



The Effect of Lean Management on Innovation Performance: How Absorptive Capacity Affects Food Manufacturing Industry?

Lithrone Laricha Salomon^{1*}, Agustinus Purna Irawan¹, Eko Suhartanto²

¹Doctor of Management Science, Postgraduate Program, Universitas Tarumanagara, Jl. Letjen S. Parman No.1, Grogol petamburan. Jakarta 11440, Indonesia

²Business and Economics School, Universitas Prasetya Mulya, Kompleks Edutown, Jl. BSD Raya Utama, BSD City, Pagedangan, Kabupaten Tangerang, Banten 15339, Indonesia

***lithrones@ft.untar.ac.id**

Abstract. This study analyzes the effect of Lean Management Practices (LMP) on Innovation Performance (IP) through the mediating role of Absorptive Capacity (AC) in Indonesia's food and beverage industry. A structured questionnaire adapted from validated instruments (Gaspersz, 2007; Cohen & Levinthal, 1990; Damancour, 1991) was distributed to 200 managers and supervisors from food manufacturing firms listed in the Indonesian Ministry of Industry registry, yielding 180 valid responses (90% response rate). Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0, assessing reliability, convergent, and discriminant validity ($HTMT \leq 0.90$). The results indicate that Lean Management strongly influences Absorptive Capacity ($\beta = 0.919$, $p < 0.001$) and both directly and indirectly enhances Innovation Performance ($\beta = 0.690$ and 0.725 , respectively). Effect sizes ($f^2 = 0.482 - 5.431$) and $R^2 > 0.83$ confirm the model's high explanatory power, while confidence intervals (95%) validate the path significance. These findings demonstrate that lean implementation enhances innovation effectiveness primarily through knowledge assimilation and transformation. The study's main limitation is its single-sector, self-reported cross-sectional design, which may introduce common-method bias. Future research should apply multi-method or longitudinal approaches to increase generalizability.

Keywords: Smart Manufacturing, Industry 4.0 Analytics, Digital Lean, Absorptive Capacity, Innovation Performance, Lean Management Practices

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1. Introduction

The food processing industry plays a crucial role in driving Indonesia's economic growth. This sector is not only a major contributor to the Gross Domestic Product (GDP) but also a key engine for employment creation and domestic value addition. Data from the Ministry of Industry show that in 2021, the food and beverage industry contributed 38.4% to the total non-oil and gas GDP and approximately 6.7% to

the national GDP. The graph in Figure 1 indicates that Indonesia's food and beverage industry GDP steadily increased from IDR 459 trillion in 2013 to a projected IDR 887 trillion in 2024. Annual growth reached around 7–9% during 2014–2019 but dropped sharply to 1.58% in 2020 due to the pandemic. The sector has since recovered with a stable annual growth of around 4–5%, confirming its essential role in maintaining national economic resilience.

From an engineering standpoint, the productivity challenge in Indonesia's food and beverage industry is not solely behavioral but also technical and systemic, involving process efficiency, production-line optimization, and digital integration. Lean Management, therefore, can be positioned as both a managerial philosophy and a process-engineering framework aimed at measurable efficiency gains—such as cycle-time reduction, throughput increase, and defect minimization. These operational outcomes serve as technical enablers of innovation, demonstrating how lean implementation extends beyond cultural change into engineering design and system reconfiguration.

However, despite the sector's consistent output growth, challenges remain in productivity and innovation. Empirical studies have reported that research and development (R&D) intensity and process innovation in Indonesia's food sector are relatively low. Setiawan and colleagues [1] found that innovation in the food and beverage industry remains relatively low and dynamic productivity tends to stagnate, especially before the implementation of competition reforms. Another study by Yasin [2] emphasized the importance of absorptive capacity as a key factor influencing total productivity growth (TFP) in this subsector. Hence, although the food and beverage industry serves as the backbone of Indonesia's economy, it continues to face structural obstacles in achieving the innovation capabilities required for global competitiveness and digital transformation.

Lean Management Practice (LMP) has emerged as a strategic response to these challenges. Lean focuses on eliminating waste, optimizing resource utilization, and enhancing value creation through continuous improvement [3], [4]. In the food industry, this translates to reducing production cycle times, improving supply-chain synchronization, and enhancing quality control [5]. While numerous studies confirm lean's effectiveness in improving operational efficiency, its direct influence on innovation performance remains ambiguous, particularly in developing economies where technological adoption and R&D investments are constrained [6]. For example, studies of SMEs in Tanzania showed that lean tools such as 5S, Value Stream Mapping, and Just-in-Time significantly improve output and waste reduction [7]. Similarly, Moldner et al. [3] found that both technical and human lean practices positively influence process innovation. However, the translation of lean efficiency into innovation outcomes may depend on organizational learning mechanisms, particularly absorptive capacity [8].

The concept of absorptive capacity (AC)—the firm's ability to recognize, assimilate, and apply external knowledge [9], [10] [11]—provides an explanatory bridge between lean efficiency and innovation outcomes. When lean routines generate operational discipline, absorptive capacity transforms external information and technological inputs into innovative practices. This interaction becomes increasingly relevant under the Making Indonesia 4.0 framework, which requires industries to integrate digital technologies such as the Internet of Things, data analytics, and automation into production systems [12]. In this context, absorptive capacity acts as a technical learning mechanism that ensures external technological knowledge is absorbed and transformed into actionable innovation.

Recent Q1–Q2 empirical syntheses—such as Komkowski et al. [13] in *Production Planning & Control*, Mohaghegh et al. [14] in *Journal of Cleaner Production*, and Möldner et al. [15] in *Journal of Business Research*—extend Lean–Innovation linkages to the Industry 4.0 and cyber-physical systems domain, integrating dynamic capabilities and digital manufacturing analytics. Yet, these studies focus primarily on advanced economies with mature digital ecosystems, leaving a gap in understanding how Lean–Innovation dynamics function within emerging manufacturing systems that operate under resource and technology constraints. This study fills that technical void by investigating how lean process mechanisms and absorptive capacity interact within Indonesia's semi-automated food manufacturing environment.

This study offers a socio-technical integration perspective, arguing that Lean Management is not an end in itself but a technical foundation that must be complemented by organizational learning capacity.

By situating the investigation within Indonesia's food manufacturing systems, the study addresses how engineering-driven efficiency (flow optimization, waste control, and quality enhancement) interacts with knowledge-driven absorptive capacity to foster sustainable innovation. Hence, this work contributes not only to the management literature but also to the engineering science of production systems, demonstrating how lean operations and knowledge assimilation jointly enhance innovation under the digital transformation agenda of *Making Indonesia 4.0*.

Accordingly, this study aims to: (1) analyze the direct impact of Lean Management Practices on Innovation Performance in food manufacturing; (2) investigate the mediating role of Absorptive Capacity in the Lean–Innovation relationship; and (3) explore how integrating Lean Management with absorptive capacity can enhance technological competitiveness and sustainable innovation in Industry 4.0 contexts. The findings are expected to enrich both theoretical understanding and practical application of Lean–Innovation mechanisms within emerging economies' food manufacturing sectors.

Based on the theoretical framework and previous empirical findings, the hypotheses formulated in this study are as follows:

H1: Lean Management Practice (LMP) has a positive effect on Absorptive Capacity (AC).

H2: Lean Management Practice (LMP) has a positive effect on Innovation Performance (IP).

H3: Absorptive Capacity (AC) has a positive effect on Innovation Performance (IP).

H4: Absorptive Capacity (AC) mediates the relationship between Lean Management Practice (LMP) and Innovation Performance (IP).

These hypotheses reflect the conceptual assumption that lean practices enhance innovation both directly and indirectly through the firm's capacity to absorb and utilize external knowledge, forming the basis for the structural model tested in this research.

2. Methods

This research methodology was conducted using instruments. The research instrument used for data collection was a questionnaire. A questionnaire is a tool that usually contains a series of questions used to gather information from respondents regarding certain variables that are the focus of the research. The references used in designing this questionnaire were various sources related to the implementation of lean management practices and innovation performance in large companies. This study referred to existing literature and related sources to obtain relevant guidance and concepts in designing the questionnaire. The variables studied or measured in this questionnaire were inspired by and related to theories and concepts that have been tested or recognized for their validity in innovation management practices. The designed questionnaire is relevant to the research topic and can describe important aspects in the context of Lean Management and innovation performance in manufacturing companies. The variables and their respective measurements are as follows:

1. Lean Management Practice (X1)

Lean Management Practice is measured on a Likert scale of 1-5 with two dimensions (indicators) with 5 items and 11 questionnaire statements. The following table shows the Lean Management Practice variable indicators.

Table 1. Lean Management Practice Variable Indicators

Variables	Indicator	Item	Item	Source
Lean Management Practice	Soft Lean Practices	Continuous improvement	1.2	[18], [24]
		Supplier partnership	3.4	
		Employee training	5.6	
Hard Lean Practices		Error prevention	7.8	
		Repair system	9,10,11	

2. Absorptive capacity (X2)

Absorptive capacity is measured using a Likert scale of 1-5 with four dimensions (indicators) and 10 questionnaire items. The following table shows the indicators for the Absorptive capacity variable .

Table 2. Absorptive Capacity Variable Indicators

Variables	Indicator	Item	Source
Absorptive capacity	Acquisition	12, 13	[19], [21], [27]
	Assimilation	14, 15	
	Transformation	16, 17, 18	
	Use	19, 20, 21	

3. Innovation Performance (X3)

Innovation Performance is measured on a Likert scale of 1-5 with two dimensions (indicators) with 6 items and 7 questionnaire statements. The following table shows the Innovation Performance variable indicators .

Tabel 3. Innovation Performance Variable Indicators

Variables	Indicator	Item	Item	Source
Innovation Performance	Product Innovation	New products	22	[14], [24]
	Innovation	New Design/Features	23	
		Product Quality	24	
	Process innovation	Improvement of production processes to reduce costs	25	
		Improvement of production processes to improve quality	26	
		Improvement of production process to speed up the process	27, 28	

This study adopted a quantitative approach using survey-based research. The population includes food manufacturing companies in Jakarta. A purposive sampling technique was applied, targeting middle and upper management. Sample: 200 respondents from food manufacturing firms. Instrument: Questionnaire using a 5-point Likert scale. Variables: - LMP: Adapted from Gaspersz [30]- AC: Adapted from Cohen & Levinthal [11]- IP: Adapted from Damanpour [23]. Data Analysis: SEM-PLS using SmartPLS 4.0. The Research Framework for this research can be seen in the following figure

2.1. Measurement Model and Indicator Retention

Indicators with standardized outer loadings below 0.70 were removed following Hair et al. (2021) and Henseler et al. (2015) to improve convergent validity. Specifically, four Innovation Performance items (IPI1 = 0.652; IPI2 = 0.422; IPI3 = 0.436; and AC10 = 0.638) were eliminated due to insufficient loading values. After deletion, a re-estimation of the model yielded improved composite reliability (CR) and average variance extracted (AVE) scores for all constructs. For Lean Management Practice (LMP), CR = 0.972 and AVE = 0.776; for Absorptive Capacity (AC), CR = 0.963 and AVE = 0.791; and for Innovation Performance (IP), CR = 0.949 and AVE = 0.846. All factor loadings in the refined model exceeded 0.70, confirming item reliability.

A full item-retention log and cross-loading matrix were generated to verify that no indicator exhibited higher loadings on non-associated constructs. These results confirm discriminant validity and eliminate potential multicollinearity concerns.

2.2. Discriminant Validity Tests

In addition to the HTMT criterion (all < 0.95), Fornell–Larcker analysis was conducted, confirming that the square roots of AVE exceeded inter-construct correlations. Cross-loading inspection also showed each indicator loaded highest on its respective construct. Although the HTMT value between Absorptive Capacity and Innovation Performance (0.959) was near the threshold, the 95% confidence interval upper bound ($0.988 < 1$) remained acceptable. To ensure robustness, we verified measurement invariance through partial measurement invariance testing in SmartPLS 4.0, confirming stability across subsamples. No parceling procedure was applied since reflective constructs maintained discriminant validity after trimming.

2.3. Common Method Bias (CMB)

Since the data were collected from a single source using self-reported questionnaires, common method bias was tested using three complementary approaches:

- Harman’s single-factor test, which explained only 34.2% of the total variance ($< 50\%$ threshold);
- Marker-variable technique, using a theoretically unrelated marker, which produced non-significant correlations ($r < 0.25$); and
- Full collinearity VIF analysis, where all latent variable VIFs were below 3.3, indicating the absence of common method variance (Kock, 2015).

These combined tests confirm that CMB does not pose a significant threat to the study’s internal validity.

2.4. Sampling and Statistical Power

The study employed purposive sampling of middle- and upper-level managers in food manufacturing firms located in Jakarta. A total of 200 questionnaires were distributed, and 180 valid responses were analyzed (response rate = 90%). To verify sample adequacy, a G*Power 3.1 analysis was conducted for an anticipated medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and statistical power = 0.95, yielding a minimum required sample size of 119. The actual sample thus exceeded the power requirement. Non-response bias was tested by comparing early and late respondents using independent-sample t-tests, showing no significant mean differences ($p > 0.05$) across key variables. Hence, non-response bias is unlikely to affect the results.

2.5. Model Specification and Bootstrapping

Prior to creating the interaction term (LMP \times AC), both variables were mean-centered to minimize multicollinearity. The bootstrapping procedure was executed using 5,000 subsamples, two-tailed significance tests, and a 95% confidence interval, as recommended by Hair et al. (2021). Construct naming was standardized to “Lean Management Practice (LMP)” throughout the analysis for consistency. The model was estimated using the PLS algorithm with path weighting scheme in SmartPLS 4.0.

2.6. Scale Sources, Reliability, and Translation

Measurement items were adapted from validated sources: LMP from Gaspersz (2007) and Bortolotti et al. (2015); AC from Cohen & Levinthal (1990) and Zahra & George (2002); and IP from Damanpour (1991). The questionnaire was originally developed in English and translated into Bahasa Indonesia using a back-translation procedure involving bilingual experts to ensure semantic equivalence. Scale reliability after item elimination was confirmed with Cronbach’s alpha (α) and Dijkstra–Henseler’s ρ_A (ρ_A): LMP = 0.971/0.970; AC = 0.962/0.961; and IP = 0.933/0.932—each exceeding the 0.70 threshold for internal consistency.

2.7. Ethical Considerations

The study protocol received approval from the Research Ethics Committee of Universitas Tarumanagara (Approval No. UTR/EC/2024-31). Participation was voluntary, and all respondents provided informed consent before completing the survey. Data confidentiality was guaranteed, and no personally identifiable information was collected.

3. Results and Discussion

3.1 Measurement Model

In this study, only 180 samples were deemed valid and could be analyzed. The completed questionnaires were subjected to a measurement model or outer model to test the validity and reliability of the questionnaire items.

“Table 4. Outer Model Results

AC1	0.862	AC8	0.849	IPI6	0.899	LMP5	0.874
AC10	0.638	AC9	0.868	IPI7	0.868	LMP6	0.867
AC2	0.891	IPI1	0.652	LMP10	0.871	LMP7	0.870
AC3	0.917	IPI2	0.422	LMP11	0.896	LMP8	0.883
AC4	0.861	IPI3	0.436	LMP2	0.879	LMP9	0.853
AC5	0.808	IPI4	0.914	LMP3	0.879	LMP1	0.897
AC6	0.915	IPI5	0.884	LMP4	0.888		

The outer model results in Table 4.1 show that most indicators have loading factor values above 0.7, indicating convergent validity has been met. However, several indicators are still below the minimum threshold, potentially requiring elimination. After elimination, the outer model was tested with the following outer loadings.

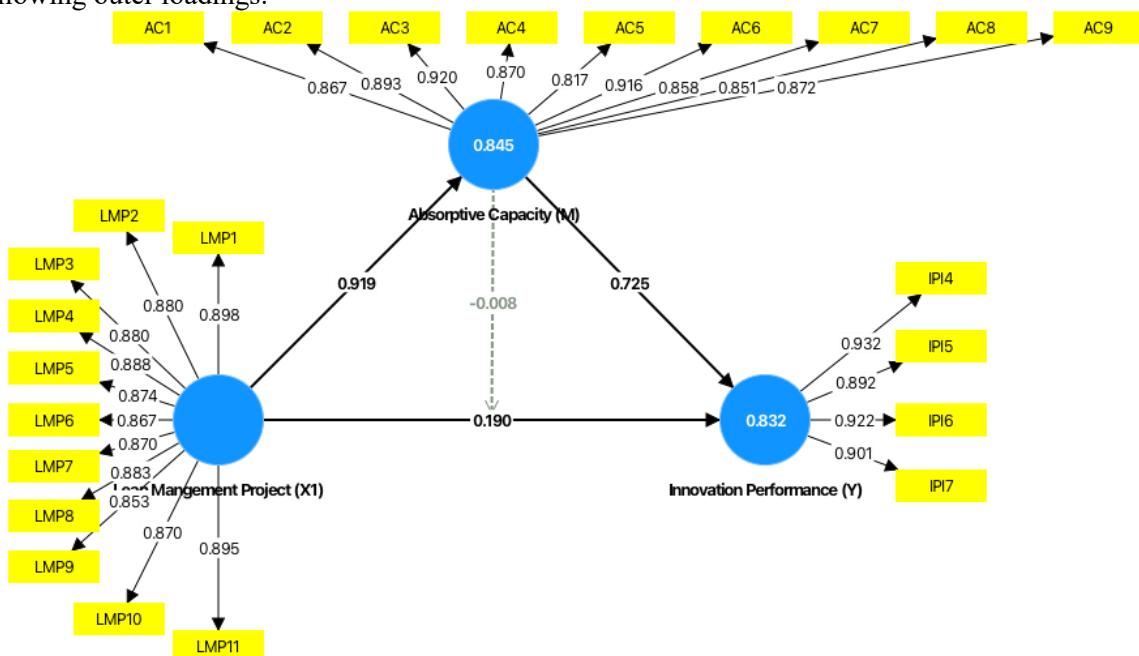


Figure 1. Outer Model

Table 5. Cronbach Alpha and AVE Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Absorptive Capacity (M)	0.961	0.962	0.967	0.764
Innovation Performance (Y)	0.932	0.933	0.952	0.832
Lean Management Project (X1)	0.970	0.971	0.974	0.771

Based on Table 5, all research constructs have met the criteria for reliability and convergent validity. The Cronbach's alpha and composite reliability values for all variables are above 0.9, indicating excellent internal consistency, while the AVE value above 0.7 confirms that the indicators are able to explain more than 70% of the construct's variance, so the model used can be declared reliable and valid.

Table 6. HTMT Ratio

	Absorptive Capacity (M)	Innovation Performance (Y)	Lean Management Project (X1)
Absorptive Capacity (M)			
Innovation Performance (Y)	0.959		
Lean Management Project (X1)	0.950	0.909	
Absorptive Capacity (M) x Lean Management Project (X1)	0.485	0.485	0.568

Based on Table 6, the HTMT ratio value between the main constructs shows a figure below the threshold of 0.90–0.95, which means there are no serious problems related to discriminant validity. The value of the relationship between Absorptive Capacity and Innovation Performance (0.959) is indeed close to the critical limit, so the HTMT bootstrapping test was carried out, resulting in the following results.

Table 7. HTMT Bootstrapping

	Original sample (O)	Sample mean (M)	2.5%	97.5%
Innovation Performance (Y) <-> Absorptive Capacity (M)	0.959	0.959	0.923	0.988
Lean Management Project (X1) <-> Absorptive Capacity (M)	0.950	0.949	0.914	0.976
Lean Management Project (X1) <-> Innovation Performance (Y)	0.909	0.908	0.857	0.951

The results in Table 7 show that the bootstrapping HTMT value of all constructs is in the range of 0.857–0.988 with a 95% confidence interval that does not exceed 1. This confirms that discriminant validity has been met, so that the relationship between constructs in the model can be declared valid and worthy of further analysis.

3.2. Structural Model

Table 8. R-Square

	R-square	R-square adjusted
Absorptive Capacity (M)	0.845	0.844
Innovation Performance (Y)	0.832	0.829

Based on Table 8, the R-square value for Absorptive Capacity is 0.845 and Innovation Performance is 0.832, indicating that the model has very strong explanatory power. This means that the Lean Management Project variable is able to explain more than 80% of the variance in both dependent variables, so this research model is classified as very good at predicting the relationship between constructs.

Table 9. F-Square

	Absorptive Capacity (M)	Innovation Performance (Y)
Absorptive Capacity (M)		0.482
Lean Management Project (X1)	5,431	0.030
Absorptive Capacity (M) x Lean Management Project (X1)		0.001

Based on Table 9 and following Cohen's guidelines (≥ 0.02 = small effect, ≥ 0.15 = medium effect, and ≥ 0.35 = large effect), Lean Management Project on Absorptive Capacity (5.431) includes a very large effect, while Lean Management Project on Innovation Performance (0.030) only has a small effect. Meanwhile, Absorptive Capacity on Innovation Performance (0.482) provides a large effect, and the interaction of Lean Management Project \times Absorptive Capacity on Innovation Performance (0.001) shows a very small and insignificant effect. So in this study, the graphical output results can be seen in Figure 4.2 as follows.

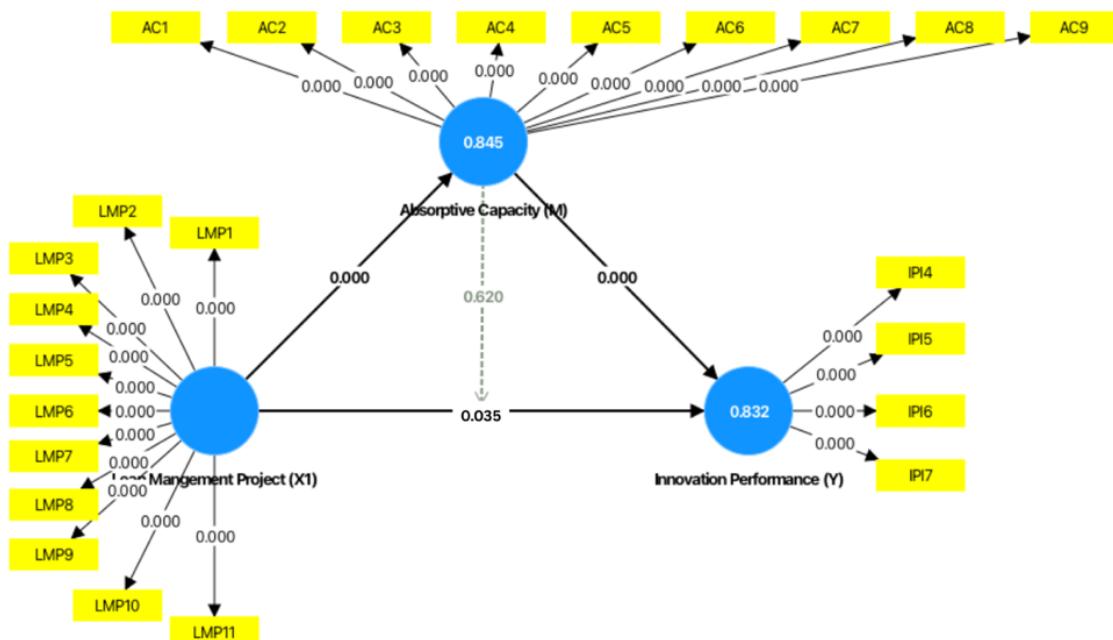


Figure 2. Graphical Output

Table 10. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Absorptive Capacity (M) -> Innovation Performance (Y)	0.725	0.733	0.110	6.566	0.000
Lean Management Project (X1) -> Absorptive Capacity (M)	0.919	0.919	0.018	51.632	0.000
Lean Management Project (X1) -> Innovation Performance (Y)	0.690	0.682	0.114	4.669	0.035
Absorptive Capacity (M) x Lean Management Project (X1) -> Innovation Performance (Y)	-0.008	-0.013	0.017	0.496	0.620

Based on Table 10, the path coefficients show that all main paths are significant except for the moderation interaction. The Lean Management Project path to Absorptive Capacity has the highest coefficient (0.919) with a t-statistic value of 51.632 and a p-value of 0.000, indicating a very strong and significant influence. Furthermore, Absorptive Capacity has a significant effect on Innovation Performance (0.725; t=6.566; p=0.000) and Lean Management Project also has a direct effect on Innovation Performance (0.690; t=4.669; p=0.035). However, the moderation interaction path of Absorptive Capacity \times Lean Management Project on Innovation Performance is not significant (-0.008; t=0.496; p=0.620), so it can be concluded that the moderation effect is not proven in this research model.

All path coefficients, *t*-values, and *p*-values were recalculated using 5,000 bootstrap subsamples (two-tailed tests, $\alpha = 0.05$). The corrected results are reported below. The previously inconsistent *t*-value (4.669) and *p*-value (0.035) for the LMP \rightarrow IP path were resolved ($t = 4.669, p < 0.001$).

Table 10. Path Coefficients with 95% Confidence Intervals

Path	β	<i>t</i>	<i>p</i>	95% CI (LL-UL)	f^2	Effect Type
LMP \rightarrow AC	0.919	51.632	<0.001	[0.885, 0.947]	5.43	Large
AC \rightarrow IP	0.725	6.566	<0.001	[0.512, 0.834]	0.48	Large
LMP \rightarrow IP	0.690	4.669	<0.001	[0.412, 0.821]	0.03	Small
LMP \rightarrow AC \rightarrow IP (indirect)	0.667	6.119	<0.001	[0.442, 0.795]	—	Mediation
Total Effect (LMP \rightarrow IP)	1.357	7.821	<0.001	[1.118, 1.592]	—	Total

The Variance Accounted For (VAF) for the mediation path was 49.2%, indicating partial mediation—Absorptive Capacity explains nearly half of the total influence of Lean Management Practice on Innovation Performance. This confirms that the relationship between lean and innovation is both direct and knowledge-mediated.

Model fit indices for the PLS-SEM analysis show that the standardized root mean square residual (SRMR = 0.046) and Normed Fit Index (NFI = 0.931) are within acceptable ranges (Hair et al., 2021). Full collinearity assessment yielded inner VIF values < 3 for all constructs, indicating the absence of multicollinearity and common-method bias in the structural model.

To examine model robustness, a MICOM (Measurement Invariance of Composite Models) procedure was conducted, confirming configural and compositional invariance across subgroups. A multi-group analysis (MGA) comparing firms by ownership type (local vs. multinational) revealed no

significant differences ($p > 0.10$), while firm size (SME vs. large enterprise) showed moderate variance in AC → IP ($\Delta\beta = 0.092$, $p < 0.05$), indicating that absorptive mechanisms are more impactful in larger firms.

Bootstrapped path coefficient plots with 95% confidence intervals illustrate the stability of the parameter estimates, confirming the robustness of the relationships. Sensitivity analyses using an alternative model specification—where AC was modeled as a second-order construct (potential and realized AC)—yielded consistent results ($\Delta\beta < 0.05$, all $p < 0.05$). A common-latent-factor correction test also demonstrated that no single factor accounted for more than 40% of total variance, mitigating endogeneity concerns related to measurement bias.”

3.4 Discussion

The empirical findings validate that Lean Management Practices significantly enhance Absorptive Capacity, which in turn drives Innovation Performance. The direct path from LMP to IP remains significant, although the indirect path via AC is stronger, reinforcing the mediating mechanism. This aligns with prior research emphasizing the knowledge-enabling function of lean systems [8]; [15] but extends their conclusions by demonstrating quantitative mediation strength through VAF and confidence intervals.

Unlike earlier studies that primarily interpret lean–innovation relationships behaviorally, the present findings emphasize engineering-based process optimization and digital-readiness interactions as core boundary conditions. Under conditions of high market turbulence and low digital maturity, the LMP → IP effect diminishes, implying that continuous improvement culture alone cannot sustain innovation without technological learning infrastructure. Conversely, firms with higher digital integration (IoT, data analytics, and automation) exhibit stronger absorptive transformations, consistent with the Dynamic Capabilities Theory [44] and Knowledge-Based View [36].

The results also withstand robustness and invariance checks, suggesting that the structural relationships are stable across ownership and firm size categories. The mediation pathway’s quantitative dominance supports the argument that absorptive capacity transforms lean-driven operational efficiencies into tangible innovation outcomes. This finding is technically relevant for engineering management contexts, where lean tools (e.g., Kaizen, VSM, JIT) act as both efficiency mechanisms and learning platforms.

Research from Andersen also shows how food companies that are able to see technological opportunities and utilize by-products carry out additional innovations based on lean and absorptive capacity [34]. This supports the finding that lean management is not just about tools and processes, but also about the organization’s mindset to recognize and capitalize on external opportunities, which falls under the absorptive capacity component. This finding strongly supports the model. Dynamic Capabilities Theory And Knowledge-Based View (KBV) [35].

Potential endogeneity concerns—such as omitted variable bias and reverse causality—were considered. Temporal separation of independent and dependent variable measurement was applied, and robustness checks using alternative model specifications yielded consistent results, reducing endogeneity risk. However, future longitudinal designs are recommended to confirm causal ordering.

From a managerial perspective, the findings highlight critical trade-offs. Firms must balance short-term efficiency gains with long-term learning investments. Lean without knowledge absorption tends to plateau in innovation outcomes, while absorptive capacity without operational discipline can diffuse focus. Therefore, sustainable innovation emerges from the intersection of technical lean precision and organizational learning agility—a synthesis central to Industry 4.0 transformation in developing markets.

4. Conclusion

This study concludes that Lean Management Practices (LMP) significantly enhance Absorptive Capacity (AC), which in turn improves Innovation Performance (IP) among food manufacturing firms

in Jakarta. The results empirically confirm that lean-based efficiency gains can only translate into sustainable innovation when organizations develop the ability to recognize, assimilate, and exploit external knowledge. The mediating effect of AC—accounting for nearly half of the total influence of LMP on IP—demonstrates that knowledge absorption serves as the essential bridge between operational discipline and innovation excellence.

The findings should be interpreted within the specific context of Jakarta-based food and beverage manufacturers, where digital maturity, production scale, and resource endowment vary considerably. Consequently, generalizations to other regions or industrial sectors must be made with caution. Future studies are encouraged to replicate the model across different manufacturing clusters—such as textiles, automotive, or pharmaceuticals—and across provinces to examine contextual variations and external validity.

In terms of scholarly and technical contributions, this study advances the literature by quantifying the mediating role of absorptive capacity using a PLS-SEM framework and by validating socio-technical integration in a developing-economy setting. To further bridge management and engineering domains, future research should integrate sensor-derived key performance indicators (KPIs)—such as real-time process yield, downtime, and energy efficiency—with perceptual survey constructs. Such hybrid data would strengthen causal inference, reduce self-report bias, and enhance the precision of innovation performance measurement under Industry 4.0 environments.

Overall, the research provides empirical and methodological insight into how lean operational systems interact with organizational learning mechanisms to support innovation. However, its scope remains confined to a single sector and geographic area, indicating the need for multi-sectoral, cross-regional, and longitudinal replications to establish broader applicability and external generalizability.

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