Informatics and Software Engineering
p-ISSN/e-ISSN: 2988-2818/2988-2222
Homepage: https://sanscientific.com/journal/index.php/ise
3(2) 55-72 (2025)
https://doi.org/10.58777/ise.v3i2.574

Research Article

Tier-Aware Entropy-ARAS Approach to Select Microcontroller Boards for Education

Sanriomi Sintaro[1*], Sandi Badiwibowo Atim[2], Vederico Pitsalitz Sabandar[3]
[1]Information System Study Program, Faculty of Mathematics and Natural Science, Sam Ratulangi University, Manado
[2]Informatics Management Study Program, University of Lampung, Bandar Lampung
[3]Mathematics Education Study Program, Faculty of Teacher Training and Education, Pattimura University, Ambon

Received: 10 December 2025; Revision: 10 January 2026;
Accepted: 19 January 2026; Available Online: 22 January 2026

Abstract
This study develops a decision-support system to recommend microcontroller and IoT learning devices for schools, universities, and training centers under realistic budget constraints, while accounting for both technical capabilities and educational suitability. The alternatives are grouped into three budget tiers and evaluated using nine criteria covering price, CPU frequency, Flash, RAM/PSRAM, connectivity, usable GPIO, ease of learning, learning resources/community, and local availability/warranty. Objective criterion weights are computed using the Entropy method, and tier-wise rankings are produced using Additive Ratio Assessment (ARAS) through utility scores relative to an ideal alternative. Indicative local price and availability information are compiled from Tokopedia, while qualitative criteria are scored using consistent rubrics to support reproducibility. The results identify ESP32-CAM + baseboard as the top recommendation in Tier 1, LILYGO T-Display S3 in Tier 2, and M5StickC Plus2 in Tier 3; across tiers, Entropy assigns the largest weights to the most discriminative criteria, particularly RAM/PSRAM and, in higher tiers, Flash. The study is limited by market price volatility, approximations of usable GPIO values, and rubric-based qualitative scoring, and it also reflects Entropy's tendency to concentrate weights on highly dispersed criteria, potentially amplifying the advantages of outliers. Overall, the proposed tier-aware Entropy–ARAS framework provides a transparent and actionable approach for educational institutions to justify device procurement and usage decisions based on budget, functionality, and learning readiness.

Keywords: Additive Ratio Assessment; Budget tiering; Decision support system; Entropy weighting; Microcontroller board selection

How to cite: Sintaro, S., Atim, S. B., & Sabandar, V. P. (2025). Tier-Aware Entropy-ARAS Approach to Select Microcontroller Boards for Education. *Informatics and Software Engineering*, *3*(2), 55–72. https://doi.org/10.58777/ise.v3i2.574

*Corresponding author: Sanriomi Sintaro (sanriomi@unsrat.ac.id)

1. Introduction

Microcontroller and Internet of Things platforms are widely adopted in vocational schools, universities, and training centers because they support experiential learning, enabling students to translate concepts into working prototypes. Recent studies report that integrating IoT microcontrollers into practicum activities can enhance engagement and skill development in vocational electronics education, reinforcing the role of embedded devices as learning enablers rather than only as project tools (Wahyudi & Yahya, 2023). In addition, educational frameworks for IoT have emphasized hands-on learning designs and device-level implementations that can be adapted across course contexts, suggesting that board selection directly affects how reliably such learning designs can be delivered (Machado et al., 2024).

However, selecting a suitable learning device remains a practical challenge for institutions because budgetary constraints, class size, and maintenance considerations typically constrain procurement. At the same time, the market offers many boards with different capabilities and levels of learning readiness. The urgency of this decision has increased as more courses incorporate connected, remotely accessible activities, including low-cost laboratory platforms that rely on embedded boards to provide practical access beyond face-to-face sessions (Abekiri et al., 2023). Although these studies demonstrate that low-cost hardware can effectively support instruction, they also imply that mismatches in device capabilities, onboarding complexity, or availability can reduce learning effectiveness and increase hidden costs when devices must be supplemented or replaced during implementation (Garefalakis et al., 2025).

From a decision-making perspective, device selection is inherently multi-criteria because it must balance technical performance with education-oriented factors such as ease of learning, availability of tutorials, and community support. Multi-criteria decision-making research highlights that criterion weighting is particularly influential in ranking outcomes, and objective weighting methods are often used to reduce dependence on purely subjective judgment (Ayan et al., 2023; Mukhametzyanov, 2021). Entropy weighting is one of the most common objective approaches. However, recent work also shows that entropy-based weights can be sensitive to modeling choices, underscoring the need for transparency and robustness checks in applied studies (Roszkowska & Wachowicz, 2024).

For the ranking stage, Additive Ratio Assessment is a utility-based method that compares each alternative to an ideal reference and provides an interpretable utility score for selection decisions. Contemporary discussions of the ARAS method highlight its practicality for ranking problems that involve both quantitative and qualitative criteria, and recent research has also extended ARAS to handle more complex criterion structures, indicating its continued relevance in modern decision-support applications (Ghram & Moalla, 2021). In addition, recent applied studies demonstrate that combining Entropy for objective weighting and ARAS for ranking is feasible and can yield clear preference orders, supporting the suitability of this hybrid approach for structured procurement decisions (Goswami & Behera, 2021).

Despite strong motivation for hands-on IoT learning and the availability of powerful multi-criteria methods, a clear gap persists in educational procurement practices and reporting. IoT education studies commonly argue for low-cost microcontroller-based learning and present platforms or frameworks for instruction. However, they rarely provide a reproducible, data-driven decision framework for selecting specific boards under realistic budget constraints and classroom-scale considerations. On the other hand, MCDM studies provide robust weighting and ranking mechanisms. However, they are often applied to domains beyond educational board procurement and do not consistently integrate education-specific criteria, such as learnability, learning resources, and local availability, alongside technical specifications. This disconnect underscores the need for a decision-support approach that is simultaneously education-aware, budget-realistic, and computationally transparent (Chakraborty et al., 2023).

The novelty of this study is the development of a tier-aware Decision Support System for selecting microcontroller and IoT learning devices by combining objective Entropy weighting and ARAS ranking, while explicitly balancing technical capability and educational readiness within predefined budget tiers. The tier-based framing is designed to prevent unfair comparisons in which higher-cost devices dominate purely technical metrics, enabling institutions to obtain the best recommendation within the budget they can actually allocate. The objectives of this study are to construct a decision matrix of commonly used learning boards, evaluate them using technical and educational criteria, compute objective criterion weights using Entropy, and produce ranked recommendations for each budget tier using ARAS. To strengthen credibility, the study also incorporates verification through reproducible recalculation and robustness checks, which are important given the known sensitivity issues in objective weighting approaches.

2. Literature Review

Recent studies consistently emphasize that microcontroller-based practicum activities help learners connect abstract programming, sensing, and control concepts with real-world system behavior. In higher education settings, ESP32 is frequently positioned as an affordable and versatile device because it supports standard peripherals while also providing built-in wireless features that enable introductory Internet of Things projects, making it suitable for repeated classroom experimentation and project-based learning(Hercog et al., 2023; Márquez-Vera et al., 2023; Surahman et al., 2021).

Alongside face-to-face practicum, remote and cloud-supported laboratories have gained strong attention, particularly when institutions need to scale access to equipment and minimize scheduling bottlenecks. A representative approach is the development of low-cost remote laboratory platforms that combine embedded boards with cloud services and web interfaces, enabling students to run experiments remotely while maintaining meaningful interaction with real devices. Work in this area shows that integrating open-source tooling and embedded control can preserve the pedagogical value of hands-on activities, especially in electronics and IoT learning contexts (Abekiri et al., 2023; Márquez-Vera et al., 2023).
However, most educational contributions focus on designing learning platforms, modules, or laboratory infrastructures rather than on offering a systematic decision-support procedure for selecting the most appropriate board for procurement and classroom use under budget constraints. Even when an ESP32-based or similar solution is justified, the rationale is often narrative. The selection space is typically limited to what the authors have already adopted, making it difficult for schools, universities, and training centers to generalize the choice across multiple alternatives and spending levels (Abekiri et al., 2023; Hercog et al., 2023).

To address selection problems with multiple conflicting considerations, multi-criteria decision making has been widely used in engineering and management domains, but the quality of outcomes depends heavily on how the criterion weights are determined. Objective weighting approaches, such as entropy, are attractive because they reduce direct subjectivity, yet several studies caution that entropy-based weights can be sensitive to the decision matrix characteristics and preprocessing choices, including normalization, potentially leading to unstable or less meaningful weights if not handled carefully. This motivates a transparent, reproducible weighting procedure and the inclusion of validation steps when entropy is used in practical decision support(L. Chen et al., 2023; P. Chen, 2021).

For the ranking stage, the Additive Ratio Assessment method has been discussed as a simple, interpretable approach that normalizes criteria performance, aggregates weighted values, and expresses results through a utility degree, which supports straightforward comparison among alternatives. The method has also been extended and integrated with other decision models across application areas, indicating its flexibility for mixed quantitative and qualitative criteria. In parallel, hybrid combinations of entropy weighting and ARAS have been applied in selection tasks to increase objectivity in weighting while retaining a straightforward utility based ranking mechanism, and comparative studies of entropy coupled decision frameworks reinforce the importance of cross checking results using baseline comparisons or sensitivity analysis (Goswami & Behera, 2021; Hatefi et al., 2021; Nana & Xu, 2021).
Taken together, the literature supports the educational relevance of low-cost IoT boards and the practicality of objective weighting plus utility-based ranking, yet it also reveals a gap in applying a structured entropy weighted ARAS decision support model specifically for educational microcontroller procurement across explicit budget tiers while simultaneously incorporating technical capability, learning ease, community support, and local availability considerations.

3. Methods

3.1 Research design and workflow

This study develops a tier-aware Decision Support System (DSS) for selecting learning devices (microcontroller and IoT development boards) under realistic procurement constraints. The DSS combines objective weighting using the Entropy method and alternative ranking using Additive Ratio Assessment (ARAS), because Entropy can derive weights from data dispersion and ARAS can provide

an interpretable utility degree relative to an ideal alternative (Duc Trung, 2021). The method is applied separately for each budget tier to ensure a fair comparison among alternatives realistically competing within the same spending range.
Normalization choices are reported explicitly because entropy-based weights can be affected by preprocessing and normalization, which underscores the need for transparency and robustness checks (Roszkowska & Wachowicz, 2024).

3.2 Alternatives and budget tiers
To ensure a fair comparison, the alternatives are grouped into three budget tiers that reflect typical purchasing ranges across schools, universities, and training centers. Each tier contains five realistic options commonly used for IoT and embedded learning activities so that the DSS output can be interpreted as the best recommendation within a specific budget ceiling rather than an overall winner dominated by higher-cost devices.

Table 1. Tier List

Tier	Budget range (IDR)	Alternatives
Tier 1	< 200,000	A1 NodeMCU ESP8266; A2 Wemos D1 Mini (ESP8266); A3 ESP32 DevKit V1; A4 ESP32-C3 Super Mini; A5 ESP32-CAM + baseboard
Tier 2	200,000-500,000	B1 Raspberry Pi Pico W; B2 ESP32-S3 DevKitC; B3 LILYGO T-Display; B4 Heltec WiFi LoRa 32; B5 ESP32 Starter Kit (board + sensor)
Tier 3	500,000-1,000,000	C1 Arduino Nano 33 IoT; C2 Arduino MKR WiFi 1010/MKR1000; C3 V-ONE IoT Kit; C4 M5StickC Plus2; C5 Wio-E5 Dev Kit (LoRa)

The DSS is executed independently for each tier, meaning that weights and rankings are computed using only the alternatives within the same budget group. This approach supports realistic decision-making by allowing institutions to choose from financially comparable options, while still allowing the study to report differentiated recommendations for entry-level, mid-range, and higher-tier learning scenarios.

3.3 Criteria definition and measurement
To represent the needs of educational implementation, the evaluation criteria combine technical performance indicators with education-oriented factors. Technical criteria capture computational capability and hardware flexibility for laboratory activities, while educational criteria capture onboarding feasibility, availability of learning support, and procurement practicality. This combination is intended to reflect how a device performs not only on paper specifications but also in real classroom adoption and sustainability. Nine criteria are used to reflect both technical capacity and educational readiness. Quantitative criteria are derived from technical specifications, while qualitative criteria are scored using a fixed rubric to ensure consistent, reproducible evaluation.

Table 2. Criteria

Code	Criterion	Type	Unit/scale	Measurement note
C1	Price	Cost	IDR	Use representative market price (e.g., median of multiple local listings)
C2	CPU frequency	Benefit	MHz	From official specifications
C3	Flash	Benefit	MB	From official specifications
C4	RAM/PSRAM	Benefit	KB/MB	RAM; include PSRAM if available
C5	Connectivity	Benefit	Score 1-5	Scored by the connectivity capability rubric
C6	Usable GPIO	Benefit	Count	Count of GPIO realistically usable for labs (exclude reserved pins if needed)
C7	Ease of learning	Benefit	Score 1-5	Scored by the learning ease rubric
C8	Learning resources/community	Benefit	Score 1-5	Scored by resources/community rubric
C9	Local availability/warranty	Benefit	Score 1-5	Scored by the local availability rubric

Quantitative values are collected from reliable specification sources, while qualitative criteria are assessed using explicit rubrics to ensure consistent scoring across alternatives and across tiers. This separation helps keep the decision matrix reproducible because each criterion has a clear measurement rule, and rubric-based criteria can be re-evaluated by other researchers using the same indicators.

3.4 Scoring rubrics for qualitative criteria

Connectivity is evaluated as an educationally relevant capability because wireless features directly determine which IoT learning modules can be delivered without additional hardware. The rubric assigns higher scores to boards that natively support the more common protocols used in learning activities, thereby reducing setup complexity and external module costs.

Table 3. C5 Connectivity rubric (1-5)

Score	Description
1	No native wireless; requires an external module for common IoT connectivity
2	Limited wireless capability or uncommon integration effort for beginner labs
3	WiFi only (sufficient for basic IoT labs)
4	WiFi + BLE (supports broader IoT and mobile integration exercises)
5	WiFi/BLE plus additional integrated long-range option (for example, LoRa), or strong multi-protocol support suitable for advanced labs

This scoring scheme prioritizes “ready-to-teach” connectivity that can be used immediately in practicum sessions. When multiple boards provide similar wireless functions, differentiation can be strengthened by considering how easily the connectivity is exposed through stable libraries and common development environments, which is reflected indirectly in the learnability and community criteria.

Ease of learning is assessed to capture the onboarding burden faced by students and instructors, including setup time, toolchain friction, and the availability of classroom-friendly examples. This criterion is crucial for introductory courses because excessive configuration complexity can consume lab time and divert attention from learning outcomes.

Table 4. C7 Ease of learning rubric (1-5)

Score	Indicators
1	Setup and tooling are complex; limited beginner-friendly examples; frequent configuration issues
2	Toolchain is available, but onboarding is still tricky for novices; moderate friction in the first lab
3	Reasonable onboarding; common IDE support; students can complete basic labs with standard guidance
4	Beginner-friendly; strong examples and stable libraries; fast iteration for class exercises
5	Effortless onboarding; minimal friction; extensive classroom-ready examples and a stable ecosystem

The rubric ensures that learnability is judged systematically rather than impressionistically. By applying the same indicators across alternatives, the DSS can reflect the practical classroom cost of adopting a device, which often matters as much as raw hardware specifications in education.

Learning resources and community support are evaluated because they influence how quickly learners can troubleshoot issues and how easily instructors can prepare teaching materials. A stronger ecosystem typically provides more examples, libraries, and peer support, reducing instructional overhead and improving the continuity of learning across semesters.

Table 5. C8 Learning resources/community rubric (1-5)

Score	Indicators
1	Sparse documentation and examples; small community
2	Some tutorials exist, but are fragmented and have limited troubleshooting content

Score	Indicators
3	Adequate documentation and common project examples
4	Strong documentation, many tutorials, and active community discussions
5	Robust ecosystem: abundant tutorials, libraries, forums, and project repositories

This criterion is treated as educational infrastructure rather than an accessory, since the availability of high-quality learning materials can compensate for differences in instructor familiarity. In practice, devices with mature ecosystems tend to be adopted more sustainably because support remains accessible even when course content evolves. Local availability and warranty are assessed to capture procurement feasibility at class scale and to reduce risks related to stock inconsistency, device variability, and after-sales uncertainty. In educational procurement, a technically strong board may still be a poor choice if it cannot be purchased reliably in sufficient quantities or if replacement and support pathways are unclear.

Table 6. C9 Local availability/warranty rubric (1-5)

Score	Indicators
1	Rarely available locally; uncertain supply; no practical warranty support
2	Sometimes available; supply inconsistent; warranty unclear
3	Generally available from multiple sellers; basic after-sales support
4	Widely available; consistent supply; clearer warranty or official distribution options
5	Very widely available; strong distribution and after-sales assurance suitable for class-scale procurement

Including this criterion helps ensure the DSS recommendations remain actionable for institutions. It also supports sustainability because consistent sourcing and after-sales support reduce disruptions during practicum delivery, especially when devices must be replaced or expanded across multiple cohorts.

3.5 Decision matrix construction

For each tier, a decision matrix is built:

$$X = \{x_{ij}\}, i = 1,2, \dots, m, j = 1,2, \dots, n \tag{1}$$

where $m = 5$ alternatives per tier and $n = 9$ criteria. Each cell x_{ij} is the value of the alternative $i$on criterion j. For C5, C7, C8, and C9, values are assigned based on the rubrics in Section 3.4.

3.6 Entropy weighting (objective weights)

Entropy weighting is used to compute the criterion weights from the data dispersion in each tier.

Step 1. Convert all criteria to "benefit direction."

C1 (Price) is a cost criterion. It is transformed to a benefit form using an inverse transform:

$$x'_{ij} = \frac{1}{x_{ij}} \text{for cost criteria} \tag{2}$$

All benefit criteria remain unchanged $x'_{ij} = x_{ij}$.

Step 2. Column normalization for entropy

For each criterion j:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{3}$$

Step 3. Compute entropy value

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), k = \frac{1}{\ln(m)} \tag{4}$$

Step 4. Degree of diversification

$$d_j = 1 - e_j \tag{5}$$

Step 5. Entropy weight

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

Entropy Example (entropy for one criterion only)
Assume Tier 1 has five CPU frequency values (C2) for illustration:
A1 = 80, A2 = 80, A3 = 240, A4 = 160, A5 = 240 (MHz), Sum = 80 + 80 + 240 + 160 + 240 = 800

Then:

$$p = \left[\frac{80}{800}, \frac{80}{800}, \frac{240}{800}, \frac{160}{800}, \frac{240}{800}\right] = [0.10,0.10,0.30,0.20,0.30] \tag{7}$$

With $m = 5$, $k = 1/\ln(5)$. Entropy is:

$$e_{C2} = -k \sum_{i=1}^{5} p_i \ln(p_i) \approx 0.9350 \tag{8}$$

Then:

$$d_{C2} = 1 - e_{C2} \approx 0.0650 \tag{9}$$

The same procedure is applied to all criteria $C1 - C9$ within the tier, and weights $w_1 - w_9$ are obtained by normalizing all d_j.

3.7 ARAS ranking

ARAS ranks alternatives by comparing them to an ideal (optimal) alternative and computing a utility degree(Goswami & Behera, 2021; Hatefi et al., 2021).
Step 1. Add ideal alternative A_0
For each criterion j:

$$x_{0j} = \max_i \quad x_{ij} \text{ for benefit}, x_{0j} = \min_i \quad x_{ij} \text{ for cost} \tag{10}$$

Step 2. Normalize including A_0
For benefit criteria:

$$\grave{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{11}$$

For cost criteria, ARAS commonly uses inverse normalization:

$$\grave{x}_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=0}^{m} \frac{1}{x_{ij}}} \tag{12}$$

Step 3. Weighted normalized matrix

$$y_{ij} = w_j \grave{x}_{ij} \tag{13}$$

Step 4. Optimality function

$$S_i = \sum_{j=1}^{n} y_{ij} \tag{14}$$

Step 5. Utility degree

$$K_i = \frac{S_i}{S_0} \tag{15}$$

Alternatives are ranked in descending order of K_i.

ARAS Example (ARAS normalization and weighting for one criterion only)
Using the illustrative Tier 1 CPU frequency values (C2), the ideal $A_0$is 240 MHz. The sum including $A_0$is:

$$240 + 80 + 80 + 240 + 160 + 240 = 1040$$

Then for A3 (240 MHz):

$$\dot{x}_{A3,C2} = \frac{240}{1040} \approx 0.2308 \tag{16}$$

If (illustratively) $w_{C2} = 0.15$, then:

$$y_{A3,C2} = 0.15 \times 0.2308 \approx 0.0346 \tag{17}$$

The full ARAS score is obtained by summing across all criteria, and $K_i$is is computed relative to S_0.

3.8 Validation and robustness checks
Validation is included because objective weighting and normalization choices can influence outcomes, and recent work highlights that entropy-based weights may change under different normalization strategies (Roszkowska & Wachowicz, 2024).

Three checks are performed.

First, the recalculation is performed using an independent tool (a spreadsheet or script) to verify that the Entropy and ARAS computations match step by step.

Second, a baseline method is used for comparison. This study uses Simple Additive Weighting (SAW) because it is widely understood and easy to implement. SAW normalization can be defined as:
For benefit:

$$r_{ij} = \frac{x_{ij}}{\max_i \quad x_{ij}} \tag{18}$$

For cost:

$$r_{ij} = \frac{\min_i \quad x_{ij}}{x_{ij}} \tag{19}$$

Then:

$$V_i = \sum_{j=1}^{n} w_j \, r_{ij} \tag{20}$$

The SAW ranking is compared with the ARAS ranking to assess consistency within each tier.

Third, a sensitivity analysis is conducted by perturbing selected weights and observing rank stability. The analysis focuses on criteria that typically drive procurement decisions in education, especially C1 (Price) and C8 (Learning resources/community). The procedure adjusts one weight upward by a fixed proportion, renormalizes the remaining weights so that $\sum w_j = 1$, recomputes ARAS rankings, and records whether the top alternative changes. Stable rankings under reasonable perturbations are interpreted as more robust recommendations.

3.9 Implementation notes for reproducibility

All matrices, rubrics, and computations are reported per tier to allow replication. The decision matrices and computed weights are presented in the Results section, while the validation outcomes and sensitivity observations are summarized in the Discussion section. Hybrid Entropy-ARAS combinations have been applied successfully in other selection contexts, supporting the feasibility of this computational workflow for transparent ranking tasks (Duc Trung, 2021; Goswami & Behera, 2021).

4. Results

This section reports the complete results for all three budget tiers, consisting of the decision matrices, Entropy-based objective weights, and ARAS-based rankings. The computations are performed separately for each tier so that each ranking reflects the best choice within a realistic budget range. For unit consistency, Flash is expressed in **MB** and RAM/PSRAM is expressed in **KB**. When a value is given as a combination such as “512 KB + 2 MB”, it is summed in KB (2 MB = 2048 KB). When Flash is given as “256 KB”, it is converted to **0.25 MB**. Values written with "+" or "~" are treated as the nearest explicit numeric value (for example, 25+ is treated as 25, ~10 is treated as 10) to keep the matrix strictly numerical and reproducible.

4.1 Explanation of the formulas and one worked example

Entropy weighting is used to obtain objective weights by measuring how much each criterion differentiates the alternatives in a given tier. If a criterion varies strongly among alternatives, it contains more information and tends to receive a larger weight. If a criterion is almost constant, its entropy becomes close to one, and its weight becomes small, because it does not help distinguish alternatives in that tier.

Because Entropy assumes higher values are better, the cost criterion (C1 Price) is first transformed into a benefit direction using the inverse:

$$x'_{ij} = \frac{1}{x_{ij}} \tag{21}$$

Each criterion column is then normalized to form a probability-like distribution:

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{22}$$

Entropy for criterion j is computed as:

$$e_j = -k \sum_{i=1}^{m} p_{ij} \ln(p_{ij}),\, k = \frac{1}{\ln(m)} \tag{23}$$

The diversification degree is:

$$d_j = 1 - e_j \tag{24}$$

Finally, the Entropy weight is:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{25}$$

After weights are computed, ARAS ranks alternatives using an ideal reference alternative A_0. For benefit criteria, the ideal uses the maximum value; for cost criteria, the ideal uses the minimum value. ARAS then normalizes the matrix, including the ideal row. For benefit criteria:

$$\grave{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{26}$$

For cost criteria, ARAS uses inverse normalization:

$$\grave{x}_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=0}^{m} \frac{1}{x_{ij}}} \tag{27}$$

The weighted normalized value is:

$$y_{ij} = w_j \grave{x}_{ij} \tag{28}$$

The ARAS optimality score is:

$$S_i = \sum_{j=1}^{n} y_{ij} \tag{29}$$

The utility degree is computed relative to the ideal score S_0:

$$K_i = \frac{S_i}{S_0} \tag{30}$$

The final ranking is determined by sorting alternatives by K from largest to smallest.
To demonstrate clearly how a criterion contributes to the final ARAS score, one example is shown using Tier 1, focusing on C4 (RAM/PSRAM) for A5 (ESP32-CAM+MB). In Tier 1, the ideal value for C4 is the maximum RAM/PSRAM:

$$x_{0,C4} = \max(x_{i,C4}) = 4096 \tag{31}$$

The ARAS normalization requires the sum including A_0:

$$\sum_{i=0}^{m} x_{i,C4} = 4096 + 50 + 50 + 520 + 400 + 4096 = 9212 \tag{32}$$

So the normalized value for A5 on C4 is:

$$\grave{x}_{A5,C4} = \frac{4096}{9212} = 0.444637 \tag{33}$$

From the Entropy results for Tier 1, the weight for C4 is $w_{C4} = 0.669573$. Therefore, the weighted normalized contribution of C4 to A5 is:

$$y_{A5,C4} = 0.669573 \times 0.444637 = 0.297717 \tag{34}$$

ARAS then sums all weighted criteria to obtain the final score S_{A5} and divides it by the ideal score S_0 to obtain K_{A5}. In Tier 1, $S_0 = 0.380465$, $S_{A5} = 0.329680$, and thus:

$$K_{A5} = \frac{0.329680}{0.380465} = 0.866519 \tag{35}$$

This example illustrates how the Entropy weight and ARAS normalization directly shape the final ranking.

4.2 Tier 1 results

The Tier 1 decision matrix in Table 7 contains the five entry-level alternatives evaluated across nine criteria. This matrix is the sole input used to compute Tier 1 Entropy weights and Tier 1 ARAS ranking.

Table 7. Decision matrix X (Tier 1)

Alternative	C1 Price (IDR)	C2 CPU (MHz)	C3 Flash (MB)	C4 RAM (KB)	C5 Conn (1–5)	C6 GPIO	C7 Ease (1–5)	C8 Community (1–5)	C9 Availability (1–5)
A1 NodeMCU ESP8266	26000	80	4	50	3	11	4	5	5
A2 Wemos D1 Mini	28000	80	4	50	3	11	5	5	5
A3 ESP32 DevKit V1	62000	240	4	520	5	25	5	5	5
A4 ESP32-C3 Mini	38000	160	4	400	4	13	4	3	4
A5 ESP32-CAM+MB	95000	240	4	4096	4	2	3	5	5

Table 7 shows that Flash (C3) is identical across all Tier 1 alternatives (4 MB). This implies that Flash does not help discriminate between options in this tier, which is reflected directly in the Entropy weighting stage.

Table 8. Entropy results (Tier 1)

Criterion	e_j	d_j	w_j
C1 Price	0.939807	0.060193	0.071337
C2 CPU frequency	0.934978	0.065022	0.077061
C3 Flash	1	0	0
C4 RAM/PSRAM	0.435025	0.564975	0.669573
C5 Connectivity	0.98809	0.01191	0.014115
C6 Usable GPIO	0.881154	0.118846	0.140849
C7 Ease of learning	0.989828	0.010172	0.012055
C8 Resources/community	0.989591	0.010409	0.012336
C9 Availability/warranty	0.997744	0.002256	0.002674

Table 8 indicates that Tier 1 is most strongly differentiated by RAM/PSRAM (C4) and GPIO (C6). This does not mean these criteria are universally "most important", but rather that, within the Tier 1 dataset, they exhibit the biggest dispersion and therefore provide the strongest separation among alternatives.

Table 9. ARAS final ranking (Tier 1)

Alternative	s_i	k_i	Rank
A5 ESP32-CAM+MB	0.32968	0.866519	1
A3 ESP32 DevKit V1	0.110924	0.291548	2
A4 ESP32-C3 Mini	0.079209	0.208191	3
A1 NodeMCU ESP8266	0.050221	0.131999	4
A2 Wemos D1 Mini	0.049501	0.130107	5

The ideal reference score for Tier 1 is $S_0 = 0.380465$. Table 9 shows that A5 ranks first because it dominates the most heavily weighted criterion (C4). A3 ranks second because it combines a high CPU frequency, strong connectivity, and a high GPIO count, even though its RAM/PSRAM is much lower than A5's.

4.3 Tier 2 results

Tier 2 represents the mid-range alternatives. Table 10 presents the Tier 2 decision matrix, which differs substantially from Tier 1 in its Flash and RAM/PSRAM variations. Entropy reflects those differences as larger weights for the criteria that vary most in this tier.

Table 10. Decision matrix X(Tier 2)

Alternative	C1 Price (IDR)	C2 CPU (MHz)	C3 Flash (MB)	C4 RAM (KB)	C5 Conn (1–5)	C6 GPIO	C7 Ease (1–5)	C8 Community (1–5)	C9 Availability (1–5)
B1 Raspberry Pi Pico W	165000	133	2	264	3	26	5	5	5
B2 ESP32-S3 DevKitC	145000	240	8	2560	5	30	4	4	5
B3 LILYGO T-Display S3	630000	240	16	8704	5	5	4	4	4
B4 Heltec WiFi LoRa 32	485000	240	8	512	5	10	3	4	4
B5 ESP32 Starter Kit	350000	240	4	520	5	25	5	5	5

Table 10 shows that most boards share similar connectivity scores, while Flash and RAM/PSRAM vary widely. This pattern typically pushes Entropy to assign higher weights to Flash and RAM/PSRAM, because those criteria produce greater discrimination.

Table 11. Entropy results (Tier 2)

Criterion	e_j	d_j	w_j
C1 Price	0.903927	0.096073	0.122877
C2 CPU frequency	0.9866	0.0134	0.017139
C3 Flash	0.877461	0.122539	0.156728
C4 RAM/PSRAM	0.572741	0.427259	0.546464
C5 Connectivity	0.989591	0.010409	0.013313
C6 Usable GPIO	0.905376	0.094624	0.121024
C7 Ease of learning	0.989828	0.010172	0.01301
C8 Resources/community	0.996198	0.003802	0.004862
C9 Availability/warranty	0.996417	0.003583	0.004583

In Table 11, RAM/PSRAM (C4) is again dominant, and Flash (C3) becomes the second strongest discriminator. Price (C1) and GPIO (C6) also contribute meaningfully because their values vary more than rubric-based criteria such as community and availability within this tier.

Table 12. ARAS final ranking (Tier 2)

Alternative	s_i	k_i	**Rank**
B3 LILYGO T-Display S3	0.291164	0.85443	1
B2 ESP32-S3 DevKitC	0.158975	0.466518	2
B1 Raspberry Pi Pico W	0.073171	0.214723	3
B5 ESP32 Starter Kit	0.071988	0.211251	4
B4 Heltec WiFi LoRa 32	0.063932	0.187612	5

The ideal reference score for Tier 2 is $S_0 = 0.340770$. The ranking in Table 12 places B3 first because it has the most significant RAM/PSRAM and Flash values, which align with the largest Entropy weights. B2 ranks second because it provides strong RAM/PSRAM and Flash at a lower price, but it does not match B3's memory scale. B1 and B5 cluster closer together because they do not compete on the most heavily weighted memory criteria, even though they score well on ease, community, and availability.

4.4 Tier 3 results

Tier 3 contains higher-cost options with different platform ecosystems. Table 13 shows a large dispersion in Flash and RAM/PSRAM, as well as a clear split between 48 MHz class boards and 240 MHz class boards, which affects the Entropy weights and the final ARAS ranking.

Table 13. Decision matrix X(Tier 3)

Alternative	C1 Price (IDR)	C2 CPU (MHz)	C3 Flash (MB)	C4 RAM (KB)	C5 Conn (1–5)	C6 GPIO	C7 Ease (1–5)	C8 Community (1–5)	C9 Availability (1–5)
C1 Arduino Nano 33 IoT	650000	48	0.25	32	4	14	5	5	4
C2 Arduino MKR 1010	1000000	48	0.25	32	4	22	5	4	3
C3 V-ONE / IoT Kit	500000	240	4	520	5	25	5	4	3
C4 M5StickC Plus2	635000	240	8	2048	5	3	5	4	4
C5 Wio-E5 Dev Kit	750000	48	0.25	64	4	20	3	3	2

Table 13 contains three alternatives with low Flash and low RAM/PSRAM, and two alternatives with much higher Flash and RAM/PSRAM. This structure typically causes Entropy to allocate the largest weights to Flash and RAM/PSRAM because these criteria separate the alternatives most strongly within the tier.

Table 14. Entropy results (Tier 3)

Criterion	e_j	d_j	w_j
C1 Price	0.984843	0.015157	0.011503
C2 CPU frequency	0.824462	0.175538	0.133218
C3 Flash	0.551382	0.448618	0.340461
C4 RAM/PSRAM	0.447548	0.552452	0.419261
C5 Connectivity	0.996198	0.003802	0.002885
C6 Usable GPIO	0.913928	0.086072	0.065321
C7 Ease of learning	0.989591	0.010409	0.007899
C8 Resources/community	0.99215	0.00785	0.005957
C9 Availability/warranty	0.982218	0.017782	0.013495

Table 14 shows that Flash (C3) and RAM/PSRAM (C4) dominate Tier 3 weighting, while CPU frequency (C2) and GPIO (C6) become meaningful secondary discriminators. Criteria such as connectivity receive low weight because their values are similar across most alternatives in this tier.

Table 15. ARAS final ranking (Tier 3)

Alternative	s_i	k_i	Rank
C4 M5StickC Plus2	0.358576	0.962579	1
C3 V-ONE / IoT Kit	0.170931	0.458857	2
C5 Wio-E5 Dev Kit	0.034106	0.091556	3
C2 Arduino MKR 1010	0.033548	0.090058	4
C1 Arduino Nano 33 IoT	0.030323	0.0814	5

The ideal reference score for Tier 3 is $S_0 = 0.372516$. The ranking in Table 15 places C4 first because it combines the strongest Flash and RAM/PSRAM, which are the two most heavily weighted criteria. C3 ranks second because it also belongs to the high-memory group, but does not match C4's Flash and RAM/PSRAM level. The remaining alternatives cluster at much lower utility values because they do not compete on the criteria that Entropy identifies as most discriminative in this tier.

5. Discussion

This section interprets the Entropy–ARAS results reported in Section 4, explains why the top alternatives emerge within each budget tier, and evaluates the robustness of the rankings using a baseline method (SAW) and a sensitivity analysis. The discussion emphasizes that Entropy weights are data-driven: they reflect how strongly each criterion varies within a tier, not necessarily how important that criterion is from a pedagogical perspective.

5.1 Overall findings and tier-wise recommendations

The tier-specific rankings produce one top recommendation per budget tier. These recommendations correspond to the alternatives with the highest ARAS utility value $\boldsymbol{K_i}$ within each tier.

Table 16. Tier-wise top recommendations and dominant criteria

Tier	**Top-ranked alternative (ARAS)**	**Dominant Entropy weights (top three)**
Tier 1	A5 ESP32-CAM+MB	C4 RAM/PSRAM (0.670), C6 GPIO (0.141), C2 CPU (0.077)
Tier 2	B3 LILYGO T-Display S3	C4 RAM/PSRAM (0.546), C3 Flash (0.157), C1 Price (0.123)
Tier 3	C4 M5StickC Plus2	C4 RAM/PSRAM (0.419), C3 Flash (0.340), C2 CPU (0.133)

Table 16 shows a consistent pattern across tiers: memory capacity (RAM/PSRAM) is the strongest discriminator, and in Tier 2 and Tier 3 Flash also becomes highly influential. This explains why the winners in Tier 2 and Tier 3 are the devices with the strongest memory profiles. In Tier 1, the presence of PSRAM in A5 produces a large spread in C4, further amplifying the weight concentration.

5.2 Why the weights are memory-dominant under Entropy

Entropy weighting assigns higher weights to criteria that provide more "information" for differentiating alternatives. Technically, a criterion receives a low entropy value when the alternatives are unevenly distributed across it, leading to a high diversification value and, consequently, a high weight. In your datasets, C4 (RAM/PSRAM) shows the biggest dispersion across all tiers because each tier includes at least one option with substantially higher memory capacity than the others. Consequently, Entropy assigns a dominant share of weight to C4. In Tier 2 and Tier 3, Flash (C3) also varies widely and becomes the second-largest discriminator.

This behavior is mathematically consistent, but it has an important interpretation: the model selects the best option under a weighting scheme that prioritizes the feature that most separates the candidates in the provided data. Therefore, the ranking is best interpreted as a tiered recommendation strongly driven by memory capacity. If an institution's learning outcomes emphasize other aspects such as expandability (GPIO), ease for beginners, or guaranteed availability, the decision model may be refined by adjusting rubric definitions or by applying an additional constraint or policy layer.

5.3 Interpretation by tier in the educational context

For Tier 1, A5 (ESP32-CAM+MB) ranks first because it dominates C4 (RAM/PSRAM), which is by far the most significant Entropy weight in this tier. This is a meaningful outcome for learning activities that truly need PSRAM, such as camera projects, image buffering, or memory-heavy processing demonstrations. However, A5 has very low usable GPIO in the input dataset, which can reduce suitability for general introductory labs involving multiple sensors and actuators. This helps explain why A3 (ESP32 DevKit V1) remains a strong second choice: it offers a high CPU frequency, the highest connectivity score, and a high number of usable GPIO, making it more flexible for broad IoT use cases, even if it does not match A5's memory.

For Tier 2, B3 (LILYGO T-Display S3) ranks first because it has the strongest RAM/PSRAM and Flash among Tier 2 alternatives, and those two criteria carry the most weight. In an educational setting, B3 is particularly suitable for projects that combine connectivity with user-facing interfaces (for example, dashboards, display-driven monitoring, or richer demo applications) and for cases where larger libraries and assets must fit comfortably. At the same time, B3's low usable GPIO in the dataset indicates a limitation for sensor-heavy practicum designs. This makes B2 (ESP32-S3 DevKitC), ranked second, a more "general-purpose lab" alternative: it still offers strong memory performance. However, it provides more usable GPIO and a much lower price, according to the provided data.

For Tier 3, C4 (M5StickC Plus2) ranks first because it leads in both Flash and RAM/PSRAM, which are the dominant criteria in this tier. This supports its role as a compact, feature-rich device for advanced demonstrations, integrated prototyping, and projects requiring larger firmware stacks. However, C4's expansion options are limited in the dataset (GPIO is low due to form factor and interface design). As a result, C3 (V-ONE / IoT Kit), ranked second, is more appropriate for learning outcomes that require broader hardware experimentation and modular sensor–actuator integration, while still benefiting from a high-performance processor and reasonable memory.

5.4 Baseline validation using SAW

To validate whether the tier-wise ranking is method-dependent, the results were compared with a baseline MCDM method, Simple Additive Weighting (SAW), using the same Entropy-derived weights. SAW uses a different normalization scheme than ARAS, so identical rankings are not guaranteed, particularly in close middle ranks. The comparison is intended to check whether the top recommendation is stable.

Table 17. ARAS vs SAW ranking comparison (using the same Entropy weights)

Tier	ARAS rank order	SAW rank order
Tier 1	A5 > A3 > A4 > A1 > A2	A5 > A3 > A4 > A1 > A2
Tier 2	B3 > B2 > B1 > B5 > B4	B3 > B2 > B1 > B5 > B4
Tier 3	C4 > C3 > C5 > C2 > C1	C4 > C3 > C2 > C5 > C1

Table 17 shows that ARAS and SAW produce the same top recommendation for all tiers. The only disagreement occurs in Tier 3 middle ranks, where SAW swaps the order of C2 and C5. This is expected because ARAS and SAW normalize and aggregate values differently, but the agreement on the top alternative supports the stability of the primary recommendation.

5.5 Sensitivity analysis on key criteria

A sensitivity analysis was conducted by increasing the weight of one criterion by a moderate factor, renormalizing the weights to keep the total at 1, and recomputing the ARAS rankings. Two criteria were tested because they are commonly decisive in educational procurement: C1 (Price) and C8 (Community/resources).

Table 18. Winner stability under moderate weight perturbation (×1.5)

Tier	Base winner	Winner after boosting C1 (Price)	Winner after boosting C8 (Community)
Tier 1	A5	A5	A5
Tier 2	B3	B3	B3
Tier 3	C4	C4	C4

The results in Table 18 indicate that the top-ranked alternative in each tier remains unchanged under moderate shifts in price emphasis and community emphasis. This is consistent with the earlier observation that memory-related criteria dominate the weight distribution; therefore, moderate changes to small-weight criteria do not overturn the winner.

When the price is emphasized excessively, the model behaves intuitively. In Tier 2, boosting the price weight by about an order of magnitude (approximately 10×) is sufficient to shift the top recommendation from B3 to B2, reflecting a strong preference for more affordable options once cost becomes dominant. In Tier 1, a huge increase in price emphasis (around 30×) shifts the winner from A5 to the cheapest alternative (A1). In Tier 3, the winner remains C4 even under very large price emphasis in this dataset, which indicates that C4's advantage on the dominant memory criteria remains strong enough to offset price differences.

5.6 Practical implications, limitations, and refinement opportunities

The proposed tier-wise Entropy–ARAS framework provides transparent and reproducible recommendations for device procurement. However, the results also show that Entropy can concentrate weight heavily on a small number of high-variance criteria. This is an important limitation in educational decision-making. If one criterion contains a strong outlier (for example, PSRAM in Tier 1), the ranking may reflect a "memory-first" preference even when the curriculum requires broad GPIO access and a variety of sensors. A practical refinement is to separate RAM and PSRAM into distinct criteria, redefine C4 as "internal RAM only," or add constraints, such as minimum GPIO thresholds, for general lab suitability.

Other limitations relate to the dataset definition. Some GPIO values were approximate (for example, "~10" or "rest used"), and some tier assignments may be affected by market price volatility. These aspects should be explicitly stated in the paper to ensure reproducibility. Future work can strengthen the model by collecting prices from multiple local sellers over a defined time window, using a documented GPIO-counting rule per board, and expanding the qualitative rubrics into more granular indicators so that education-centered criteria contribute more variance and therefore gain greater influence under objective weighting.

6. Conclusion

This study proposed a tier-aware Decision Support System for selecting microcontroller and IoT learning devices for schools, universities, and training centers under realistic budget constraints. The model combines Entropy weighting to derive objective criterion weights from the decision matrix and ARAS to rank alternatives using a utility-based score relative to an ideal reference. The evaluation used nine criteria that integrate technical specifications and education-oriented considerations, including price, processing capability, memory, connectivity, GPIO usability, ease of learning, community/resources, and local availability.

The results demonstrate that the proposed approach can generate clear recommendations for each budget tier. In Tier 1, the highest-ranked alternative was ESP32-CAM + baseboard (A5). In Tier 2, the highest-ranked alternative was LILYGO T-Display S3 (B3). In Tier 3, the highest-ranked alternative was M5StickC Plus2 (C4). Across tiers, Entropy assigned the largest weights to criteria with the biggest dispersion, which in the provided datasets were primarily RAM/PSRAM (C4) and, for Tier 2 and Tier 3, Flash (C3). As a consequence, the tier winners were devices that strongly outperform others on memory-related criteria, making them well-suited for learning scenarios that require larger firmware stacks, richer libraries, or memory-intensive applications.

Validation showed that the top recommendations were stable. A baseline comparison using SAW produced the same top alternative in each tier, and a sensitivity analysis that increased the weights of price and community by a moderate factor did not change the winners. These checks support the robustness of the main procurement recommendation within each tier under reasonable weighting uncertainty.

Despite these strengths, the study also highlights an important limitation of objective weighting: Entropy may concentrate weight on a small number of high-variance criteria, leading the ranking to favor outlier advantages such as PSRAM, even when course outcomes emphasize expandability, multi-sensor integration, or beginner-friendliness. Future work can improve alignment with educational priorities by refining criterion definitions, for example, separating RAM and PSRAM, formalizing GPIO usability rules, extending rubric granularity for learnability and resources, and collecting price and availability data across a defined market window. Overall, the proposed tier-aware Entropy–ARAS framework provides a transparent and reproducible basis for device procurement decisions, balancing budget feasibility with functional and educational suitability.

Recommendation

Educational institutions should procure devices using the tier-wise results rather than a single global comparison. For Tier 1, ESP32-CAM is recommended when memory-intensive or camera-based modules are required; otherwise, the ESP32 DevKit V1 is a practical general-purpose alternative due to its higher usable GPIO count. For Tier 2, LILYGO T-Display S3 is recommended for interface-rich IoT demonstrations, while ESP32-S3 DevKitC is preferable for sensor-heavy labs. For Tier 3, the M5StickC Plus2 is recommended for compact, advanced prototyping, while the V-ONE IoT Kit is recommended for modular experimentation that requires more expansion.

Limitations and avenues for future research

This study is limited by the decision matrix inputs, including price volatility, approximate GPIO usability values, and rubric-based qualitative scores that may vary across institutions. Methodologically, Entropy weighting can concentrate weight on highly dispersed criteria (notably memory), potentially underrepresenting pedagogical priorities such as ease of learning and ecosystem support when their scores are similar across alternatives. Future research should collect market data over a defined time window, formalize GPIO usability rules per board, separate RAM and PSRAM into distinct criteria, and compare additional MCDM methods (e.g., TOPSIS or VIKOR) with broader sensitivity scenarios.

Funding
This research received no external funding.

Acknowledgment
The authors would like to acknowledge Tokopedia as a key source for collecting indicative local price ranges and availability information used to construct the decision matrices. The authors also thank the instructors and laboratory assistants who provided practical insights on classroom usability, procurement constraints, and the applicability of the evaluation criteria and scoring rubrics in school and university learning contexts.

Competing interests
The authors declare that they have no competing interests. The selection of alternatives, scoring rubrics, and analysis procedures was conducted for academic purposes, and the authors have no financial or commercial relationships with the manufacturers of the evaluated devices or with Tokopedia beyond its use as a public source for indicative price and availability data.

ORCiD ID:
Sanriomi Sintaro: https://orcid.org/0000-0002-7188-307X
Vederico Pitsalitz Sabandar : https://orcid.org/0009-0007-1877-3836

References

Abekiri, N., Rachdy, A., Ajaamoum, M., Nassiri, B., Elmahni, L., & Oubail, Y. (2023). Platform for hands-on remote labs based on the ESP32 and NOD-red. *Scientific African*, *19*, e01502. https://doi.org/10.1016/j.sciaf.2022.e01502

Ayan, B., Abacıoğlu, S., & Basilio, M. P. (2023). A Comprehensive Review of the Novel Weighting Methods for Multi-Criteria Decision-Making. In *Information* (Vol. 14, Issue 5, p. 285). https://doi.org/10.3390/info14050285

Chakraborty, S., Chatterjee, P., & Das, P. P. (2023). Additive Ratio Assessment (Aras) Method. In *Multi-Criteria Decision-Making Methods in Manufacturing Environments* (pp. 171–181). Apple Academic Press. https://doi.org/10.1201/9781003377030-15

Chen, L., Wang, X., Wang, Y., & Gao, P. (2023). Improved entropy weight methods and their comparisons in evaluating the high-quality development of Qinghai, China. *Open Geosciences*, *15*. https://doi.org/10.1515/geo-2022-0570

Chen, P. (2021). Effects of the entropy weight on TOPSIS. *Expert Systems with Applications*, *168*, 114186. https://doi.org/https://doi.org/10.1016/j.eswa.2020.114186

Duc Trung, D. (2021). A combination method for a multi-criteria decision-making problem in the turning process. *Manufacturing Review*, *8*, 1–17. https://doi.org/10.1051/mfreview/2021024

Garefalakis, M., Kamarianakis, Z., & Panagiotakis, S. (2025). Remote Laboratory for developing an IoT system. *Proceedings - 28th Pan-Hellenic Conference on Progress in Computing and Informatics with International Participation, PCI 2024*, 315–323. https://doi.org/10.1145/3716554.3716602

Ghram, M., & Moalla, H. (2021). ARAS-H: A ranking-based decision aiding method for hierarchically structured criteria. *RAIRO - Operations Research*, *55*. https://doi.org/10.1051/ro/2021083

Goswami, S. S., & Behera, D. K. (2021). Implementation of the ENTROPY-ARAS decision-making methodology in the selection of the best engineering materials. *Materials Today: Proceedings*, *38*, 2256–2262. https://doi.org/https://doi.org/10.1016/j.matpr.2020.06.320

Hatefi, S. M., Asadi, H., Shams, G., Tamošaitienė, J., & Turskis, Z. (2021). Model for the sustainable material selection by applying integrated Dempster-Shafer evidence theory and Additive Ratio Assessment (ARAS) method. In *Sustainability (Switzerland)* (Vol. 13, Issue 18, p. 10438). https://doi.org/10.3390/su131810438

Hercog, D., Lerher, T., Truntič, M., & Težak, O. (2023). Design and Implementation of ESP32-Based IoT Devices. In *Sensors* (Vol. 23, Issue 15, p. 6739). https://doi.org/10.3390/s23156739

Machado, R. P., Norbisrath, U., & Jubeh, R. (2024). IoT Educational Framework Case Study: Devices as Things for Hands-on Collaboration. *Journal of Engineering Education Transformations*, *37*(Special Issue 2), 385–392.

https://doi.org/10.16920/jeet/2024/v37is2/24066
Márquez-Vera, M. A., Martínez-Quezada, M., Calderón-Suárez, R., Rodríguez, A., & Ortega-Mendoza, R. M. (2023). Microcontroller programming for control and automation in undergraduate biotechnology engineering education. *Digital Chemical Engineering*, *9*, 100122. https://doi.org/10.1016/j.dche.2023.100122
Mukhametzyanov, I. (2021). Specific character of objective methods for determining weights of criteria in MCDM problems: Entropy, CRITIC, SD. *Decision Making Applications in Management and Engineering*, *30*, 104–2620. https://doi.org/10.31181/dmame210402076i
Nana, L., & Xu, Z. (2021). An overview of the ARAS method: Theory development, application extension, and future challenges. *International Journal of Intelligent Systems*, *36*. https://doi.org/10.1002/int.22425
Roszkowska, E., & Wachowicz, T. (2024). Impact of Normalization on Entropy-Based Weights in Hellwig's Method: A Case Study on Evaluating Sustainable Development in the Education Area. *Entropy (Basel, Switzerland)*, *26*(5). https://doi.org/10.3390/e26050365
Surahman, A., Sintaro, S., & Samsugi, S. (2021). *Aplikasi internet of things (IoT) dengan ESP8266 dan Android* (A. Surahman & S. Sintaro (eds.); 1st ed.). Universitas Teknokrat Indonesia.
Wahyudi, & Yahya, M. (2023). The Role of the Use of IoT (Internet of Things) Microcontrollers in the Electronics vocational education sector in Practicum Learning. *Journal of Embedded Systems, Security and Intelligent Systems*, 91–96. https://doi.org/10.59562/jessi.v4i2.921