

Constructing Eight Smart Building–Safety Dimensions Through PRISMA Mapping and Fuzzy Mamdani Evaluation

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Article Information	ABSTRACT
Article History Received : December 06, 2025 Revised : December 19, 2025 Published : January 04, 2026	The integration of smart buildings and Internet of Things (IoT)–based safety systems is becoming increasingly important in response to the growing demand for intelligent, safe, and responsive buildings. However, prior studies predominantly focus on technological performance or isolated safety applications, with limited attention to structured readiness mapping at the dimensional level. Addressing this gap, this study proposes a novel eight-dimensional smart building–safety readiness model by integrating a PRISMA 2020–guided systematic literature review (SLR), concept mapping, and Fuzzy Mamdani evaluation. The SLR resulted in five key articles that underpin eight core dimensions: Building Management, Automation and Control, IoT Connectivity, Decision Analytics, Adaptive Response, Safety and Maintenance, Energy and Sustainability, and Automation Dominance. The Fuzzy Mamdani analysis was applied to 23 validated readiness indicators and showed that all dimensions fall within the <i>Average</i> category, with fuzzy values ranging from 54 to 61. These findings indicate that the readiness level for implementing smart building–safety in Indonesia is at a stable intermediate stage, with no dimension lagging significantly behind. Practically, the proposed dimensional model can support policymakers in prioritizing regulatory focus, assist building practitioners in identifying readiness gaps, and provide researchers with a structured framework for advancing smart building–safety integration.
Keywords: <i>Smart Building Dimesions;</i> <i>Fuzzy Mamdani;</i> <i>Concept Mapping;</i> <i>Systematic Literature Review (SLR);</i> <i>PRISMA 2020.</i>	

INTRODUCTION

The rapid growth of IoT and automation is transforming modern building management, especially in smart building and safety applications. In Indonesia, rising urbanization increases the need for adaptive and safety-oriented buildings, yet implementation remains limited by high costs, insufficient human resource capacity, and weak regulatory support (Indrawati et al., 2017; Attaufiq & Rahman, 2025). Smart and sustainable technology adoption in green-building projects is also still suboptimal (Mantow, 2025). Globally, IoT-based monitoring has proven effective through real-time sensing and predictive analytics (Zhang, 2025). Recent studies have shown that integrating IoT sensing, building information modeling (BIM), and artificial intelligence can enhance indoor safety management through real-time monitoring and intelligent hazard detection (Liu et al., 2020). Although practitioners show strong conceptual readiness, research on IoT, smart buildings, and building safety still tends to develop in fragmented thematic clusters, limiting the availability of integrative and structured perspectives for practical implementation (Hakimi et al., 2024).

To address this gap, this study develops an Eight-Dimension Readiness Model for IoT-based smart building–safety integration in Indonesia. The model synthesizes PRISMA-guided systematic literature review findings with concept mapping and Fuzzy Mamdani evaluation applied to validated readiness indicators. The resulting framework maps readiness across eight core dimensions and highlights their relative strengths and weaknesses, providing a multidimensional foundation for advancing both conceptual development and practical implementation of smart building–safety systems.

RESEARCH METHODS

The study employs a systematic literature review (SLR) guided by PRISMA 2020 (Page et al., 2021), supported by bibliometric analysis using Biblioshiny and VOSviewer to identify keyword patterns, thematic clusters, and conceptual linkages (Aria & Cuccurullo, 2017; Van Eck & Waltman, 2010). In parallel, 23 validated readiness indicators were tested through item correlation, Cronbach's Alpha, and structural reliability following established procedures in IoT and smart building readiness research (Waqar et al., 2024), and subsequently processed using the Fuzzy Mamdani method to generate adaptive readiness values (Kontogiannis et al., 2021).

The integration of SLR findings, fuzzy outputs, and validated indicators was synthesized through concept mapping, where indicators were grouped into higher-order categories based on thematic and functional coherence. Concept mapping offers a structured way to represent and organize conceptual relationships, enabling the formation of coherent dimensional groupings as demonstrated by Fitriansyah et al. (2025). This process resulted in the eight Smart Building–Safety dimensions presented in Figure 1.

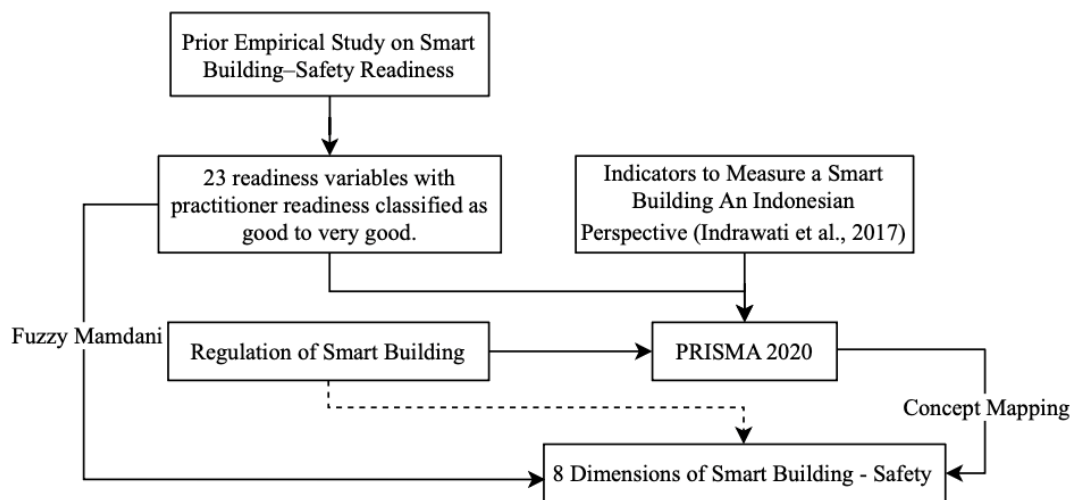


Figure 1. Mind Mapping of Developing Smart Building Safety Dimensions Based on Literature Review and Regulatory Analysis

Systematic Literature Review

The literature search was conducted through the Scopus database using keywords that directly represent the core components of this study, namely smart building, IoT, building safety, and the fuzzy method. The search query used is as follows:

("smart building" OR "intelligent building")
 AND ("building safety" OR "safety system" OR "fire safety")
 AND ("Internet of Things" OR "IoT")
 AND ("fuzzy logic" OR "fuzzy control" OR "fuzzy inference" OR "fuzzy decision")

conducted. This pattern also reveals the presence of emerging themes that are still new and not widely studied, as well as niche themes that are already mature but developing within a narrow research space. This depiction serves as the initial foundation for understanding the direction of the literature before entering the eligibility stage.

Screening

Screening of titles and abstracts produced 18 relevant articles. Bibliometric analysis at this stage shows a clear narrowing of themes, indicating stronger alignment with the research focus. During the PRISMA screening stage, thematic patterns become more directed, with broad themes converging into dominant clusters related to IoT, smart buildings, automation, artificial intelligence, and fire or emergency rescue topics. IoT, automation, and architectural design strengthen as core groups, while AI, machine learning, and fire-related issues form strong supporting clusters. Articles unrelated to the research scope—such as those on smart cities, general data mining, or non-building technologies—are filtered out. This stage marks a shift from a broad thematic landscape to a more specific and well-defined research domain.

Eligibility

A full reading of the 18 articles yielded 5 studies that met the eligibility criteria. At this stage, keyword relationships became more concentrated and coherent. The VOSviewer overlay in the PRISMA eligibility phase showed a research map that was far more focused than in earlier stages, with remaining keywords converging around internet of things, accident prevention, artificial intelligence, decision making, and anomaly detection.

This demonstrates that the retained articles are those directly relevant to the integration of intelligent technologies and building safety. The thematic shift toward a tighter cluster indicates that the screening process effectively removed less relevant studies, leaving core literature that underpins further analysis, particularly regarding IoT and AI for risk mitigation and decision-making in building environments.

Included

The inclusion stage produced 5 final articles that served as the foundation for formulating the eight dimensions of smart building–safety. Figure 4 shows that the keywords in these articles are closely connected. The map illustrates how safety management and safety management systems link to intelligent buildings, which then connect to information management as a central point. From there, the network extends toward newer themes such as facilities management and facility management.

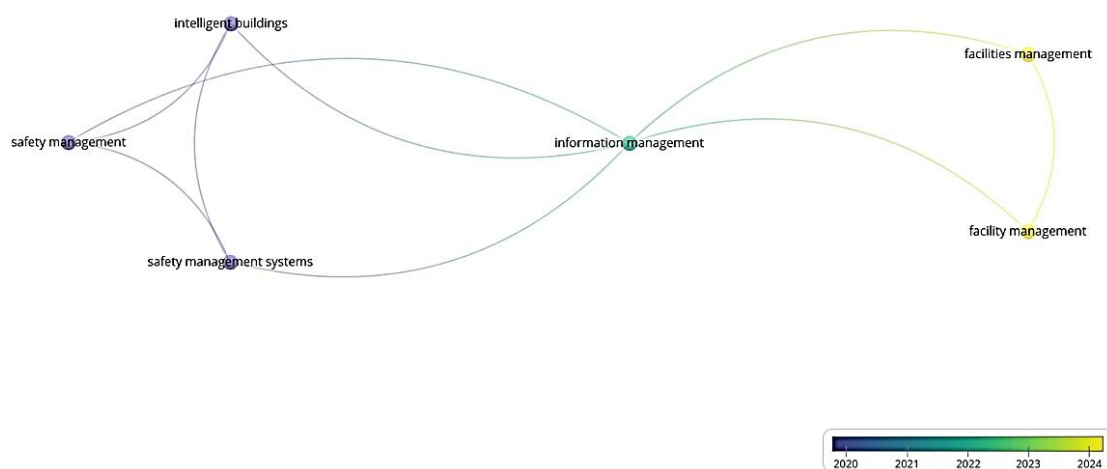


Figure 4. Keyword Co-Occurrence Network of the Five Final Included Articles

The five final articles discuss the following topics: IoT for building safety monitoring (Almatared et al., 2024), anomaly detection using deep learning (Cicero et al., 2023), IoT-based fire monitoring (Mohammadiounotikandi et al., 2023), large-scale data-driven safety monitoring systems (Zhang, 2025), and the use of fuzzy logic in smart-building decision making (Martín Toral et al., 2023). These five articles form the conceptual basis for the eight dimensions of the study, namely building management, automation & control, IoT connectivity, decision analytics, adaptive response, safety & maintenance, energy sustainability, and automation dominance.

PRISMA Diagram

The PRISMA diagram is used to summarize the entire literature selection process. This diagram is presented in Figure 5 following the PRISMA 2020 format (Page et al., 2021).

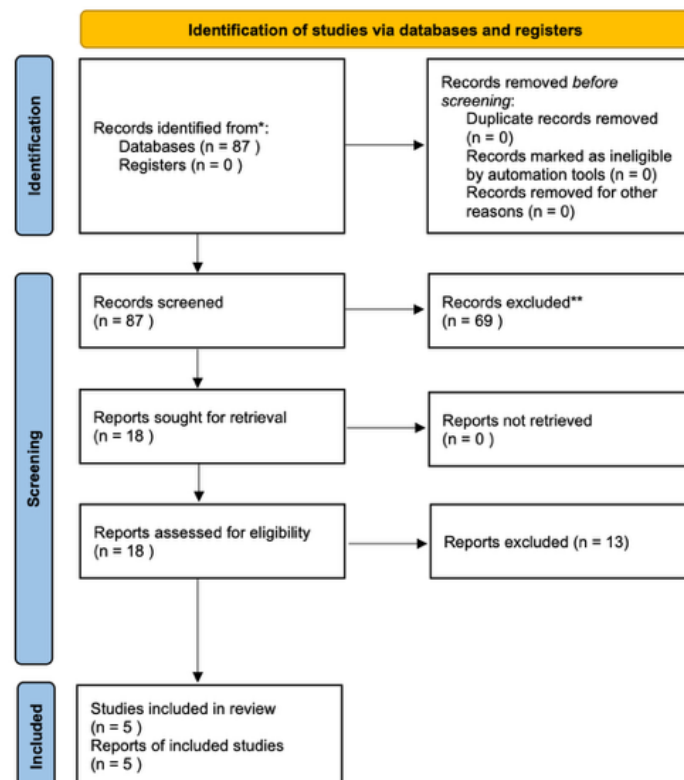


Figure 5. PRISMA 2020 Diagram

The PRISMA instrument in Figure 5 illustrates the step-by-step screening process. From the initial 87 identified articles, screening for topical relevance reduced the set to 18. An eligibility assessment based on focus, methodology, and thematic contribution further narrowed the literature to 5 articles. These five studies formed the basis for the final synthesis and discussion. Although the number decreased substantially, the process ensured that only literature with strong relevance and sufficient quality was included in the study.

Research Instrument

The research instrument consists of 23 readiness indicators developed based on prior literature related to smart buildings and building safety. These indicators have been applied and validated in previous studies, demonstrating good construct validity and internal consistency, with 20 indicators retained and a Cronbach's Alpha value of 0.884. Therefore, the instrument is considered reliable and suitable for further analysis. In this study, the validated indicators are directly employed as inputs for dimension mapping and the fuzzy Mamdani process without re-testing.

Fuzzy Mamdani Method

The fuzzy Mamdani method is used to process the 23 readiness indicators into a readiness value that is smoother and more adaptive to the uncertainty of respondents' perceptions. Fuzzy Mamdani was chosen because it is able to process linguistic data and produce numerical outputs through rule-based logic (Kontogiannis et al., 2021). The fuzzy Mamdani method is used to process the 23 readiness indicators into a single readiness value. The process consists of fuzzification, rule evaluation (inference), and defuzzification. In the fuzzification stage, Likert scores are converted into membership degrees using triangular membership functions (triangular fuzzy numbers) with output parameters: Low (0,0,50), Medium (25,50,75), and High (50,100,100). The general membership functions used are:

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x < b \\ \frac{c-x}{c-b}, & b \leq x < c \\ 0, & x \geq c \end{cases} \quad (1)$$

The fuzzy rules (rule base) are arranged as follows:

1. IF Score IS Low THEN Assessment IS Poor
2. IF Score IS Medium THEN Assessment IS Average
3. IF Score IS High THEN Assessment IS Good

The inference stage uses the min operator to obtain the rule activation level and firing strength:

$$\alpha_i = \frac{\sum(\mu_i \times freq)}{N} \quad (2)$$

In the defuzzification stage, the crisp readiness value is calculated using the centroid method:

$$Z^* = \frac{\sum z \cdot \mu_{agg}(z)}{\sum \mu_{agg}(z)} \quad (3)$$

Output of the fuzzy Mamdani process is a single readiness value, which is then used as the basis for forming the smart building–safety dimensions. All fuzzy stages are carried out without presenting the resulting values in the methodology section; the final readiness value is presented in the results section of the study.

Integration of Indicators into the Eight Smart Building–Safety Dimensions

The integration of indicators combines PRISMA-guided SLR findings—particularly the five key articles—with fuzzy Mamdani results and indicator categorization approaches used in prior smart building studies (Indrawati et al., 2017). This integration is conceptually based on thematic alignment, functional relevance, and linkage patterns in the literature, consistent with indicator-based frameworks applied in information modeling and multidimensional assessment studies (Roby et al., 2025). Recent IoT-based safety research further supports this approach by demonstrating the role of multi-sensor integration and intelligent monitoring in building safety decision-making and integrated safety management (Pan et al., 2025; Almatared et al., 2024). The process results in eight main dimensions—Building Management, Automation & Control, IoT Connectivity, Decision Analytics, Adaptive Response, Safety & Maintenance, Energy Sustainability, and Automation Dominance—which form the basis for systematic mapping of the 23 readiness indicators.

RESULTS AND DISCUSSION

PRISMA 2020 (SLR)

The final SLR stage shows a consistent pattern of IoT integration in building safety systems. Zhang (2025) highlights the role of digital and sensor-based monitoring for detecting structural anomalies, while Martín Toral et al. (2023) emphasize the need for computational logic and automated decision-making to manage uncertain sensor data. IoT applications in real-time fire monitoring using temperature, smoke, and environmental sensors are reinforced by Almatared et al. (2024), and Cicero et al. (2023) show that streaming-based anomaly detection helps predict hazards before failures occur. Mohammadiounotikandi et al. (2023) further demonstrate that integrating IoT sensors into fire protection systems enhances monitoring effectiveness and supports automated safety controls.

Fuzzy Mamdani Logic

The research instrument consists of 23 readiness indicators developed based on prior literature related to smart buildings and building safety. These indicators have been applied and validated in previous studies, demonstrating good construct validity and internal consistency, with 20 indicators retained and a Cronbach's Alpha value of 0.884, as commonly reported in readiness and adoption studies (Waqar et al., 2024). Therefore, the instrument is considered reliable and suitable for further analysis. In this study, the validated indicators are directly employed as inputs for dimension mapping and the fuzzy Mamdani process without re-testing, following established fuzzy Mamdani-based assessment practices that integrate validated indicators to manage uncertainty in multidimensional evaluation (Kontogiannis et al., 2021; Bukowski & Werbinska-Wojciechowska, 2025).

Table 1. Statistic Summary of 23 Indicators

Statistic	Score
Minimum Mean	3,625
Maximum Mean	4,35
Average (Mean)	4,027
(Grand Standard)	0,723
General Categorize Perception	Average

Based on these statistics, Triangular Fuzzy Number (TFN) parameters were established for the Low, Medium, and High categories, following the triangular membership function as in (1). TFN parameters presented in Table 2 indicate the linguistic boundary points for each category, with a–b–c determined based on the Grand Mean and Grand Std. These parameters serve as the basis for converting score values into fuzzy membership degrees.

Table 2. Parameter of Triangular Fuzzy Number (TFN)

Category	a	b	c
Low	1.000	1.000	3,304
Medium	3,304	4,027	4,75
High	4,75	5.000	5.000

Fuzzification process was then carried out for each Likert score from 1 to 5, producing three membership degrees (μ_{Low} , μ_{Medium} , μ_{High}) for each linguistic category. Results are shown in Table 3. Scores 1–3 have dominant membership in the Low category, while score 4 falls within the Medium category, and score 5 fully belongs to the High category. This pattern indicates that the membership functions operate consistently with the initial data distribution.

Table 3. Fuzzy Membership Degrees for the 1–5 Scale

Skor	μ Low	μ Medium	μ High
1	1	0	0
2	0,566	0	0
3	0,132	0	0
4	0	0,962	0
5	0	0	1

The next stage is inference, which is carried out based on the Mamdani fuzzy rules: IF Score is Low THEN Assessment is Poor, IF Score is Medium THEN Assessment is Average, and IF Score is High THEN Assessment is Good. The activation level of each rule is calculated using firing strength according to (2), combining membership degrees with the frequency of score occurrences. Results of this inference then form the fuzzy output curve, which becomes the basis for the defuzzification process.

Defuzzification is conducted using the centroid method as in (3), producing a crisp readiness value for each indicator. Summary in Table 4 shows that the centroid values range from 50.874 to 62.345, with an average value of 56.561. Based on the interpretation range (0–33 Poor; 33–67 Average; 67–100 Good), this value falls within the Average category, indicating that practitioner readiness in implementing smart building–safety is at a moderate yet consistent level

Table 4. Summary Results of Defuzzification (Centroid)

Item	Score
Minimum	50,874
Maximum	62,345
Average	56,561
Category	Average

To obtain a readiness overview at the dimension level, centroid values of the indicators were grouped into the eight smart building–safety dimensions. Results in Table 5 show that the fuzzy values of each dimension range from 54 to 61, all of which fall into the Average category. No dimension falls into the Poor or Good categories, indicating that readiness for smart building–safety implementation in Indonesia is relatively uniform and does not show significant gaps across dimensions.

Table 5. Fuzzy Score of Eight Dimensions Smart Building–Safety

Dimension	Indicator	Fuzzy	Category
Building Management	Q1, Q2, Q3	61	Average
Automation & Control	Q8, Q9, Q10	55	Average
IoT Connectivity	Q7, Q11, Q12, Q13	55	Average
Decision Analytics	Q14, 15, Q16, Q17	60	Average
Adaptive Response	Q9, Q10, Q18, Q19	54	Average
Safety & Maintenance	Q4, Q5, Q6	57	Average
Energy & Sustainability	(global fuzzy)	57	Average
Automation Dominance	Q20, Q21, Q23	55	Average

Fuzzy Mamdani results support the SLR finding that the eight smart building–safety dimensions have a stable and relevant structure. The relatively uniform readiness profile shows that these dimensions are not only conceptually strong but also aligned with practitioner

perceptions in Indonesia. The fuzzy Mamdani outcomes therefore serve as the basis for mapping the readiness indicators (Q1–Q23) into the eight dimensions. Table 5 presents the complete mapping of the 23 indicators and the mean fuzzy values for each dimension, as shown in Figure 6. All dimensions fall within the 53.94–60.43 range, which based on fuzzy criteria (0–33 Poor, 33–67 Average, 67–100 Good) consistently places them in the *Average* category. This pattern is consistent with empirical studies showing that smart building adoption is often characterized by high awareness and demand but partial and non-integrated implementation due to cost constraints and system complexity (Singh & Dhawan, 2023).

Similar transitional readiness conditions are also reported in IoT-based safety systems, where technological capability advances faster than organizational and operational maturity (Mohammadiounotikandi et al., 2023). Moreover, fuzzy-based multi-criteria evaluations indicate that trade-offs among economic, technical, and integration factors commonly yield moderate rather than extreme readiness outcomes (Aldhaheer et al., 2022). These values are derived from aggregated centroid results, while the Energy & Sustainability dimension uses a global fuzzy value representing overall readiness. Compared with studies conducted in more fully integrated smart building contexts, the Average readiness levels observed here indicate a lower but stable maturity position, reflecting an early-to-intermediate adoption stage in Indonesia. The consistent *Average* category indicates that Indonesia's smart building–safety readiness is at a moderately stable level, with no dimension lagging or achieving high maturity.

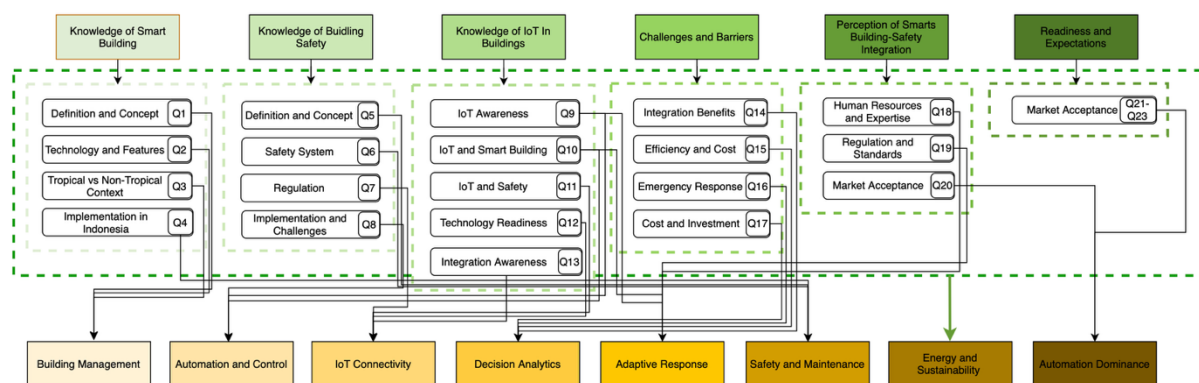


Figure 6. Concept Mapping of Readiness Variables and Indicators into Eight Smart Building–Safety Dimensions

As illustrated in Figure 6, the concept mapping integrates the 6 readiness variables and 23 indicators into a coherent structure that leads to the 8 smart building–safety dimensions. This reinforces consistency between the instrument framework, SLR thematic patterns, and Fuzzy Mamdani results, reflecting recent findings that emphasize the need for coherent integration between sensing, decision support, and maintenance processes in smart building safety systems (Fath et al., 2024), providing a clear foundation for advancing smart building–safety implementation.

CONCLUSION

This study integrates SLR findings and Fuzzy Mamdani analysis to form eight IoT-based smart building–safety readiness dimensions. The SLR highlights consistent themes IoT connectivity, automation, fire detection, decision analytics, and adaptive response which are synthesized into a coherent dimensional framework. Fuzzy Mamdani results show that all 8 dimensions fall within the Average category, with scores ranging from 54 to 61, indicating balanced but moderate readiness across building management, automation, IoT integration, and safety-related capabilities.

Overall, the findings suggest that Indonesia's smart building–safety readiness is at a stable mid-level stage. The eight dimensions demonstrate conceptual and empirical alignment, providing a solid basis for advancing technical capacity, integration strategies, and policy development toward safer and more efficient smart building systems.

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