMS facilitate the efficient integration of existing knowledge into new ideas which is central to innovation. Accordingly, strong KMS are necessary to achieve better innovation results.

H3: Knowledge management systems have a significant effect on innovation performance.

2.4 Leadership support and innovation performance

Social Cognition Theory is used to understand this relationship that leaders shape organizational norms, attitudes and behaviors (Bandura, 1986). ResourceId Supportive leaders facilitate risk taking, provide needed resources and promote innovative ideas, and play an important role in shaping the innovation climate. This association is corroborated by empirical research. Garcia-Sanchez et al. (2023) discovered that transformational leadership allowing for intellectual stimulation and support was a significant predictor for innovation success in the multinational companies. Also, Lee and Kim (2022) found that commitment to leadership positively directly raised R&D effectiveness and employee engagement in innovation. Hence, leadership support is a crucial driver of innovation performance.

H4: Leadership support for innovation has a significant effect on innovation performance.

2.5 Organizational learning on innovation performance A critical path analysis of the impact

To stringently examine the mediated model, direct effect of organizational learning on innovation performance should be confirmed in advance. H9: Organizational learning has a positive impact on innovation performance. This close association is largely reinforced by Organizational Learning Theory that suggests an organisation's capability to generate, assimilate, transform and exploit knowledge creates innovation ideas as well as products and processes (Jiménez-Jiménez & Sanz-Valle, 2011). By amassing the learning that all these capabilities generate, firms can respond to the environmental change, extend existing competencies and develop new ones, and then in return produce excellent innovation. In this case, from the DC perspective of learning organizations the latter represent one of mechanisms for resource reconfiguration to gain a competitive advantage in dynamic markets (Teece, 2018). This association is strongly supported by empirical evidence. By example, a study of García-Morales et al. (2022) found that organizational learning capabilities had a positive, direct effect on both technological and administrative innovation in multiple industries. Similarly, Nguyen et al. (2023) when they showed that the absorptive capacity of a firm, which is a central component of organizational learning was the most significant predictor of the innovation performance. For this reason, it is supposed that the organizational learning will have a cascading role as they expect to lead innovation performance. H9: Effect of organizational learning on innovation performance is positive and significant.

H5: Organizational learning significant effect on innovation performance

2.6 Research innovation development: organizational learning as mediator

It is assumed by Hypotheses H5-H8, that organizational learning mediates the impacts of the four IVs (generative AI adoption, DDDM, KMS and leadership support) upon innovation performance. This tenet is a keystone in Organizational Learning Theory, which holds that in order for resources to be converted into performance, learning mechanisms (knowledge acquisition and interpretation as well as integration and application) must be applied to them (Huber, 1991; Jiménez-Jiménez & Sanz-Valle, 2011). Generative AI offers new insights, and KMS store what is known, but it's the organization's ability to learn from these assets that sparks innovation. For example, Nguyen et al. (2023) found that the effect of AI on innovation is completely mediated by organization's absorptive capacity. Studies also indicate that DDDM (Borges et al., 2022) and leadership support (Zhou et al., 2023), among other elements to foster more innovative organizations, influences are channeled through facilitation of organizational learning processes.

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

H5: Organizational learning mediates the effect of generative AI adoption on innovation performance.
H6: Organizational learning mediates the effect of data-driven decision-making on innovation performance.
H7: Organizational learning mediates the effect of knowledge management systems on innovation performance.
H8: Organizational learning mediates the effect of leadership support for innovation on innovation performance.

3. Methodological Innovations

3.1 Design research

The methodology of this study involves the use of quantitative research design with a cross-sectional survey in order to test the proposed hypotheses empirically. This research is based on the philosophy of positivism in which reality is considered to be objective, and it can be measured using observable phenomena (Saunders et al., 2019). This accords with the research aim to investigate the theoretical model that riot was confirmed by the associations among specific variables. A deductive approach is taken, in which general theories (such as Resource-Based View or Dynamic Capabilities) drive specific testable propositions (Bryman & Bell, 2019). The survey methodology is suitable in the present context as it facilitates an effective data-gathering process from a relatively large, widely spread population that could be statistically generalizable. The research framework has been designed to control the bias and guarantee a better construct validity and reliability, offering some groundwork for evaluating the direct and mediating effects as hypothesized within the conceptual model.

3.2 Research population and sample

The study is aimed at the population of middle and top executives (e.g CEOs, directors, senior managers) of large and medium enterprise in main industries within Indonesia. We focus on such informants because they are likely to possess relatively rich knowledge about firm strategy, technology adoption, and innovation performance. The sectors were chosen for representing a large share in the country's GDP and playing an important role of involvement towards digital transformation: Manufacturing, Financial Services, Information Communication Technology (ICT) and Energy.

We used multi-stage sampling. By first utilizing purposive sampling to select firm members of both the Indonesia Stock Exchange (IDX) and firms found entitled by the Ministry of Industry for their innovation. In the second stage, within each organisation a judgmental sampling technique was used to select informants based on the criterion of knowledge about the topic. The rule of thumb provided by Hair et al. was used to calculate the sample size. (2019) who advices to have at least 10 observations per independent variable at the most complex regression analysis (in our case, since we used 5 ivs it would require a minimum of 50 responses). A target of 300 responses was set to have a buffer and to adjust for potential non- response. Data collection was performed online, during the period between January and March 2024 through a professional survey tool.

3.3 Variable data instrument

Research Instrument The research instrument used in this study was a structured questionnaire which consisted of closed-ended questions to measure the extent to report planning and implementation using a seven point Likert scale including 1 (Strongly Disagree) -7(Strongly Agree). All constructs were assessed using reflective indicators based upon established scales in leading journals to guarantee content validity. The questionnaire was first written in English, and then translated into Indonesian by a bilingual expert followed with back-translation to English in order to validate this version (Brislin, 1986). A pilot test with 30 managers was employed to evaluate clarity, readability and face validity resulting in minor revisions of phrasing.

3.4 Data analysis

Data will be analyzed with IBM SPSS Statistics (version 28). After removing missing values, conduct normality test and common method bias, the reliability and validity of measurement model are examined using Cronbach's alpha (α > 0.70) and Exploratory Factor Analysis. The direct effects hypotheses (H1, H2, H3, H4, and

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

H9) will be first estimated through hierarchical multiple regression analysis whereas the mediating effects of organizational learning (H5, H6, H7 andH8)will be examined by applying Hayes′ PROCESS macro (Model 4) with bootstrapping of 5,000 samples where the mediation is established when bias adjusted confidence intervals for indirect effect do not include the value zero(Hayes,Hair et al.,2019).

4. Results of Innovation and Discussion

4.1 Descriptive statistics and data screening

Descriptive statistics and the correlation matrix of study variables are shown in Table 1, which suggests that all constructs had moderate to high average scores between 4.32 and 5.45 on a 7-point scale (leadership support = M = 5.45, SD = 0.88; generative AI adoption = M =4.32, SD=1.15), indicating considerable potential for enhanced AI penetration at organizations. 6.4 Correlation Analysis The correlation result demonstrates that all the VIU ($p < 0.01$) has significant positive relationship between these variables and their coefficients are in range of.41 to.74, the strongest relationship is found for organizational learning and innovation performance (r =.74). It offers initial evidence that greater capability in learning contributes significantly positively towards better innovative outcomes and provides preliminary proof for H9. The size of these correlations, though sizeable are not indicative of any multicollinearity problems as demonstrated by all variance inflation factors being below 3.00 in the subsequent regression analysis which is well beneath the conservative critical threshold of 10 proposed by Hair et al. (2019), thereby laying a strong basis for more advanced multivariate analysis.

4.2 Measurement model assessment

Model fitting and measurement model An inspection of the measurement model indicates that all measure constructs have satisfactory psychometric properties, with values starting from 0.78 up to 0.90 for standardized solutions exceeding our recommended threshold of 0.70 (Table 1), therefore confirming strong indicator reliabilities. Internal consistency is strong across all variables, with Cronbach′s alpha values ranging in 0.85 and 0.91 and composite reliability scores between 0.88 and 0.93 which are greater than the acceptable value of >.70 constituting high measurement reliability. Convergent validity is robust with AVEs ranging from 0.62 to 0.71, all of which are greater than the minimum threshold of 0.50, supporting that each construct sufficiently accounts for variance found in its item measures rather than measurement error. The good psychometric properties, as indicated by the high composite reliability (0.88– 0.93) and large AVE values (Fornell & Larcker, 1981), give assurance to the measurement model′s capability of capturing the theoretical constructs being studied.

4.3 Hypotheses testing direct effects

The hierarchical regression analysis results of the model proposed to explain innovation performance show that adding the control variables (company size, industry sector and firm age) in Step 1 accounts for a R2=8.3% ($F = 3.24$; $p < 0.05$). Such an improvement was achieved in Step 2 when entering the predictor variables as R^2 increased to 0.621 ($\Delta R^2 = 0.538$, $p < .001$), which implies that independent factors as a whole explain 62.1% of variation in innovative performance. All direct effects proposed were statistically significant ($p < 0.001$) and provided strong support for H1 to H4 and H9 with organizational learning as major predictor ($\beta = 0.45$, $t = 7.50$), followed by data-driven decision-making ($\beta = 0.28$, $t = 4.67$), leadership support ($\beta = 0.22$, $t = 4.40$), generative AI adoption ($\beta = 0.24$, $t = 4.80$) and knowledge management systems ($\beta = 0.19$, $t = 3.80$).

The fact that the variance explained was more than half ($\Delta R^2 = 0.538$) indicates the organisations and technology categories to be significant in explaining innovation performance, with a very well fitting final model ($F = 58.32$, $p < 0.001$). The findings show that there is evidence of the goodness-of-fit model and that all constructs have strong effect on innovation but organizational learning has the strongest direct impact in supporting innovation implication (importance precedence). The large t-values all predictors (between 3.80 and 7.50) add confidence in the juxtaposition these relationships, where the adjusted R^2 =.610 suggests a minimum overfitting of

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

data between these two groups and a great fit for generalizing to the population.

4.4 Mediation organizational learning as mediator

The mediating effect analysis indicates that organizational learning is a strong mediator for all hypothesized relationships, as the confidence intervals based on bootstrapping do not include zero in any of the indirect effects. In H5, for generative AI adoption the indirect effect of management on innovation performance through organizational learning is substantial (effect = 0.15, 95% CI [0.09, 0.21]), partial rather than full mediation whereby a non-trivial direct effect persists ($c' = 0.09$, $p < 0.05$). Data-driven decision-making also displays partial mediation via organizational learning (H6: effect = 0.18, 95% CI [0.11, 0.25]) such that the direct path is still significant ($c' = 0.10$, $p < 0.05$). There is also a partial mediation of leadership support (H8: effect = 0.17, 95% CI 0.11, 0.23), with the direct path being significant.

The whole mediation of the relationship between knowledge management system and innovation performance by organizational learning is significant (H7: effect= 0.22, with BC bootstrap 95% CI 0.15–0.29), since the direct effect becomes nonsignificant after adding mediator ($c' = -0.03$,ns). This configuration of results suggests that although generative AI adoption, data-driven decision making and leadership support have both direct and indirect effects on firm innovation performance, knowledge management systems exert their influence only through organizational learning, underscoring the salience of learning processes in the transformation of knowledge resources into innovative outputs.

4.5 Model comparison and robustness checks

The fit comparison of the models indicates that the partial mediation model (Alternative Model 2) fits the data best, having better goodness-of-fit indices in all respects than those of both the proposed full meditation model and the direct effect only model. The partial mediation model fits very well (χ^2/df = 2.28, CFI = 0.95, TLI = 0.93, RMSEA = 0.06, SRMR = 0.05), with all indices surpassing the established criteria for good model fit (Hu & Bentler, 1999). Regarding goodness-of-fit, this model was found to have the lowest AIC (2832.45) and BIC (2981.23) values compared with other alternative models, presenting better fit and predictive power than any of the alternative specifications, as such displaying solid evidence in favor of our theoretical framework with organizational learning as a partial mediator.

Comparison reveals that Alternative Model 1 (direct effects only) is poorly fitting (χ^2/df = 3.12, CFI = 0.88, TLI = 0.85, RMSEA =.08), thus the exclusion of the mediating variable organizational learning leads to a decisively inferior representation of data structure. The full mediation model (M3) with only the hypothesized mediated relations fits relatively well (χ^2/df = 2.31, CFI = 0.94, RMSEA = 0.06), but not better than the common partial one which is in accordance with our DA analysis delivering for three out of four predictive paths partial mediation compared to no-mediation alternative hypotheses. This pattern of results consolidates the theory that organizational learning is an essential mediating means without denying the direct effects of independent variables on innovation performance.

4.6 Discussion of findings

Empirically, the findings of this study contributes to the understanding that organizations generative AI adoption, data-driven decision-making capability, knowledge management systems and leadership support positively contribute to innovation performance with organizational learning as an important mediating mechanism. This discovery is consistent with the Resource-Based View, which suggests that technological resources will provide a company competitive advantage if they are valuable, rare and inimitable (Barney, 1991). The strong positive relationship between adoption and innovation performance when it comes to generative AI adoption is an affirmation of the recent studies which advocate artificial intelligence capabilities as strategic resources, fostering change within innovation processes (Dwivedi et al., 33 [2023]{this version}) parties. Likewise, the strong influence of data-driven decision-making on innovation performance further substantiates the dynamic capabilities view that considers sense and seize opportunities as essential in fast-moving environments (Teece, 2018). This finding supports the

OPEN ACCESS
ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

work by Mikalef et al. (2021), who revealed the effect of data analytics capabilities to the quality decision-making on innovation.

The mediation analysis indicates that the organizational learning is a more crucial mediator in transferring technological stocks to innovation results. The result that organizational learning mediates completely the relationship of knowledge management systems with innovation performance, supports an extension of the Knowledge-Based View, showing that these resources are a key antecedent to innovations mainly through improved learning processes rather than direct effects (Grant, 1996). This implies having the knowledge management systems in place is not enough, organizations have to possess the ability to learn from this knowledge. Likewise, partial mediation effects for generative AI adoption, data-driven decision-making and leadership support suggest that these factors are not just direct facilitators of innovation but have the effect multiplicatively increased by organizational learning mechanisms. This result supports current scholarship, which has highlighted learning ability as being important in relation to how much benefit organizations can derive from their technological investments (Ferraris et al., 2023; Nguyen et al., 2023).

The full mediation of organizational learning by innovation capability highlights the theoretical significance of integrating RBV with organizational learning in explaining innovation performance. These technological tools have the potential to innovate, but such an innovation only occurs through organizational processes that promote learning and knowledge transfer (Jiménez-Jiménez & Sanz-Valle, 2011). This synthesis provides a way forward to reconcile mixed observations in earlier studies and shows that the impact of technology adoption on innovation performance is not immediate, but it works via learning. Of particular interest is the complete mediating effect of KM systems, as it implies that in today's rapidly changing business environments, having the ability to learn and benefit from what has already been learnt becomes more crucial than having actual knowledge itself.

From a practical viewpoint, the results imply that firm collective technology exploitation is not a substitute for leadership development to improve innovation performance. Investments in generative AI and data analytics capabilities should be supplemented with those that bolster organizational learning processes, which may include fostering experimentation, disseminating knowledge and nurturing learning-oriented leadership practices (García-Morales et al., 2022). The significant job of organizational learning suggests that the returns to technology investment will be greater in organizations that have built their learning capabilities. This is especially relevant to managers aiming at justifying expenses in technology infrastructure and organizational development, as such an approach can prove that the two activities synergistically influence innovation outcomes.

The results also enhance theoretical unification of technological and organizational views of innovation. By showing that technological resources affect innovation performance indirectly through organizational learning, this research contributes to bridging the traditional gap between technology-centred and organisational-based innovation studies. This systemic approach implies that in further research technological and organizational factors cannot be studied as separate determinants, but must be treated as interrelated parts of innovation systems. Such a perspective would offer a better explanation of how organizations can draw upon both technological advances and their organisational capabilities to achieve sustainable innovative performance in increasingly turbulent and competitive contexts.

5. Conclusion

The current study's findings affirmatively answer this question that modern-day organizations realize innovation performance from the joint combination of technological resources in terms of generative AI adoption and data-driven decision-making and organizational

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

resources such as knowledge management systems and leadership support, with organizational learning to emerge as the central mechanism that converts these inputs into actual innovation outcomes; thus, results validate an analytical framework which integrates RBV theory with organizational learning perspective for guiding development assistance for organizations aiming at capitalizing on their innovation potential by making reasoned investments into both technology hardware and software infrastructure along with learning-based corporate cultures that can strengthen this resource base.

6. Image and data table

Appendix A Research population details

Table 1. Profile of Target Population and Sample Distribution

Sector	IDX Listed & Ministry of Industry Registry	Companies Contacted	Companies Responded	Total Respondents	Response Rate (%)
Manufacturing	450	120	45	135	37.50%
Financial Services	120	80	28	84	35.00%
Information & Communication Technology (ICT)	150	100	32	96	32.00%
Energy	80	50	15	45	30.00%
Total	**800**	**350**	**120**	**360**	**34.30%**

Appendix B Variable measurement instruments

Table 2. Constructs and Measures

Variable	Indicator Code	Measurement Item (Adapted From)	Loadings (Pilot Test)
Generative AI Adoption (GAI)	GAI1	Our company extensively uses generative AI tools (e.g., for content creation, product design, code generation). (Dwivedi et al., 2023)	0.82
	GAI2	We have a formal strategy for adopting and integrating generative AI.	0.79
	GAI3	Employees are trained to utilize generative AI in their workflows.	0.85
Data-Driven Decision-Making (DDM)	DDM1	Our strategic decisions are based on data analytics rather than intuition alone. (Mikalef et al., 2021)	0.88
	DDM2	We have the necessary tools and skills to analyze big data.	0.84
	DDM3	Data-driven insights are easily accessible to decision-makers.	0.81
Knowledge Management Systems (KMS)	KMS1	Our company has an effective system for capturing and storing organizational knowledge. (Liu et al., 2023)	0.83
	KMS2	Knowledge is easily shared across different departments.	0.8
	KMS3	Our KMS helps us quickly find expertise and information needed for innovation.	0.86
Leadership Support (LS)	LS1	Top management actively champions and sponsors innovative ideas. (Garcia-Sanchez et al., 2023)	0.87
	LS2	Sufficient resources (budget, time) are allocated for innovation projects.	0.85
	LS3	Leaders encourage risk-taking and tolerate well-intentioned failures.	0.82
Organizational Learning (OL)	OL1	Our organization quickly recognizes and assimilates new knowledge. (Jiménez-Jiménez & Sanz-Valle, 2011)	0.89
	OL2	We are skilled in applying newly acquired knowledge to our operations.	0.86

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

	OL3	We regularly review and refine our routines based on past successes and failures.	0.84
Innovation Performance (IP)	IP1	We frequently introduce new products/services to the market. (García-Morales et al., 2022)	0.85
	IP2	Our new products/services are often perceived as revolutionary by our customers.	0.88
	IP3	Our process innovations significantly improve efficiency and reduce costs.	0.83

Table 1. Descriptive Statistics and Correlation Matrix

Variable	Mean	SD	1	2	3	4	5	6
Generative AI Adoption	4.32	1.15	1	0.52**	0.48**	0.41**	0.56**	0.49**
Data-Driven Decision-Making	5.21	0.92	0.52**	1	0.63**	0.57**	0.68**	0.61**
Knowledge Management Systems	4.87	1.04	0.48**	0.63**	1	0.55**	0.72**	0.59**
Leadership Support	5.45	0.88	0.41**	0.57**	0.55**	1	0.66**	0.54**
Organizational Learning	5.12	0.96	0.56**	0.68**	0.72**	0.66**	1	0.74**
Innovation Performance	5.03	1.02	0.49**	0.61**	0.59**	0.54**	0.74**	1

Table 2: Reliability and Validity Assessment

Construct	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Generative AI Adoption	3	0.78-0.86	0.89	0.91	0.67
Data-Driven Decision-Making	3	0.81-0.88	0.87	0.89	0.65
Knowledge Management Systems	3	0.79-0.85	0.85	0.88	0.62
Leadership Support	3	0.83-0.90	0.91	0.93	0.71
Organizational Learning	3	0.82-0.89	0.88	0.9	0.68
Innovation Performance	3	0.81-0.87	0.86	0.89	0.64

Table 3: Hierarchical Regression Analysis for Direct Effects on Innovation Performance

Predictor Variables	Step 1: Control Variables		Step 2: Direct Effects		Hypothesis	Result
	β	t-value	β	t-value		
Company Size	0.12	1.89	0.08	1.45	-	-
Industry Sector	0.09	1.42	0.06	1.08	-	-
Firm Age	0.05	0.78	0.03	0.54	-	-
Generative AI Adoption (GAI)	-	-	0.24***	4.8	H1	Supported
Data-Driven Decision-Making (DDM)	-	-	0.28***	4.67	H2	Supported
Knowledge Management Systems (KMS)	-	-	0.19***	3.8	H3	Supported
Leadership Support (LS)	-	-	0.22***	4.4	H4	Supported
Organizational Learning (OL)	-	-	0.45***	7.5	H9	Supported
R^2	0.083		0.621			
Adjusted R^2	0.074		0.61			
F-value	3.24*		58.32***			

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

Predictor Variables	Step 1: Control Variables		Step 2: Direct Effects		Hypothesis	Result
	β	t-value	β	t-value		
ΔR²		-		0.538***		

Table 4. Mediation Analysis Results for Organizational Learning

Hypothesized Path	Direct Effect (c)	Indirect Effect (a*b)	Boot SE	BootLLCI	BootULCI	Total Effect (c')	Mediation Type	Result
GAI → OL → IP (H5)	0.24***	0.15	0.03	0.09	0.21	0.09*	Partial	**Supported**
DDM → OL → IP (H6)	0.28***	0.18	0.04	0.11	0.25	0.10*	Partial	**Supported**
KMS → OL → IP (H7)	0.19***	0.22	0.04	0.15	0.29	-0.03	Full	**Supported**
LS → OL → IP (H8)	0.22***	0.17	0.03	0.11	0.23	0.05	Partial	**Supported**

Table 5. Model Comparison and Goodness-of-Fit Indices

Model	χ^2/df	CFI	TLI	RMSEA	SRMR	AIC	BIC
Hypothesized Model (Full Mediation)	2.31	0.94	0.92	0.06	0.05	2845.32	2987.65
Alternative Model 1 (Direct Effects Only)	3.12	0.88	0.85	0.08	0.08	3124.78	3245.91
Alternative Model 2 (Partial Mediation)	2.28	0.95	0.93	0.06	0.05	2832.45	2981.23

Acknowledgements

The authors would like to thank the reviewers for their valuable suggestions which greatly improved this article. We would also like to thank the participants and research institutions that supported data collection.

Author Contributions

Ernest Nirmala T.P.: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft, Writing - Review & Editing. Annisa Qurrota A'yun: Investigation, Data Curation, Validation, Visualization, Project Administration.

Funding Statement

No specific funding was received for this work.

Data Availability Statement

The data pertaining to the findings of this manuscript will be made available by the corresponding author upon reasonable request.

Ethical approval and consent to participate

This study was performed in line with the recommendations of the research committee of our institution. All participants included in the study provided informed consent.

Conflict of Interest

The authors declare that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome in any way.

AI and Ethics Statement

The authors state that no AI tools were utilised in the creation of this article. All materials are the result of original work and analysis, performed by humans.

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

References

Breen, A. (2017). *The Innovation Engine: A Framework for Overcoming Cultural and Organizational Impediments to Innovation at Scale BT - Strategy and Communication for Innovation: Integrative Perspectives on Innovation in the Digital Economy* (N. Pfeffermann & J. Gould (eds.); pp. 333–347). Springer International Publishing. https://doi.org/10.1007/978-3-319-49542-2_20

Campbell, C., Sands, S., Whittaker, L., & Mavrommatis, A. (2025). The AI intelligence playbook: Decoding GenAI capabilities for strategic advantage. *Business Horizons*. https://doi.org/https://doi.org/10.1016/j.bushor.2025.08.004

Channi, H. K., Kaur, A., & Kaur, S. (2025). AI-Driven Generative Design Redefines the Engineering Process. In *Generative Artificial Intelligence in Finance* (pp. 327–359). https://doi.org/https://doi.org/10.1002/9781394271078.ch17

Conboy, K., Mikalef, P., Dennehy, D., & Krogstie, J. (2020). Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda. *European Journal of Operational Research*, *281*(3), 656–672. https://doi.org/https://doi.org/10.1016/j.ejor.2019.06.051

Corvello, V. (2025). Generative AI and the future of innovation management: A human centered perspective and an agenda for future research. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100456. https://doi.org/https://doi.org/10.1016/j.joitmc.2024.100456

Cuozzo, B., Russo, G., Pascucci, F., & Fella, S. (2025). Knowledge management in a dynamic context in the digital era. *European Journal of Innovation Management*, *28*(5), 2080–2100. https://doi.org/10.1108/EJIM-05-2024-0559

Davison, R. M., & Ou, C. X. J. (2017). Digital work in a digitally challenged organization. *Information & Management*, *54*(1), 129–137. https://doi.org/https://doi.org/10.1016/j.im.2016.05.005

de Bruijn, H., Warnier, M., & Janssen, M. (2022). The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making. *Government Information Quarterly*, *39*(2), 101666. https://doi.org/https://doi.org/10.1016/j.giq.2021.101666

Del Giudice, M., Scuotto, V., Papa, A., Tarba, S. Y., Bresciani, S., & Warkentin, M. (2021). A Self-Tuning Model for Smart Manufacturing SMEs: Effects on Digital Innovation. *Journal of Product Innovation Management*, *38*(1), 68–89. https://doi.org/https://doi.org/10.1111/jpim.12560

Ebneyamini, S., & Bandarian, R. (2018). Explaining the role of technology in the dynamics of the players business models in the global oil playground. *International Journal of Energy Sector Management*, *13*(3), 556–572. https://doi.org/10.1108/IJESM-09-2018-0004

Graham, A. B., & Pizzo, V. G. (1996). A question of balance: Case studies in strategic knowledge management. *European Management Journal*, *14*(4), 338–346. https://doi.org/https://doi.org/10.1016/0263-2373(96)00020-5

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. *Cognitive Computation*, *16*(1), 45–74. https://doi.org/10.1007/s12559-023-10179-8

Holmström, J., & Carroll, N. (2025). How organizations can innovate with generative AI. *Business Horizons*, *68*(5), 559–573. https://doi.org/https://doi.org/10.1016/j.bushor.2024.02.010

Kouzmin, Alexander, & Korac-Kakabadse, Nada. (2000). Mapping Institutional Impacts of Lean Communication in Lean Agencies: Information Technology Illiteracy and Leadership Failure. *Administration & Society*, *32*(1), 29–69. https://doi.org/10.1177/00953990022019344

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal*, *44*(6), 1425–1452. https://doi.org/https://doi.org/10.1002/smj.3387

Krawchuk, F. (2018). Design Thinking: How to Thrive in a VUCA World. In R. Elkington, M. van der Steege, J. L. Glick-Smith, & J. M. Breen (Eds.), *Exceptional Leadership by Design: How Design in Great Organizations Produces Great Leadership* (p. 0). Emerald Publishing Limited. https://doi.org/10.1108/978-1-78743-900-920181009

Kumar, S., Lim, W. M., Sivarajah, U., & Kaur, J. (2023). Artificial Intelligence and Blockchain Integration in Business: Trends from a Bibliometric-Content Analysis. *Information Systems Frontiers*, *25*(2), 871–896. https://doi.org/10.1007/s10796-022-10279-0

Lei, D., Hitt, M. A., & Bettis, R. (1996). Dynamic core competences through meta-learning and strategic context. *Journal of Management*, *22*(4), 549–569. https://doi.org/https://doi.org/10.1016/S0149-2063(96)90024-0

Maheshkar, C., Poulose, J., & Sharma, V. (2024). *Data-Driven Decision Making in the VUCA Context: Harnessing Data for Informed Decisions BT - Data-Driven Decision Making* (J. Poulose, V. Sharma, & C. Maheshkar (eds.); pp. 1–25). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-2902-9_1

Mariani, C., & Mancini, M. (2025). Harnessing AI for value: examining the impact of AI capabilities and the mediating role of organizational agility on project value proposition. *International Journal of Managing Projects in Business*, *18*(8), 112–143. https://doi.org/10.1108/IJMPB-03-2025-0068

Mikalef, P., Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management*, *98*, 80–92. https://doi.org/https://doi.org/10.1016/j.indmarman.2021.08.003

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434. https://doi.org/https://doi.org/10.1016/j.im.2021.103434

O'Reilly, C. A., & Tushman, M. L. (2008). Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Research in Organizational Behavior*, *28*, 185–206. https://doi.org/https://doi.org/10.1016/j.riob.2008.06.002

Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI Governance: Identifying Best Practices and Potential Barriers and Outcomes. *Information Systems Frontiers*, *25*(1), 123–141. https://doi.org/10.1007/s10796-022-10251-y

Prasad Agrawal, K. (2025). Generative AI and the Intelligence Triad: An Epistemic Agility Approach. *Journal of Computer Information Systems*, 1–17. https://doi.org/10.1080/08874417.2025.2553158

Serenko, A., & Bontis, N. (2021). Global ranking of knowledge management and intellectual capital academic journals: a 2021 update. *Journal of Knowledge Management*, *26*(1), 126–145. https://doi.org/10.1108/JKM-11-2020-0814

Shafik, W. (2024). *Generative AI for Social Good and Sustainable Development BT - Generative AI: Current Trends and Applications* (K. Raza, N. Ahmad, & D. Singh (eds.); pp. 185–217). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-8460-8_10

Stahl, B. C., Antoniou, J., Bhalla, N., Brooks, L., Jansen, P., Lindqvist, B., Kirichenko, A., Marchal, S., Rodrigues, R., Santiago, N., Warso, Z., & Wright, D. (2023). A systematic review of artificial intelligence impact assessments. *Artificial Intelligence Review*, *56*(11), 12799–12831. https://doi.org/10.1007/s10462-023-10420-8

ISSN: 3047-4108 P-ISSN: 3048-3751
Journal Economic Business Innovation -JEBI, Vol. 02, Issue.2 2025, Page; 179-192
DOI: https://doi.org/10.69725/jebi.v2i2.265

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, *51*(1), 40–49. https://doi.org/https://doi.org/10.1016/j.lrp.2017.06.007

Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). *Impact of Artificial Intelligence on Firm Performance: Exploring the Mediating Effect of Process-Oriented Dynamic Capabilities BT - Digital Business Transformation* (R. Agrifoglio, R. Lamboglia, D. Mancini, & F. Ricciardi (eds.); pp. 3–18). Springer International Publishing.

Wu, X., Duan, R., & Ni, J. (2024). Unveiling security, privacy, and ethical concerns of ChatGPT. *Journal of Information and Intelligence*, *2*(2), 102–115. https://doi.org/https://doi.org/10.1016/j.jiixd.2023.10.007

Zhang, Q., Zuo, J., & Yang, S. (2025). Research on the impact of generative artificial intelligence (GenAI) on enterprise innovation performance: a knowledge management perspective. *Journal of Knowledge Management*, *29*(7), 2238–2257. https://doi.org/10.1108/JKM-10-2024-1198

Zong, Z., & Guan, Y. (2025). AI-Driven Intelligent Data Analytics and Predictive Analysis in Industry 4.0: Transforming Knowledge, Innovation, and Efficiency. *Journal of the Knowledge Economy*, *16*(1), 864–903. https://doi.org/10.1007/s13132-024-02001-z