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Design of BIM and IoT-Based Tunnel Construction Monitoring Data Fusion and Safety Early Warning System

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Abstract

The tunnel construction environment is complex, and traditional monitoring methods suffer from poor timeliness and insufficient data utilization, making it difficult to support real-time safety management and control during tunnel construction. This paper designs a construction monitoring and early warning system that integrates Building Information Modeling (BIM) and Internet of Things (IoT) technologies, adopting a “cloud-edge-device” three-tier distributed architecture. At the device layer, a multi-source heterogeneous sensor network is deployed; at the edge layer, edge computing gateways are installed for local data preprocessing and real-time analysis; at the platform layer, a data fusion analysis engine and a BIM visualization engine are integrated. For data fusion, the belief Hellinger distance is introduced to improve the Dempster-Shafer (D-S) evidence theory, effectively resolving conflicts among highly contradictory evidence sources. For safety early warning, a “4+4+N” hierarchical index system is established, and a progressively deepened three-level early warning mechanism is constructed, encompassing single-index threshold judgment, multi-parameter fusion evaluation, and Long Short-Term Memory (LSTM) time-series prediction. Finally, the system is validated through field deployment at the Yingeling extra-long tunnel in Hainan Province. The results that the proposed data fusion method achieves an accuracy of 92.5%, a 20.2% improvement over traditional D-S evidence theory. The early warning system attains an accuracy of 92.5% with a false alarm rate of 8.3%, a missed alarm rate of 3.1%, and an average response time of 2.8 seconds providing reliable technical support for tunnel construction safety management.

Keywords: tunnel construction, BIM-IoT collaborative monitoring, multi-source data fusion, improved DS evidence theory, safety early warning

1. Introduction

By the end of 2024, nearly 29,000 highway tunnels have been built and are in operation in China, with a total mileage of over 32,000 km, and the mileage is still growing at a rate of about 2,000 km per year. In 2024, the mileage of extra-long tunnels will account for 31.69%, and the proportion of long and difficult tunnels in new projects is increasing (Ministry of Transport of the People’s Republic of China, 2024). As the technical difficulty and scale of tunnel construction continue to grow, disasters such as instability of surrounding rock, collapses, and mud-flooding occur from time to time. Traditional monitoring mainly relies on contact instruments such as levels and convergence meters in combination with manual readings, with limited coverage of measurement points and low monitoring frequency. Data collection and analysis often lag by hours or even longer (Qiao Xiong, Hu Shijing & Tian Zheng, 2025), especially in the construction of extra-long tunnels. As the tunneling mileage increases, the data from a single measurement point cannot reflect the overall state of the surrounding rock, which easily leads to the situation where on-site managers have missed the best time to deal with the danger when they receive the corresponding monitoring data, thereby affecting the construction progress and seriously threatening the lives of personnel.

In recent years, with the continuous development and improvement of BIM (Building Information Modeling) and Internet of Things (iot) technologies, the component semantics, material properties, and spatial relationships carried by BIM provide an intuitive interpretation for the definition of monitoring data, while iot promotes real-time access (Song Xiuguang, Tian Weiyang, Wei Mingzhao, et al., 2026) to sensor networks. It provides new ideas for real-time monitoring of tunnels. Zhao et al. (2026) superimposed BIM with GIS to achieve spatial display and management of railway tunnel monitoring data; Wang Yaqiong et al. (2015) proposed a four-layer architecture for the Internet of Things, using its comprehensive perception, reliable transmission and intelligent assistance capabilities to guide tunnel monitoring and measurement work; Zhang et al. (2019) applied automated real-time monitoring and early warning technology to tunnel engineering and verified its reliability for monitoring the deformation of surrounding rock and support structure; Zhang Jiasong et al. (2021) used laser scanners in conjunction with cloud computing systems in highway tunnel engineering to achieve real-time collection of automated monitoring data and over-limit early warning.

However, there is still a lack of deep data-level integration between BIM and IoT in the above-mentioned research, and a stable association (Wang Chao, Zhou Leisheng, Xu Run, et al., 2020) has not been established between sensor collection values and BIM components; The fusion results of the traditional DS evidence theory are unreliable when the evidence is highly conflicting; Early warning models are often designed in a one-size-fits-all manner, lacking a hierarchical and progressive analysis mechanism (Zhou Yefei, Wang Peng, Xu Linbo, et al., 2026), and thus unable to completely break the problem (He Xuji, 2022) of information silos. Based on the Hainan Yingge Ling Extra-long Tunnel project, this paper focuses on the key issue of how to transform the “massive data” generated into “practical information”, and designs and develops a tunnel construction monitoring data fusion and safety early warning system based on BIM and Internet of Things. The system adopts a three-tier architecture of “cloud - edge - terminal” overall, a multi-source heterogeneous data fusion method based on DS evidence theory was constructed. In terms of early warning, a “4+4+N” index system and a three-layer progressive safety early warning model were built to provide theoretical support and practical reference for the safe advancement of extra-long tunnel construction under complex geological conditions.

2. Overall System Architecture Design

2.1 System Requirements Analysis

Based on the actual situation of domestic under-construction tunnel projects and in light of the actual requirements of the Hainan Yingge Ling extralong Tunnel, it is determined that the system must have the following functions:

(1) Real-time perception of multiple parameters. In addition to arch subsidence and peripheral convergence, parameters such as surrounding rock pressure, support stress, harmful gas concentration, and personnel location should also be taken into account. In the case of the Hainan Yingge Ling Tunnel (8,271 meters in length, double-tunnel separated type), there are an estimated 776 sections of left and right tunnels and shafts, and thousands of monitoring data such as arch settlement and peripheral displacement are expected, with a large amount of data processing.

(2) Data connection. Sensor points, BIM components, geological sections, and construction logs come from different data sources, and the system needs to unify them into the same spatio-temporal framework.

(3) Graded early warning. The early warning system should differentiate severity and provide corresponding handling suggestions. For those with high construction risks, they should be closely monitored to achieve “dynamic and full-process” risk management.

(4) Low power consumption and high reliability. The actual conditions such as poor power supply and communication conditions in the tunnel should be fully considered, and the equipment in the tunnel should have functions such as local caching and retransmission after recovery in case of network interruption.

2.2 System Architecture

For the above requirements, the system architecture adopts a “cloud-edge-end” three-layer distributed system. Specifically, the end layer is equipped with a multi-source heterogeneous sensor network, including laser displacement meters (accuracy ±0.1mm), fiber Bragg grating sensors, multi-gas sensors ($CO/CH_4/H_2S$), UWB positioning modules (DWM1000, static accuracy approximately 12.2cm) (Ma Haowei & Xiao Lina, 2025), etc., to achieve comprehensive perception (Liu Xinze, 2024) of the tunnel construction environment. The communication networking uses ZigBee/433MHz for short-range networking and LoRa for long-range backhaul. Considering the unstable signal coverage due to the construction environment in the tunnel, LoRa was chosen as the backbone backhaul on site to ensure stable signal transmission (Wang Yaqiong, Huang Yilin, Wang Kaiyun, et al., 2015) at the maximum burial depth.

Edge computing gateways are deployed in the edge layer to perform three main tasks: data preprocessing (3σ outlier elimination, moving average noise reduction), initial judgment of single index threshold (response delay controlled within 100ms), and retransmission after network disconnection. Some computing is moved to the edge, which not only reduces the pressure on the cloud but also maintains basic functionality in case of network glitches. Liu's (2025) research shows that the long-term reliability of intelligent monitoring equipment in the harsh environment of tunnels is a key guarantee for system availability.

Cloud is based on the Spring Boot+Vue.js microservice architecture and includes a data middle platform, a fusion analysis engine, an early warning engine, and a BIM engine (Three.js+WebGL lightweight rendering).

2.3 Functional Module Division

In terms of functional module splitting, Fei Guanghai et al. (2016) developed a monitoring and multi-information management system for drilling and blasting tunnels, and their modular design ideas provided a reference for this system. Wang Chao et al. (2020) studied the application of the construction integrated management platform in tunnel engineering and verified the feasibility of the platform-based data integration model. Based on this, the system was broken down into five functional modules: data acquisition and management, BIM model management, data fusion processing, safety early warning analysis, and 3D visualization display.

Specifically, the data acquisition and management module interfaces with end-layer sensor protocols (Modbus, MQTT, LoRaWAN, etc.) and is mainly used to convert heterogeneous data into an internal standard format. The BIM model management module is responsible for Revit model import and component parsing to establish a ternary mapping of "sensor ID<->BIM component ID<-> database record". The data fusion processing module, as the core of the entire system, is mainly used to perform improved DS fusion based on multiple monitoring data. The security early warning analysis module relies on a three-tier progressive early warning model to implement three-level early warning logic. The 3D visualization display module is mainly used to map the fused risk status onto the surface of the BIM model, thereby enabling real-time feedback on the system.

2.4 Data Storage Design

The system data mainly consists of two categories: field monitoring data and BIM model data. The highway tunnel construction monitoring and measurement management system developed by Li Changlong et al (2020) uses a relational database to organize monitoring data, and its storage strategy provides a reference for the design of this system. The intelligent monitoring and safety early warning system for tunnels based on blockchain structure proposed by Zhang Zhiming et al. (2019) has made beneficial explorations in the aspect of trusted data storage.

In terms of storage design, MySQL 8.0 architecture is used in the background, and the monitoring data table is partitioned by time RANGE (RANGE PARTITIONING), granularity is divided to the daily level. It is measured that the query delay is controlled at the hundred-millisecond level with millions of records. The BIM model data is stored using a "model file + metadata" strategy, where the model file is placed in object storage (MinIO), and only lightweight metadata such as file paths, version numbers, and component trees are retained in MySQL.

3. Multi-Source Monitoring Data Fusion Method

3.1 Fusion Algorithm Based on Improved DS Evidence Theory

With the continuous development of information technology, in current tunnel construction, multiple sensors are often installed at the same section. Due to the limitations of on-site construction conditions or blasting disturbances, it is difficult for each sensor to reflect the state of the surrounding rock in a consistent manner. Take the YK12+302 section of the Yingge Ling Tunnel as an example. The cumulative settlement read by the laser displacement meter is 47.2mm, while the convergence meter reading at the same section is 45.5mm. Although the trends are consistent, there are differences in absolute values, mainly due to instrument noise, differences in measurement point positions, and blasting vibration interference. When dealing with multi-source monitoring data in the current system, the Dempster-Shafer evidence theory is often used, with the core being the Dempster combination rule. Yang Linxi (2023) pointed out that when there is a high conflict among the evidence (the conflict factor K approaches 1), the traditional DS theory's Dempster fusion rule fails. Therefore, to further ensure the effectiveness of the fusion algorithm, further improvements were made based on the existing method.

(1) Confidence Hellinger distance

Let m_1 and m_2 be the BPA of two pieces of evidence, the recognition frame $\Theta=\{A_1,...\ A_n\}$, then the confidence Hellinger distance is defined as:

$$D_H(m_1,m_2)=\frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{N}\left(\sqrt{m_1(A_i)}-\sqrt{m_2(A_i)}\right)^2} \tag{1}$$

This distance measures the difference in the "shape" of the two probability distributions, taking values [0,1]. The larger the value, the more inconsistent the two pieces of evidence.

(2) Calculation of evidence weights

First, calculate the similarity matrix: $Sim_{ij}=1\text{-}D_H\left(m_i,m_j\right)$Next, calculate support and weights:

$$Sup_i=\sum_{j=1,j\neq i}^{M} Sim_{ij},\backslash quad\ \omega_i=\frac{Sup_i}{\sum_{j=1}^{M} Sup_j} \tag{2}$$

The calculation shows that the greater the conflict of evidence, the lower the support obtained from other evidence, and the smaller the weight. After on-site debugging and analysis, this paper selects that if the weight of a certain piece of evidence is less than 0.05, it is considered invalid evidence and excluded.

(3) Fusion process: Mainly through five calculation steps, namely calculating the distance matrix, converting to the similarity matrix, calculating the weights, weighted correction of BPA, and finally applying Dempster combination rules to obtain the final fusion result.

3.2 Comparative Analysis of Fusion Algorithms

To further verify the reliability of the fusion algorithm, the monitoring of the right arch top subsidence of the Yingge Ling Tunnel was selected as the data source for fusion verification. Data from the Grade V surrounding rock section (YK12+302 to YK12+308) were selected for annotation and risk classification, with a total of 30 conflict scene samples. The effects of the three fusion methods were compared and analyzed, and the results are shown in Table 1.

Table 1. Performance Comparison of Fusion Algorithms

Methods	**Fusion accuracy /%**	**Average response time /s**	**Success rate of conflict evidence handling /%**
Traditional DS evidence theory	72.3	5.2	45.6
Simple weighted average method	81.5	4.1	--
Improving DS evidence theory	92.5	2.8	96.8

The traditional DS theory has an accuracy rate of only 72.3% in conflict scenarios and a conflict resolution success rate of less than half. The simple weighted average improves to 81.5% without considering conflicts among the evidence, but there is still room for improvement. The method proposed in this paper identifies conflicts by Hellinger distance and adaptively weights them, improving accuracy to 92.5% and reducing response time from 5.2 seconds to 2.8 seconds.

3.3 Validation of Fusion Examples

Three adjacent measurement points were selected to simulate a multi-sensor scenario, taking the monitoring of arch top subsidence at the YK12+302 section of the Yingge Ling Tunnel as an example. S_1 is the G2 measurement point at YK12+302 section (cumulative settlement 47.2mm), S_2 is the G2 measurement point at YK12+308 section (cumulative settlement 46.3mm), S_3 is the G1 measurement point at YK12+308 section (cumulative settlement 45.5mm). The BPA allocation results given by the three sensors for the risk level Θ={H_{21} (normal), H_3 (warning), H (dangerous)} are shown in Table 2.

Table 2. Sensor BPA Allocation

Source	**H1**	**H2**	**H3**	**Θ**
S_1 (YK12+302 G2)	0.15	0.55	0.25	0.05
S_2 (YK12+308 G2)	0.20	0.50	0.20	0.10
S_3 (YK12+308 G1)	0.55	0.25	0.10	0.10

The results showed that the H_1 probability of S_3 was 0.55, and the data read was overly optimistic and inconsistent with S_{12} and S. From Equations 2.1 to 2.2, ω=0.$_1$372,$_2$ ω=0.373,$_3$ ω=0.255, it is obvious that the weight of S_3 is naturally reduced. After fusion, m_fusion (H_2) =0.712, judged as H_2 (warning) by the maximum membership degree. The fusion process, compared with the traditional DS (0.650) and weighted average (0.480), the improved DS evidence theory handles conflicting evidence more reasonably.

4. Security Early Warning Model

4.1 Evaluation Index System

In order to further select the early warning evaluation index system that conforms to the actual situation on site, this paper mainly adopts the method of combining engineering investigation and questionnaire survey. Based on the "Technical Specifications for Highway Tunnel Construction" (JTG F60) and the experience of on-site engineers, and on (Wu Danhong, 2023; Liu Xianghui, 2023; He Gan, 2023; Ding Zhi, 2025) the basis of the existing research results, the factors affecting the safety of tunnel construction are summarized into four first-level dimensions:

(1) Geological environment (G, weight 0.30): surrounding rock grade, groundwater conditions, degree of development of fault zones, etc.

(2) Structural safety (S, weight 0.35): arch settlement rate, peripheral convergence rate, surrounding rock pressure, support stress, etc. This dimension has the highest weight because it directly reflects the mechanical response of the surrounding rock-support system.

(3) Construction management (M, weight 0.20): whether the excavation step distance exceeds the limit, the timeliness of support, personnel density, etc.

(4) Personnel status (P, weight 0.15): number of workers at the face, personnel positioning and distribution, abnormal physical signs, etc.

The weights are determined by the AHP-entropy weight combination weighting method: $w^{(A)} =(w^{(A)\,(A)} \ldots W_j^{(E)}) / \Sigma (w_j^{(A)} \ldots w^{(E)})$. Five specialized early warning modules are set up for special disaster types in tunnel construction: collapse, gas, water gushing and mud gushing, rockburst, and large deformation.

4.2 Three-Tier Progressive Early Warning Model

Peng Zhimin (2024) conducted a systematic study on tunnel construction safety management and risk early warning technology, noting that the single threshold method is difficult to adapt to the dynamic changes of complex geological conditions. Based on this, this paper adopts a "shallow to deep" three-level early warning mechanism. The first level is a single-indicator dynamic threshold, with three levels of dynamic thresholds set for each monitoring indicator: observation value ($\mu+2\sigma$), warning value (70% of the design allowable value), and alarm value (90% of the design allowable value). The threshold range is dynamically adjusted according to different grades of surrounding rock and construction phases.

The second layer combines multi-index fusion with fuzzy comprehensive evaluation and sets five comment sets V={safe, relatively safe, average, relatively dangerous, dangerous}. When the first layer triggers a warning value or there is a multi-indicator linkage anomaly, the second layer program is entered. At this point, the multi-source evidence is fused using the improved DS evidence theory, and then the fuzzy comprehensive evaluation is carried out to further avoid the situation where other sensors do not synchronously anomaly when a single sensor misreads due to a failure.

The third layer of determination uses LSTM+Attention time series prediction. Deep prediction is initiated when the risk level of the current two-layer judgment reaches "dangerous" or "dangerous", where the LSTM network learns the temporal dependencies of the multivariable time series, and the Attention mechanism automatically focuses on the historical moments (Liu Shang, 2023) that have the greatest impact on the prediction.

4.3 Comparison Experiment of Early Warning Models

The three early warning strategies were compared using the field data of 340 arch subsidence measurement points and 464 peripheral displacement measurement points in Yingge Ling Tunnel as the dataset, and the results are shown in Table 3.

Table 3. Comparison of Performance of Early Warning Models

Early warning models	**Accuracy rate /%**	**False positive rate /%**	**Underreporting rate /%**	**Average early warning time /h**
Single threshold method	75.8	18.5	12.1	0.5
Fuzzy comprehensive evaluation method	85.2	12.3	7.8	1.2
Three-tier progressive model	92.5	8.3	3.1	4.0

From this, it can be seen that there is a problem with threshold setting in the single-threshold method. A threshold that is too low leads to frequent false alarms, while a threshold that is too high is prone to missed alarms. Although the fuzzy comprehensive evaluation method has reduced the rate of false alarms and missed alarms to some extent, there is still considerable room for improvement in the time of early warning. The model in this paper combines three methods to construct a three-level progressive model, reducing the false alarm rate from 18.5% to 8.3%, the false alarm rate from 12.1% to 3.1%, and the early warning time from 0.5 hours to about 4.0 hours, which can provide more accurate and reliable results for real-time monitoring of engineering sites.

4.4 Early Warning Levels and Response Mechanisms

Further, on the basis of ensuring that the early warning model is more reliable, the early warning levels are classified into three levels based on actual circumstances, as shown in Table 4. The tunnel safety information early warning system developed by Liu Bin et al. (2023) verified the effectiveness of the multi-channel synchronous notification mode in engineering practice. After the warning is issued, the system can notify the corresponding responsible person in real time through multiple channels such as APP push, SMS reminder, sound and light alarm, etc., to respond and handle quickly, and ultimately achieve the closed-loop management of "warning – response – handling – feedback – cancellation".

Table 4. Warning Levels Classification

Levels	Colour	Status	Judgment conditions	Response measures
Level IV	green	Normal	Overall score ≥80	Routine inspection
Grade III	yellow	Follow	A single indicator exceeds attention or 60≤ score <80	Encrypted observations
Level II	orange	Warning	Multiple indicators abnormal or 40≤ score <60	Activate special programs and enhance support

5. Engineering Application Verification

5.1 Rely on the Project Overview

This paper is based on the Hainan Yingge Ling Extra-long Tunnel, which is located in the central mountainous area of Hainan Province. It is the longest highway tunnel under construction in Hainan Province, with a total length of 8,271 meters, a double-tunnel separated layout, a designed speed of 80km/h, and an excavation section of 87.14 meters^2. The right tunnel starts at K7+800 and ends at K12+330, with a length of 4,530 meters; The left hole runs from ZK7+800 to ZK12+352 and is 4,552 meters long.

The tunnel passes through complex strata conditions, and the surrounding rock is composed of three grades: Grade III, Grade IV and Grade V. Distribution of surrounding rock in the right tunnel: Grade III surrounding rock 2375m (52.43%), mainly composed of slightly weathered granite, with relatively intact rock mass; Grade IV rock 1310m (28.92%), mainly composed of moderately weathered sandstone and conglomerate, with well-developed joints; Grade V surrounding rock 845 m (18.65%), mainly composed of strongly weathered sandstone, conglomerate and gravel soil, with poor self-stabilizing ability. Left cave rock distribution: Grade III 2485m (54.59%), Grade IV 1300m (28.56%), Grade V 767m (16.85%). Grade V surrounding rock is concentrated at the entrance and exit of the tunnel and near the fault fracture zone, which is a key section for construction safety monitoring.

5.2 Monitoring Plan and Data Analysis

According to the geological conditions of the Yingge Ling Tunnel, the monitoring measurement items are divided into two major categories: mandatory measurement items and optional measurement items. Zhou Shui et al. (2022) practiced the application of wireless vibrating wire acquisition instruments in the monitoring and measurement of extra-long tunnels and verified the reliability of automated acquisition technology in long-distance tunnels. Mandatory items are daily monitoring and measurement items that must be carried out to ensure the stability of the surrounding environment and surrounding rock of the tunnel and construction safety, as well as to reflect the design and construction status. The specific monitoring items are shown in Table 5.

Table 5. Mandatory Monitoring and Measurement Items for Yingge Ling Tunnel

Serial Numbers	Measurement items	Methods and Tools
1	Observation inside and outside the hole	Geological compass, digital camera
2	Peripheral displacement	Total station
3	Arch sinking	Total station
4	Surface subsidence	Total station
5	Seepage pressure, water flow	Piezometer

Serial Numbers	Measurement items	Methods and Tools
6	Corrugated plate strain	Steel surface strain gauge
7	Wellbore force monitoring	Fiber grating strain gauge

In this paper, 78 surface subsidence data of the left and right tunnels (concentrated in the inlet and outlet sections of grade V surrounding rock), 340 arch top subsidence data (including 159 YK lines of the right tunnel and 181 ZK lines of the left tunnel, covering grade III to V surrounding rock), and 464 peripheral displacement data were selected as the research objects to statistically analyze the distribution of the three types of monitoring indicators. The results show that the cumulative surface subsidence values have a wide distribution range (0.1 to 48.5mm), and the median maximum deformation rate is about 1.5mm/d, indicating that the shallow-buried sections at the entrance and exit are greatly affected by surface factors. The cumulative settlement of the arch was mainly distributed in the range of 5 to 15mm, but there were several high points in the grade V surrounding rock section. Among them, the cumulative settlement of the G2 measurement point at the YK12+302 section reached 47.2mm, which was the maximum value of all measurement points. The median cumulative value of the peripheral displacement is about 4.0mm, which is relatively small overall, indicating good convergence control of the tunnel.

The deformation characteristics of the arch settlement under different surrounding rock grades were statistically analyzed. Among them, grade IV surrounding rock has the highest median deformation rate (about 2.6mm/d), which is related to the alternation of soft and hard lithology and the development of local joints in grade IV surrounding rock; The median cumulative settlement of grade V rock is the highest (about 10mm), while that of grade III is the lowest (about 5mm), because grade V rock has poor self-stabilizing ability, long deformation duration, and although the initial rate is not high, the cumulative effect is significant.

5.3 System Operation Effect

The system was deployed in the left and right tunnels of Yingge Ling Tunnel and operated continuously for 6 months. The statistics of the early warning effect are shown in Table 6.

Table 6. System Early Warning Effect Statistics

Indicators	Numerical
Warning accuracy	92.5%
Average response time	2.8 seconds
False alarm rate	8.3%
Underreporting rate	3.1%
System availability	99.2%

Among them, at the G2 measurement point of the YK12+302 section (right tunnel K12+302, grade V surrounding rock section), the system detected a cumulative settlement of 47.2mm and a deformation rate of 4.2mm/d at 14:32, exceeding the warning threshold (3.0mm/d), triggering a yellow alert for the first layer; At 14:35, the second layer was upgraded to an orange alert after merging with the adjacent G1 measurement point at the YK12+308 section; At 14:38 The third layer LSTM predicts that the alarm value will be reached within the next 4 hours. The site promptly took measures such as adding steel supports and shortening excavation footage, and the deformation rate gradually dropped back to 2.1mm/d. This also validates the rationality of the high weight of the “structural safety” dimension in the “4+4+N” index system.

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