

GENERATIVE AI INTEGRATION AND CORE BUSINESS FUNCTIONS: EVIDENCE FROM VIETNAMESE SMALL AND MEDIUM-SIZED ENTERPRISES

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Abstract: *This article identifies the determinants affecting the integration of Generative Artificial Intelligence (GenAI) into core business functions of small and medium-sized enterprises (SMEs) in Vietnam. Grounded in the Technology-Organization-Environment (TOE) framework, the research used a cross-sectional survey of 202 directors, managers, and senior decision-makers from 20 SMEs across Hanoi, Hai Phong, Da Nang, Nha Trang, and Ho Chi Minh City. Confirmatory Factor Analysis and Structural Equation Modeling were conducted in R (lavaan, maximum-likelihood estimation), with 5,000-resample bootstrapping to test mediating effects. The measurement model showed that technological, organizational, and environmental factors have direct effects on GenAI adoption and indirect effects on CBF. Recommendations are proposed on strengthening organizational readiness, technological infrastructure, environmental responsiveness, and performance measurement.*

Keywords: *core business functions, GenAI integration, SMEs, TOE framework, Vietnam*

I. Introduction

In the era of rapid digital transformation, artificial intelligence (AI) has emerged as one of the most powerful forces reshaping modern business operations. According to Chu and Nguyen (2025), AI enhances the customer shopping experience and improves decision-making capabilities for both businesses and users. In fact, decision-making within small and medium-sized enterprises (SMEs) has improved thanks to the integration of (AI) in general, and Generative AI (GenAI) in particular, into core business functions (CBF). However,

this integration among Vietnam's SMEs faces challenges, including limited knowledge and skills for effective implementation, data security concerns, insufficient senior management support, and resource constraints.

While digital transformation has received increasing attention in Vietnam, the integration of GenAI remains limited and unsystematic. Financial, technological, and human resources have driven adoption. Many SMEs in Vietnam use GenAI mainly for supporting activities such as marketing and customer service, while integration into core functions remains in an early, fragmented stage.

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According to Nguyen (2022), technological infrastructure and data readiness are decisive for SMEs' GenAI deployment. However, Vietnam's SMEs still lag behind large enterprises on these dimensions and mainly use GenAI to support rather than restructure operations.

Vietnam has recently been identified as one of the highest-adopting countries for GenAI in Southeast Asia, making it a research priority to understand the conditions that translate adoption into genuine performance gains. This study therefore identifies and analyzes the determinants affecting the integration of GenAI into the CBF of Vietnam's SMEs, and proposes recommendations based on the findings.

II. Literature review

2.1. Integration of GenAI into core SME business functions

SMEs embed GenAI tools into its regular business activities in a purposeful, strategically intentional manner through three dimensions: breadth, depth and strategic intentionality. GenAI tools have been shown to reshape decision-making, enable automation, and foster innovation (Chowdhury et al., 2023). SMEs that integrate GenAI into task performance can optimize core workflows and strengthen responsiveness to customers and markets (Peres et al., 2023), improving performance, product innovation, and customer relationship management (Tominc et al., 2024). Realizing GenAI's practical value requires well-structured data, leadership, and IT readiness to address barriers such as limited budgets, workforce skill gaps, and weak technological infrastructure (Chatterjee et al., 2022).

For Vietnam's emerging-economy SMEs, GenAI adoption depends on both internal factors and external factors

(Nguyen, 2022). Regarding CBF, Peres et al. (2023) note that peripheral use of GenAI improves convenience without reshaping production processes, whereas Benbya et al. (2024) identify strategic decision-making, new product development, and operational management as the core functions most affected by deeper GenAI integration. In this study, CBF are defined as the central, value-creating activities of an SME known as financial management, human resource management, operations, and strategic decision-making which are operationalized through performance outcomes of these functions.

2.2. Factors influencing GenAI integration into core business functions

Integration is shaped by three groups of factors: technological, organizational, and environmental. Technological factors (TF) generate tangible benefits namely higher productivity, better decision-making, new ways to engage customers (Abrokwah-Larbi & Awuku-Larbi, 2024). Compatibility between GenAI tools and existing workflows is a key driver of adoption (Schwaeke et al., 2025), and tools that integrate smoothly into current operations are preferred for their demonstrated efficiency (Chowdhury et al., 2023). For Vietnam's SMEs specifically, the maturity of the national technology ecosystem is decisive (Nguyen, 2022).

Organizational factors (OF) encompass internal resources, skills, and managerial support (Badghish & Soomro, 2024). SMEs' readiness to integrate GenAI depends on managerial support, financial resources, and digital capabilities (Merhi & Harfouche, 2024). Limited finances constrain infrastructure investment, while employee digital skills determine how effectively GenAI tools are used (Lutfi et al., 2022).

Environmental factors (EF) strongly shape GenAI integration (Badghish & Soomro, 2024). According to Flavián et al. (2022), SMEs also face institutional, market, and technological pressures that can enable or hinder adoption and performance. Others researchers identify that competitive markets push SMEs toward GenAI adoption to gain or defend advantage (Chatterjee et al., 2023), and streamline operations and enable new products and services (Chuma & de Oliveira, 2023).

2.3. The Technology-Organization-Environment framework

The TOE framework (Tornatzky & Fleischer, 1990) is a major theoretical

2.4. Conceptual framework

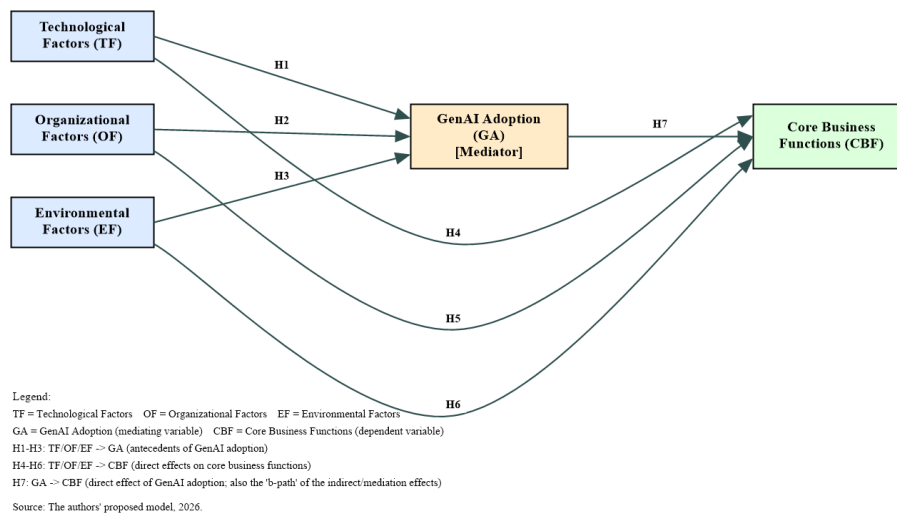


Figure 1. Conceptual Model

This study's conceptual framework builds on the TOE framework (Tornatzky & Fleischer, 1990). It extends it by incorporating GenAI adoption as a mediating factor linking the three TOE dimensions to CBF (Figure 1). The model specifies seven hypotheses: H1 (TF → GA), H2 (OF → GA), H3 (EF → GA), H4 (TF → CBF), H5 (OF → CBF), H6 (EF → CBF), and H7 (GA → CBF).

foundation for research on organizational technology adoption, proposing that a firm's adoption decision is shaped by three interconnected dimensions: technological, organizational and environmental context. TOE is well suited to studying GenAI integration in SME's CBF for two reasons. First, it operates at the organizational level, aligning with firm-level strategic adoption decisions, whereas the Technology Acceptance Model (TAM) focuses on individual-level behavior (Mogaji et al., 2024). Second, it is flexible enough to accommodate specific context variables while preserving theoretical consistency across studies (Badghish & Soomro, 2024).

(Source: The authors' proposed model, 2026)

III. Research method

3.1. Research design

This study applied a quantitative, cross-sectional design to examine the relationships among TF, OF, EF, GA, and CBF in Vietnam's SME context, consistent with prior technology-integration research (Hair et al., 2018). A hypothetico-deductive approach guided

the process, with theoretical propositions from the TOE framework operationalized into measurable variables and tested via structural equation modeling.

3.2. Measurement instrument

Five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) and multi-item were adapted from validated instruments. Each of the five variables was measured with four indicator items. TF (TF1-TF4: technology infrastructure, GenAI-workflow compatibility, ecosystem maturity, data security capability). OF (OF1-OF4: managerial support, financial resources, digital skills, innovation-friendly culture). EF (EF1-EF4: government policy, competitive pressure, vendor support, stakeholder expectations). GenAI adoption (GA1- GA4: breadth, depth, strategic intentionality, and planned expansion of GenAI use). CBF (CBF1-CBF4: operational efficiency, competitive position, strategic performance, and decision-making support).

3.3. Sampling and data collection

The target population comprised senior decision-makers of SMEs in Hanoi, Hai Phong, Da Nang, Nha Trang, and Ho Chi Minh City. Data collection followed a design of 210 respondents who were screened to hold a management position

with influence over technology decisions and have prior experience using GenAI tools. The respondents were surveyed across 20 SMEs, with 11 respondents from the same firm. Eight responses were subsequently excluded due to a data-entry error, leaving a final analytic sample of 202. The survey was administered online. The pilot study with 20 managers preceded full data collection to assess clarity and preliminary reliability, and the instrument was refined accordingly.

3.4. Analytical procedure

Data analysis proceeded in two stages using R. First, confirmatory factor analysis (CFA) evaluated the measurement model's psychometric properties, including reliability, convergent validity (CR, AVE), and overall model fit (Chi-square/df, CFI, TLI, RMSEA, SRMR). Through applying the criteria of Hu and Bentler (1999) and Hair et al. (2019), items with standardized loadings below 0.60 would have been removed. Second, structural equation modeling (SEM) tested the hypothesized direct and indirect relationships using standardized path coefficients (beta), z-values, and p-values. A bootstrapping procedure with 5,000 resamples was used to construct bias-corrected 95% confidence intervals for the indirect effects mediated by GenAI adoption.

IV. Results and discussion

4.1. Results

4.1.1. Descriptive statistics and reliability

Table 1. Descriptive statistics and reliability testing for factors affecting the integration of GenAI into CBF in Vietnam's SMEs

Construct	No. of items	Cronbach's Alpha	Mean	Std. Deviation
Technological factors (TF)	4	0.852	3.047	1.248
Organizational factors (OF)	4	0.875	2.960	1.276
Environmental factors (EF)	4	0.852	3.041	1.292
GenAI Adoption (GA)	4	0.869	2.985	1.256
Core business functions (CBF)	4	0.842	2.988	1.249

(Source: The researchers' own calculations from survey data, 2026)

All five constructs achieved Cronbach's Alpha values above 0.8 (0.842-0.875), well above the recommended threshold of 0.7 (Hair et al., 2019). This indicates strong internal consistency. OF recorded the highest reliability ($\alpha = 0.875$) and the lowest mean score (2.960). This suggested that while respondents' perceptions of organizational readiness are the most internally consistent, SMEs still rate their own organizational readiness as only moderate. TF had the highest mean (3.047), indicating relatively

more favorable perceptions of technology infrastructure and ecosystem maturity than of the other TOE dimensions. Standard deviations were similar across constructs (1.248-1.292), indicating comparable response dispersion and no evidence of restricted variance that would bias subsequent correlation or path estimates.

4.1.2. Confirmatory factor analysis evaluated measurement model

CFA was conducted in R to evaluate the psychometric properties of the measurement model before structural testing.

Table 2. Standardized factor loadings

Construct	Items	Standardized loadings	p-value
TF	TF1 / TF2 / TF3 / TF4	0.774 / 0.761 / 0.761 / 0.776	<0.001
OF	OF1 / OF2 / OF3 / OF4	0.826 / 0.787 / 0.773 / 0.806	<0.001
EF	EF1 / EF2 / EF3 / EF4	0.748 / 0.731 / 0.787 / 0.809	<0.001
GA	GA1 / GA2 / GA3 / GA4	0.791 / 0.737 / 0.794 / 0.839	<0.001
CBF	CBF1 / CBF2 / CBF3 / CBF4	0.835 / 0.710 / 0.699 / 0.786	<0.001

The table 2 shows that all 20 items exceeded the recommended 0.60 threshold, indicating that each item reliably represents its intended construct; no item was removed. CBF1 (0.835) and GA4 (0.839) recorded the highest loadings, indicating

that operational-efficiency perceptions and planned GenAI expansion are the strongest indicators of their respective constructs, while CBF3 (0.699) and TF2/TF3 (0.761) were comparatively weak, though still well above the acceptance threshold.

Table 3. Measurement model fit indices

Fit index	Value	Threshold	Result
Chi-square/df	159.089 / 160 (approx. 0.994)	close to 1	Good
CFI	1.000	> 0.90	Good
TLI	1.001	> 0.90	Good
RMSEA [90% CI]	0.000 [0.000-0.032]	< 0.08	Good
SRMR	0.038	< 0.08	Good
GFI	1.000	> 0.90	Good

Table 3 illustrates that the measurement model demonstrated an excellent fit to the data (CFI = 1.000,

TLI = 1.001, RMSEA = 0.000, SRMR = 0.038), with all indices comfortably exceeding their respective thresholds.

Table 4. Composite Reliability and Average Variance Extracted

Construct	Composite Reliability (CR)	AVE
TF	0.852	0.590
OF	0.875	0.637
EF	0.853	0.592
GA	0.870	0.626
CBF	0.845	0.577

Table 4 shows that all constructs met the criteria for convergent validity ($CR > 0.7$, $AVE > 0.5$). OF recorded both the highest composite reliability ($CR = 0.875$) and the highest AVE (0.637), presenting the strongest measurement precision among the five constructs. CBF recorded the lowest AVE (0.577), still above the 0.5 threshold, indicating comparatively more measurement error, consistent with CBF's being the weakest-loading item identified in Table 2. Taken together, these results confirm that the

five latent constructs are well represented by their respective observed indicators and that the dataset was suitable for subsequent structural equation modeling.

4.1.3. Structural equation model tested hypotheses

The structural model estimated with the same ML procedure, standard errors and confidence intervals were obtained via bootstrapping (5,000 resamples, bias-corrected percentile method).

Table 5. Hypothesis testing results - standardized structural paths

Hypothesis	Path	Standardized beta	SE	z	p-value	Result
H1	TF -> GA	0.243	0.082	2.959	0.003	Supported
H2	OF -> GA	0.476	0.080	5.928	<0.001	Supported
H3	EF -> GA	0.236	0.069	3.428	0.001	Supported
H4	TF -> CBF	0.351	0.071	4.952	<0.001	Supported
H5	OF -> CBF	0.299	0.093	3.206	0.001	Supported
H6	EF -> CBF	0.205	0.071	2.864	0.004	Supported
H7	GA -> CBF	0.228	0.108	2.110	0.035	Supported (marginal)

(Source: The researchers' own calculations, 2026)

All seven hypotheses were supported. OF exerted the strongest influence on GenAI adoption ($\beta = 0.476$), and the strongest direct influence on CBF from TF ($\beta = 0.351$). GenAI adoption itself had a statistically significant, though comparatively modest, direct effect on CBF ($\beta = 0.228$, $p = 0.035$), regarding the weakest of the seven paths and close to the conventional 0.05

threshold. The model explained 53.0% of the variance in GenAI adoption and 67.6% of the variance in CBF.

4.1.4. Mediation analysis

A bootstrapping procedure (5,000 resamples, bias-corrected 95% confidence intervals) was used to test whether GenAI adoption mediates the relationships between the TOE antecedents and CBF.

Table 6. Bootstrap results for indirect effects (mediation via GenAI adoption)

Indirect path	Indirect effect	SE	p-value	95% Bootstrap CI	Conclusion
TF -> GA -> CBF	0.055	0.030	0.062	[-0.001, 0.116]	Inconclusive (CI borderline)
OF -> GA -> CBF	0.108	0.056	0.054	[0.001, 0.222]	Marginal (CI excludes zero narrowly)
EF -> GA -> CBF	0.054	0.031	0.085	[0.000, 0.122]	Inconclusive (CI borderline)

Indirect effects were estimated with 5,000 bootstrap resamples; 95% percentile confidence intervals are reported (lavaan, `boot.ci.type = 'perc'`). Significance is judged from these confidence intervals rather than the accompanying

Wald p-values, because the sampling distribution of an indirect effect (a product of two coefficients) is typically skewed; the two criteria can therefore disagree near the boundary, as they do here. On this basis, only the OF -> GA -> CBF

indirect path clearly excludes zero, and even then only marginally (lower bound 0.001). The TF → GA → CBF and EF → GA → CBF indirect paths are best read as inconclusive rather than as evidence for or against mediation: their confidence-interval lower bounds differ by only 0.001 ([-0.001, 0.116] versus [0.000, 0.122], the latter rounding to 0.000 at three decimal places), a difference too small to support a

firm significant/non-significant distinction between the two paths. Overall, we characterize the evidence for GenAI adoption as a mediating mechanism as weak and largely inconclusive-marginal at best for the organizational-factors path, and too close to the zero boundary to interpret for the technological- and environmental-factors paths.

Table 7. Direct and indirect effects on CBF

Path	Total standardized effect	p-value	95% CI
TF → CBF (total)	0.406	<0.001	[0.274, 0.532]
OF → CBF (total)	0.407	<0.001	[0.264, 0.537]
EF → CBF (total)	0.258	<0.001	[0.131, 0.396]

Table 7 reports the direct and indirect effects of TOE factors on CBF. Unlike the indirect effects in Table 6, all three total effects are clearly significant and substantial, confirming that TOE readiness affects CBF predominantly through direct channels rather than through GenAI adoption alone. The weakest link in this mediation chain is the GA → CBF path (beta = 0.228, p = 0.035), itself only marginally significant. An indirect effect is the product of two path coefficients; therefore, this weak b-path constrains all three indirect effects reported in Table 6.

4.2. Discussion

This study confirms that TF, OF, and EF have significant positive effects on both GenAI adoption and CBF. OF emerged as the strongest antecedent of GenAI adoption (beta = 0.476), consistent with prior findings that managerial support, financial resources, and digital capabilities are decisive for technology readiness (Jatobá et al., 2023). TF showed the strongest direct effect on CBF (beta = 0.351), reinforcing the role of a mature technology ecosystem as a critical enabler of firm-level performance (Schwaeke et al., 2025).

(Source: The researchers' own calculations, 2026) EF, though smaller in magnitude (beta = 0.205), remained significant, confirming the relevance of government policy and competitive pressure (Badghish & Soomro, 2024; Flavián et al., 2022).

GenAI adoption itself was confirmed as a significant direct predictor of CBF (H7 supported). However, the mediation analysis provides a more cautious picture than initially hypothesized: rather than a strong mediating mechanism, GenAI adoption carries only a partial, and in one case non-significant, mediating role. Most of the influence of TF, OF, and EF on CBF is mediated by direct channels rather than by GenAI integration alone. GenAI adoption is thus a meaningful predictor in its own right, but should not be overstated as the primary mechanism linking TOE readiness to business performance; other unmeasured likely also contribute.

This more conservative interpretation refines, rather than overturns, the theoretical contribution of extending the TOE framework. GenAI adoption is a relevant but partial mediator, whose explanatory power for the TF pathway should be verified with larger samples.

4.3. Limitations

Several limitations should be acknowledged. First, the sample retains a nested structure: 202 respondents were from 20 SMEs, with multiple respondents per firm in most cases. The reported standard errors, p-values, and confidence intervals assume independent observations and may therefore understate the true uncertainty, particularly for the mediation results. Second, the cross-sectional design does not permit strong causal claims. Third, the bootstrap CIs for two of the three indirect paths had lower bounds near zero, and one crossed zero, suggesting the sample is underpowered for precise estimation of indirect effects in further studies. Fourth, self-reported measures may be subject to common method bias. Finally, the sample was drawn from five major urban centers and may not generalize to Vietnam's digitally developed regions. Future research should collect the enterprises so that multilevel SEM can properly separate within-firm and between-firm effects, and should target a larger number of independent firms.

V. Conclusions and recommendations

5.1. Conclusions

This study identifies the key factors affecting the integration of GenAI and its influence on CBF among Vietnam's SMEs, using primary survey data from 202 respondents from 20 SMEs. CFA confirmed a well-fitting, reliable measurement model, and structural equation modeling provided robust evidence that technological, organizational, and environmental factors significantly influence both GenAI adoption and CBF. OF had the strongest influence on GenAI

adoption, underscoring managerial support, financial resources, and digital capabilities in Vietnam's SME context, while technological readiness showed the strongest direct association with improved CBF.

GenAI adoption itself had a significant, positive direct effect on CBF, affirming that the depth and strategic intentionality of GenAI use matters for outcomes. However, the mediating role of GenAI adoption should be interpreted with caution: bootstrap testing showed that the indirect effect of TF through GenAI adoption did not reach significance, while the indirect effects of organizational and environmental factors, though significant, were only marginal. This indicates that TOE readiness influences CBF predominantly through direct channels, only partially through GenAI integration itself, and is a more credible conclusion than assuming GenAI adoption is the primary transmission mechanism.

This research is noteworthy for empirically testing, using real survey data and a well-specified structural model, whether GenAI adoption mediates the TOE-CBF relationship. Rather than confirming a strong, unconditional mediating role, the findings show that GenAI adoption is a meaningful direct predictor of performance.

5.2. Recommendations

Based on the findings drawn from the study, the following recommendations are proposed to enhance the effectiveness of GenAI adoption into SMEs' CBF in Vietnam:

First, Vietnam's SMEs should strengthen their environmental responsiveness to sustain the momentum of GenAI adoption by proactively complying

with government regulations and leveraging policy incentives. Policymakers should establish clear legal frameworks and fiscal support to lower integration barriers.

Second, Vietnam's SMEs should treat technological infrastructure as a foundational enabler, not merely a support function. Investments in cloud computing, data management, cybersecurity, and digital literacy generate benefits beyond GenAI use, exerting TF's strong and direct effects on CBF, not solely through GenAI adoption.

Third, Vietnam's SMEs should continue to position GenAI as a strategic driver of CBF, embedding it in financial forecasting, HR planning, product development, and customer relationship management. GenAI integration should be recognized as one contributing mechanism to pursue alongside broader organizational and technological readiness, rather than as a single solution.

Finally, Vietnam's SMEs and researchers should improve measurement of CBF using both financial and non-financial indicators, and track GenAI's contribution as adoption matures. A more comprehensive assessment can therefore provide stronger evidence of how GenAI contributes to improvements in operational efficiency, competitive position, and strategic performance over time.

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TÍCH HỢP TRÍ TUỆ NHÂN TẠO TẠO SINH VÀ CÁC CHỨC NĂNG KINH DOANH CỐT LÕI: BẰNG CHỨNG TỪ CÁC DOANH NGHIỆP NHỎ VÀ VỪA VIỆT NAM

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Tóm tắt: Bài viết này xác định các yếu tố quyết định ảnh hưởng đến việc tích hợp trí tuệ nhân tạo tạo sinh (GenAI) vào các chức năng kinh doanh cốt lõi của doanh nghiệp nhỏ và vừa (DNNVV) tại Việt Nam. Dựa trên khung lý thuyết Công nghệ - Tổ chức - Môi trường (TOE), nghiên cứu sử dụng khảo sát cắt ngang đối với 202 giám đốc, nhà quản lý và người ra quyết định cấp cao từ 20 DNNVV tại Hà Nội, Hải Phòng, Đà Nẵng, Nha Trang và Thành phố Hồ Chí Minh. Phân tích nhân tố khẳng định và mô hình cấu trúc tuyến tính được thực hiện trên phần mềm R (gói lavaan, phương pháp ước lượng hợp lý cực đại), kèm theo kỹ thuật bootstrapping với 5.000 mẫu lặp lại để kiểm định các tác động trung gian. Mô hình đo lường cho thấy các yếu tố công nghệ, tổ chức và môi trường có tác động trực tiếp đến việc ứng dụng GenAI và tác động gián tiếp đến các chức năng kinh doanh cốt lõi. Nghiên cứu đề xuất một số khuyến nghị nhằm tăng cường mức độ sẵn sàng của tổ chức, hạ tầng công nghệ, khả năng thích ứng với môi trường và công tác đo lường hiệu quả hoạt động.

Từ khóa: chức năng kinh doanh cốt lõi, tích hợp GenAI, doanh nghiệp nhỏ và vừa, khung lý thuyết TOE, Việt Nam

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