# RESEARCH ON ESTABLISHING A SET OF CRITERIA FOR ASSESSING THE SMART LEVEL OF MANUFACTURING FACTORIES

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***Summary**:*

*With the development of science and technology, the trend of constructing smart factories is rapidly unfolding worldwide, including in Vietnam. However, currently, there are diverse and inconsistent interpretations and evaluations of the smartness level of a factory. By synthesizing international studies and expert opinions through the Analytic Hierarchy Process (AHP) analysis tool, the authors propose to establish a set of criteria to quantitatively assess the smart level of industrial factories. These criteria serve as a tool to assist managers in planning smart strategies, determining the appropriate (smart) investment level in each development stage to both sustain current production and create room for future development.*

**Keywords:** *Smart factory; a set of criteria; AHP.*

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## 1. Overview of smart factories

With the rapid development of science and technology, today's manufacturing plants are facing with numerous challenges. Diverse customer's demands for product customization led to smaller production batches and frequent changes, resulting in more waste when keeping the operating in traditional ways. To stay competitive, manufacturing plants need to optimize equipment capacity, reduce waste, minimize inventory time, and efficiently use the company's resources... All these issues can be addressed through the intelligent transformation of manufacturing plants.

After collecting and reviewing published works from reputable international journals and surveying expert opinions, we observed various interpretations of "smart factories" based on different research perspectives. Depending on the scope of influence and the level of detail in these concepts, they can be broadly categorized into three main groups: Technical and Technological approach, Operational approach, and Macro approach.

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*Technical and Technological Approach:* According to this approach, a smart factory is equipped with intelligent devices and modern technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and sensors,... These components can be connected and sharing data to establish a virtual system alongside the physical one. While this approach has advantages of identifying the specific technologies for smart factories, it also may have disadvantages of overlooking the investment efficiency and the macro and micro impacts of smart factories. Representatives of this approach include B. Chen et al. (2018), Navid Shariatzadeh et al. (2016), Chui Young Yoon (2019),...

*Operational Approach:* The operational approach focuses on assessing the efficiency of operations such as product quality, reaction time, and the flexibility of the manufacturing organization,… when implementing smart factories. In this perspective, a smart factory is one that is comprehensively connected internally and externally, automatically receives and analyzes data, and configures itself to optimize production processes. This approach has the advantage of meeting specific customer requirements while reducing production costs, maximizing factory profits, minimizing investment payback time, and enhancing reputation. However, it may not clearly identify what to invest in and what are the macroeconomic impacts. Representatives of this approach include Jung et al. (2021), Mabkhot et al. (2018),…

*Macro Approach:* The macro approach defines a smart factory as one that quickly and optimally meets customer needs to save resources for society, protect the environment, maintain a competitive advantage, and enhance the competitive capacity of the industry and the country. While beneficial for long-term and broad objectives, this approach poses challenges for small and medium-sized enterprises (SMEs), particularly those with limited potential. A representative of this perspective is Jay Lee (2015) who emphasize the benefits of smart factories for stakeholders and socio-economic impacts.

Despite differing views on smart factories, each group of author provides unique perspectives and definitions however, there are certain commonalities between them. Analyzing these viewpoints, we propose a definition of a smart factory as a combination of all three approaches-technical and technological, operational, and macro. This definition is as follows: *"A smart factory is equipped with automated machinery, infrastructure, sensors, and experienced human personnel. The human-machine systems are interconnected, as well as connected to external entities, allowing the factory to automatically or semi-automatically collect* *and analyze information about the environment, customer needs, and partners. The system can self-configure or reconfigure to optimize the production process, save resources, protect the environment, and enhance the competitive capacity of the factory, industry, and country".*

The distinctiveness of a smart factory compared to traditional factories is evident through its benefits, including:

- Smart factories can proactively detect and respond to events that help improve quality, productivity, reduce production downtime and improve overall equipment performance. Through the application of digital technology, it is possible to simulate new products in advance and evaluate the bottlenecks that will be encountered. Smart factories are enabled to proactive supply chain changes and flexible warehousing, optimizing other factory logistics operations including packaging and shipping. Smart factories can open new business opportunities, revenue streams and create sustainable competitive advantages. In addition, it can also automate the arrangement and prediction of product errors, thereby conducting preventive maintenance to prevent downtime. With smart factories, we can process and analyze data in real time near the time of data generation to react quickly to abnormalities in the production processes;
- In marketing and sales activities, smart manufacturing technology allows businesses to understand the market, to predict and adapt to customer preferences, trends and needs. In supply chain management, through IoT data analysis, smart manufacturing can forecast demand, optimize inventory, and monitor suppliers and consumers;
- Smart factories help improve product quality and production processes, meeting customer needs through statistical process control, quality yield management and reliability analysis. The application of electronic signatures in the approval and authentication of online processes in manufacturing can help with regulatory compliance to standardize, automate, and monitor quality by design (Deploying quality functions QFD).

In conclusion, "the trend of factories becoming smart become inevitable if manufacturing plants and businesses want to survive and thrive in the Era of Industrial revolution 4.0. However, the process of transforming into a smart factory requires significant investment, and without detailed planning, a factory may face bankruptcy before increasing profits. Therefore, the challenge for managers is to determine the appropriate (intelligent) investment level in each development stage, allowing for the maintaining of current production and creating room for future development. Thus, the criteria for assessing the level of factory intelligence serve as a measurement tool to help managers plan intelligent strategies for their factories.

## 2. Propose criteria to evaluate the factory's intelligence or smartness level

As the concept stated in the previous section, whether smartening old factories or investing in new ones completely, they must still ensure the general requirement that they can automatically or semi-automatically make decisions depending on environmental conditions. Decisions here include strategic levels, operational management levels or configuration parameters of machines and equipment. The environment here includes both the internal and external environment of the factory such as customer requirements, the capabilities of supply partners, the condition and accuracy of machinery and production equipment, and qualifications level of workers,…

Jay Lee (2015) has proposed a model to evaluate smart factory levels. Level 1 is the connectivity of elements throughout the system. Level 2, the data collected by sensors must be converted into useful, actionable information. Level 3, ability to share and synchronize on the network; at this level, all information is processed, compared, shared,... throughout the system, based on which future activities can be predicted. Level 4, self-awareness, based on monitoring data, the system is self-aware, thereby supporting managers in making decisions. Level 5, self-configuration capability, on a cognitive basis, the system can self-configure to meet the factory's tasks.

Mabkhot et al (2018) have proposed a 2-level set of requirements for smart factories, comprising 6 requirements in level 1 (including capabilities such as modularization, interaction, distribution, virtualization, service orientation and real-time response) and 26 requirements in level 2. In 2019, Iman Abdul Waheed and his colleagues used this set of level 1 requirements to propose a basic design model of a smart factory.

Baotong Chen and colleagues (2017) used a hierarchical model to propose a smart factory model composed of 4 layers, including: input layer (input data input); storage application layer (cloud, server); connection network layer (factory-wide connection); hardware equipment layer. Philipp Osterrieder et al (2019) proposed a smart factory model consisting of 4 layers: Control layer (the highest layer in the smart factory); cloud layer and intelligent processing; data layer; physical layer (including direct production equipment such as robots). Additionally, they introduced a corresponding smart factory research model in 8 domains including: decision making; network system - physical equipment; data processing; information technology infrastructure; digital transformation; human-computer interaction; connecting all things; cloud services and manufacturing.

Rabab Benotsmane et al. (2019) compared the characteristics between traditional and smart factories. They referred to key elements constituting smart factories, including smart production process; smart supply; smart applications; data analysis; human resources; and equipment and products. All these elements must be synchronously connected by the Internet of Things (IoT) technology.

Thus, the criteria for evaluating the smart level of a factory have been proposed by researchers focusing on 3 groups of criteria: technology infrastructure investment, operational exploitation, and ensuring the overall efficiency indicators of a smart factory. Firstly, investing in technology infrastructure is the first and core step to building a smart factory. Indeed, the basis of a smart factory must be done by machines and technology instead of humans. Thanks to the characteristics of continuous work and unlimited working capacity, machines can process and execute large amounts of information in a short period of time that humans cannot. Like other systems, a smart factory needs sensors, information collection devices, information processing components (processing chips, storage) for decision-making, execution components, and a connectivity system (network). In addition to hardware, technologies and software must also be applied such as Cyber Physical System (CPS), Industrial Internet of Things (IIoT), BigData, Artificial Intelligence (AI),... Secondly, despite the importance of technology infrastructure investment, the success of a smart factory is determined using these technologies in operation and production management. A factory that is invested very well but cannot integrate processes into the system cannot be considered smart. Therefore, criteria for operational and production management capabilities also play a decisive role in smartening the factory. Finally, efficiency indicators are quantitative indicators that demonstrate the success of building a smart factory. If the investment is good, the operation is good, but the efficiency indicators are not too different from traditional factories, it cannot be called a smart factory.

Based on the above analysis, the authors propose three groups of level I criteria corresponding to three aspects of the problem. Continuing with a branch analysis, the authors propose Level II criteria. For example, from the first group of criteria on technology infrastructure investment, we propose typical technologies that need to be invested in for a smart factory (including 05 technologies), and similarly for groups 2 and 3. The full set of criteria to evaluate the smart level of the factory is proposed according to Table 1 below.

**Table 1.** Set of criteria (proposed) for smart factory assessment

| No. | Level I criteria | Level II criteria |
|---|---|---|
| 1 | Group of criteria on infrastructure investment (A1) | Digitalization of equipment (A11) |
| 2 | | Modularization and standardization of communication and connection (A12) |
| 3 | | Connecting and sharing data (A13) |
| 4 | | Equip devices with self-processing capabilities (A14) |
| 5 | | Level of CPS technology application (A15) |
| 6 | Group of criteria for exploitation and operation (A2) | Human resource level in understanding and operating smart factories (A21) |
| 7 | | Digitalization and process intelligence (A22) |
| 8 | | Planning, implementation, and adjustment (A23) |
| 9 | | Supply chain management and forecasting (A24) |
| 10 | | Collect and analyze operational data (A25) |
| 11 | Group of effectiveness criteria (A3) | Ability to handle unexpected changes (A31) |
| 12 | | Time to prepare and adjust plans (A32) |
| 13 | | Product quality (A33) |
| 14 | | Factory market share (A34) |
| 15 | | Unit profit and total profit (A35) |

*Source: Authors*

After proposing the draft set of criteria, the authors conducted an expert survey to confirm and supplement additional criteria (if any). The surveyed experts included researchers, leaders of manufacturing plants with at least 5 years of experience in the field. The synthesized questions included agreement with the proposed criteria or not agree, and at the end of each group of Level I and Level II criteria, there were open-ended questions to supplement the criteria. The results of the expert survey are summarized in Table 2 below.

**Table 2.** Results of the expert survey on proposed criteria

| **Criteria** | **A11** | **A12** | **A13** | **A14** | **A15** | **A21** | **A22** | **A23** |
|---|---|---|---|---|---|---|---|---|
| **Agree** | 99% | 98% | 100% | 97% | 98% | 96% | 99% | 95% |
| **Criteria** | A24 | A25 | A31 | A32 | A33 | A34 | A35 | |
| **Agree** | 97% | 100% | 97% | 98% | 96% | 99% | 95% | |

*Source: Authors*

Based on the results above, the authors concluded that most opinions agreed with the proposed criteria, and there were no additional criteria suggested. However, the above set of criteria only allows for a preliminary understanding of a smart factory but is not sufficient to assess the level of smartness comprehensively. This is because each criterion contributes differently and has different difficulty level in implementing them varies.

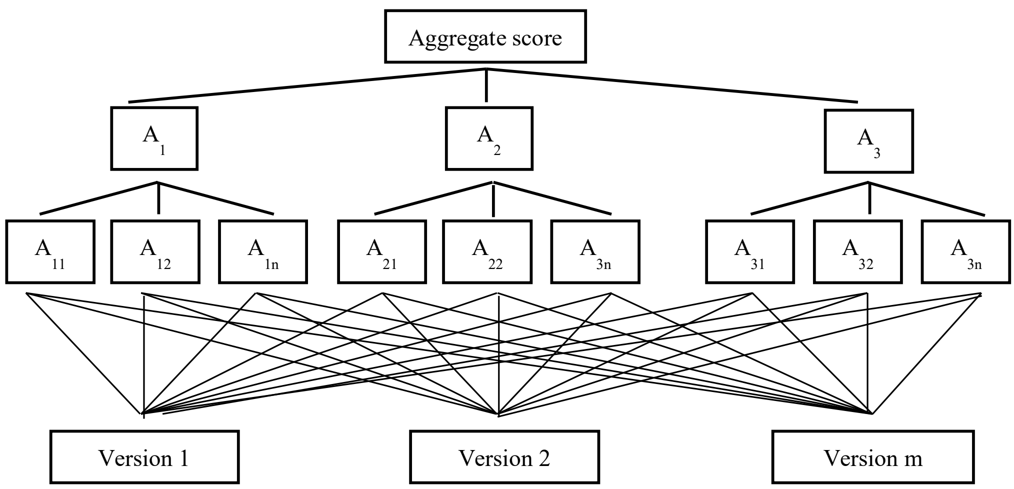
To address these shortcomings and move towards a quantitative set of criteria for factory assessment, we employed the Analytic Hierarchy Process (AHP) tool to evaluate the importance (or weights) of each criterion. This process helps construct a comprehensive scoring scale. The detailed analysis process will be presented in Section 3 of this paper.

## 3. Applying the AHP analytical hierarchy method to synthesize a set of criteria

AHP is a decision-making method proposed in 1980 by Thomas L. Saaty. This quantitative analysis method is commonly used for multi-objective decision-making based on the analysis of comparative criteria. In the context of the presented problem, the goal is to determine the weights reflecting the individual contributions of criteria to the overall score for a smart factory. Based on pairwise comparisons, AHP can be described with 3 main principles: analysis, evaluation, and synthesis, with specific steps as follows:

***Step 1:*** *Constructing the AHP hierarchy tree*

The objective of this step is to hierarchically structure the criteria with enough detail for a quantitative assessment. As each criterion may have a different difficulty level in implementation, AHP uses weights to express this difference. In the model, from option 1 to option m represent a set of different weight values.




*Source: Deng et al. (1989)*

**Figure 1.** AHP hierarchical tree model

***Step 2:*** Building the matrix comparing the importance between criteria

The purpose of this step is to cross-compare pairs of criteria, assessing the relative importance between criteria within a pair. Specifically, the authors collect expert opinions on the importance of criteria through a survey. The data is then statistically processed for mean and variance values. If the sample variance is smaller than the standard value, the data is accepted; otherwise, in-depth interviews are conducted.

The importance between criteria at level I and between sub-criteria is represented in a symmetrical matrix. If criterion Ai is evaluated by experts with an importance level of 5, and criterion Aj is evaluated with an importance level of 3, the relative importance of Ai to Aj is 5/3, while the importance of Aj to Ai is 3/5. Criteria pairs are compared at the same level in the AHP hierarchy, as shown in the matrix tables below.

**Table 3.** Matrix of importance between level 1 criteria

| **Criteria** | **A1** | **A2** | **A3** |
|---|---|---|---|
| A1 | 1.00 | 1.09 | 1.05 |
| A2 | 0.92 | 1.00 | 0.97 |
| A3 | 0.95 | 1.04 | 1.00 |

**Table 4.** Importance matrix between level 2 criteria of criterion A1

| **Criteria** | **A11** | **A12** | **A13** | **A14** | **A15** |
|---|---|---|---|---|---|
| A11 | 1.00 | 1.08 | 1.02 | 1.25 | 1.20 |
| A12 | 0.92 | 1.00 | 0.94 | 1.15 | 1.11 |
| A13 | 0.98 | 1.07 | 1.00 | 1.23 | 1.18 |
| A14 | 0.80 | 0.87 | 0.82 | 1.00 | 0.96 |
| A15 | 0.83 | 0.90 | 0.85 | 1.04 | 1.00 |

**Table 5.** Importance matrix between level 2 criteria of criterion A2

| **Criteria** | **A21** | **A22** | **A23** | **A24** | **A25** |
|---|---|---|---|---|---|
| A21 | 1.00 | 0.90 | 1.02 | 1.08 | 1.00 |
| A22 | 1.12 | 1.00 | 1.14 | 1.21 | 1.12 |
| A23 | 0.98 | 0.88 | 1.00 | 1.06 | 0.98 |
| A24 | 0.92 | 0.83 | 0.94 | 1.00 | 0.92 |
| A25 | 1.00 | 0.90 | 1.02 | 1.08 | 1.00 |

**Table 6.** Importance matrix between level 2 criteria of criterion A3

| **Criteria** | **A31** | **A32** | **A33** | **A34** | **A35** |
|---|---|---|---|---|---|
| A31 | 1.00 | 1.09 | 1.01 | 1.09 | 1.05 |
| A32 | 0.92 | 1.00 | 0.93 | 1.01 | 0.97 |
| A33 | 0.99 | 1.07 | 1.00 | 1.08 | 1.04 |
| A34 | 0.92 | 0.99 | 0.93 | 1.00 | 0.96 |
| A35 | 0.95 | 1.03 | 0.96 | 1.04 | 1.00 |

***Step 3:*** Calculating weights for criteria

After completing the matrix, the next step involves summing the values of the matrix by column. Subsequently, each value in the matrix is divided by the column sum to obtain the corresponding value Wij (according to the standard principle of the AHP method and normalization). The weight of each criterion is the average of the Wij values calculated for each row. The result is a weight matrix with one column and n rows.

**Table 7.** Weight matrix of level I criteria

| Criteria weight | A1 | A2 | A3 | Weight (W) |
|---|---|---|---|---|
| A1 | 0.35 | 0.35 | 0.35 | 0.35 |
| A2 | 0.32 | 0.32 | 0.32 | 0.32 |
| A3 | 0.33 | 0.33 | 0.33 | 0.33 |

**Table 8.** Matrix for calculating the weights of level 2 criteria in criterion A1

| Weight | A11 | A12 | A13 | A14 | A15 | Weight (W1n) |
|---|---|---|---|---|---|---|
| A11 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |
| A12 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| A13 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |
| A14 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |
| A15 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |

**Table 9.** Matrix for calculating the weights of level 2 criteria in criterion A2

| Weight | A21 | A22 | A23 | A24 | A25 | Weight (W2n) |
|---|---|---|---|---|---|---|
| A21 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| A22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |
| A23 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |
| A24 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 | 0.18 |
| A25 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |

**Table 10.** Matrix for calculating the weights of level 2 criteria in criterion A3

| Weight | A31 | A32 | A33 | A34 | A35 | Weight (W3n) |
|---|---|---|---|---|---|---|
| A31 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 |
| A32 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| A33 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 |
| A34 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 | 0.19 |
| A35 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 | 0.20 |

***Step 4:*** Checking the consistency of expert or manager evaluations

The objective of this step is to verify the consistency of the collected data. In the AHP technique, Saaty (2008) suggests examining the Consistency Ratio (CR). The CR indicates the consistency and agreement of opinions among experts and managers during the evaluation process. If CR $\leq$ 0.1 (10%), the results are acceptable, indicating that the evaluations of the experts are relatively consistent and have an appropriate level of reliability. Conversely, if CR > 0.1, the evaluations are inconsistent, and the judgments may be somewhat random, requiring a reassessment and reconsideration.

$$CR = CI/RI. \tag{1}$$

In there:

CI is the consistency index.

RI is random index.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

n is the number of criteria and λmax is the eigenvalue of the comparison matrix.

$$\lambda_{max} = \frac{1}{n} \cdot \left[ \frac{\sum_{n=1}^{n} W_{1n}}{W_{11}} + \frac{\sum_{n=1}^{n} W_{2n}}{W_{22}} + \frac{\sum_{n=1}^{n} W_{3n}}{W_{33}} + \ldots + \frac{\sum_{n=1}^{n} W_{nn}}{W_{nn}} \right] \tag{3}$$

Checking the conditions for consistency, the authors concluded that the criteria were acceptable because the experts' assessments were relatively consistent.

## 4. Applying the criteria to evaluate the level of intelligence of a factory

### *4.1. Measurement and evaluation of achievement on each criterion*

The smart level of a factory is assessed based on three first-level criteria and 15 second-level criteria, as analyzed above. However, in addition to the importance level determined by the AHP method, the factories must also be evaluated for the achievement level of each criterion. Referring to published documents in section 2 and considering expert opinions, the authors propose a method for measuring the criteria as outlined in the table 11:

**Table 11.** Measurement methods of evaluation criteria

| No | Criteria I level | Criteria II level | Measurement |
|---|---|---|---|
| 1 | Infrastructure investment group (A1) | Digitalization of equipment (A11) | The proportion of digitalized equipment |
| 2 | | Modularization and | The proportion of machines (machine |

| No | Criteria I level | Criteria II level | Measurement |
|---|---|---|---|
| | | standardization of communication and connection (A12) | clusters) that are modularized |
| 3 | | Connection and data sharing (A13) | Measured on a 5-level scale:<br>Level 1: Machines and modules are fully connected to each other on one network.<br>Level 2: Elements can "shake hands" in data sharing.<br>Level 3: Elements compute together and provide optimal parameters.<br>Level 4: Parts select optimal parameters.<br>Level 5: Fully automatic in collecting, analyzing information, and self-configuring optimally. |
| 4 | | Equipped with self-processing capability for devices (A14) | The proportion of elements equipped with computers alongside controllers (PLC) to increase intelligence. |
| 5 | | CPS technology application level (A15) | CPS (Cyber physical system) is a technology system that allows building a virtual entity on the internet network of industrial objects parallel to physical entities. This allows humans to observe and interact with physical objects through virtual objects. This criterion measures the proportion of entities deployed and the realism level of virtual objects. |
| 6 | Exploitation and operation criteria (A2) | Labor force level in understanding and operating smart factories (A21) | The proportion of labor force that has been trained (short-term and long-term) on smart factory. |
| 7 | | Digitalization and intelligentization of processes (A22) | The proportion of processes that are digitalized or becoming intelligent. |
| 8 | | Planning, implementation, and adjustment of plans (A23) | The proportion of plans that are automatically optimized on computers or semi-automatically with computer assistance. |
| 9 | | Supply chain management and forecasting (A24) | Partners and customers are connected to the factory's network to receive, process, exchange, and transmit information in real-time |
| 10 | | Collection and analysis of operation data (A25) | The degree of automatic collection and analysis of information for operational purposes |

| No | Criteria I level | Criteria II level | Measurement |
|---|---|---|---|
| 11 | Efficiency criteria group (A3) | Ability to handle unexpected changes (A31) | Time and degree of optimization to handle changes |
| 12 | | Time to create and adjust plans (A32) | The degree of shortening time compared to traditional factories or industry average |
| 13 | | Product quality (A33) | The degree of quality improvement after becoming intelligent |
| 14 | | Market share of the factory (A36) | The degree of market share increase after becoming intelligent |
| 15 | | Unit profit and total profit (A37) | The degree of profit increase (after deducting costs and depreciation of smart factory investment) after becoming intelligence |

*Source: Authors*

### *4.2. Building a score table and a synthesis score reflecting the smart level of the factory*

The scores for the criteria (level 1 and 2) are calculated based on the actual scores achieved for each criterion and the weight of that criterion. The weights of the criteria, built in step 3, represent the percentage contribution of each criterion to the higher-level criterion. To calculate the contribution ratio to the total score, you only need to multiply the calculated weight by the weight of the higher-level criterion. The contribution ratio table and the method of synthesizing scores are shown in the table 12.

**Table 12.** Using the proposed set of criteria to evaluate the factory's smart level

| No | Criteria I level | Criteria II level | Weight | Value | Score |
|---|---|---|---|---|---|
| 1 | Infrastructure investment group (A1) | Digitalization of equipment (A11) | 7.66 | | |
| 2 | | Modularization and standardization of communication and connection (A12) | 7.08 | | |
| 3 | | Connection and data sharing (A13) | 7.55 | | |
| 4 | | Equipped with self-processing capability for devices (A14) | 6.15 | | |
| 5 | | CPS technology application level (A15) | 6.39 | | |
| 6 | Exploitation and operation | Labor force level in understanding and operating smart factories (A21) | 6.38 | | |

| | | | | | |
|---|---|---|---|---|---|
| | criteria (A2) | | | | |
| 7 | | Digitalization and processes intelligence building (A22) | 7.12 | | |
| 8 | | Planning, implementation, and adjustment of plans (A23) | 6.26 | | |
| 9 | | Supply chain management and forecasting (A24) | 5.89 | | |
| 10 | | Collection and analysis of operation data (A25) | 6.38 | | |
| 11 | Efficiency criteria group (A3) | Ability to handle unexpected changes (A31) | 6.94 | | |
| 12 | | Time to create and adjust plans (A32) | 6.40 | | |
| 13 | | Product quality (A33) | 6.86 | | |
| 14 | | Market share of the factory (A36) | 6.35 | | |
| 15 | | Unit profit and total profit (A37) | 6.60 | | |
| | | **Aggregate score** | | | |

*Source: Authors*

Therefore, for a specific factory, the evaluator reviews, and scores according to Table 11. After obtaining the scores, they are entered into the value column on Table 12. The score for each criterion (component score) is calculated by multiplying the weight column and the value column. The total component scores of the criteria will be synthesized into an overall score reflecting the intelligence level of the factory.

## 5. Conclusion

The paper initially provides a scientific basis for constructing a set of criteria for evaluating the smart level of industrial factories (the index of a business's readiness for smart production). When researched and developed, this will be a tool to help managers determine the starting point, expand the scale of the business, and develop strategies and plans to sustain growth and comprehensively transition to smart production in Vietnam.

To assess the level of intelligence, factories need to rely on the actual content currently being implemented, referencing the measurement standards in Table 11. After obtaining the evaluation score, multiply it by the weights in Table 12 and calculate the synthesis score. The synthesis score out of a total of 100 points reflects the intelligence level of the factory. For example, if the score is 100/100, the factory is considered fully intelligent.

Thus, compared to the initial goal, the paper has fundamentally clarified the concept of a smart factory, utilized the AHP method, calculated a set of indices and weights for each criterion as a basis for the intelligence of factories. However, the newly synthesized criteria are based on international publications and calculations based on expert opinions, so they still have a theoretical nature, although ensuring consistency. To increase the practicality of the study, it is necessary to expand data surveys to a complete set of factories, including partially smart factories, long-term invested old factories, foreign direct investment (FDI) factories, and factories in various industries./.

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