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Determinants of CODP Positioning and Their Effects on Supply Chain Outcomes: An Empirical Investigation in the Furniture Sector

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Abstract

This study investigates the determinants of Customer Order Decoupling Point (CODP) placement and its impact on supply chain performance within Bangladesh's furniture industry, using a reputed furniture company as a case study. A Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was employed to examine how Product Customization (PC), Production Flexibility (PF), and Manufacturing Strategy (MS) influence CODP positioning, and how CODP subsequently affects Lead Time Performance (LTP), Service Level (SL), and Cost Efficiency (CE). Data were collected through structured questionnaires from supply chain and operations personnel. The measurement model demonstrated strong reliability and validity ($\alpha = 0.72–0.94$, CR = 0.83–0.96, AVE = 0.63–0.89). CODP was well explained ($R^2 = 0.809$), with PC having a significant positive effect, whereas PF and MS were not significant. CODP placement significantly reduced SL and CE but did not affect LTP. The findings show that high customization shifts CODP downstream, increasing responsiveness but raising costs and lowering service levels. The study proposes strategies such as modular design, limited buffers, preconfigured components, and ERP-based scheduling to mitigate these trade-offs. This research contributes context-specific empirical evidence for optimizing CODP positioning in Bangladesh's emerging furniture manufacturing sector.

Keywords
Customer Order Decoupling Point, PLS-SEM, Supply Chain Performance, Product Customization, Average Variance Extracted.

1. Introduction

The Customer Order Decoupling Point (CODP) plays a critical role in determining how manufacturing systems balance efficiency and responsiveness. CODP defines the point in the supply chain where production shifts from forecast-driven (push) to order-driven (pull) activities (Hoekstra & Romme, 1992). A strategically positioned CODP allows firms to improve responsiveness to customer demand while simultaneously controlling inventory and production costs (Olhager, 2003). In industries characterized by high product variety and customization—such as the furniture industry—CODP becomes even more important because the location of the decoupling point directly influences lead time, service level, and operational performance (Christopher & Towill, 2002).

Furniture manufacturers in emerging economies like Bangladesh are increasingly adopting customization-oriented strategies to meet diverse customer requirements. However, these firms often lack advanced production systems, making CODP placement challenging. As customization increases, the CODP typically moves downstream, leading to cost and service-level trade-offs (Yang & Burns, 2003). Despite CODP's strategic importance, empirical studies in developing countries remain limited, particularly within Bangladesh's growing furniture sector (Islam & Mia, 2022). To address this gap, this study investigates the drivers of CODP—specifically product customization, production flexibility, and manufacturing strategy—and examines how CODP placement influences key supply chain performance indicators such as lead time, service level, and cost efficiency. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this research provides empirical evidence relevant to furniture manufacturing in Bangladesh.

1.1 Objectives

The objectives of this research revolve around:

- To identify the key operational and strategic drivers influencing CODP positioning, focusing on product customization, production flexibility, and manufacturing strategy.
- To examine the relationship between CODP placement and supply chain performance outcomes, including lead time performance, service level, and cost efficiency.
- To develop a PLS-SEM model that empirically validates the causal relationships among CODP drivers and performance indicators in the context of a furniture manufacturing firm.
- To provide practical recommendations for optimizing CODP placement to balance customization requirements with cost, responsiveness, and service-level performance.

2. Literature Review

2.1 Customer Order Decoupling Point (CODP)

CODP represents the boundary between activities driven by forecasting and those triggered directly by customer orders (Hoekstra & Romme, 1992). Its placement determines whether a company adopts Make-to-Stock (MTS), Assemble-to-Order (ATO), or Make-to-Order (MTO) strategies (Olhager, 2003). Studies emphasize that CODP significantly influences responsiveness, inventory levels, and production cost structures (Christopher & Lee, 2004).

2.2 Product Customization and CODP

Product customization is widely recognized as a major determinant of CODP positioning (Gosling, Naim & Towill, 2007). Higher customization typically pushes CODP further downstream because production must respond directly to customer-specific requirements (Yang & Burns, 2003). This shift improves responsiveness but increases cost and operational complexity (Christopher & Towill, 2002).

2.3 Production Flexibility and CODP

Production flexibility enables firms to accommodate variability in product mix and volume without significantly affecting performance (Gosling et al., 2007). High flexibility can potentially allow upstream CODP placement while still maintaining service levels. However, empirical studies show mixed results, especially in resource-constrained environments typical of developing countries (Islam & Mia, 2022).

2.4 Manufacturing Strategy and CODP

Manufacturing strategy—encompassing delivery reliability, cost focus, quality control, and responsiveness—provides the structural foundation for positioning CODP appropriately (Olhager, 2003). When aligned with customer demand patterns, manufacturing strategy supports CODP decisions that improve operational effectiveness (Christopher & Towill, 2002).

2.5 CODP and Supply Chain Performance

Researchers have established that CODP directly affects operational outcomes such as lead time, service level, and cost efficiency (Christopher & Lee, 2004). Downstream CODP shifts enhance customization but may increase production cost and reduce service level efficiency if inventory buffers are insufficient (Yang & Burns, 2003). The need to balance responsiveness and efficiency makes CODP a critical strategic decision for firms operating under high customization demands.

2.6 Gap in Existing Research

While CODP has been studied across various industries worldwide, limited empirical evidence exists for Bangladesh, particularly in the furniture sector—a rapidly expanding industry with growing customization demand (Islam & Mia, 2022). This study addresses this gap using a PLS-SEM approach to evaluate CODP drivers and their effect on supply chain performance.

3. Methods

3.1 Research Design

This study examines how the Customer Order Decoupling Point (CODP) affects supply chain performance in Bangladesh's furniture industry, using a reputed furniture manufacturing company as the case firm. The research followed a structured process that included problem identification, literature review, hypothesis development, survey design, pilot testing, and data collection from employees. After data screening, the measurement and structural models were analyzed using PLS-SEM in SmartPLS to evaluate reliability, validity, and the significance of hypothesized relationships. Bootstrapping ensured robust path estimation. This methodology integrates real industry data with a suitable analytical approach for small samples and complex supply chain relationships (Table 1- Table 6).

Table 1. Summary of Research Steps

Step No.	Research Activity	Description
1	Problem Identification	Defined research objectives focusing on CODP at firm.
2	Literature Review	Reviewed CODP, MTS/ATO/MTO, and supply chain performance metrics.
3	Hypothesis Development	Formulated 6 hypotheses linking CODP and performance outcomes.
4	Survey Design	Created questionnaire with 21 items across 7 constructs.
5	Pilot Testing	Tested survey for clarity and reliability with a small group.
6	Data Collection	Gathered responses from firm's employees across departments.
7	Data Preprocessing	Screened and cleaned data before analysis.
8	Measurement Model Evaluation	Assessed reliability (Alpha, CR) and validity (AVE, discriminant validity).
9	Structural Model Testing	Ran PLS-SEM with bootstrapping for hypothesis testing.
10	Results Interpretation	Analyzed path coefficients, t-values, and p-values.

3.2 Conceptual Model

Product Customization (PC), Product Flexibility (PF), Manufacturing Strategy (MS), CODP Position, Lead Time Performance (LTP), Service Level (SL), Cost Efficiency (CE) are the variables for conceptual model. Among the variables PC, PF, MS are independent variables and CODP_POSITION, LTP, SL, CE are dependent variables (Figure 1).

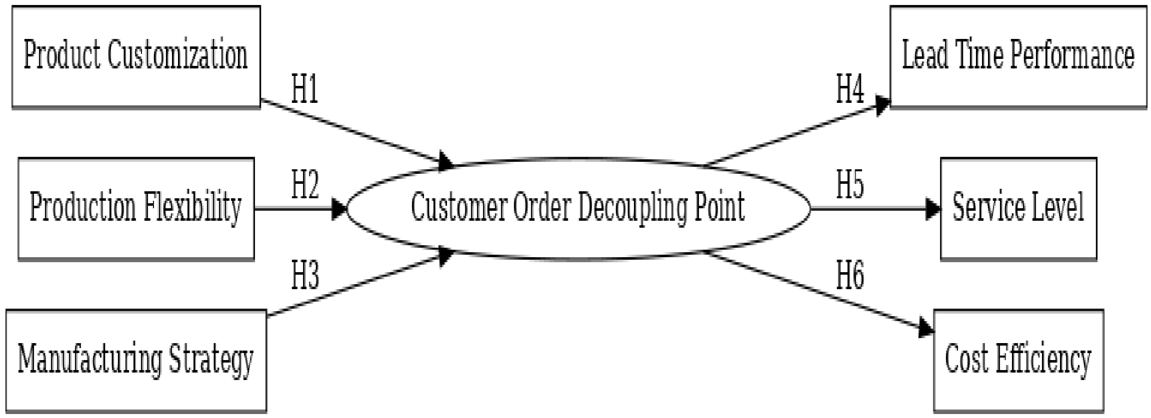

Figure 1. Conceptual model for SEM

Table 2. Hypotheses of the Study

Hypothesis No.	**Path**	**Expectation**
H1	Product Customization → CODP	Customization pushes CODP downstream.
H2	Production Flexibility → CODP	Flexibility enables later CODP placement.
H3	Manufacturing Strategy → CODP	Manufacturing strategy influences CODP.
H4	CODP → Lead Time Performance (LTP)	Downstream CODP impacts delivery speed.
H5	CODP → Service Level (SL)	Later CODP affects customer satisfaction.
H6	CODP → Cost Efficiency (CE)	Downstream CODP reduces cost efficiency.

3.3 Data Analysis Using PLS-SEM

PLS-SEM was used to analyze the measurement and structural relationships among the study constructs. SmartPLS software was employed, and the analysis followed three key steps.

1. Measurement Model Evaluation

The reliability and validity of the constructs were evaluated using established acceptance standards from Hair et al. (2019):

- Cronbach's Alpha ≥ 0.70 indicates acceptable reliability.
- Composite Reliability (CR ≥ 0.70) confirms internal consistency.
- Average Variance Extracted (AVE ≥ 0.50) verifies convergent validity.
- Discriminant validity was assessed using the Fornell–Larcker criterion, where the square root of AVE must exceed inter-construct correlations (Fornell & Larcker, 1981).

2. Structural Model Testing

The structural relationships were tested through:

- Bootstrapping (5,000–20,000 samples) to obtain robust t-values and p-values.
- A path was considered significant if t-value ≥ 1.96 ($p < 0.05$), following Hair et al. (2019).

3. Model Fit and Evaluation

- R^2 values were used to assess the variance explained in dependent constructs (LTP, SL, CE, CODP).
- Path coefficients (β) indicated the strength and direction of relationships among constructs.

3.4 Recommendation Process

Based on the results of the PLS-SEM model, recommendations for CODP placement were developed by analyzing the strength and direction of significant relationships. The approach considers how product customization, service level, and cost efficiency interact with CODP decisions. Using these relationships, the process identifies CODP positions that can minimize service delays and unnecessary production costs while still supporting customization requirements.

4. Results

4.1 Measurement Model Evaluation

The measurement model was assessed through indicator reliability, internal consistency, and validity. All item loadings exceeded the recommended threshold (> 0.60). Reliability was confirmed with Cronbach's Alpha and Composite Reliability (CR) values above 0.70, while convergent validity was supported with AVE values greater than 0.50. Discriminant validity was established using the Fornell–Larcker criterion.

Table 3. Factor loadings

	CE	**CODP_POSITION**	**LTP**	**MS**	**PC**	**PF**	**SL**
CE1	0.828						
CE2	0.918						
CE3	0.859						
CODP_POS1		0.941					
CODP_POS2		0.952					
CODP_POS3		0.938					
LTP1			0.954				
LTP2			0.626				
LTP3			0.766				
MS1				0.901			
MS2				0.797			
MS3				0.882			
PC1					0.88		
PC2					0.833		
PC3					0.923		
PF1						0.727	
PF2						0.816	
PF3						0.85	
SL1							0.829
SL2							0.94
SL3							0.965

Table 4. Cronbach's Alpha, C.R. and AVE.

Constructs	Cronbach's alpha(>0.6)	Composite reliability (rho_a)(>0.7)	Composite reliability (rho_c)	Average variance extracted (AVE)(>0.5)
CE	0.837	0.840	0.902	0.755
CODP_POSITION	0.939	0.943	0.961	0.891
LTP	0.805	0.812	0.832	0.630
MS	0.831	0.883	0.896	0.742
PC	0.852	0.856	0.911	0.773
PF	0.718	0.732	0.841	0.638
SL	0.902	0.976	0.938	0.834

Table 5. Discriminant validity (Fornell-Larcker criterion)

Constructs	CE	CODP_POSITION	LTP	MS	PC	PF	SL
CE	**0.869**						
CODP_POSITION	-0.820	**0.944**					
LTP	0.427	-0.394	**0.794**				
MS	-0.759	0.744	-0.235	**0.861**			
PC	-0.860	0.878	-0.399	0.843	**0.879**		
PF	-0.562	0.759	-0.031	0.717	0.720	**0.799**	
SL	0.378	-0.360	0.812	-0.113	-0.271	0.089	**0.913**

Note: Bold represents the square root of AVE

Therefore, based on the results in Table 5, the Fornell-Larcker criterion for discriminant validity is satisfied for all constructs in this model, confirming that each construct is empirically distinct from the others.

4.2 Structural Model Evaluation

The structural model examined the hypothesized relationships among constructs. Product Customization had a significant positive effect on CODP placement, while Production Flexibility and Manufacturing Strategy showed no significant influence. CODP negatively affected Service Level and Cost Efficiency but had no significant effect on Lead Time Performance. The R^2 value (0.809) for CODP indicated strong explanatory power (Figure 2).

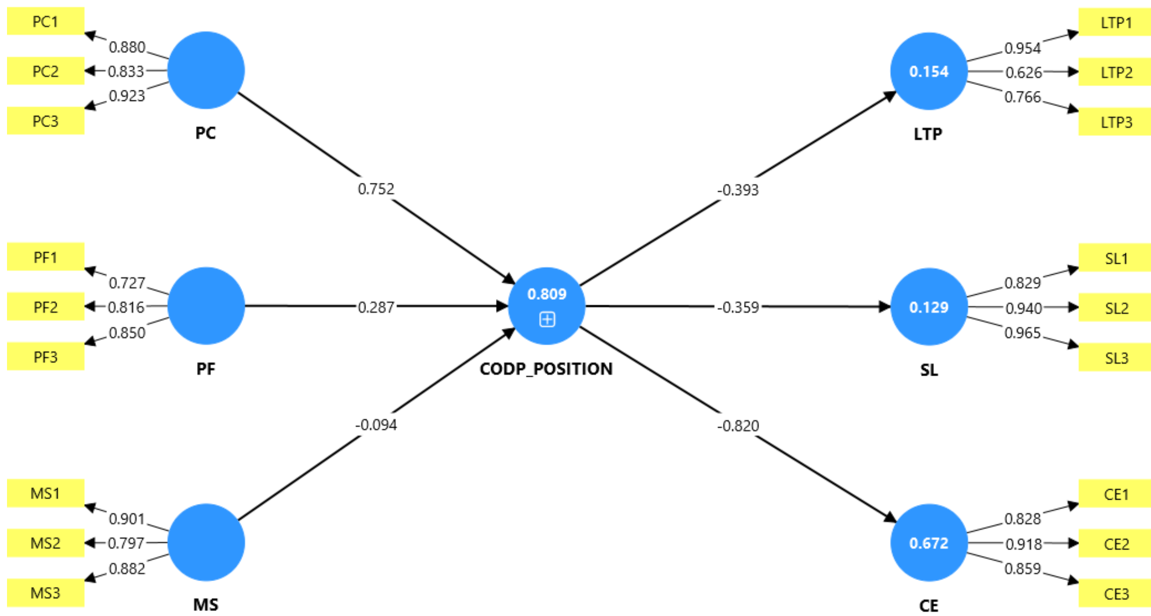

Figure 2. Path coefficient of the structural model (PLS algorithm) and R^2 values.

4.3 Hypothesis Result

Table 6. Hypothesis test with Bootstrap results of the model

Hypothesis	Path	β (Original)	t-Value	p-Value	Significant?
H1	Product Customization → CODP	0.754	3.83	0	✅ Yes
H2	Production Flexibility → CODP	0.284	1.73	0.084	❌ No
H3	Manufacturing Strategy → CODP	−0.095	0.44	0.66	❌ No
H4	CODP → Lead Time Performance (LTP)	−0.394	1.3	0.194	❌ No
H5	CODP → Service Level (SL)	−0.360	2.23	0.026	✅ Yes
H6	CODP → Cost Efficiency (CE)	−0.820	10.94	0	✅ Yes

Below is the detailed explanation for each hypothesis based on the provided **β values**, **t-values**, and **p-values**:

H1: Product Customization → CODP:

- Path coefficient: 0.754 (t = 3.83, p = 0.000)
- The path coefficient of 0.754 with a t-value of 3.83 and p-value of 0.000 indicates a strong positive and significant relationship between Product Customization and CODP. The results show that product customization significantly contributes to improving CODP. Thus, **H1 is supported**.

H2: Production Flexibility → CODP:

- Path coefficient: 0.284 (t = 1.73, p = 0.084)

- The path coefficient of 0.284 with a t-value of 1.73 and p-value of 0.084 indicates a positive but borderline relationship. Since the p-value is greater than 0.05, the result is not significant at the 5% level. Hence, **H2 is not supported** at this significance level.

H3: Manufacturing Strategy → CODP:
- Path coefficient: -0.095 (t = 0.44, p = 0.66)
- The path coefficient of -0.095 with a t-value of 0.44 and a p-value of 0.66 indicates an insignificant negative relationship between Manufacturing Strategy and CODP. This result shows that manufacturing strategy does not significantly influence CODP. Hence, **H3 is not supported**.

H4: CODP → Lead Time Performance (LTP):
- Path coefficient: -0.394 (t = 1.3, p = 0.194)
- The path coefficient of -0.394 with a t-value of 1.3 and p-value of 0.194 indicates a negative but insignificant relationship between CODP and Lead Time Performance. Since the p-value is greater than 0.05, this relationship is not significant. Thus, **H4 is not supported**.

H5: CODP → Service Level (SL):
- Path coefficient: -0.360 (t = 2.23, p = 0.026)
- The path coefficient of -0.360 with a t-value of 2.23 and p-value of 0.026 shows a negative but significant relationship between CODP and Service Level. This indicates that CODP negatively affects Service Level, and the relationship is significant at the 5% level. Hence, **H5 is supported**.

H6: CODP → Cost Efficiency (CE):
- Path coefficient: -0.820 (t = 10.94, p = 0.000)
- The path coefficient of -0.820 with a t-value of 10.94 and p-value of 0.000 indicates a very strong negative and highly significant relationship between CODP and Cost Efficiency. This suggests that CODP has a very strong negative impact on Cost Efficiency, and the relationship is highly significant. Hence, **H6 is supported**.

4.4 Sample Sizes of Different Sizes Consistency and Stability Analysis

To further examine the consistency and stability of the structural model results, a long analysis was conducted using the bootstrapping method with varying sample sizes. This involved performing the analysis based on 5,000, 10,000, and 20,000 resamples. The aim was to determine if path coefficients, T-statistics, and P-values were reproducible in different runs of resampling, which would confirm the reliability of the relations derived. Table 7 presents the output of this analysis. Upon scrutiny of Table 7, path coefficients for each hypothesis (H1, H2, H3, H4, H5 and H6) are always the same regardless of any of the three bootstrap sample sizes (5,000, 10,000, and 20,000). This consistency of estimated effect sizes is a strong indicator of the stability of the relationships in the model.

Table 7. Results of bootstrapping with 5,000, 10,000 and 20,000 samples

Sample size	Hypothesis	Path coefficient (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Result
5000	H1: PC → CODP	0.754	0.74	0.196	3.83	0	Failed to reject
	H2: PF → CODP	0.284	0.27	0.164	1.73	0.084	Rejected
	H3: MS → CODP	-0.095	-0.09	0.215	0.44	0.66	Rejected
	H4: CODP → LTP	-0.394	-0.38	0.303	1.3	0.194	Rejected
	H5: CODP → SL	-0.36	-0.345	0.161	2.23	0.026	Failed to reject
	H6: CODP → CE	-0.82	-0.805	0.075	10.94	0	Failed to reject
10000	H1: PC → CODP	0.752	0.738	0.192	3.92	0	Failed to reject

	H2: PF → CODP	0.287	0.273	0.157	1.83	0.067	Rejected
	H3: MS → CODP	-0.094	-0.089	0.204	0.46	0.645	Rejected
	H4: CODP → LTP	-0.393	-0.379	0.309	1.27	0.204	Rejected
	H5: CODP → SL	-0.359	-0.344	0.169	2.12	0.034	Failed to reject
	H6: CODP → CE	-0.82	-0.806	0.077	10.69	0	Failed to reject
20000	H1: PC → CODP	0.752	0.739	0.19	3.93	0	Failed to reject
	H2: PF → CODP	0.287	0.274	0.159	1.81	0.07	Rejected
	H3: MS → CODP	-0.094	-0.09	0.206	0.46	0.646	Rejected
	H4: CODP → LTP	-0.393	-0.38	0.307	1.28	0.201	Rejected
	H5: CODP → SL	-0.359	-0.345	0.165	2.17	0.03	Failed to reject
	H6: CODP → CE	-0.82	-0.807	0.076	10.68	0	Failed to reject

5. Discussion

The results of this study demonstrate that the most important element affecting CODP placement is product customization. According to Yang and Burns (2003), manufacturing activities tend to move closer to the order stage when customers need customized items. This is consistent with the theory that increased customization usually pushes the CODP downstream.

In this case, however, CODP was not significantly impacted by manufacturing strategy or production flexibility. This result can be a result of practical restrictions in Bangladesh's furniture manufacturing industry, where limits like fixed capacity, minimal automation, and manual procedures lessen the impact of flexibility or strategic goals on real production decisions. Previous research on manufacturing systems in poor nations has identified similar difficulties (Islam & Mia, 2022).

The findings also demonstrate certain operational difficulties that arise when the CODP is moved downstream. Businesses may find it difficult to sustain service levels when more operations are directly dependent on client orders, and production costs frequently increase as a result of frequent modifications, decreased batch efficiency, and greater coordination efforts. These consequences account for the study's negative correlation between CODP and both service level and cost efficiency.

Overall, it can be suggested that although customization is still necessary to satisfy customers, there are real trade-offs. Therefore, manufacturers need to strike a balance between providing customization and controlling its effects on manufacturing costs and service performance.

5.1 Managerial Implications

The results of this study offer several important insights for managers in the furniture manufacturing sector. Since product customization was found to be the strongest driver of CODP placement, managers should carefully evaluate how much customization they can realistically support without compromising efficiency. Introducing modular product designs, preconfigured components, or standardised subassemblies can help maintain customization options while reducing pressure on downstream production activities. The negative effect of CODP on service level and cost efficiency also highlights the need for better production planning and scheduling tools. Managers can benefit from implementing digital tracking systems, improving capacity planning, and developing more flexible workforce arrangements to handle variations in customer demand. By understanding how CODP placement influences both responsiveness and cost, decision-makers can choose a more balanced approach that supports customer expectations while maintaining operational stability.

6. Conclusion

This research successfully set out to understand what influences where a furniture company places its Customer Order Decoupling Point (CODP) and how that decision affects performance. Using a robust statistical method (PLS-SEM), we tested a model linking key drivers to the CODP and its outcomes.

The clearest finding is that product customization is the main force pushing the CODP later in the production process (with a strong statistical relationship, $\beta = 0.754$). However, moving the CODP downstream to accommodate customization comes with significant trade-offs: it directly hurts service levels ($\beta = -0.360$) and dramatically reduces cost efficiency ($\beta = -0.820$). Notably, we found that production flexibility and manufacturing strategy did not have a significant impact on CODP placement in this context.

These results make the CODP a highly useful framework for managers. It clearly shows the operational cost of customization. By understanding these cause-and-effect relationships, companies can make smarter, more balanced decisions about production planning, product design, and how much variety to offer.

For future research, exploring other factors—like level of automation or supply chain stability—could provide an even fuller picture. Studying more companies across different industries would also help confirm how widely these findings apply.

In short, this study confirms that the CODP is a powerful, practical concept. It effectively captures how the pressure to customize products reshapes manufacturing performance, providing a solid basis for both future research and improved managerial decision-making.

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Biographies

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