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Optimal Mediation Strategy for Industry 4.0 Integration in Improving Operational Performance

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Abstract. *Digital transformation through Industry 4.0 (I4.0) offers significant potential to enhance efficiency and flexibility in manufacturing processes. However, its implementation often fails due to organizational unpreparedness and the lack of integration with Lean and Agile principles. This study aims to analyze the impact of I4.0 on operational performance (OP) and to examine the mediating role of Leagility Competencies (LC). The research involved 130 manufacturing companies in Indonesia that have adopted I4.0 technologies for at least three years and possess internal digital systems. The technologies implemented include Internet of Things (IoT), big data analytics, cloud manufacturing, and AI-driven control. Despite the widespread adoption of advanced technologies, many companies have not provided adequate training to develop LC among their employees. The study employs Structural Equation Modeling using the Partial Least Squares (SEM-PLS) approach. The results indicate that the direct effect of I4.0 on OP is not statistically significant (β = 0.118; p = 0.159), whereas the indirect effect through LC is significant (β = 0.290; t > 1.96). These findings highlight the critical role of LC in bridging I4.0 adoption with operational performance improvement. The study underscores the importance of organizational readiness, particularly in cultivating internal competencies based on Lean and Agile principles, to fully realize the benefits of I4.0 implementation.*

Keywords: *Competencies; Leagility; Operational; Performance.*

1. Introduction

Industry 4.0 (I4.0) has become a revolutionary paradigm in the manufacturing sector. By integrating advanced technologies such as the Internet of Things (IoT),(Restuputri et al., 2024), artificial intelligence (AI), and cyber-physical systems(Gomes et al., 2020), the adoption of I4.0 is expected to improve operational efficiency, flexibility, and competitiveness. However, the implementation of I4.0 in the manufacturing industry often faces challenges.(Dai et al., 2020). One of the main problems is implementation failure due to hasty implementation without adequate preparation.

Previous manufacturing systems, such as Lean Manufacturing (LM) and Agile Manufacturing

(AM), were not optimized, and companies began adopting the I4.0 trend. As a result, many organizations were unable to improve operational performance (OP). Furthermore, they faced new, more complex challenges, such as process inefficiencies and increased operational costs.(Pagliosa et al., 2019)These problems are further exacerbated by the increasing complexity in the unresolved production and distribution chains.(Kamble, Gunasekaran, & ..., 2020)

Various efforts have been identified to mitigate the problems arising from the implementation of I4.0. One of these is the use of digital technology to improve visibility and control in the supply chain.(Qureshi et al., 2023). Several studies have shown that the use of technologies such as sensors, IoT(Vates et al., 2021), and big data platforms (Bauer et al., 2018) for real-time data monitoring and analysis can help identify inefficiencies and minimize waste. However, implementing I4.0 is not as easy as imagined and is often exacerbated by forced implementation.

Efforts to determine the optimal position of I4.0 in improving OP are ongoing, but no consensus has been reached among researchers. I4.0 acts as a mediating variable.(Matondang, 2023; Sharma et al., 2022)and moderation(Journal et al., 2024; Tortorella & Giglio, 2018)in various studies. The adoption of I4.0 is expected to bridge new technologies with legacy manufacturing systems such as LM and AM. Unfortunately, study results related to mediation and moderation effects still show inconsistencies, largely due to inadequate organizational and infrastructure readiness.

Some studies also use I4.0 as an independent variable.(Kamble, Gunasekaran, & Dhone, 2020; Rossini et al., 2021; Seng et al., 2021; Varela et al., 2019),However, implementation still faces challenges. Barriers such as resistance to change, limited technical competency, and integration complexity pose significant challenges.

LM and AM as two dominant approaches in modern manufacturing emphasize efficiency and flexibility.(Gelaw et al., 2024; Gunasekaran, 1998)However, the challenges of I4.0 demonstrate that neither can operate independently. A more strategic integration is needed, namely through an approach that combines the efficiency of LM and the responsiveness of AM.

A series of problems arising from inconsistent implementation of I4.0 as an independent variable have created a gap in the literature. This study offers a solution by introducing Leagility Competencies (LC) as a mediating variable, which is expected to increase the effectiveness of I4.0 implementation in improving manufacturing operational performance.

Leagility Competencies (LC) integrate Lean principles, which emphasize efficiency and waste elimination, with Agile principles, which emphasize flexibility and adaptability to change. In the context of uncertainty and technological disruption, LC enables organizations to maintain operational efficiency while remaining responsive to market dynamics. This competency was developed byBudianto et al. (2025)through the Resource-Based View (RBV) approach, which views internal resources including skills, structures, and processes as key to building sustainable capabilities that can bridge the needs of efficiency and agility simultaneously.

2. Research Methods

This research uses a mixed methods approach, a combination of quantitative and qualitative approaches. The quantitative approach is used to examine the relationships between variables through statistical analysis, while the qualitative approach aims to gain a deeper understanding of the implementation of Industry 4.0 (I4.0), Leagility Competencies (LC), and their impact on Operational Performance (OP). This approach was chosen to provide a more comprehensive and triangulated picture of the phenomenon under study (Jermsittiparsert et al., 2021; Creswell & Plano Clark, 2018).

3. Results and Discussion

This study employed a quantitative approach to examine the relationships between variables formulated in the conceptual framework through statistical analysis based on Structural Equation Modeling–Partial Least Squares (SEM-PLS). This method was chosen because it is capable of handling model complexity involving direct and indirect relationships between latent constructs, and is suitable for data with non-normal distributions and relatively limited sample sizes. This quantitative analysis includes an overview of respondents, a descriptive evaluation of the research variables, and testing of the measurement and structural models to validate the established hypotheses.

Quantitative data collection in this study involved 100 respondents representing various manufacturing companies in Indonesia. Each respondent was selected based on specific criteria, namely holding at least a supervisory position or equivalent, with the assumption that they had an adequate understanding of the company's operational conditions and digitalization strategy. Respondents were selected purposively to ensure the data obtained was relevant to the research focus, which examines Industry 4.0 integration and agility competencies.

The distribution of respondents reflects the diversity of geographic regions and industrial sectors in Indonesia. Based on company location, respondents came from:

1) West Java, Central Java, and East Java – as the center of the national manufacturing industry.

2) Banten and DKI Jakarta – as strategic areas for industrial and logistics areas.

3) Sumatra, Kalimantan, and Sulawesi – as a representation of industrial areas outside Java, to capture the dynamics of national industrial regionalization.

In terms of industrial sectors, respondents were divided relatively evenly into five large categories:

1) Food and beverage industry,
2) Chemical and pharmaceutical industry,
3) Electronics and hardware industry,
4) Furniture and wood processing industry, as well as
5) Textile and garment industry.

Each sector represents a proportion of approximately 15–18% of the total respondents, indicating that this research covers a broad spectrum in the context of manufacturing applications.

A review of respondents' education levels shows that the majority had a high school diploma or equivalent, with a significant proportion holding diplomas, bachelor's degrees, and some even completing master's and doctoral degrees. This demonstrates the diversity of educational backgrounds, providing a varied perspective when completing the questionnaire and reflecting the real-world conditions of the managerial workforce in the manufacturing sector. In terms of industrial scale, respondents came from:

1) Small companies (number of employees <100),
2) Medium-sized companies (100–500 employees), and
3) Large companies (number of employees >500),

with a relatively proportional distribution. This allows for a more comprehensive analysis of the effectiveness of Industry 4.0 implementation and LC competencies, both in companies with limited resources and in large companies with complex production systems.

In the Operational Performance variable, the Manufacturing Unit Cost and Manufacturing Cycle Time indicators had the highest mean values. This indicates that respondents perceived the production system to be quite efficient in terms of cost and time. This finding supports the assertion that operational efficiency in manufacturing companies is largely determined by the synergy between technological capabilities and operational agility (Vásquez-Torres et al., 2021).

The identified statistical values also show that there are no outliers or extreme deviations in respondents' perceptions, so that this data can be declared eligible to proceed to the inferential analysis stage using SEM-PLS.

Discriminant validity was analyzed using the Fornell-Larcker criterion, by comparing the square root of the AVE value with the correlation between constructs. The results showed that the square root of the AVE value for each construct was higher than the correlation with other constructs, thus it can be concluded that each construct has clear differences and does not overlap with each other.

Construct reliability was tested using two indicators: Cronbach's Alpha and Composite Reliability (CR). Cronbach's Alpha values ranged from 0.847 to 0.915, while CR values ranged from 0.897 to 0.934. All values exceeded the recommended threshold (Cronbach's Alpha > 0.6 and CR > 0.7), indicating that the construct has excellent and consistent internal reliability.

The measurement model (outer model) was analyzed to test convergent validity, discriminant validity, and construct reliability, to ensure that the indicators used statistically accurately and consistently load the latent construct. The convergent validity test in this study used the outer loading values from bootstrapping results, which include the original sample estimate, t-statistic, and p-value for each indicator.

The outer loading test results show that all indicators have loading values above 0.70, which is the minimum threshold according to Hair et al.'s (2021) standards. Furthermore, bootstrapping results show that the t-statistic value for all indicators is greater than 1.96 with a p-value below 0.05, indicating that the loading is significant at the 95% confidence level.

Discriminant validity testing was conducted using the Fornell-Larcker criterion. The square root of the AVE value of each construct was compared with the correlation between other constructs. The test results showed that the square root of the AVE of each construct was higher than the correlation with other constructs, indicating that the constructs were clearly discriminatory from each other.

Construct reliability tests showed excellent results. Cronbach's Alpha values ranged from 0.847 to 0.915, while Composite Reliability (CR) values ranged from 0.897 to 0.934. All of these values are well above the recommended thresholds ($\alpha > 0.6$ and CR > 0.7), indicating that the instrument has strong internal consistency.

Qualitative data collection in this study was conducted through in-depth semi-structured interviews, aimed at exploring perceptions, experiences, and implementation strategies for Industry 4.0 and Leagility Competencies in improving Operational Performance (OP) in manufacturing companies. This method was chosen to obtain more contextual and in-depth data to complement the previously obtained quantitative findings.

Interviews were conducted online via video and audio calls to reach informants across Indonesia. Interviews took place from the second week of May to the third week of May 2025.

Each interview lasted between 45 and 75 minutes and was recorded for transcription and content validation. Questions covered operational strategy, challenges in digitalization implementation, human resource readiness, and the role of lean-agile integration in real-world practice.

The interview instrument was developed based on the results of a quantitative study and a literature review on the integration of Lean Manufacturing (LM) and Agile Manufacturing (AM) in the context of industrial digitalization. Validation of the interview guide was conducted based on the principles of content validity through consultation with experts in the fields of production systems and digital manufacturing transformation.

Qualitative data analysis was conducted using thematic coding techniques, which identify patterns and themes emerging from interview transcripts. These themes were then linked to the research's theoretical framework to strengthen interpretation and triangulate the data.

Some important findings from the correlation between indicators are as follows:

1) Internet of Things (IoT)(I4.0.1) has the highest correlation with Manufacturing Cycle Time (OP5) at 0.402, followed by Manufacturing Unit Cost (OP3) at 0.378 and Reject Cost (OP2) at 0.358. This shows that IoT adoption has the potential to help in production time efficiency and reduce production costs and the cost of defective products.

2) Artificial Intelligence (AI)(I4.0.2) shows the highest correlation with Reject Cost (OP2) at 0.355, but low with Stock Opname (OP4) (0.126). This indicates that the use of AI is likely to play a greater role in reducing defects and costs than stock control.

3) Cyber-Physical Systems (CPS)(I4.0.3) has a moderate correlation with Reject Cost (OP2) and Manufacturing Unit Cost (OP3), 0.349 and 0.321 respectively, reflecting its potential in integrating physical and digital systems for production cost efficiency.

4) Big Data Analytics(I4.0.4) and Distributed Computing (I4.0.5) showed a similar relationship to OP2 to OP5 with a correlation range of 0.264 to 0.336. This indicates that big data analysis and distributed computing can also contribute to operational performance improvement, although not dominantly.

5) Smart Manufacturing(I4.0.6) shows the highest correlation with Manufacturing Unit Cost (OP3) of 0.292 and Manufacturing Cycle Time (OP5) of 0.201. Although positive, the contribution of intelligent manufacturing technology to increasing efficiency is not yet very strong in this data.

In general, the correlation between I4.0 technology and operational performance indicators shows a positive but not high value, ranging from 0.126 to 0.402.

This finding aligns with the results of the first hypothesis test, where the direct relationship between I4.0 and Operational Performance was insignificant ($\beta = 0.118$; $t = 1.412$; $p = 0.159$). This means that although the implementation of I4.0 technology tends to improve operational performance, its direct effect is not strong enough to be considered significant, so Hypothesis 1 is rejected.

The analysis results show that Industry 4.0 (I4.0) has a significant effect on Lean Capabilities (LC) with a value of $\beta = 0.420$, $t = 4.881$, and $p = 0.000$. This indicates that the higher the application of Industry 4.0 technology, the higher the lean capabilities of the company.

This finding is reinforced by the results of the correlation between indicators, which generally show a positive and moderate to strong relationship between I4.0 technology elements and lean capability elements:

1) Smart Manufacturing (I4.0.6)has a high correlation with the Reconfiguration manufacturing system (LC3) of 0.614. This illustrates that intelligent manufacturing technology enables production systems to be more flexible and easily reconfigurable.

2) Cyber-Physical Systems (I4.0.3)shows a strong correlation with Flexibility of layouts to changes (LC4) of 0.567, indicating that integration between physical and digital systems supports the flexibility of production layouts that are adaptive to change.

3) Artificial Intelligence (I4.0.2)has a moderate relationship with the Change-based 5S implementation (LC7) indicator of 0.501, as well as Critical point-based value stream mapping (LC5) of 0.492, which reflects the role of AI in supporting data-based and priority-based lean system optimization.

4) Big Data Analytics (I4.0.4)correlates well with Data and knowledge-based innovation (LC2) at 0.542, strengthening the role of big data as a basis for decision-making in innovation and lean process improvement.

5) Internet of Things (I4.0.1)and Distributed Computing (I4.0.5) also showed a fairly good correlation with TPM Optimization (LC6) and Evaluation of core competencies (LC8) with correlation values ranging from 0.466 – 0.505, indicating that device connectivity and distributed data processing support increased equipment efficiency and evaluation of internal capabilities.

This consistent and significant correlation indicates that the implementation of Industry 4.0 technology not only impacts direct efficiency but also strengthens lean foundations such as system flexibility, data-driven innovation, optimization of total productive maintenance, and evaluation of core competencies. Thus, Hypothesis 2 is accepted, where there is a significant and positive influence between the implementation of Industry 4.0 and the strengthening of Lean Capabilities in the company.

The analysis results show that Lean Capabilities (LC) has a positive and significant effect on Operational Performance (OP). The path coefficient value of 0.715 with a t-statistic value of 11.393 and a significance level of 0.000 indicates a very strong influence and is statistically supported. The t-value is well above the threshold of 1.65 and the p-value is less than 0.05, so this hypothesis is accepted.

Based on the effect size (f^2) value of 1.047, the influence of LC on OP is considered strong because it exceeds the criteria for a large category ($f^2 \geq 0.35$). This indicates that the contribution of LC in explaining variations in operational performance is quite dominant in the structural model used. From the R^2 value of 0.593, it can be concluded that 59.3 percent of the variation in operational performance can be explained by Lean Capabilities and other constructs in the model. In addition, the Q^2 value of 0.356 indicates that the model has high predictive relevance for OP variables, so it can be relied upon for prediction purposes.

Furthermore, the results of the correlation analysis between indicators strengthen the relationships found at the construct level. Indicator LC7 (Total Productive Maintenance) has a high correlation with indicator OP3 (production speed) at 0.650. This reflects the importance of TPM in driving operational efficiency. Indicator LC6 (implementation of 5S based on change) also shows a strong relationship with OP4 and OP5, at 0.508 and 0.538, respectively, indicating that cleanliness, orderliness, and work discipline practices significantly contribute to the achievement of operational results.

In addition, the LC8 indicator (adaptive employee competency) correlates highly with OP3, OP4, and OP5, namely 0.546; 0.453; and 0.502, respectively. This indicates that flexible employee competency and readiness to adapt to lean changes are essential for optimal performance. Therefore, based on the results of the structural model estimation and the correlation support between indicators, hypothesis 3, which states that Lean Capabilities have a positive effect on Operational Performance, is accepted.

The results of the hypothesis testing indicate that the direct relationship between Industry 4.0 (I4.0) and Operational Performance (OP) represented by H1 is not statistically significant, with a coefficient value of 0.118, a t-statistic of 1.412 (<1.65), and a p-value of 0.159 (>0.05). This indicates that the direct implementation of I4.0 is not yet strong enough to improve the company's operational performance.

However, an interesting finding emerged when considering the role of Leagility Competencies (LC) as a mediator. In H2 and H3, the relationship between I4.0 and LC and LC and OP showed significant results, with coefficients of 0.420 (t = 6.625; p = 0.000) and 0.715 (t = 11.393; p = 0.000), respectively. This indicates that companies that develop leagile competencies after adopting I4.0 principles have a greater opportunity to improve their operational performance. Furthermore, in H4, the indirect path I4.0 → LC → OP has a coefficient of 0.290, with a t-statistic of 5.115 and a p-value of 0.000, which means it is statistically significant.

This fact confirms that the influence of I4.0 on OP becomes significant only when it is through Leagility Competencies. When compared to the direct influence on H1 (0.118), the indirect effect through LC on H4 (0.290) shows an increase in influence of 145.76% [(0.290 - 0.118) / 0.118 × 100]. This means that the contribution of Leagility Competencies as a mediator is able to increase the effectiveness of I4.0 adoption on operational performance more than twofold. Thus, the existence of this mediation is very crucial in strengthening the relationship between technology and operational results.

Based on these findings, the fourth hypothesis (H4) is declared accepted, because the mediating role of Leagility Competencies is proven to be significant and is able to increase the impact of I4.0 on Operational Performance substantially.

Table Hypothesis Testing, Model Fit (R^2), and Predictive Relevance (Q^2) in SEM-PLS

H	Paths	Coefficient (β)	T >1.65	p < 0.05	f2	Remark

1	I4.0→OP	0.118	1,412	0.159	0.029	R(+) not significant
2	I4.0→LC	0.420	6,625	0.000	0.198	A(+) significant
3	LC→OP	0.715	11,393	0.000	1,047	A(+) significant
4	I4.0→LC→OP	0.290	5.115	0.000		A(+) significant

f2: 0.02- 0.15 Weak Effect; f2: 0.15-0.35 Sufficient Effect; f2: ≥ 0.35 Strong Effect
R2>>>>>LC=0.165; OP=0.593

Construct Cross validated Redundancy

Variable	SSO	SSE	Q^2 (=1-SSE/SSO)	Annotation
I.4.0	588,000	588,000		
LC	784,000	713,895	0.089	Predictive
OP	392,000	252,285	0.356	Predictive

Q2>0 indicates well the observed values (Predictive relevance)
Q2<0 indicates no predictive relevance

Note: A: accepted, R: Rejected
Correlation Table between Indicators

	I40.1	I40.2	I40.3	I40.4	I40.5	I40.6	LC1	LC2	LC3	LC4	LC5	LC6	LC7	LC8	OP2	OP3	OP4	OP5
I40.1	1,000	0.668	0.577	0.673	0.718	0.594	0.169	0.236	0.194	0.313	0.217	0.216	0.212	0.333	0.358	0.378	0.264	0.402
I40.2	0.668	1,000	0.581	0.649	0.692	0.668	0.278	0.207	0.139	0.088	0.177	0.096	0.146	0.376	0.355	0.249	0.126	0.189
I40.3	0.577	0.581	1,000	0.625	0.640	0.519	0.347	0.309	0.255	0.301	0.468	0.328	0.294	0.500	0.349	0.321	0.282	0.263
I40.4	0.673	0.649	0.625	1,000	0.684	0.655	0.230	0.271	0.157	0.178	0.210	0.245	0.194	0.324	0.306	0.336	0.164	0.264
I40.5	0.718	0.692	0.640	0.684	1,000	0.693	0.303	0.223	0.181	0.273	0.278	0.246	0.206	0.403	0.352	0.288	0.179	0.292
I40.6	0.594	0.668	0.519	0.655	0.693	1,000	0.282	0.134	0.239	0.263	0.211	0.152	0.202	0.442	0.269	0.292	0.137	0.201
LC1	0.169	0.278	0.347	0.230	0.303	0.282	1,000	0.672	0.551	0.409	0.421	0.372	0.447	0.588	0.421	0.365	0.210	0.372
LC2	0.236	0.207	0.309	0.271	0.223	0.134	0.672	1,000	0.512	0.591	0.391	0.590	0.440	0.550	0.453	0.383	0.484	0.548
LC3	0.194	0.139	0.255	0.157	0.181	0.239	0.551	0.512	1,000	0.573	0.517	0.421	0.507	0.602	0.401	0.551	0.451	0.511
LC4	0.313	0.088	0.301	0.178	0.273	0.263	0.409	0.591	0.573	1,000	0.477	0.566	0.445	0.551	0.440	0.423	0.530	0.636
LC5	0.217	0.177	0.468	0.210	0.278	0.211	0.421	0.391	0.517	0.477	1,000	0.493	0.616	0.598	0.458	0.539	0.455	0.422
LC6	0.216	0.096	0.328	0.245	0.246	0.152	0.372	0.590	0.421	0.566	0.493	1,000	0.616	0.539	0.506	0.547	0.508	0.538
LC7	0.212	0.146	0.294	0.194	0.206	0.202	0.447	0.440	0.507	0.445	0.616	0.616	1,000	0.517	0.576	0.650	0.443	0.441

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LC8	0.333	0.376	0.500	0.324	0.403	0.442	0.588	0.550	0.602	0.551	0.598	0.539	0.517	1,000	0.471	0.546	0.453	0.502
OP2	0.358	0.355	0.349	0.306	0.352	0.269	0.421	0.453	0.401	0.440	0.458	0.506	0.576	0.471	1,000	0.644	0.572	0.510
OP3	0.378	0.249	0.321	0.336	0.288	0.292	0.365	0.383	0.551	0.423	0.539	0.547	0.650	0.546	0.644	1,000	0.549	0.519
OP4	0.264	0.126	0.282	0.164	0.179	0.137	0.210	0.484	0.451	0.530	0.455	0.508	0.443	0.453	0.572	0.549	1,000	0.691
OP5	0.402	0.189	0.263	0.264	0.292	0.201	0.372	0.548	0.511	0.636	0.422	0.538	0.441	0.502	0.510	0.519	0.691	1,000

The findings from the in-depth interviews support the quantitative results. All interviewees emphasized that implementing I4.0 faces challenges, particularly in terms of human resource and infrastructure readiness. Meanwhile, the success of digital transformation is largely determined by an adaptive and efficient lean-agile-based operational structure. In practice, LC indicators such as the change-based 5S and adaptive competencies are key to optimal technology adoption.

The interviewee also stated that sensor-based (IoT) systems are only effective when combined with TPM and visual management, along with a continuous improvement process. This statement reinforces the argument that the impact of IoT on operational performance is not a direct relationship, but rather depends on the structural and cultural readiness of the organization.

These findings add to the literature suggesting that the impact of I4.0 on OP is highly contextual and not universal. Studies such as Kamble et al. (2020) and Rossini et al. (2021) also show that without synergy with internal strategies (e.g., LM and AM), I4.0 implementation will have limited impact.

The main theoretical contribution of this research is to introduce Leagility Competencies as a new integrative framework that combines efficiency (lean) and responsiveness (agile), and makes it a mediating channel in optimizing digital technology. With the Resource-Based View (RBV) perspective, LC acts as a dynamic capability needed to respond to changes in the technological and market environment simultaneously.

4. Conclusion

This study aims to address the key issues related to improving the operational performance of manufacturing companies through the integration of Industry 4.0 and strengthening internal competencies. Based on the analysis, it can be concluded that the implementation of Industry 4.0 does not automatically improve operational performance if it is carried out in a technology-centric manner without considering the readiness of human resources and the organization. Improving operational performance depends on the extent to which the company is able to build leagility competencies—namely the ability to remain efficient and adaptive in facing market and technological dynamics. This competency has proven to be a crucial link that bridges digital technology with the need for flexible and responsive business processes. Thus, Industry 4.0-based digital transformation will only be effective if accompanied by a strengthened organizational structure, an agile work culture, and a production system that supports rapid change. Leagility competencies have proven to be a key element in an integrative strategy between lean and agile approaches to drive operational efficiency and competitiveness sustainably.

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