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Responsible Generative AI Capability, Decision-Making Quality and Sustainable Performance: Evidence from Vietnamese SMEs

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ABSTRACT: This study investigates the relationships among responsible generative artificial intelligence capability (RGAIC), managerial decision-making quality (MDQ) and sustainable performance (SP) in Vietnamese small and medium-sized enterprises (SMEs). Drawing on the resource-based view and the triple bottom line, RGAIC is conceptualised as a higher-order organisational capability combining GenAI integration, data governance and security, output verification and fairness, and human oversight and accountability. A cross-sectional survey yielded 300 valid managerial responses from 300 GenAI-using SMEs in Hanoi. A two-stage partial least squares structural equation modelling (PLS-SEM) procedure and 5,000 bootstrap resamples were employed. The reported results show positive associations between RGAIC and MDQ ($\beta = 0.431$), RGAIC and SP ($\beta = 0.211$), and MDQ and SP ($\beta = 0.288$). The indirect association via MDQ is also positive ($\beta = 0.124$), consistent with complementary mediation. The model explains 18.6% of the variance in MDQ and 18.0% in SP. The findings shift attention from access to GenAI tools toward organisational capability to use them responsibly, while identifying decision quality as one plausible pathway linked to sustainability outcomes. Because the data are cross-sectional and non-probability sampled, causal and population-wide claims are not warranted.

KEYWORDS: generative AI, responsible AI capability, managerial decision-making quality, sustainable performance, SMEs, Vietnam.

1. INTRODUCTION

Generative artificial intelligence (GenAI) can support information synthesis, option generation, business communication and managerial analysis. Its accessible interfaces may lower adoption barriers for SMEs, yet implementation introduces risks concerning inaccurate outputs, sensitive information, bias, intellectual property and accountability [9, 17, 19]. The NIST Generative AI Profile treats governance, verification and human oversight as integral risk-management considerations [3]. Consequently, technology access and frequency of use are insufficient proxies for organisational value creation.

AI capability research explains how firms combine technological, data-related and human resources to create value [14–16]. Responsible-AI research instead examines policies, safeguards and repeatable governance practices [1, 18, 21]. These perspectives are complementary but do not fully establish whether the capacity to use GenAI responsibly is related to sustainable business outcomes through better managerial decisions. Related research links AI capabilities to decision-making performance [10] and the use of AI or GenAI to selected business and sustainability outcomes [2, 4, 5]. The specific mediating role of managerial decision quality remains important to examine in resource-constrained SMEs.

This article addresses three questions: (i) how can responsible GenAI capability be represented as an integrated organisational construct; (ii) how is that capability associated with decision-making quality and sustainable performance; and (iii) does decision-making quality statistically mediate their association? The empirical setting comprises 300 SMEs in Hanoi whose managers have used GenAI in decision processes. Although the title refers to Vietnamese SMEs, the study does not claim national representativeness. The contribution lies in a theoretically grounded capability construct and an empirical mediation test, not in demonstrating causal effects.

2. RESEARCH CONTENT

2.1. Conceptual foundations and hypothesis development

Responsible generative AI capability (RGAIC) is defined here as an organisation's repeatable ability to combine technology, information, personnel, routines and safeguards when using GenAI to generate value while managing associated risks. Four complementary domains comprise this higher-order capability: (GAI) GenAI adoption and process integration; (DGS) data governance and security; (VTF) verification, transparency and fairness; and (HAA) human oversight and accountability. This operational definition draws on AI capability research [14–16, 20] and responsible-AI governance literature [1, 3, 18, 21]. Unlike a count of tools or usage frequency, RGAIC represents coordinated organisational practices.

The resource-based view (RBV) argues that value depends on the productive orchestration of capabilities rather than possession of isolated resources [6, 14]. For GenAI, enterprise knowledge, reliable data, verification routines and accountable judgment may complement one

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another. Managerial decision-making quality (MDQ) refers to the perceived quality, appropriateness and effectiveness of decisions informed by GenAI; it is treated as a proximal management outcome, not as an objective audit of all decisions. Prior evidence suggests a relationship between AI capabilities and decision-making performance [10]. Sustainable performance (SP) follows the triple bottom line (TBL), distinguishing economic (ECO), social (SOC) and environmental (ENV) dimensions [8, 12]. A multidimensional specification is preferable to equating sustainability with short-term profitability.

Four hypotheses follow. H1 proposes a positive relationship between RGAIC and MDQ because better governance may improve the reliability and usability of AI-supported information. H2 predicts a positive association between RGAIC and SP through operational learning and responsible resource use. H3 proposes that higher MDQ is associated with stronger SP, as more timely and appropriate decisions may support economic, social and environmental objectives. H4 proposes a positive indirect relationship from RGAIC to SP through MDQ. These are hypotheses concerning statistical relationships; the cross-sectional design cannot establish temporal causation.

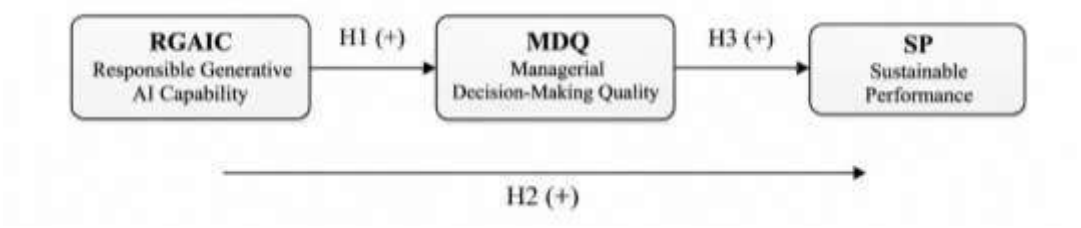

Figure 1. Proposed research model and hypothesised relationships
Source: Authors' conceptual model. H1–H4 describe hypothesised associations; arrow direction is theoretical.

2.2. Survey design, measurement and analysis

The study used a structured cross-sectional questionnaire in Hanoi in 2026. Eligible enterprises had used GenAI for at least three months, and respondents were owners or managers who had participated in at least one GenAI-supported management decision. A purposive sample, controlled snowball referrals and quotas by enterprise size and sector were used because a complete sampling frame of GenAI-using SMEs was unavailable. Of 360 questionnaires distributed, 334 were returned (92.8%). Twelve failed the minimum GenAI-use criterion, eight lacked relevant decision participation, and fourteen were excluded for missing or inconsistent responses. The final dataset comprises 300 managers, each representing a different enterprise. SME eligibility was assessed against the government classification cited in the original study [7].

The instrument comprises 24 indicators across eight first-order constructs (three per construct), with five-point Likert responses. Seven subject-matter experts assessed wording, relevance and comprehensibility. A two-stage PLS-SEM approach was used for higher-order modelling, with measurement assessment covering outer loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE) and heterotrait–monotrait ratios (HTMT). Structural evaluation involved collinearity (VIF), explained variance (R^2), effect sizes (f^2), bootstrap path estimates and indirect effects; 5,000 bootstrap resamples were drawn. The source further reports a 10-fold cross-validation check on latent/composite scores, which should not be equated automatically with standard PLSpredict diagnostics [11].

Table 1. Measurement domains and item allocation

Construct	Codes	Content
GAI	GAI1–GAI3	GenAI exploitation and integration
DGS	DGS1–DGS3	Data governance and security
VTF	VTF1–VTF3	Verification, transparency and fairness
HAA	HAA1–HAA3	Human oversight and accountability
MDQ	MDQ1–MDQ3	Managerial decision-making quality
ECO	ECO1–ECO3	Economic performance
SOC	SOC1–SOC3	Social performance
ENV	ENV1–ENV3	Environmental performance

Source: Adapted and compiled in the original research from [3, 10–16, 18–21].

2.3. Sample composition

The sample contains 105 microenterprises (35.0%), 150 small enterprises (50.0%) and 45 medium-sized enterprises (15.0%). Management positions include owners/directors (43.0%), deputy directors (12.7%), department managers/deputies (31.7%) and project/operations managers (12.7%). In terms of reported GenAI experience, 11.7% had used it for three to under six months, 24.7% for six to under twelve months, 41.0% for one to under two years and 22.7% for at least two years. These distributions describe the achieved sample rather than the population of Vietnamese SMEs.

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Table 2. Selected respondent and enterprise characteristics (N = 300)

Characteristic	Category	n	%
Size	Micro / Small / Medium	105 / 150 / 45	35.0 / 50.0 / 15.0
Sector	Trade, retail and real estate	84	28.0
	Professional, finance, education, health services	72	24.0
	Industry, manufacturing and construction	54	18.0
	IT and digital technology	45	15.0
	Logistics, tourism and hospitality	36	12.0
	Agriculture and other sectors	9	3.0
Position	Owner/director / Deputy director	129 / 38	43.0 / 12.7
	Department management / Project-operations management	95 / 38	31.7 / 12.7
GenAI use	3–<6 / 6–<12 months / 1–<2 / ≥2 years	35 / 74 / 123 / 68	11.7 / 24.7 / 41.0 / 22.7

Source: Authors' calculations.

2.4. Measurement-model results

The reported standardised outer loadings range from 0.812 to 0.875, above the common 0.708 reference point. Across the eight constructs, Cronbach's alpha lies between 0.760 and 0.832, CR between 0.862 and 0.900, and AVE between 0.676 and 0.749. These figures support internal consistency and convergent validity against conventional PLS-SEM benchmarks [11], conditional on the specified reflective measurement model. They do not by themselves validate the higher-order construct specification or eliminate common-method concerns.

Table 3. Reliability and convergent validity

Construct	Loadings	Mean	SD	Alpha	CR	AVE
GAI	0.845–0.865	3.559	0.821	0.816	0.891	0.732
DGS	0.812–0.832	3.341	0.789	0.760	0.862	0.676
VTF	0.818–0.853	3.451	0.848	0.780	0.872	0.695
HAA	0.836–0.875	3.756	0.794	0.809	0.887	0.724
MDQ	0.856–0.871	3.594	0.800	0.832	0.900	0.749
ECO	0.818–0.864	3.527	0.805	0.800	0.883	0.716
SOC	0.835–0.850	3.416	0.837	0.798	0.881	0.712
ENV	0.823–0.858	3.136	0.858	0.798	0.881	0.712

Source: Authors' calculations.

The largest reported HTMT ratio is 0.748 between ECO and SOC, below the commonly applied conservative criterion of 0.85. The other reported pairwise ratios also remain below that criterion, suggesting adequate differentiation at the first-order construct level. In particular, MDQ appears distinguishable from the component capability dimensions, which matters when interpreting mediation. Nevertheless, confidence intervals for HTMT and detailed higher-order validity diagnostics would improve transparent reporting.

Table 4. Heterotrait–monotrait (HTMT) matrix

	GAI	DGS	VTF	HAA	MDQ	ECO	SOC	ENV
GAI								
DGS	.613							
VTF	.615	.538						
HAA	.632	.573	.567					
MDQ	.481	.476	.371	.318				
ECO	.335	.360	.359	.333	.458			
SOC	.265	.204	.249	.268	.390	.748		
ENV	.152	.218	.189	.147	.249	.512	.446	

Source: Authors' calculations.

2.5. Structural paths and mediation

Bootstrapping results support all four proposed relationships at the reported conventional significance threshold. RGAIC is positively related to MDQ ($\beta = 0.431$, $t = 8.961$, $p < 0.001$; 95% CI 0.334–0.521), consistent with H1. RGAIC also has a positive direct association with SP ($\beta = 0.211$, $t = 3.509$, $p < 0.001$; 95% CI 0.087–0.325), consistent with H2. The path from MDQ to SP is positive ($\beta = 0.288$, $t = 5.067$, $p < 0.001$; 95% CI 0.173–0.397), consistent with H3. The estimated indirect path through MDQ equals 0.124 ($t = 4.245$, $p < 0.001$; 95% CI 0.070–0.184), supporting H4. Because the direct and indirect paths have the same sign and are both statistically distinguishable from zero, the pattern is described as complementary statistical mediation.

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Table 5. Hypothesis tests based on 5,000 bootstrap resamples

Hyp.	Path	β	SE	t	p	95% CI	Result
H1	RGAIC → MDQ	.431	.048	8.961	<.001	.334–.521	Supported
H2	RGAIC → SP	.211	.060	3.509	<.001	.087–.325	Supported
H3	MDQ → SP	.288	.057	5.067	<.001	.173–.397	Supported
H4	RGAIC → MDQ → SP	.124	.029	4.245	<.001	.070–.184	Supported

Source: Authors' calculations.

The model explains R^2 = 0.186 for MDQ and R^2 = 0.180 for SP, indicating that most observed variation remains unexplained. The reported f^2 value is 0.228 for RGAIC → MDQ, versus 0.044 for RGAIC → SP and 0.083 for MDQ → SP; these support a relatively stronger link to decision quality than to the final outcome. Maximum reported VIF is 1.228. The supplementary cross-validation values (Q^2_CV = 0.171 for MDQ and 0.164 for SP) are positive within the calculation used in the source, but prediction should be documented with explicit fold design, benchmark models and error metrics before broad claims of out-of-sample superiority.

Table 6. Model explanatory and supplementary predictive statistics

Endogenous	R^2	Adj. R^2	Q^2_CV	Path	f^2	VIF	Effect size
MDQ	.186	.183	.171	RGAIC → MDQ	.228	1.000	Medium
SP	.180	.175	.164	RGAIC → SP	.044	1.228	Small
SP	.180	.175	.164	MDQ → SP	.083	1.228	Small

Source: Authors' calculations.

2.6. Discussion and implications

The results are consistent with the argument that GenAI value depends on the organisation's ability to integrate tools into controlled routines rather than simply provide access to applications. The positive RGAIC–MDQ association gives empirical support to the relevance of data governance, output verification and accountable human judgment alongside technical integration. It extends AI capability reasoning [14–16] by embedding responsible-use routines in the proposed competence architecture, while also resonating with the call to operationalise responsible AI rather than treat governance as a separate compliance statement [1, 18].

The positive direct link between RGAIC and SP is compatible with studies connecting AI adoption or capabilities to selected economic and sustainability-related indicators [2, 4, 5, 13]. However, the present study measures a composite sustainability construct through managerial responses, not independently audited emissions, labour outcomes or accounts. Thus, it does not prove that GenAI deployment has reduced environmental impacts or caused a rise in profits. The modest R^2 for SP further implies that competition, industry differences, finance, leadership and market conditions remain material alternative explanations.

The mediation result is especially informative. MDQ represents an organisational process through which better information discipline and oversight might become relevant to broader business objectives. The indirect coefficient is statistically positive while the direct association remains positive; decision-making quality is therefore one possible pathway, not a complete explanation. Cross-sectional measurement does not establish the timing needed for causal mediation, and common respondent assessment could inflate associations. Follow-up longitudinal studies with objective outcomes and independently collected decision metrics are necessary.

For managers, the findings motivate a practical governance cycle: identify a decision process where GenAI could add value; define permissible input data and access permissions; verify consequential model outputs against trustworthy sources; document human approval and responsibility; and monitor decision quality, operating costs, worker impacts and resource-use indicators. SMEs may start with limited, low-risk use cases and expand only after demonstrating data quality and managerial oversight. These are managerial implications derived from the model, not interventions whose effectiveness was tested in this survey.

For Hanoi policymakers and SME-support organisations, literacy programmes should combine tool use with organisational data stewardship, evaluation skills and risk controls. Support could include sector-appropriate templates for data handling, decision review and accountability, along with practical measurement guidance. The policy reference in the Vietnamese source [23] describes a local digital-transformation initiative, but the present associations should not be interpreted as proof that any specific public programme will produce improvements. Programme evaluation should use baseline and follow-up indicators instead of participation counts alone.

Methodological interpretation also requires care in higher-order construct analysis. Although the source reports a two-stage PLS-SEM procedure, the manuscript does not reproduce all higher-order weights, confidence intervals or diagnostics for the formation of RGAIC and SP. Future reporting should specify whether each higher-order relationship is reflective or formative and provide the corresponding evaluation criteria. Particularly where dimensions have complementary rather than interchangeable meanings, the distinction influences what a composite coefficient can reasonably represent. The present article accordingly retains the original model specification without inferring additional unreported tests or treating the four RGAIC dimensions as independently estimated causal drivers. This distinction is important when translating statistical evidence into organisational capability recommendations.

The sustainability results should likewise be interpreted dimensionally. Economic, social and environmental performance have different operational units and time horizons. A perceived improvement in sustainability may reflect managers' overall assessments, whereas causal claims about pollution, labour conditions or resource intensity would require measured outcomes over time. For replication, research teams could obtain matched accounting data, energy-use records, personnel indicators and auditable decision logs, ideally at more than one observation point. The present sample is sufficient for the analyses reported in the source but was not selected probabilistically from a national sampling frame. Sector-

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specific comparisons would also need measurement invariance checks and adequate subgroup sizes before differences could be interpreted as substantive.

The reported positive mediation coefficient is compatible with the proposed theoretical ordering; however, alternative pathways cannot be ruled out. Stronger organisations may both implement responsible AI governance and make better decisions, or managers reporting higher overall performance may evaluate AI-related practices more favourably. Subsequent studies could address these rival explanations through multiple informants, temporally separated measures and pre-specified controls. A controlled pilot comparing changes in decision quality before and after governance training might complement observational modelling, but its design and outcomes would require independent empirical data rather than extrapolation from the current coefficients.

3. CONCLUSIONS AND RECOMMENDATIONS

3.1. Conclusions

This study examines responsible generative AI capability, managerial decision-making quality and sustainable performance using 300 responses from GenAI-using SMEs in Hanoi. It proposes a four-domain higher-order capability and reports positive structural associations among RGAIC, MDQ and SP. The indirect coefficient ($\beta = 0.124$) is consistent with complementary mediation, while the modest explanatory power of the sustainability model indicates that additional determinants and pathways are relevant. The central contribution is to link responsible GenAI capability with decision quality as a plausible, measurable management mechanism rather than equating technology use with business value.

3.2. Recommendations, limitations and future research

Enterprises should develop repeatable policies for GenAI integration, data protection, verification and human accountability, and evaluate results through decision and sustainability indicators that can be independently checked. The study is constrained by cross-sectional self-reported data, purposive and referral sampling, and geographic coverage limited to Hanoi; consequently, findings cannot be generalised to all Vietnamese SMEs or read as causal effects. Future work should use longitudinal designs and objective economic, environmental and workforce indicators, test measurement invariance across sectors, report higher-order construct diagnostics in full, and investigate moderators such as AI literacy, organisational governance maturity and enterprise size.

REFERENCES

1) Akbarighatar, P. (2025). Operationalizing responsible AI principles through responsible AI capabilities. AI and Ethics, 5(2), 1787–1801. https://doi.org/10.1007/s43681-024-00524-4
2) Alwakid, W. N., & Dahri, N. A. (2025). Harnessing AI capabilities and green entrepreneurial orientation for sustainable SME performance using SEM analysis approach. Technology in Society, 83, 103007. https://doi.org/10.1016/j.techsoc.2025.103007
3) Autio, C., Schwartz, R., Dunietz, J., Jain, S., Stanley, M., Tabassi, E., Hall, P., & Roberts, K. (2024). Artificial Intelligence Risk Management Framework: Generative Artificial Intelligence Profile (NIST AI 600-1). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AI.600-1
4) Badghish, S., & Soomro, Y. A. (2024). Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology–Organization–Environment Framework. Sustainability, 16(5), 1864. https://doi.org/10.3390/su16051864
5) Bahaw, P., Forgenie, D., Sadiq, G., & Sookhai, S. (2025). Generative AI for business sustainability: Examining usability, usefulness, and triple bottom line impacts in small and medium enterprises. Sustainable Futures, 10, 100815. https://doi.org/10.1016/j.sftr.2025.100815
6) Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108
7) Government of Vietnam. (2021). Decree No. 80/2021/ND-CP of 26 August 2021 detailing and guiding implementation of certain provisions of the Law on Support for Small and Medium-Sized Enterprises. https://vbpl.vn/bonongnghiep/Pages/vbpq-thuoctinh.aspx?ItemID=158783
8) Elkington, J. (1997). Cannibals with forks: The triple bottom line of 21st century business. Capstone. https://books.google.com/books?id=QLg9PgAACAAJ
9) Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. Business & Information Systems Engineering, 66, 111–126. https://doi.org/10.1007/s12599-023-00834-7
10) Guthrie, C. H., Fosso-Wamba, S., Queiroz, M. M., & Cai, H. (2025). The impact of artificial intelligence capabilities on decision-making performance: A longitudinal study. Journal of Global Information Management, 33(1), 1–27. https://doi.org/10.4018/JGIM.395344
11) Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.
12) Khan, E. A., & Quaddus, M. (2015). Development and validation of a scale for measuring sustainability factors of informal microenterprises – A qualitative and quantitative approach. Entrepreneurship Research Journal, 5(4), 347–372. https://doi.org/10.1515/erj-2014-0017
13) Liu, A., & Wang, S. (2024). Generative artificial intelligence (GenAI) and entrepreneurial performance: Implications for entrepreneurs. The Journal of Technology Transfer, 49(6), 2389–2412. https://doi.org/10.1007/s10961-024-10132-3
14) 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/10.1016/j.im.2021.103434
15) Mikalef, P., Islam, N., Parida, V., Singh, H., & Altwaijry, N. (2023a). Artificial intelligence (AI) competencies for organizational performance: A B2B marketing capabilities perspective. Journal of Business Research, 164, 113998.

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https://doi.org/10.1016/j.jbusres.2023.113998
16) Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2023b). Examining how AI capabilities can foster organizational performance in public organizations. Government Information Quarterly, 40(2), 101797. https://doi.org/10.1016/j.giq.2022.101797
17) OECD. (2025a). Generative AI and the SME workforce: New survey evidence. OECD Publishing. https://doi.org/10.1787/2d08b99d-en
18) OECD. (2025b). AI adoption by small and medium-sized enterprises: OECD discussion paper for the G7. OECD Publishing. https://doi.org/10.1787/426399c1-en
19) Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. The Journal of Strategic Information Systems, 34(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885
20) Rajaram, K., & Tinguely, P. N. (2024). Generative artificial intelligence in small and medium enterprises: Navigating its promises and challenges. Business Horizons, 67(5), 629–648. https://doi.org/10.1016/j.bushor.2024.05.008
21) Sahoo, S., Kumar, S., Donthu, N., & Singh, A. K. (2024). Artificial intelligence capabilities, open innovation, and business performance – Empirical insights from multinational B2B companies. Industrial Marketing Management, 117, 28–41. https://doi.org/10.1016/j.indmarman.2023.12.008
22) Someh, I., Wixom, B. H., Beath, C. M., & Zutavern, A. (2022). Building an artificial intelligence explanation capability. MIS Quarterly Executive, 21(2), 143–163. https://doi.org/10.17705/2msqe.00063
23) Hanoi People's Committee. (2026). Plan No. 232/KH-UBND of 18 June 2026 on digital transformation for small and medium-sized enterprises in Hanoi, 2026–2030. https://vanban.hanoi.gov.vn/van-ban/ke-hoach-chuyen-doi-so-cac-doanh-nghiep-nho-va-vua-tren-dia-ban-thanh-pho-ha-noi-giai-doan-2026-2030-255303

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