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PESQUISA EMPÍRICA

Determinants of metacognition in physics learning among high school students: a mixed-methods and machine learning approach

Determinantes da metacognição na aprendizagem de física entre estudantes do ensino médio: uma abordagem de métodos mistos e aprendizado de máquina

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Abstract. Metacognition in physics fundamentally shapes how students map out, oversee, and assess their cognitive steps during problem-solving. To untangle the complex factors behind this ability, we adopted an explanatory sequential mixed methods framework. First, we deployed a machine learning model via the Unsupervised Possibility Fuzzy C-Means (UPFC) algorithm in R, allowing us to group students based on structural similarities in their metacognitive profiles. We then followed up with qualitative, in-depth interviews analyzed through thematic coding in Atlas.ti to contextualize these groups. Our analytics uncovered two distinct student groups: those with high metacognitive engagement and those with low engagement. The driving forces behind these profiles stem from both the inside and outside. Internally, students' capacity for self-evaluation, active task monitoring, and cognitive resilience when facing tough physics problems proved decisive. Externally, the classroom climate, active teacher scaffolding, resource accessibility, and emotional backing from family and peers heavily steered their development. Ultimately, these dynamics offer actionable blueprints for educators aiming to cultivate sharper metacognitive habits in the physics classroom.

Keywords: Metacognition, Physics learning, High school students, Machine learning, Mixed methods.

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Resumo. A metacognição na física molda fundamentalmente a forma como os alunos planejam, supervisionam e avaliam suas etapas cognitivas durante a resolução de problemas. Para desvendar os fatores complexos por trás dessa habilidade, adotamos uma estrutura explicativa sequencial de métodos mistos. Primeiramente, implementamos um modelo de aprendizado de máquina por meio do algoritmo Unsupervised Possibility Fuzzy C-Means (UPFC) em R, o que nos permitiu agrupar os alunos com base em similaridades estruturais em seus perfis metacognitivos. Em seguida, realizamos entrevistas qualitativas aprofundadas, analisadas por meio de codificação temática no Atlas.ti, para contextualizar esses grupos. Nossas análises revelaram duas coortes distintas de alunos: aqueles com alto engajamento metacognitivo e aqueles com baixo engajamento. Os fatores que impulsionam esses perfis têm origem tanto interna quanto externa. Internamente, a capacidade de autoavaliação, o monitoramento ativo da tarefa e a resiliência cognitiva dos alunos ao enfrentar problemas complexos de física mostraram-se decisivos. Externamente, o clima da sala de aula, o apoio ativo do professor, a acessibilidade aos recursos e o suporte emocional da família e dos colegas influenciaram fortemente seu desenvolvimento. Em última análise, essas dinâmicas oferecem planos práticos para educadores que buscam cultivar hábitos metacognitivos mais apurados na sala de aula de física.

Palavras-chave: Metacognição, Aprendizagem de Física, Alunos do Ensino Médio, Aprendizado de Máquina, Métodos Mistos.

Introduction

Educators long have recognized metacognition as a cornerstone of academic success, especially when students face conceptually dense and structurally demanding subjects like

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physics. Mastering physics forces a student to look beyond mere rote formula application; it demands rigorous conceptual framing, mathematical fluency, and – crucially – the agility to regulate and critique one's own thought patterns in real-time (Buwono et al., 2025; Dulger & Ogan-Bekiroglu, 2025). When students stumble in physics, the bottleneck is rarely just a lack of content knowledge. More often, they simply do not notice *how* they think, failing to plan their attack, track their understanding, or pivot when hitting a logical wall. These overarching self-regulatory habits define metacognition (Dulger & Ogan-Bekiroglu, 2025; Pertiwi & Kitthawee, 2025). Pinpointing what drives or derails high schoolers' metacognition in physics is therefore vital if we hope to design better instruction and rescue sinking learning outcomes.

Theoretically, metacognition splits into two core components: knowledge of cognition and regulation of cognition. Metacognitive knowledge means knowing who you are as a learner, understanding what a specific task demands, and selecting which strategies will work best. Regulation, on the other hand, is the active side – the ongoing planning, monitoring, and post-task evaluation done while tackling a problem (Dulger & Ogan-Bekiroglu, 2025; Haeruddin, 2020; Sukarelawan, 2021; Taasoobshirazi, 2015). In a physics classroom, knowledge might look like a student recognizing whether a prompt requires a conceptual pivot or raw quantitative calculation. Regulation is the internal dialogue: checking intermediate calculations, questioning if an answer makes physical sense, and rewriting a strategy when an error pops up.

While robust metacognition clearly yields better grades, sharper problem-solving skills, and deeper conceptual retention, the reality in high schools remains deeply discouraging. Too many students approach physics mechanically. They jump straight into plugging numbers into equations without reflecting on the underlying physics laws, rarely audit their own logic, and almost never check if their solutions are physically plausible (Abdelrahman, 2020; Torregrosa & Albarracín, 2026; Utami et al., 2023). This widespread inertia brings us to a pressing question: what internal and external forces shape the growth of physics metacognition in high schoolers?

To unearth these forces, traditional educational research has historically relied on isolated quantitative surveys or purely qualitative case studies. While quantitative metrics offer a broad bird's-eye view of student groups, they inevitably flatten the nuanced, lived experiences of individual learners. Conversely, while qualitative interviews provide rich context, they lack the statistical scalability needed to identify systemic patterns across larger student populations. To bridge this gap, this study departs from conventional methodologies by blending a machine learning approach with in-depth qualitative inquiry through an explanatory sequential mixed methods design (Creswell, 2014, 2018).

Specifically, we deploy an unsupervised machine learning algorithm – Unsupervised Possibility Fuzzy C-Means (UPFC) – to partition students based on structural similarities in their metacognitive profiles without the bias of predefined labels. Unlike traditional rigid clustering methods, UPFC acknowledges that a student's cognitive habits are fluid and can overlap across multiple profiles with varying degrees of membership. Following this quantitative mapping, we conduct semi-structured interviews analyzed through thematic coding to unpack the "why" and "how" behind the emerging data clusters. By merging

advanced data analytics with narrative evidence, this study aims to comprehensively map the internal and external determinants of high school students' physics metacognition, ultimately providing educators with actionable, data-driven blueprints to cultivate sharper metacognitive habits in the classroom.

Methods

To untangle the complex factors behind students' physics metacognition, this investigation utilizes an explanatory sequential mixed-methods design (QUANT→qual), structured so that the quantitative phase establishes a baseline before the qualitative phase explores deeper insights (Creswell & Plano, 2018). This sequence allows the initial numerical findings to directly guide the subsequent qualitative inquiry. In the first phase, we deploy an unsupervised machine learning algorithm to categorize and cluster students according to structural similarities in their metacognitive patterns. We then transition to the qualitative phase, using targeted case studies to bring deep contextual understanding to these emerging metacognitive profiles and the hidden forces that drive them.

Participants

The participant pool for the qualitative phase consists of high school students purposively selected from the initial broad sample. Rather than choosing randomly, we track and select individuals who represent varying operational tiers of metacognitive ability in physics learning, drawing directly from the data points established during the preceding quantitative cluster analysis.

This study involved a total sample of N = 138 high school students aged 15-18 years from both public 4 schools. All participants completed the quantitative stage using a self-administered opinionnaire. Subsequently, employing a sequential explanatory design, a purposive sample of n = 16 students representing high metacognitive performance profiles was selected for semi-structured qualitative interviews.

Materials

Our data collection architecture pairs a validated multi-dimensional opinionnaire with semi-structured diagnostic interviews. The core instrument, a physics metacognitive ability opinionnaire, is structurally mapped across six fundamental regulatory dimensions: metacognitive knowledge, planning, monitoring, evaluation, information management, and debugging (Haeruddin et al., 2020; Sukarelawan, 2021; Taasoobshirazi, 2015). Built using a Likert-scale framework, the tool underwent rigorous expert evaluation and extensive statistical testing to guarantee empirical validity and reliability before deployment.

The opinion instrument consists of 17 statements rated on a 4-point Likert scale. It was developed based on the metacognitive framework proposed by Alpindo (2026). Content validity was established by a panel of seven experts in Physics Education and Educational Psychology, yielding Aiken’s V validity indices ranging from 0.83 to 0.96; these values

indicate the instrument's items are valid, as they exceed the critical V-table value of 0.75. Construct validity was demonstrated using confirmatory factor analysis (CFA), with factor loadings exceeding 0.3, confirming the construct validity of the items. Internal consistency was confirmed by Cronbach's alpha value of $\alpha = 0.94$. The CFA scores and Cronbach's alpha value were obtained through a pilot study involving 475 high school students.

The qualitative phase employed a semi-structured interview protocol comprising 10 open-ended questions, formulated based on themes identified during the quantitative modeling. Qualitative data were analyzed using Thematic Analysis based on the framework established by Braun and Clarke (2006). For the qualitative layer, we developed semi-structured interview protocols specifically engineered to explore how students actively plan, monitor, and evaluate their own cognitive steps when navigating complex physics laws and problem-solving hurdles. To process these streams, we execute all quantitative scripts within the R programming environment, while managing and coding the qualitative interview transcripts using ATLAS.ti.

Procedures

The fieldwork progressed through two distinct operational steps. First, in the quantitative phase, the entire student cohort completed the multidimensional opinionnaire. We then crunched these metrics to map out distinct student clusters based on statistical similarities in their self-regulatory behaviors. To ensure mathematical precision, we verified the optimal number of clusters by cross-evaluating Silhouette width, the Elbow method via Within-Cluster Sum of Squares (WSS), and the Gap Statistic. Moving into the qualitative phase, we invited selected students – focusing particularly on those who demonstrated highly developed metacognitive profiles – to participate in deep semi-structured interviews. These sessions aimed to expose the underlying internal and external forces shaping their cognitive reflection habits. Finally, we integrated the empirical data from both phases into a unified explanatory model to provide a holistic interpretation of the dataset.

Data Analysis

The quantitative analysis utilizes both descriptive statistics and advanced cluster modeling to organize students into groups based on their active metacognitive profiles. As noted, we establish the absolute mathematical validity of our cluster boundaries through three independent validation techniques: Silhouette, Elbow (WSS), and the Gap Statistic. Once the optimal cluster count is fixed, we run the clustering process via the Fuzzy C-Means (FCM) algorithm (Yağcı, 2022). To profile students' metacognitive behaviors, the Unsupervised Possibilistic Fuzzy C-Means (UPFC) algorithm was chosen over conventional clustering methods (such as standard K-Means or traditional Fuzzy C-Means). Unlike crisp partitioning or standard Fuzzy C-Means (FCM) – which can be overly sensitive to noise and outliers due to the constrained membership sum condition ($\sum u_{ij} = 1$) – UPFC integrates both fuzzy membership degrees and possibilistic typicality values. This dual-component approach allows the algorithm to distinguish between genuine cluster membership and atypical data

points, effectively handling noisy self-report responses and preventing extreme or erratic data points from distorting cluster centroids. Unlike traditional rigid partitioning methods, this machine learning algorithm acknowledges that human cognitive habits are inherently fluid; it allows a single student's data profile to overlap across multiple groups with varying membership degrees, thereby providing a far more realistic and adaptive representation of student characteristics. We execute all data analytics and modeling scripts using the R programming environment (Cebeci, 2020; Kassambara & Mundt, 2020).

Concurrently, we process the qualitative interview data using a rigorous thematic analysis framework, which involves iterative transcript coding, constant comparative categorization, and the systematic synthesis of overarching themes. In the final synthesis, we blend the results of both phases. We specifically use the qualitative narratives to unpack, enrich, and explain the numerical boundaries identified by the machine learning algorithm, focusing heavily on isolating the concrete internal and external determinants that dictate a high schooler's physics metacognition.

Results

Quantitative Results

Prior to performing the cluster analysis, we determined the optimal number of clusters through a rigorous evaluation process. Specifically, we employed three widely recognized cluster validation techniques: the Silhouette method, the Elbow method based on Within-Cluster Sum of Squares (WSS), and the Gap Statistic. Applying these independent methods ensured the robustness, stability, and empirical validity of the final clustering solution. The comparative outcomes of these statistical evaluations are detailed side by side in Figure 1.

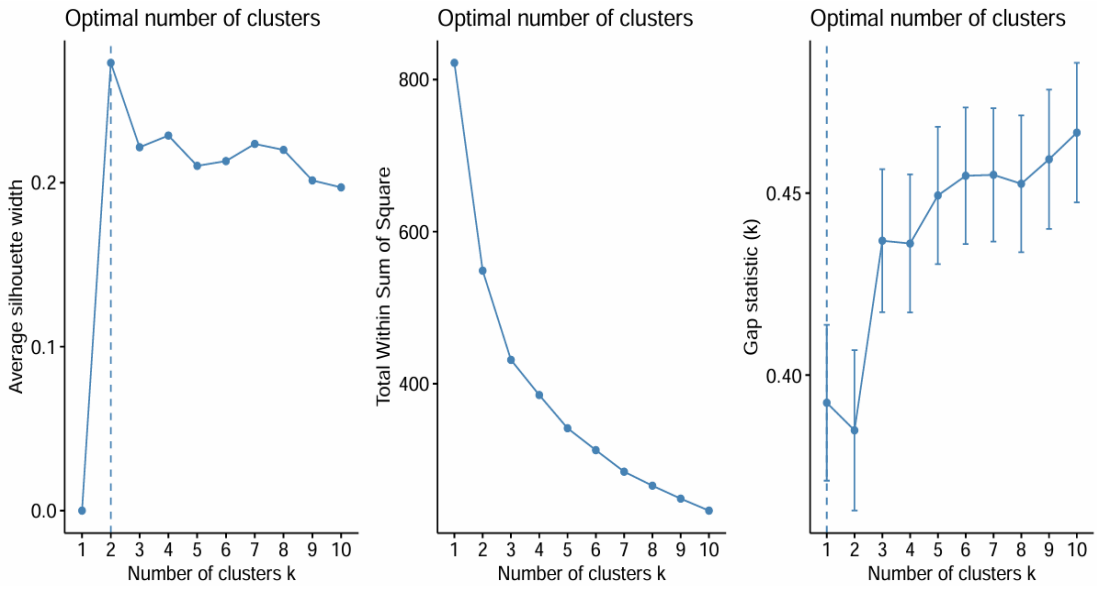


Figure 1. Results of Analysis of the Optimal Number of Clusters.

Figure 1 illustrates how we contrasted the three evaluation frameworks to determine the optimal cluster configuration. In the Silhouette plot (left), where the horizontal axis represents the number of clusters (k) and the vertical axis indicates the average silhouette value, a distinct peak emerges precisely at k = 2, highlighted by the vertical dashed line. This peak proves that partitioning the dataset into two distinct clusters yields the highest grouping quality, reflecting tight intra-cluster similarity alongside sharp, well-defined separation between the groups.

Concurrently, the Elbow (WSS) plot (center) tracks internal variability within the clusters across the vertical axis. The WSS curve drops sharply from k = 1 to k = 2 before flattening into a much more gradual decline. This structural shift indicates a clear "elbow" around the k = 2–3 range, demonstrating that adding more clusters beyond this threshold fails to achieve any substantial reduction in within-cluster variance. This confirms that the most efficient and mathematically defensible cluster boundary lies within this specific range.

Finally, the Gap Statistic plot (right) displays calculated gap values alongside their corresponding error bars for each potential cluster configuration. The vertical dashed line solidly reaffirms k = 2 as the optimal number of clusters, marking the smallest k value that secures a relatively high and stable gap metric within an acceptable margin of error.

This particular result verifies that the clustering architecture of our observed data is significantly more structured and reliable than that of randomly generated data when divided into two groups. Taken together, all three validation techniques consistently point to two (k = 2) as the optimal cluster count. This absolute mathematical consensus suggests that splitting the data into two groups provides the most representative, clean, and statistically valid solution for capturing the underlying structure of the dataset.

The clustering evaluation suggested that a two-cluster solution was the most appropriate. The average Silhouette Index reached its highest value at k = 2 (approximately 0.27), indicating the best balance between within-cluster cohesion and between-cluster separation. Although the Elbow Method suggested an elbow around k = 3, the decrease in within-cluster sum of squares beyond this point was relatively gradual. The Gap Statistic did not provide strong evidence for a larger number of clusters. Therefore, k = 2 was selected as the optimal clustering solution.

Following this validated recommendation, we subsequently classified the students into two primary clusters based on their specific indicators of metacognitive ability. The structural profiling of these resulting clusters is detailed in Figure 2.

Figure 2 presents the distinct profiles of the two groups derived from the cluster analysis, mapping them across six fundamental dimensions of metacognitive ability: Knowledge, Planning, Monitoring, Evaluation, Information Management, and Debugging. While the horizontal axis separates the two identified groups (Cluster 1 and Cluster 2), the vertical axis tracks the standardized values (z-scores) for each operational dimension.

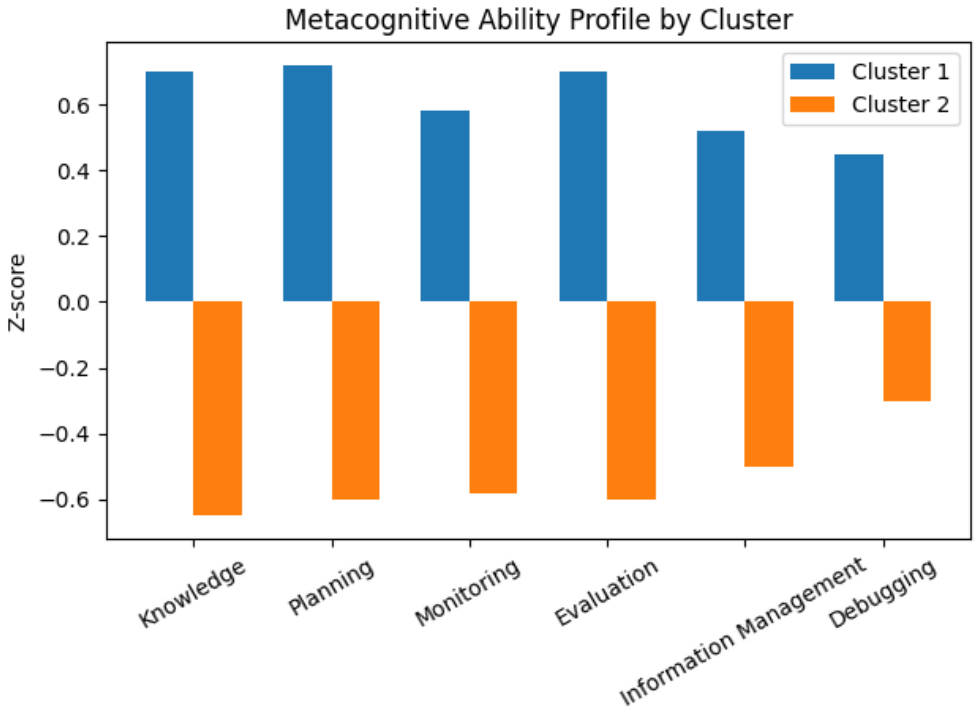


Figure 2. Results of Analysis of Cluster Forming Indicators.

Cluster 1 displays positive values across every single dimension, proving that the individuals within this cohort operate above the average level in all measured aspects. Their most prominent peaks emerge within the Planning and Evaluation dimensions, closely followed by Knowledge and Monitoring. Although their scores for Information Management and Debugging are relatively lower than their other metrics, they remain firmly rooted within the positive range. This overarching pattern reveals that Cluster 1 represents a group of learners with strong, well-balanced, and highly developed metacognitive abilities across all functional dimensions.

An opposing trend defines Cluster 2, where the data points plunge into negative values across all metacognitive dimensions, indicating that the individuals in this cohort perform below the baseline average. The most pronounced deficits are concentrated in Knowledge, Planning, Monitoring, and Evaluation. Although Information Management and Debugging score slightly higher compared to their other dimensions, they still fail to break out of the negative zone. Therefore, Cluster 2 clearly reflects a cohort of students struggling with relatively low metacognitive abilities.

Overall, Figure 2 demonstrates a sharp, unambiguous separation between the two groups, clearly distinguishing a high-ability cohort (Cluster 1) from a low-ability cohort (Cluster 2). These visual patterns reinforce our earlier validation metrics, proving that a two-cluster solution offers the most accurate representation of the data structure and establishes a solid interpretative foundation for categorizing students based on their metacognitive profiles. Using these established parameters, we plotted individual students into their respective groups, as visualized in the cluster coordinate map in Figure 3.

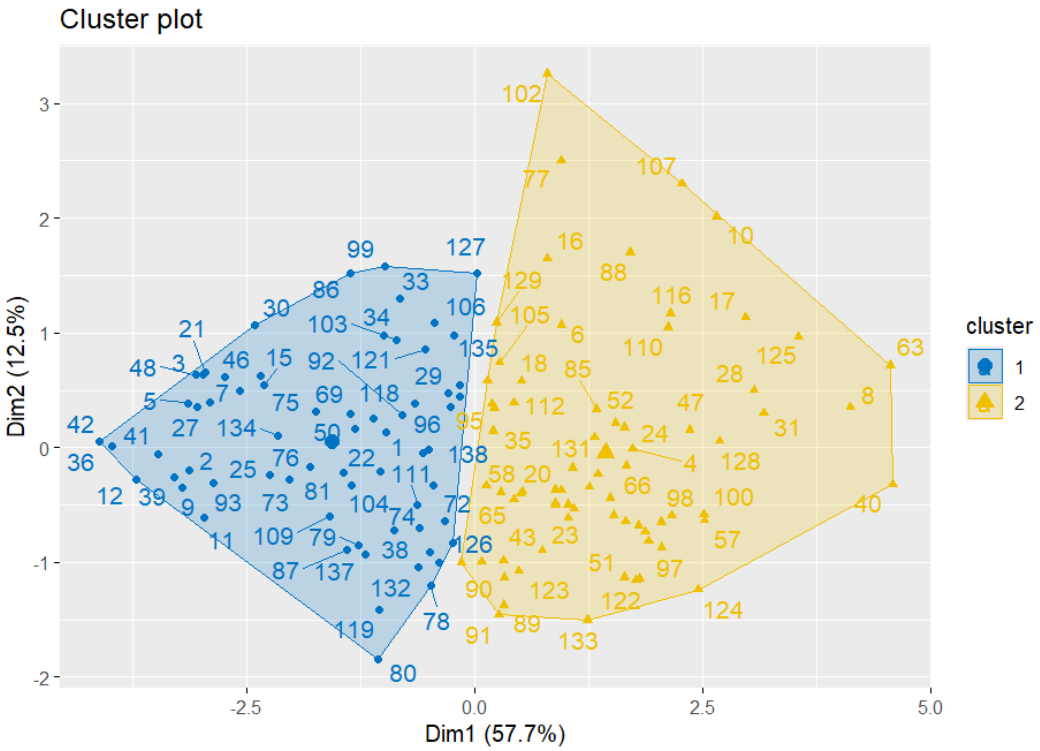


Figure 3. Cluster Analysis Results.

Figure 3 projects the respondent distribution across the two clusters using two principal dimensions derived from data reduction. Within this coordinate space, each plotted point represents an individual respondent, with the numbers adjacent to the points indicating distinct respondent identities. The horizontal axis (Dim1) accounts for a substantial 57.7% of the total variance, while the vertical axis (Dim2) explains 12.5%. Combined, these two principal dimensions capture approximately 70.2% of the total variance, confirming that they comprehensively represent the overall structure of the empirical dataset.

Cluster 1 is mapped via blue points, which concentrate tightly on the left side of the plot within the negative values of Dim1. This compact distribution suggests that the members of this group share highly homogeneous characteristics, with the surrounding blue polygon illustrating the precise boundary of the cluster. Conversely, Cluster 2 is represented by yellow points distributed predominantly on the right side of the plot within the positive values of Dim1. This cohort exhibits a much wider spatial dispersion compared to Cluster 1, indicating a greater degree of heterogeneity among its members. The yellow polygon outlines the expansive coverage area of Cluster 2.

In sum, Figure 3 highlights an unencumbered, clear separation between the two clusters, particularly along the dominant Dim1 axis, with only minimal overlap occurring around the zero mark. This distinct separation demonstrates that the groups are cleanly isolated, allowing for meaningful interpretation of the grouping outcomes. This visualization supports our previous validation tests and provides a concrete representation of the distribution, proximity, and variance among individuals within each cluster. Moving forward, we utilize these cluster assignments as an analytical baseline to identify and unpack the internal and

external determinants of students' metacognitive abilities by directly comparing high- and low-performing groups in the qualitative phase.

As depicted in the coordinate plot (Figure 3), Cluster 1 (high-performing/high-engagement profile) forms a geometrically compact cluster, indicating high internal homogeneity. Conversely, Cluster 2 (low-performing profile) demonstrates substantial spatial dispersion along the primary components. Rather than representing a uniform 'below-average' baseline, qualitative post-hoc exploration and latent density analysis reveal that Cluster 2 encompasses distinct cognitive bottlenecks—ranging from severe monitoring deficits to low affective resilience. This spatial dispersion underscores that low-ability students do not suffer from a singular, standardized deficit, but rather present heterogeneous learning profiles that demand targeted, differentiated interventions.

Qualitative Results

In alignment with our explanatory sequential mixed-methods framework, the qualitative analysis functions as a direct extension and contextual explanation of the preceding quantitative findings. This subsequent qualitative phase was specifically designed to explore the underlying factors that shape and drive students' metacognitive abilities in physics. To extract the most meaningful insights, we examined these factors among students who were identified by the cluster analysis as possessing high-level physics metacognition. Through rigorous thematic analysis conducted in ATLAS.ti, we successfully isolated several core themes governing physics metacognition, as visually structured in Figure 4.

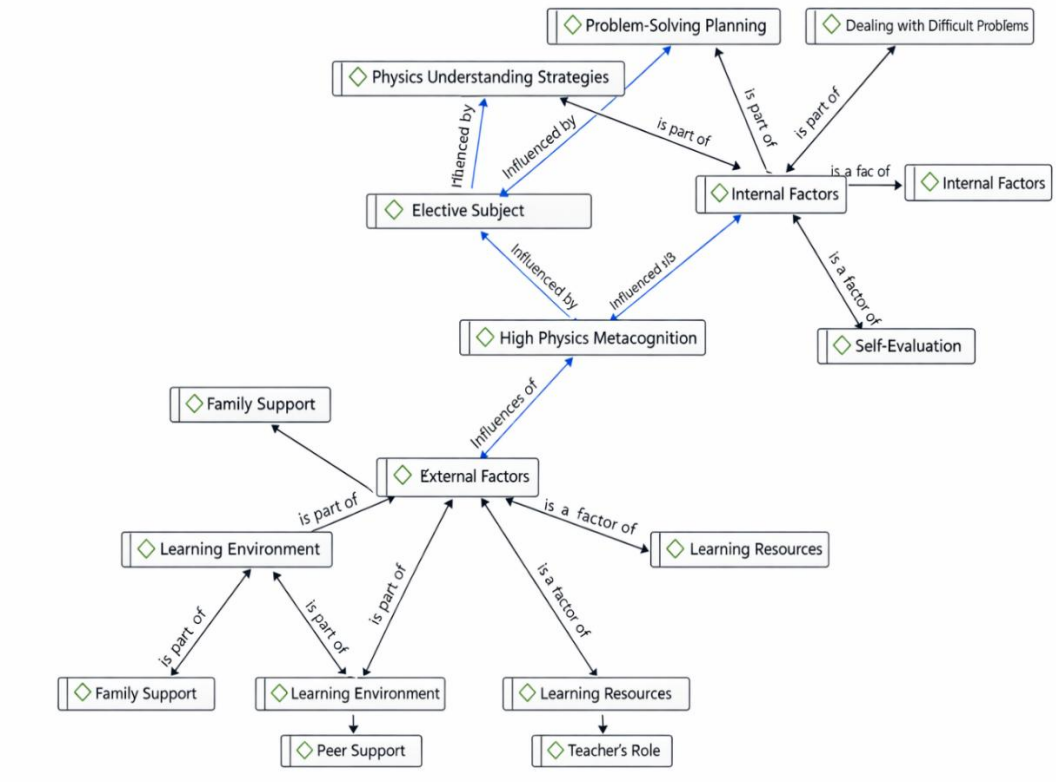


Figure 4. Results of Thematic Analysis of Factors Influencing Physics Metacognition.

To identify themes, respondents were asked 10 questions regarding physics-related metacognitive skills. The following is an excerpt from an interview with one of the respondents concerning the planning indicator.

Excerpt A: Developing Systematic Steps

"Look for the steps first. Like, create the steps first. Know them first, sir. Make them known first. Then create the steps."

A respondent's response when asked what the first thing they do when given a physics problem. Demonstrates metacognitive awareness to map the problem situation before rushing to calculate.

Excerpt B: Selective Formula Selection

"Looking for the formula, I usually don't look at what's in the problem, like Newton's, right? So, I look for Newton's formula and then sort it out. I get Newton's formula and then I find gravity, so I use the gravity formula."

An explanation of how the respondent selects relevant formulas based on known variables, demonstrating directed and adaptive formula planning skills.

The qualitative findings demonstrate that students' conceptual understanding and problem-solving agility in physics do not develop in a vacuum; rather, they are forged by a dynamic, continuous interplay between internal and external factors, with high-level physics metacognition acting as the central mediating construct. This core insight underscores that effective physics learning depends on far more than mere conceptual mastery; its success relies fundamentally on a student's capacity to actively regulate, monitor, and reflect on their own cognitive steps.

Internal factors – most notably self-evaluation capacity, proactive task monitoring, and the cognitive resilience to tackle challenging problems – play a critical role in anchoring students' metacognitive regulation. These internal habits enable learners to critically assess their actual depth of understanding, catch and correct conceptual errors early, and sustain cognitive focus when grinding through complex, multi-layered tasks. Consequently, students who possess these stronger internal metacognitive habits naturally deploy systematic, structured, and deeply reflective problem-solving strategies rather than relying on random formula guessing.

Simultaneously, external factors step in to actively reinforce and mature this developing metacognitive capacity. A supportive classroom environment, intentional teacher facilitation, seamless access to high-quality learning resources, and emotional backing from peers and family collectively amplify students' metacognitive engagement. Specifically, instructional practices that embed probing questions, encourage reflective feedback, and utilize problem-based learning prove highly instrumental in stimulating active metacognitive processes.

Ultimately, the results suggest that high-level physics metacognition thrives at the intersection of an individual's internal self-regulatory capacities and the external conditions of a resource-rich, supportive learning ecosystem. Optimizing physics instruction therefore requires an integrated approach that simultaneously trains students' internal self-regulatory skills while providing a encouraging, stimulating learning environment.

Discussion

The Polarization of Students' Physics Metacognitive Profiles

The statistical convergence demonstrated during the quantitative analysis conclusively indicates that the metacognitive landscape of senior high school physics students in the Riau Islands is best defined by a bifurcated structure. The absolute consensus among the Silhouette width, the Within-Cluster Sum of Squares (WSS) Elbow method, and the Gap Statistic ensures that dividing the participant pool into exactly two groups ($k = 2$) is not a methodological artifact, but an accurate reflection of distinct cognitive partitions within the student population (Arima et al., 2008; Rahmati & Wijayanto, 2021; Rajkumar et al., 2019). This dual-cluster pattern aligns directly with contemporary theories of self-regulated learning, which suggest that under traditional educational setups, students' meta-level awareness naturally polarizes into two broad competency tiers: those who actively control their cognitive trajectories and those who rely on mechanical learning routines.

The visual separation across the six fundamental dimensions – Knowledge, Planning, Monitoring, Evaluation, Information Management, and Debugging – highlights a deep developmental gap between Cluster 1 and Cluster 2 (Koyunlu Ünlü & Dökme, 2019; Pamungkas et al., 2019; Sukarelawan, 2021; Taasoobshirazi & Farley, 2013). Cluster 1 exhibits positive z-scores across all indicators, establishing this cohort as advanced metacognitive learners. Their most pronounced strengths appear in the Planning and Evaluation dimensions. This specific trend indicates that high-metacognition students do not approach abstract physics tasks randomly. Instead, they act as active strategic planners who carefully analyze problem structures, identify underlying physical principles, map out step-by-step solutions, and continually critique their results against logical benchmarks. When faced with multi-layered equations, these students actively monitor their progress, ensuring that their conceptual understandings match their quantitative calculations.

Conversely, Cluster 2 presents a deeply concerning trend for science education, with scores across all six dimensions plunging below the average baseline. This widespread deficit indicates a condition of low metacognitive awareness, where students lack both the theoretical knowledge of how they learn and the practical strategies needed to regulate their cognitive processes. When dealing with complex physics challenges, students in Cluster 2 typically fall back on mechanical formula-plugging. They often skip the essential conceptual framing phase, blindly inserting numbers into memorized equations without evaluating whether the mathematical outputs match physical reality. This systematic failure to plan, monitor, and evaluate cognitive actions frequently blocks deep conceptual retention, leaving these students vulnerable to long-term academic struggles in science tracks.

Spatial Dynamics and Classroom Heterogeneity

Examining the spatial distribution within the principal component coordinate map yields critical pedagogical insights into the structural differences between the two student groups. The coordinate space shows that Cluster 1 (the high-metacognition cohort) forms a highly compact and tightly clustered geometric shape. This proximity implies strong internal

homogeneity among advanced students; those who have successfully developed mature metacognitive frameworks tend to exhibit highly consistent, structured, and stable learning behaviors. Their self-regulatory practices follow a reliable cognitive path, allowing them to systematically unpack complex scientific prompts.

In sharp contrast, Cluster 2 (the low-metacognition group) occupies a much wider and more scattered spatial footprint. This pronounced dispersion reveals significant heterogeneity among struggling students. It demonstrates that the nature, root causes, and severity of metacognitive deficiencies vary dramatically from one struggling learner to another. For instance, one student within Cluster 2 might struggle primarily with a foundational lack of declarative knowledge regarding physics concepts, while another might grasp the concept but completely lack the procedural planning skills required to execute a multi-step solution.

This internal variation carries direct practical implications for physics teachers. It suggests that uniform, rigid remedial interventions are mathematically and pedagogically ill-suited for this group. Educators cannot rely on a single “one-size-fits-all” instruction model to support struggling students. Instead, classroom interventions must be adaptively designed and carefully differentiated to diagnose and target the specific cognitive blocks troubling individual students within this diverse, low-performing cohort (Alpindo et al., 2024).

The Synergy of Internal and External Determinants

By utilizing an explanatory sequential mixed-methods framework, this study looks past mere statistical grouping to explore the underlying dynamics that cause these variations. The qualitative narratives unpack the numerical boundaries identified by the machine learning algorithm, revealing that high-level physics metacognition does not develop in isolation. Instead, it is continuously forged at the intersection of an individual's internal cognitive mechanics and external environmental catalysts (Chieng & Tan, 2021; Razkane et al., 2025).

The qualitative findings show that high-metacognition students rely heavily on a combination of strong internal self-evaluation capacities, proactive task monitoring, and cognitive resilience when tackling complex, non-routine problems (Didiş Körhasan & Pospiech, 2024; Osman et al., 2025; Zepeda et al., 2015; Zhang et al., 2023). Proactive task monitoring serves as an internal tracking system, allowing students to spot conceptual errors or mathematical slips early in the problem-solving process and dynamically adjust their strategies before their solutions collapse (Malmberg et al., 2021).

This continuous monitoring is supported by an honest self-evaluation capacity, which enables students to objectively audit their own understanding, identify hidden misconceptions, and consciously measure their actual mastery of abstract laws. Furthermore, cognitive resilience represents the psychological and analytical endurance required to handle demanding tasks that require integrating multiple physical principles simultaneously (Pozas et al., 2020; Sayre & Irving, 2015; Yusuf & Widyaningsih, 2020). Together, these internal mechanisms encourage a systematic, structured, and deeply reflective approach to physics, steering students away from superficial, impulsive formula-guessing.

However, the qualitative data also demonstrates that these internal self-regulatory habits require a supportive external learning ecosystem to mature. A healthy classroom environment, intentional teacher facilitation, seamless access to high-quality learning resources, and encouraging social support from family and peers collectively serve as the necessary infrastructure to activate and reinforce students' metacognitive behaviors.

Classroom environments that emphasize probing questions, reflective feedback loops, and open-ended, problem-based tasks are highly effective at stimulating students' higher-order thinking. When teachers shift their roles from traditional lecture-based information transmitters to active cognitive guides, they provide the essential scaffolding students need to question their own assumptions and verbalize their internal thinking processes (Alpindo et al., 2024; Payoungkiattikun et al., 2025).

Additionally, emotional and motivational backing from families and peer groups creates a safe academic environment. This social support builds the confidence, and persistence students need to confront difficult physics concepts without fear of failure. Ultimately, high-level physics metacognition thrives when an individual's internal drive matches a rich, encouraging external educational community.

Methodological and Practical Implications

From a methodological standpoint, the successful integration of the UPFC clustering algorithm with qualitative thematic analysis confirms the strength of using an explanatory sequential mixed methods design to study complex educational constructs. While the quantitative machine learning phase offers a scalable, data-driven, and objective map of student profiles without predefined biases, the subsequent qualitative case studies successfully explain the real-world experiences, underlying motivations, and environmental influences that define those data points. This mixed approach provides a comprehensive view that neither quantitative metrics nor qualitative narratives could achieve on their own.

Practically, these findings offer clear, actionable blueprints for curriculum developers and physics educators who want to improve student performance. To help students transition out of low-metacognition habits, modern physics instruction must intentionally move away from traditional, rote-memorization teaching methods. Lesson plans should explicitly integrate metacognitive strategy training alongside core physics content.

For example, teachers can use structured problem-solving worksheets that require students to explicitly write down their “Planning Phase” (identifying assumptions and drawing free-body diagrams), their “Monitoring Phase” (checking units and intermediate signs), and their “Evaluation Phase” (reflecting on whether the calculated vector makes physical sense). By changing the classroom culture to value and reward the reflective process rather than just the final numerical answer, schools can help students build the self-regulatory habits needed to master physics and succeed in broader scientific fields.

Limitations of the Study

Despite the theoretical and empirical contributions of this study, several methodological limitations must be acknowledged. First, the quantitative assessment relied on a self-report opinionnaire, which measures students' self-perceived metacognitive behaviors rather than direct, real-time cognitive processing during task execution. Consequently, the data carry inherent risks of distortion due to social desirability bias or a lack of self-criticism, particularly within the lower-performing student cluster. Second, the geographical scope was strictly concentrated on secondary school students within the Riau Islands region of Indonesia. The unique socioeconomic, archipelagic infrastructural, and regional cultural characteristics of this context may limit the direct generalizability of the empirical findings to vastly different educational settings – such as highly urbanized environments or fully digitized school systems – without prior contextual adaptation. Future research should integrate process-tracing methodologies (*e.g.*, think-aloud protocols or real-time behavioral log tracking) and replicate this mixed-methods framework across broader, cross-regional demographics to validate and refine the identified metacognitive profiles.

Conclusion

This study successfully maps the complex landscape of high school physics metacognition by bridging an advanced machine learning approach with contextual qualitative evidence. Through the application of the Unsupervised Possibility Fuzzy C-Means (UPFC) algorithm, we established a robust statistical foundation that solidifies a two-cluster model as the most accurate representation of student profiles. This framework effectively isolates two distinct student groups: a highly proficient group characterized by balanced, above-average self-regulatory habits, and a struggling group trapped in mechanical, below-average learning routines. The subsequent qualitative findings successfully dismantle the "why" behind this divide, proving that high-level physics metacognition is forged at the continuous intersection of internal cognitive mechanics and external environmental catalysts. Specifically, internal drivers – such as self-evaluation capacity, proactive task monitoring, and cognitive resilience – dictate how systematically a student navigates physics laws. Meanwhile, external dimensions – including a supportive classroom climate, targeted teacher scaffolding, accessible learning resources, and emotional backing from families and peers – serve as the necessary infrastructure to activate and mature these internal habits.

These findings carry vital practical implications for modern physics education. Because the low-metacognition cohort exhibits deep structural heterogeneity, educators must abandon “one-size-fits-all” instructional models in favor of adaptive, differentiated teaching strategies that target specific cognitive bottlenecks. To rescue students from mechanical formula-plugging, instructional designs must explicitly integrate metacognitive scaffolding, such as embedding probing questions, providing reflective feedback loops, and shifting toward problem-based learning tasks that reward conceptual reflection over raw memorization. Ultimately, cultivating sharper metacognitive habits in the physics classroom requires an integrated approach: schools must actively train students' internal self-regulatory

mechanisms while simultaneously nurturing a rich, supportive external learning ecosystem that encourages cognitive exploration.

In summary, while this study provides valuable insights into the synergistic mechanisms of metacognition in physics education, the empirical findings must be interpreted within the specific educational landscape of the Riau Islands. The identified low-performing profile heterogeneity reinforces the need for differentiated instruction tailored to local infrastructural and socioemotional realities.

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