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PRINCIPAL COMPONENTS ANALYSIS AND DEMATEL APPROACH FOR INVESTIGATING RELATIONSHIPS AMONG INDUSTRY 4.0 BARRIERS

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Abstract:
The research work is devoted to investigate a compact set and finding interrelationships among Industry 4.0 barriers. For this purpose the two well known techniques namely Principal Components Analysis (PCA) and Decision Making Trial and Evaluation Laboratory (DEMATEL) were used along with reliability testing. First of all with the help of expert's opinions (a group of 10 experts) and literature survey the list of 16 barriers was prepared. In the next step a systematically designed 5-Point Likert's scale based questionnaire containing 16 barriers was circulated to 220 respondents around the country for providing responses for investigating their intensity of importance. Based on their responses reliability testing as well as identification of principal components using principal component analysis was performed. and a questionnaire was sent to a group of 3 experts for investigating the importance of investigated 4 principal components and their responses was fed to the DEMATEL algorithm which yielded the degree of importance of barriers as well as cause effect relationships among them.
Keywords: Industry 4.0 Barriers, Principal Components Analysis (PCA) and Decision Making Trial and Evaluation Laboratory (DEMATEL), Cronbatch's alpha, Relationship.

Introduction
According to Pozzi *et al.* (2023) [1] the impact of Industry 4.0 and its opportunities are expected to be significant for manufacturers. It aims to fully integrate and automate manufacturing systems and optimize flows along the whole value chain while transforming conventional relationships among suppliers, producers and customers. Seena *et al.* (2022) [2] added that the digital transformation of enterprises currently developing through Industry 4.0 initiatives promises to revolutionize their systems regarding cost reductions and expansion of business opportunities. Industry 4.0 aims to create a smart interconnected value chain through digital technologies that allow for the integration of physical objects, virtual models and services. Interconnectivity is at the very center of Industry 4.0 with a shift in the production paradigm due to the increasing digitalization of the value chain and real-time data exchange among connected actors, objects, and systems. The production process is expected to be controlled, monitored and improved in real-time through constant analysis of information gathered from IoT devices into embedded and connected systems.
Conducted study on the adoption and implementation of Industry 4.0 technologies have been difficult, due to barriers of adoption faced by manufacturing companies, such as low maturity level of digital technologies in the industry as well as the existing multiplicity of equipment within the factory, acquired from a variety of suppliers with various communication capabilities. He further adds that while Industry 4.0 promises large technological improvements firms face multiple challenges in its adoption. Industry 4.0 requires a shift of the companies decision-making focus from the development of technologies to the adoption and implementation decision of integrated interoperable technologies. It is based on the widespread implementation of cyber-physical systems which are heterogeneous computational systems and bear communication capabilities achieved by means of the Internet of Things combined with an array of digital technologies such as big data and analytics, augmented reality, simulation and artificial intelligence.

Considering the above mentioned facts the present research work is devoted to the investigations on Industry 4.0 barriers and aims at generalization of barriers and finding the relationship among them.

Objectives of the Research
Following objectives were decided before starting the research work:
a) To investigate the compatible set of Industry 4.0 barriers.
b) To determine the relationships among the industry 4.0 barriers.

Literature Review
This section described the different academic aspects of the research work and portrays the contributions of the researchers in the field and concludes with the investigated gaps in the research. different researchers in the field of industry 4.0 have highlighted its different aspects. The research work conducted by Cordeiro et al. (2024) [3] evaluated the impact of barriers experienced by Brazilian companies in adopting Industry 4.0. Agarwal et al. (2024) [4] identified and prioritized the nine barriers based on research and expert view points on GSM challenges. During the research work the analytical hierarchy process (AHP) was used to prioritize the barriers. Proceeding in the same manner, the aim of the research work conducted by Lu et al. (2024) [5] investigated how to integrate CE and Industry 4.0 in sustainable supply chain management (SSCM) in order to improve operational efficiency and sustainability performance. This study provides an analysis of the dynamic changes of drivers and barriers when integrating circular economy and Industry 4.0 and their related applications in operations and SCM through a systematic review of literature. From the results a theoretical framework was derived for future research development.
Govindon and Arompotzis (2023) [6] presented the large businesses perceive the vital usefulness of Industry 4.0. They recognize how beneficial its implementation is to reinforce business competitiveness and to conserve or even better, to increase their market share. Their research work proposes a framework to assist industries in promoting Industry 4.0 through two phases. In the initial phase the case company's level of readiness is evaluated, and in the second phase the barriers that exist within the implementation of Industry 4.0 (based on the company's readiness obtained from the previous phase) are analyzed. both phases have been carried out at a Danish case industry which is a third-tier supplier of anti-noise shims and back plates for manufacturers of disc brake linings.
Jankowska et al. (2023) [7] studied in twofold. First, it tries to identify and characterize the barriers businesses face in the implementation of Industry 4.0 technologies investigating the barriers impact on the adoption of Industry 4.0 tools. Second it seeks whether the higher level of adoption is followed by the enterprises enhanced innovation performance. Sarkar et al. (2023) [8] developed a framework by integrating the fuzzy set theory the evidential reasoning approach and the expected utility theorem for identifying the severity value of port logistics barriers under the Industry 4.0 era for emerging economies and prioritizes them based on various perspectives. The study identifies multiple risks associated with the barriers and intensity-based categorization of the risks is performed for risk profiling.
Zheng et al. (2021) [9] was intended to provide a systematic literature review answering the following research question: What are the applications of Industry 4.0 enabling technologies in the business processes of manufacturing companies. Similarly Gho Bakhloo (2020) [10] presented the interpretive structural modeling technique to model the contextual relationships among the Industry 4.0 sustainability functions. Results of the research work indicate that sophisticated precedence relationships exist among various sustainability functions of Industry 4.0.
Culot et al. (2019) [11] conducted a research work focusing on cyber security issue for Industry 4.0 based applications. whereas Dalenogare et al. (2018) [12] conducted a statistical analysis for observing the potential of Industrial 4.0 parameters.
There was very limited research papers were found. which focused on the generalization of industry 4.0 barriers and on interrelationships among the barriers.

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Methodology Adopted

In the present research work two solution techniques namely principal component analysis (PCA) along with the reliability analysis and Decision making trial and evaluation laboratory (DEMATEL) were used to investigate the generalized set of industry 4.0 barriers and investigating their relationships among the barriers.

Reliability Test

Often used to indicate the accuracy of a test, reliability is defined by shah Alam et al. (2008) [13] as the consistency of a set of measurements or of a measuring instrument. The consistency of a measuring device is at the heart of reliability. Validity and trustworthiness of an instrument go hand in hand Alpha, created by Lee Cronbach in 1951 is a measure of the test's or scale's internal consistency and may take on values between 0 and 1. Internal consistency is a measure of how well a test's items are linked to one another and how well they all assess the same underlying idea or construct. The reliability coefficient, alpha, improves when there is a correlation between test items. The following formula may be used to get Cronbatch's alpha (Tavakol & Dennick, 2011) [14].

$$\propto = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_y^2}{\sigma x^2}\right) \tag{3.1}$$

where,
K is the number of components;
σ_x^2 is the variance of the observed total test scores; and
σ_{yi}^2 is the variance of component *i* for the current sample of persons.

Principal Component Analysis

Principal component analysis (PCA) is a statistical technique that was first developed by Pearson in 1901. It can help in reducing the size of high-vector data collections. Feature extraction and representation both benefit from this. In the academic world PCA is often discussed. Principal component analysis is a time-honored technique for data analysis according to Ilin and Raiko (2010) [15]. It finds the linear transformations of data that retain the greatest information. The purpose of principal components analysis is to find a small set of composite variables that can explain as much variation in the observable variables (components) as feasible. According to Kothari (2004, p. 330) [16] the principal components technique to factor analysis seeks to optimize the sum of squared loadings of each factor retrieved in turn.

There are two primary methods for determining factor solutions. These include techniques like principal components analysis and factor analysis. Principal component analysis takes the whole variation as input and generates components with small quantities of unique variance and, at times incorrect variance. Component analysis introduces unique scalars (1's) into the diagonal of the correlation matrix to capture the full range of variation in the factor matrix. Common factor analysis, on the other hand places communalities along the diagonal. The term "community" is used to refer to estimates of the common variation among the variables. Factors generated by a common factor analysis are based only on shared variance. In factor analysis, there are three types of variance that must be understood by the researcher before the optimal model can be selected.

a) **Common variance** is defined as that variance in a variable that is shared with all other variables in the analysis.
b) **Specific variance** (sometimes called unique) is that variance associated with only a specific variable.
c) **Error variance** is the variance due to unreliability in the data-gathering process, measurement error or a random component in the measured phenomenon.

SAS and SPSS (Statistical Product and Service Solutions and Statistical Package for the Social Sciences) typically employ Principal components analysis as the extraction technique contributing to the software's widespread acceptance and application. The following are the stages involved in applying principal component analysis to a problem.

The aim of Principal components analysis is the construction out of a given set of variables *Xj*'s (*j* = 1, 2… *k*) of new variables (*pi*) called *principal components* which are linear combinations of the *Xs*. Thus,

$$\begin{aligned} p_1 &= a_{11} X_1 + a_{12} X_2 + .+ a_{1k} X_k \\ p_2 &= a_{21} X_1 + a_{22} X_2 + \ldots + a_{2k} X_k \\ &\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ p_k &= a_{k1} X_1 + a_{k2} X_2 + \ldots a_{k2} X_2 \end{aligned} \tag{3.2}$$

The method is being applied mostly by using standardized variables, *i.e.*,

$$z_j = \frac{(X_j - \bar{X}_j)^2}{\sigma_j} \tag{3.3}$$

The term a_{ij} is called *loading*.

Following steps are usually involved in principal components analysis:

a) Estimates of aij's are obtained with which X's are transformed into orthogonal variables i.e., the principal components.
b) Next step is the regression of Y on these principal components, i.e.,
$$Y = y_1 p_1 + y_2 p_2 + \ldots.. + y_m p_m (m<k) \tag{3.4}$$
c) From the a_{ij} and y_{ij}, one can find b ij of the original model, transferring back from p's into the standardized X's.

The extracted and retained primary components are then rotated from their original location to enhance the factor's interpretability. Each factor's characteristic root (sum of squared loadings) is the amount of variation it accounts for in the whole model. When these roots are divided by the number of variables the distinctive roots show as a proportion of the total variance explained. To generate factor scores for use in further study and as inputs in a variety of other multivariate analyses the variables are regressed against each component loading (Kothari, 2004, pp. 330, 332) [9].

Decision Making Trial and Evaluation Laboratory (DEMATEL)

The DEMATEL method relies on parallel comparisons to get a conclusion. It is used to the investigation of the hypothesized relationships between the factors. The main advantage of this approach is that it makes the specialists more comfortable in discussing their thoughts on the factors. This is the main benefit of using this method. The following points outline the method's constituent parts:

Step 1: Generation of Direct relation Matrix (X)

To identify the model of the relations among the n criteria, an n × n matrix is first generated, as follows.

$$X = \begin{bmatrix} 0 & \cdots & x_{n1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & 0 \end{bmatrix} \tag{3.5}$$

Step 2: Computation of Normalized Direct-relation Matrix (N)

In the next step, direct-relation matrix (N) was created, as follows.

$$N = \frac{1}{k} * X \tag{3.6}$$

… where, $k = max\{max \sum_{j=1}^{n} x_{ij}, \sum_{i=1}^{n} x_{ij}\}$

Step 3: Computation of Total Relation Matrix (T)

In the next step, direct-relation matrix (T) was created, as follows.

$$\mathrm{T} = \mathrm{N} \times (I - N)^{-1} \tag{3.7}$$

Step 4: Setting of Threshold Value

The next step included settling on a cutoff point at which new data may be accessed and analysed The incomplete connections are ignored and a network relationship map is produced based on the results of this calculation, which uses it. First, we get the threshold value by averaging the values in matrix T. All of the T matrix entries below the threshold value should then be reset to zero.

Step 5: Final Output and create a Causal Diagram

In the next step, final outputs in the terms of D+R and D-R are calculated, using the following expressions and cause effect diagram is created.

$$D = \sum_{j=1}^{n} T_{ij} \tag{3.8}$$

$$D = \sum_{j=1}^{n} T_{ij} \tag{3.9}$$

Step 6: Interpretation of Results

The next step is to draw a cause and effect diagram to make sense of the data. Each element's importance to the system is represented by D+R, while the extent to which each component affects the system is represented by D-R. A positive value of D-R indicates an effect whereas a negative value indicates a causal variable.

Case Study

The present section is based on the details of research work carried out for the purpose of identifying and investigating the relationships among Industry 4.0 barriers. the details of which are presented in the Figure 4.1.

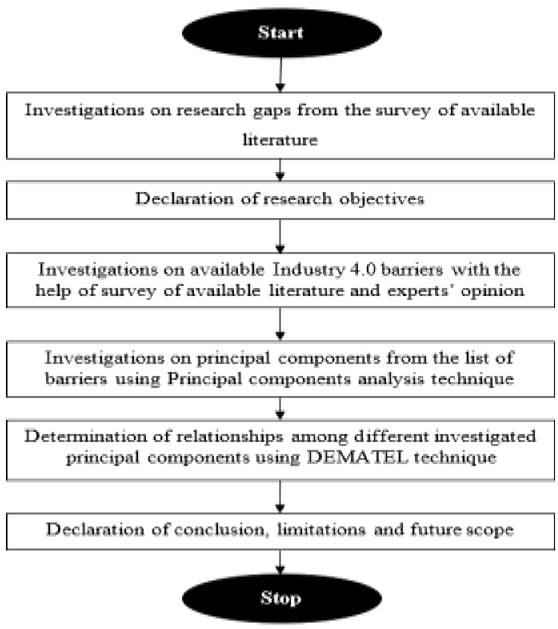

Figure 4.1: Methodology used in the Research Work

Details of different steps mentioned in Figure 4.1 are presented as follows:

a) After investigating the research gaps as well as objectives of the proposed research. first of all with the help survey of available literature as well as experts' opinions a list of Industry 4.0 barriers was investigated. Table 4.1 presented the profiles of experts involved in experts opinions.

Table 4.1: Profiles of Experts consulted for providing opinions

S. No	Respondents Number	Domain	Work experience (Years)	Designation
1	Expert 1	Industry	19	Manager
2	Expert 2	Subject expert	22	Professor
3	Expert 3	Policy maker	30	Legal advisor
4	Expert 4	Investor	14	Businessman
5	Expert 5	Subject expert	17	Professor
6	Expert 6	Policy maker	30	Asst. General Manager
7	Expert 7	Investor	14	Entrepreneur
8	Expert 8	Subject expert	22	Professor
9	Expert 9	Industry	30	Asst. General Manager
10	Expert 10	Industry	22	Executive Manager

As the result of experts' opinions following list of 16 barriers were obtained.

Table 4.2: Industry 4.0 barriers (literature review and experts' opinions)

S. No	Industry 4.0 barriers
1	Technology availability and compatibility
2	Low maturity of technology and seamless integration
3	Information technology infrastructure
4	Cyber security and privacy
5	Capability to manage big data
6	Requirement for high initial investment
7	Uncertainty of return on investment
8	Availability of reference architecture and standards
9	Government support and legal issues
10	Complexity in supply chain integration and coordination
11	Employee fear and resistance to change
12	Education and training programs
13	Knowledge, awareness, and competence of Industry 4.0
14	Management commitment and leadership
15	Availability of skilled workforce
16	Organization structure and culture

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b) In the next step the principal components from the investigated list of barriers with the help of principal components analysis. For this purpose a systematically designed questionnaire was circulated to 220 industry personnel as well as academic experts. Table 4.3 presented the responses.

Table 4.3: Details of Responses Obtained

S.No	Parameter	Response
1	Type of questionnaire	5– point Likert's scale based
2	Number of parameters in the questionnaire	16
3	Numbers of questionnaire sent	220
4	Number of complete responses obtained	212
5	Response Ratio	96.36 percent

After getting enough number of responses (96.36 percent), in the next step with the help of SPSS 22.0 software and principal component analysis (PCA) was performed this yielded five principal components along with justified values of Cronbatch's alpha for different sub-component and total principal components as a whole the details of which are presented in Table 4.4.

Table 4.4: Details of Principal Components Analysis and Cronbatch's Alpha

S.No	Principal Components	Sub-components	Factor loadings	Cronbatch's Alpha
1	**Technology factors**	Technology availability and compatibility	0.858	0.659
2		Low maturity of technology and seamless integration	0.856	
3		Information technology infrastructure	0.844	
4		Cyber security and privacy	0.847	
5		Capability to manage big data	0.893	
6	**Compliance factors**	Government support and legal issues	-0.833	
7	**Organizational factors**	Knowledge, awareness, and competence of Industry 4.0	0.846	
8		Management commitment and leadership	0.948	
9		Organization structure and culture	0.796	
10		Complexity in supply chain integration and coordination	0.737	
11		Requirement for high initial investment	0.882	
12	**Employee related issues**	Availability of skilled workforce	0.987	
13		Education and training programs	0.915	
14		Employee fear and resistance to change	0.736	
15		Availability of reference architecture and standards	0.883	
16		**Uncertainty of return on investment**		

The above table tells about the declaration of four principal components, along with their sub components and an unallocated sub-component (uncertainty on return of investment) along with the justified value of cronbatch's alpha.

c) The interrelationships among the investigated principal components were investigated with the help of DEMATEL technique the details of which are presented as follows.
First of all with the help of three expert's opinions the direct relation matrix was drawn as shown below.

Table 4.5: Opinions and Direct Relation Matrix

Opinions					
Experts Opinions	**Industry 4.0 Parameters**	**Technology Factors**	**Compliance factors**	**Organizational Factor**	**Employee related issue**
Expert 1	Technology factors	0	4	4	3
	Compliance factors	3	0	3	4
	Organizational factors	4	3	0	3
	Employee related issues	3	3	4	0
Expert 2	Technology factors	0	3	4	3
	Compliance factors	3	0	3	4
	Organizational factors	4	3	0	3
	Employee related issues	4	3	4	0
Expert 3	Technology factors	0	3	4	3
	Compliance factors	3	0	3	4
	Organizational factors	3	3	0	4
	Employee related issues	4	3	4	0
Direct Relation Matrix					
1	Technology factors	0	3.333	4	3
2	Compliance factors	3	0	3	4
3	Organizational factors	3.666	3	0	3.333
4	Employee related issues	3.666	3	4	0

Normalization values for direct relation matrix elements were investigated. The details of normalized direct relation matrix are presented as follows.

Table 4.6: The Normalized Direct-Relation Matrix

Factors	Skill factors	Technology factors	Organizational factors	Financial factors
Technology factors	0	0.303	0.364	0.273
Compliance factors	0.273	0	0.273	0.364
Organizational factors	0.333	0.273	0	0.303
Employee related issues	0.333	0.273	0.364	0

The threshold value must be obtained in order to calculate the internal relations matrix. Accordingly partial relations are neglected and the network relationship map (NRM) is plotted. Only relations whose values in matrix T is greater than the threshold value are depicted in the NRM. To compute the threshold value for relations, it is sufficient to calculate the average values of the matrix T. After the threshold intensity is determined all values in matrix T which are smaller than the threshold value are set to zero that is the causal relation mentioned above is not considered. In this study, the threshold value is equal to 3.422. The model of significant relations is presented in Table 4.7.

Table 4.7: The Total Relation Matrix

	Skill factors	Technology factors	Organizational factors	Financial factors
Technology factors	3.29	3.263	3.716	3.483
Compliance factors	3.434	2.965	3.59	3.466
Organizational factors	3.465	3.176	3.372	3.425
Employee related issues	3.626	3.324	3.808	3.352

The total relation matrix using the threshold value of 0.631 was constructed as follows.

Table 4.8: Total- relationships Matrix by Considering the Threshold Value

	Skill factors	Technology factors	Organizational factors	Financial factors
Technology factors	0	0	3.716	3.483
Compliance factors	3.434	0	3.59	3.466
Organizational factors	3.465	0	0	3.425
Employee related issues	3.626	0	3.808	0

The final output as well as casual diagram was created and presented in Table 4.9.

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Table 4.9: The Final Output

	R	D	D+R	D-R
Skill factors	13.815	13.752	27.566	-0.063
Technology factors	12.729	13.455	26.184	0.727
Organizational factors	14.486	13.438	27.924	-1.048
Financial factors	13.725	14.11	27.835	0.384

The following figure shows the model of significant relations. This model can be represented as a diagram in which the values of (D+R) are placed on the horizontal axis and the values of (D-R) on the vertical axis. The position and interaction of each factor with a point in the coordinates (D + R, D-R) are determined by coordinate system. According to the diagram and table above each factor can be assessed based on the following aspects:

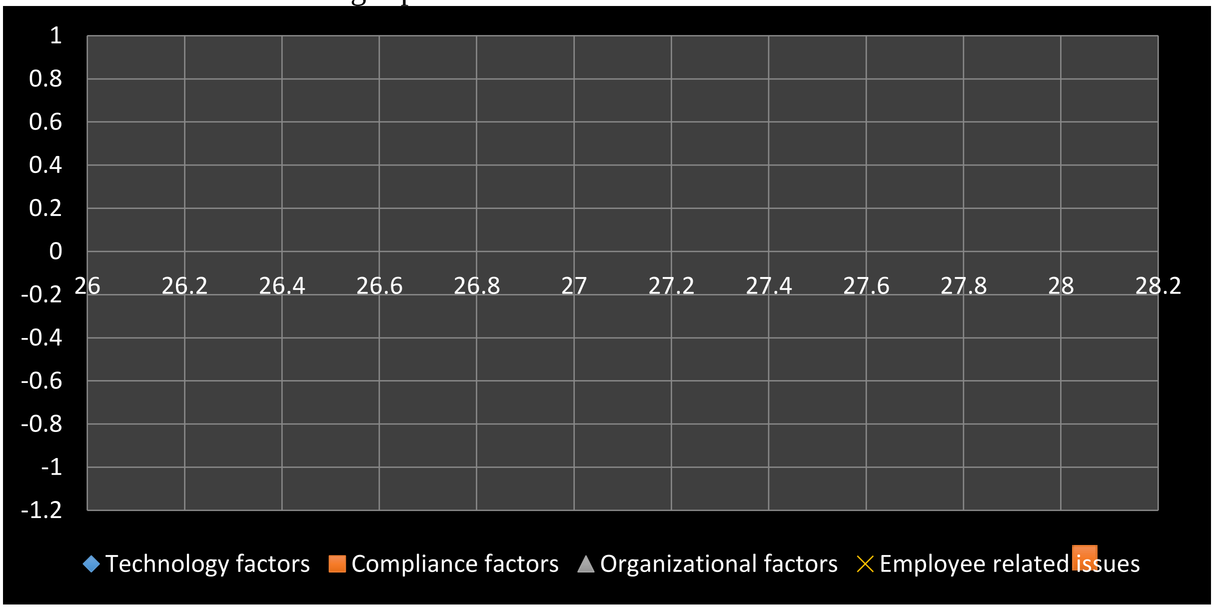

Figure 4.2: Cause-Effect Diagram

Conclusion, Limitations and Future Scope of the Research

The conclusion of research work are as follows:

a) Horizontal vector (D + R) represents the degree of importance between each factor plays in the entire system. In other words, (D + R) indicates both factor are dominating impact on the whole system. **In terms of degree of importance, Organizational factors is ranked in first place and Employee related issues, Technology factors and Compliance factors, are ranked in the next places.**

b) The vertical vector (D-R) represents the degree of a factor's influence on system. In general, the positive value of D-R represents a causal variable, and the negative value of D-R represents an effect. **In this study, Compliance factors, Employee related issues are considered to be as cause variables, Technology factors, Organizational factors are regarded as effects.**

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Following are the limitations of the research work:

a) The research work is limited a particular number of Industry 4.0 barriers.

b) The research work is also limited to investigations using DEMATEL technique only.

Following points represent the future scope of the research work:

a) A broader research work involving a greater numbers of Industry 4.0 barriers may be initiated.

b) An extensive research consisting a large number of investigation techniques may be started.

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