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Exploring Psychological–Cognitive Energy Literacy Profiles of High School Students and the Role of Gender as a Predictor: A Latent Profile Analysis

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Abstract

Growing global energy and sustainability challenges require citizens to make informed decisions about energy production, consumption, and conservation. Promoting energy literacy among young people is therefore increasingly recognized as an important educational objective. However, most previous research has adopted variable-centred approaches that focus on average levels of knowledge and attitudes, potentially overlooking meaningful differences among learners. By adopting a psychological–cognitive operationalization of energy literacy, the present study addressed this gap through a person-centred approach. Additionally, the role of gender as a predictor of profile membership was investigated. A convenience sample of N = 363 Italian secondary school students completed an adapted four-tier diagnostic instrument that measured both content knowledge and confidence judgements, alongside a 12-item attitudes towards energy survey. Latent profile analysis was conducted using standardized knowledge, confidence judgements, and attitude scores as profile indicators. The predictive role of gender was examined using a classification-error-adjusted three-step analysis. Three distinct profiles emerged: *Overconfident and with Lower Attitudes* (55.6%), *Calibrated and with Higher Attitudes* (38.0%), and *Knowledgeable, Calibrated and with Higher Attitudes* (6.3%). Gender did not significantly predict profile membership after classification uncertainty was taken into account. Overall, our results highlight the value of person-centred approaches for capturing internal heterogeneity in students' knowledge about and attitudes towards energy-related issues and suggest that effective energy education should foster not only conceptual understanding but also well-calibrated metacognitive self-assessment. Such efforts may better support students as future citizens to engage meaningfully with future environmental and sustainability challenges.

Keywords: energy literacy; secondary education; latent profile analysis; attitudes towards energy; energy conceptions; sustainability education; multi-tier assessment

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1. Introduction

Energy is widely regarded as one of the most significant challenges of the contemporary world [1,2]. Global issues such as climate change, resource depletion, and energy insecurity have intensified the need for citizens to be capable of making informed decisions about energy production, consumption, and policy [3,4]. Researchers therefore increasingly recognise that individuals should be able to understand complex energy systems, critically evaluate information, communicate effectively about energy issues, participate in democratic decision-making processes and contribute to sustainable energy transitions [5]. In

other words, they should acquire adequate *energy literacy* [6,7]. High school students are a critical target group within the wider population since they will soon assume more active roles in society and face increasingly complex socio-scientific issues. However, despite the growing relevance of energy-related issues, research consistently indicates that many secondary school students exhibit limited comprehension of fundamental energy concepts, yet express favourable attitudes towards sustainability and energy conservation [8–10]. This discrepancy between the knowledge of energy concepts and the attitude towards energy raises significant concerns about the development of energy literacy and the effectiveness of educational interventions in supporting it [11].

Yet, although energy literacy is recognised as a multidimensional construct, the majority of studies have investigated its components separately. Consequently, there is a dearth of research on how these dimensions coexist within individual learners. Person-centred approaches, including latent profile analysis (LPA), are a more suitable methodology for identifying distinct subgroups of students with similar levels of energy literacy, enabling more effective instructional interventions to be designed, developed and implemented. The present study aims to address this gap by applying LPA to identify profiles of secondary school students based on their knowledge of energy concepts, confidence judgments and self-reported attitudes towards energy. To this end, the study used a newly developed, four-tier instrument to assess both conceptual understanding of energy and metacognitive monitoring, as well as a new, unidimensional attitude scale. The objective is to explore how these three factors combine and what these patterns reveal about students' knowledge about and attitudes towards energy issues in their lives. The results of the study are intended to provide a more effective basis for designing sustainability and energy education curricula.

2. Literature Review

2.1. Conceptualizing Energy Literacy

As pointed out above, in recent decades, energy literacy has emerged as a significant topic of interest, spanning various disciplines including education, policy, sustainability, and decision-making [6,7]. One of the first conceptualisations of energy literacy was proposed by DeWaters and colleagues [12,13], who defined it as a multidimensional construct encompassing a basic understanding of energy concepts, awareness of the impacts of energy production and consumption on society and the environment, knowledge of everyday energy use, and the adoption of responsible energy-related behaviours. The authors developed a theoretical framework for understanding energy literacy, drawing on research findings in scientific, technological, and environmental education. This framework comprises three interconnected dimensions: cognitive (knowledge and skills); affective (attitudes, values, awareness and personal responsibility); and behavioural (actions and behavioural intentions). Martins et al. [14] hypothesize that the popularity of this model is related to the more general consensus that energy-related decision-making cannot be adequately implemented through knowledge alone, but requires an investigation into the interaction between what individuals know, how they evaluate energy issues and their subsequent behaviour. However, other conceptualisations have also been adopted in subsequent years. Brounen et al. [15] define energy literacy primarily from an economic perspective, emphasising individuals' ability to evaluate the trade-off between the higher initial costs of energy-efficient technologies and the long-term financial and energy savings associated with their adoption. Trotta et al. [16] extend this perspective by including awareness of personal energy consumption, understanding of energy pricing mechanisms, willingness to engage in energy-saving practices, and the ability to seek and process energy-related information. Similarly, Blasch et al. [17] propose the concept of

energy-related financial literacy, emphasising not only an understanding of energy issues, but also the quantitative and analytical competencies necessary for evaluating energy-related investments and making economically informed decisions. The U.S. Department of Energy [18] offers a broader interpretation, defining energy literacy as a comprehensive understanding of the nature and role of energy in the world and everyday life, coupled with the ability to apply this knowledge to address questions and solve problems. This definition explicitly acknowledges the importance of applying knowledge to real-world decision-making and action, thereby going beyond mere information acquisition. Synthesising these perspectives, Martins et al. [14] propose an integrative framework that combines energy knowledge, financial literacy, attitudes and behavioural competencies within a single conceptual model. The authors suggest that effective participation in contemporary energy systems increasingly depends on citizens' ability to comprehend energy production, consumption and environmental impacts. It is also crucial for citizens to be able to evaluate the costs, savings, investments, and financial consequences associated with energy-related choices. Consequently, energy literacy is conceptualised as an interdisciplinary construct that bridges scientific understanding, environmental awareness, economic reasoning and everyday decision-making.

Recent studies have further expanded the concept of energy literacy. Das and Richman [19] proposed a conceptualisation of public energy literacy as the "possession of general knowledge regarding energy, energy-related issues, and the use of energy in everyday life" (p. 49). In this conceptualization, energy literacy affects an individual's system of values in order to facilitate the informed utilisation of energy and engagement in energy transitions. The public energy literacy framework thus highlights the particular relevance of energy literacy in contemporary societies, where citizens are expected to engage not only as energy consumers, but also as participants in public debates and policy processes about environmental sustainability. Furthermore, the researchers posit that energy literacy should be broad enough to avoid favouring expertise or technical knowledge alone, instead capturing the competencies necessary for meaningful civic engagement in energy-related issues. Similarly, research studies carried out in New Zealand [20,21] proposed that energy literacy should encompass not only knowledge, attitudes and intended behaviours, but also agency. This is defined as the capacity of individuals to influence energy-related decisions within their families and social communities. From this perspective, an individual with adequate energy literacy is not merely a knowledgeable energy consumer, but an active citizen who can engage with issues such as energy justice, climate change, public policy, technological innovation and collective social transformation [22]. Based on this result, Gladwin and colleagues [23] proposed that energy literacy can be understood through the interconnected dimensions of knowing (understanding what energy is), being (understanding how energy shapes social and cultural life) and doing (applying this knowledge through individual and collective action). This framework highlights the importance of envisioning scenarios and shaping future energy systems, thereby establishing energy literacy as a vital skill for navigating the societal changes required for a low-carbon future.

Finally, research on energy literacy at the higher education level is more limited. Cotton et al. [24] found that undergraduate courses provide a unique environment in which the cognitive, affective and behavioural dimensions can be developed simultaneously through interaction with formal curricula, informal learning opportunities, peer networks and campus sustainability initiatives.

2.2. Assessing Students' Energy Literacy

The first energy literacy assessment studies were carried out by DeWaters and Powers, who developed a comprehensive energy literacy questionnaire for secondary school

students in the United States. This instrument was designed to explicitly measure energy literacy through three distinct subscales addressing knowledge, attitudes and behaviours. In one of their studies [11], which involved 955 students, the authors found that overall mean scores ranged from 39% to 46% across various grade levels, with only a small fraction of students obtaining scores greater than 80%. Although attitude and behaviour scores showed slight improvement, ranging from 56% to 72%, the study highlighted a significant shortcoming in basic scientific understanding of energy.

Subsequent studies have adopted similar multidimensional approaches to assess energy literacy in various national contexts. For example, Yeh et al. [25] developed a scale to assess the energy knowledge, attitudes towards energy issues, sense of responsibility, and readiness to act in energy crisis contexts of Taiwanese junior high school students. Their findings revealed that, although students generally viewed energy conservation positively, their understanding of key energy concepts, especially those related to energy systems, renewable energy technologies, electricity generation, and climate change, was found to be limited. The study also revealed that misconceptions about energy can significantly impact individuals' ability to evaluate energy-related information and participate in informed decision-making. Das and Richman [19] developed and validated a public energy literacy instrument based on the cognitive, affective, and behavioural framework of DeWaters et al. for informal educational settings. Using the instrument with a sample of Toronto residents revealed relatively low levels of energy-related knowledge despite generally positive attitudes towards energy conservation and high self-reported engagement in energy-saving behaviours. A substantial lack of knowledge was identified in relation to electricity consumption, energy generation, and energy governance. This finding further confirmed that citizens may express environmental concern and adopt pro-environmental practices without having a comprehensive understanding of energy systems. Aguirre-Bielschowsky et al. [20,21] conducted a series of study with 9- and 10-year-olds in Dunedin and found that the children in their sample showed a high level of awareness regarding the financial cost of electricity. In general, the children's understanding of energy was frequently framed around financial reasons rather than environmental concerns. While most children had favourable attitudes towards sustainable electricity use, they showed little interest in their own behaviour or in influencing their families' energy habits.

Finally, Lee et al. [26] explored predictors of energy-saving behaviour in a study with 600 12th-grade students in Northern, Central, and Southern Vietnam. Using structural equation modelling, the study revealed that students' energy knowledge was predominantly moderate to low (averaging 5.46 out of 10), while their perceived values, attitudes and intentions showed a higher level of endorsement. The findings suggest that content knowledge indirectly affects energy-saving intentions and behaviour via the mediation of personal values and attitudes. The study also identified the media as the predominant source of energy knowledge for the students. A similar result was obtained by Akitsu and Ishihara [27], who conducted a study involving 1070 lower secondary school students (aged 13–15) in Japan. Their findings suggest that fundamental energy knowledge depends on scientific literacy, critical thinking ability, and an environmentally oriented worldview. Furthermore, the impact of awareness of consequences on attitudes towards energy-saving behaviour is mediated by environmental values and family discussions concerning energy-related issues.

3. The Present Study

The reviewed literature indicates that, despite the growing importance of energy literacy in educational research and practice, relatively little attention has been devoted to understanding how its different dimensions coexist and interact within individual learners.

In particular, energy-related knowledge, attitudes, and behaviours do not necessarily align, and often develop at different rates. Consequently, individuals may have strong environmental attitudes despite having limited knowledge of energy concepts, or conversely, have substantial knowledge but not consistent attitudes towards energy-saving behaviours. These findings imply that energy literacy is characterized by considerable heterogeneity among learners. However, despite such variability, the majority of existing studies in the field have adopted a variable-centred perspective, focusing on the relationships between variables at an aggregate level. While this approach has yielded valuable insights into the predictors of energy literacy, it may obscure meaningful differences among individuals by emphasizing average patterns within a population.

In contrast, person-centred approaches seek to identify subgroups of individuals who share similar configurations of characteristics, thereby providing a more nuanced understanding of learner diversity. By examining how different but related dimensions cluster within individuals, person-centred analyses can reveal latent profiles that would remain hidden in traditional correlational analyses. This approach is particularly significant in the context of energy literacy, where previous studies have identified inconsistencies between knowledge, attitude, and intended behaviour. Identifying distinct energy literacy profiles could reveal various types of learners, including those who demonstrate strong environmental concern but limited conceptual understanding; those who possess substantial knowledge yet exhibit weak pro-environmental attitudes; and those who show consistently high levels across all dimensions. Understanding these distinctions is relevant from both a theoretical and a practical viewpoint, as it contributes to the refinement of the conceptualization of energy literacy and facilitates the development of tailored educational interventions that are more aligned with the distinct requirements of diverse learner groups.

However, the assessment of actual behaviour related to energy in educational settings is often problematic because high school students may have limited opportunities to make independent energy-related decisions. Moreover, many of the contexts traditionally used to measure energy-related behaviour concern households and individual responsibility for energy consumption [28], which can be problematic to extend to political processes that foster sustainable energy transitions. Consequently, the present study will adopt a psychological-cognitive oriented operationalization of energy literacy, focusing on energy-related content knowledge and attitudes. To implement such operationalization of energy literacy and thus explore in more detail whether students often show poor performance when dealing with tasks about energy concepts because of the presence of misconceptions or a lack of knowledge about these concepts, in the present study, we will investigate also the confidence judgement of one's own energy content knowledge. Confidence judgment is defined as the retrospective self-belief of success in a specific cognitive task, typically measured after having answered a questionnaire or a single item of a test [29,30]. If confidence judgment exceeds the performance score, the student demonstrates an *overconfidence* bias, while if the confidence judgment is lower than performance score, the student shows an *underconfidence* bias. Similar scores of confidence judgment and performance score signal an overall metacognitive calibration, reflecting students' awareness of their own content knowledge [31]. From this perspective, integrating confidence judgments with energy-related content knowledge and attitudes may provide new insights into psychological–cognitive profiles of students' energy literacy, while maintaining conceptual grounding in previous research. The first research question that guided the study was as follows:

- *RQ1. What distinct latent psychological–cognitive profiles of students' energy literacy can be identified among students based on their energy-related content knowledge, confidence judgments and attitudes?*

Furthermore, the literature review highlights a paucity of research addressing gender disparities in energy literacy [32]. The few existing studies frequently yield contradictory findings regarding the relationship between content knowledge and energy-related attitudes among male and female students [10]. The present study aims to address this gap by examining whether gender predicts the specific configurations of these dimensions, as well as the probability of membership in the emerging latent profiles. Consequently, the second research question that guided the study was as follows:

- *RQ2. To what extent does gender predict students' membership in the emerging latent psychological–cognitive profiles defined by energy content knowledge, response confidence, and energy-related attitudes?*

4. Methods

4.1. Sample and Procedure

A convenience sample of N = 363 Italian high school students (n = 160 female, 44.1%; n = 203 male, 55.9%) was recruited for this study. Participants were enrolled in the final three years of upper secondary education, distributed across the 11th grade (n = 168, 46.3%), 12th grade (n = 139, 38.3%), and 13th grade (n = 56, 15.4%). The data collection took place between winter 2021 and spring 2022. Data about the age of the students were not collected. The involved students voluntarily participated in a 6 h, out-of-school educational activity focused on energy and sustainability. Prior to participation, all students had covered core energy concepts (such as mechanical work, energy forms, energy transfer, conservation, and degradation) within their standard physics curriculum. Additionally, basic aspects of sustainability had been addressed in the transversal civic education curriculum. Although there were no strict academic prerequisites for participation, these non-compulsory, out-of-school activities typically attract highly motivated students. A total of 20 schools from the authors' university province participated in the initiative, with an average of 18.0 students per school (SD = 25.0; Min = 1; Max = 117). There was no statistically significant association between gender and schools (Fisher's exact test with Montecarlo simulation, $p = 0.204$). Regarding institutional curricular tracks, twelve schools were STEM-oriented, namely, mathematics, physics, and natural sciences account for approximately 50% of curricular hours, while the remaining eight were humanities-focused, with STEM subjects covering roughly 30% of curricular hours. School recruitment was conducted through a public call issued at the beginning of the school year; consequently, no predetermined number of students was invited to participate. Within each participating school, a designated teacher disseminated an internal call and served as responsible for communication with the university. Interested students voluntarily applied to participate in the activity through the procedures established by their schools. School principals subsequently provided institutional authorization for the school involvement in the initiative. Participation in the activity did not yield any academic extra credits, grade advantages or preferential access to other educational opportunities, granting only a certificate of attendance. The survey was administered at the beginning of the activity as an integral diagnostic and instructional component of the activity itself. Therefore, all participating students were expected to complete it.At the beginning of the questionnaire, students were informed that data would have been processed for research purposes according to EU Regulation. In particular, full data anonymization was carried out in accordance with international data protection principles of the General Data Protection Regulation/GDPR guidelines on anonymous information, satisfying all statutory requirements for statistical and academic research.

4.2. Measures

To measure energy content knowledge, we designed a 10-item, 4-tier questionnaire built on existing instruments [33]. Each item features a multiple-choice tier to assess declarative knowledge (tier 1) and a multiple-choice tier to assess reasoning (tier 3). After each tier, in agreement with the adopted psychological–cognitive operationalization of energy literacy, we added a confidence judgement tier (tier 2 and 4). Each item featured a real-world scenario (e.g., a gymnast, a car, an arrow, etc.) in which four key ideas related to the energy concept were addressed [33]: forms (3 items), transfers (3 items), conservation (2 items) and degradation (2 items). An example item is reported in Figure 1.

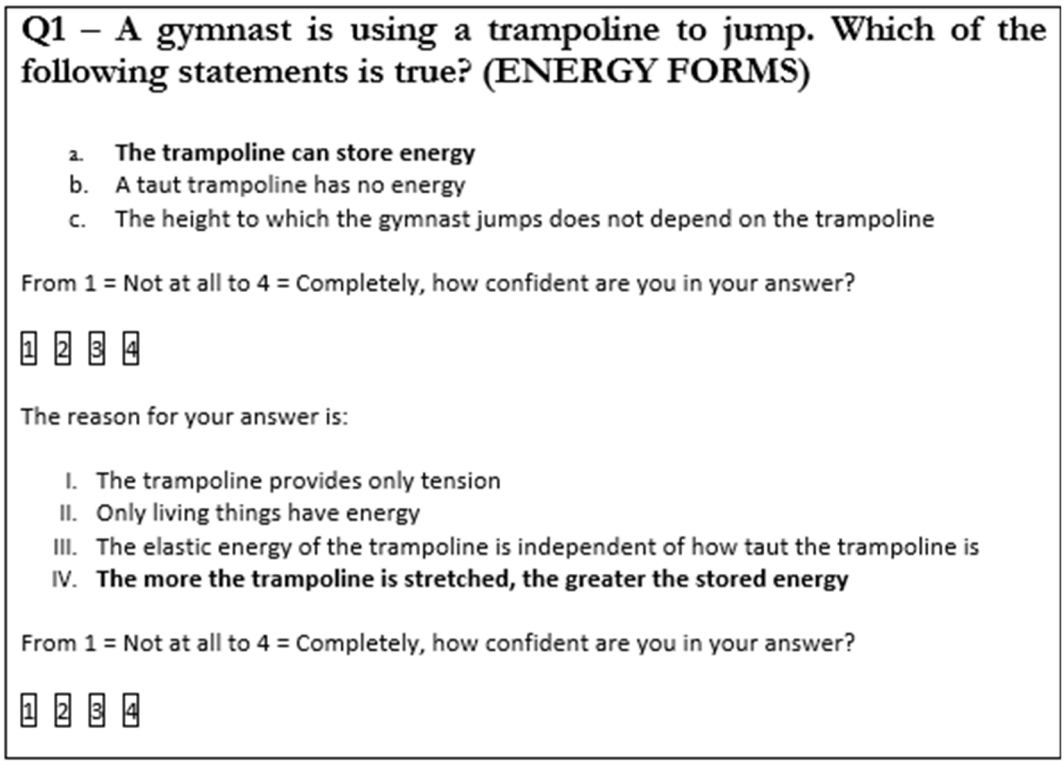


Figure 1. Example item on energy forms from the content knowledge questionnaire. Correct answers are in bold face. Adapted from [33].

To assess students' energy-related attitudes, a 20-item questionnaire was specifically designed for this study, partly adapted from previously validated instruments [34,35]. The selection of the items to include in the final version of the instrument was refined through focus-group discussions with a panel of four physics and science teachers from the participating schools. The questionnaire covered three specific attitudinal dimensions, chosen during the focus-group discussions: (1) views toward energy-saving behaviours (9 items, e.g., *"A large amount of energy is wasted because people overuse air conditioners in the summer and heaters in the winter"*); (2) attitudes toward renewable energy sources (4 items, e.g., *"I believe that devices powered by clean energy are simply more expensive"*); and (3) perception of energy-related climate anxiety (7 items, e.g., *"If things continue this way, we will soon face a major energy crisis"*). Participants indicated their agreement with each statement using a 5-point Likert scale ranging from 1 (not at all) to 5 (completely). Negative items were reverse coded prior to analysis so that higher scores reflected more positive environmental attitudes and higher awareness.

4.3. Data Analysis

Missing data. Given the diagnostic nature of the questionnaire, all survey items were mandatory and consequently, we had no missing data.

Content knowledge questionnaire. First, we calculated a combined score for the responses to the declarative knowledge and reasoning tiers (tier 1 and 3). In particular, we chose a conservative scoring method, giving 1 point if both tiers were correct and 0 otherwise. Then, we calculated item difficulty and discrimination for the ten combined items. Finally, we calculated reliability of the 10 combined items using McDonald's ω, whose value was interpreted according to literature about reliability of concept inventories [36]. For the confidence tiers (tier 2 and 4), given the choice of combining the scores of the declarative knowledge and reasoning tiers, we calculated a combined average confidence score. This choice was supported a priori by their significant correlation at item level ($p < 0.001$) and post hoc by the resulting McDonald's $\omega = 0.93$, which can be considered excellent. Finally, we evaluated whether the combined items showed evidence of overconfidence or underconfidence bias, or if they were metacognitively calibrated. To do so, we visually inspected the normalized confidence–difficulty plot of the 10 items. Taking into account that the confidence ratings varied from 1 to 4, the normalized confidence for each combined item was calculated as follows:

$$Normalized\ confidence\ score = \frac{Average\ confidence\ -\ 1}{3}$$

In the confidence–difficulty plot, points not placed on the bisector, which represents a calibration reference since it signals numerical equality between normalized mean confidence and the combined success rate, identify aggregate discrepancies between confidence and performance. Specifically, points above the diagonal line correspond to items that show overconfidence, namely the normalized average score of the combined tiers is higher than the difficulty of the item. In this case, students on average felt more confident than their actual performance. Conversely, points below the diagonal line correspond to items that show underconfidence, namely students performed better than what they retrospectively judged.

Attitudes towards energy questionnaire. We first performed a confirmatory factor analysis (CFA) using all 20 items to inspect if the expected three-factor structure was confirmed. Maximum likelihood was used as an estimation method. The hypothesized three-factor measurement model did not reach convergence, likely due to the process of selecting items from different scales. We hence decided to fit a one-factor measurement model. The CFA in this case reached convergence, but the fit was poor: $\chi^2 = 574.721$, $d.o.f. = 170$, $p < 0.001$, $CFI = 0.571$, $TLI = 0.548$, $RMSEA = 0.081$, and $SRMR = 0.0939$. After removing eight poor-fitting items and examining suggested *modification indices*, the initial model was re-specified by introducing four covariances between the error terms. These changes were made iteratively, including only those parameters that showed clear theoretical plausibility (e.g., similar item wording or strong conceptual proximity), leading to a significant improvement in the model's overall fit: $\chi^2 = 81.955$, $d.o.f. = 50$, $p = 0.003$, $CFI = 0.948$, $TLI = 0.931$, $RMSEA = 0.042$, and $SRMR = 0.0444$. More details about the CFA are reported in Section S1 of Supplementary Materials. Finally, we calculated reliability of the retained 12 items, obtaining a value of McDonald's $\omega = 0.75$, which can be considered acceptable given the diversity of the themes addressed in the items. A total score for the attitudes towards energy was hence obtained by averaging the scores of the 12 retained items. For comparison purposes, we performed a linear regression analysis to investigate whether the total score of the attitudes towards energy was associated with the combined score of declarative knowledge and reasoning tiers and with the average confidence score.

RQ1. To answer RQ1, we performed a latent profile analysis (LPA), a theoretically based, person-centred statistical technique that aims to identify hidden subgroups or types of individuals within a population according to common configurations and patterns of observed indicators. Unlike traditional variable-centred methods, LPA accounts for individual heterogeneity by assigning participants to distinct latent classes based on posterior membership probabilities [37]. According to our theoretical framework, we used three indicators: (i) the combined score of the declarative knowledge and reasoning tiers (tier 1 and 3); (ii) the normalized average score of the respective confidence tiers (tier 2 and 4); and (iii) the attitudes towards energy scale score. The three indicators were *z*-standardized. The reason for using standardized values was twofold: first, the indicators were originally measured on entirely different scales with unequal ranges and variances. In LPA, variables with larger raw scales and higher variances mathematically dominate the model's log-likelihood estimation function, artificially inflating their weight in determining profile distances, while masking the contribution of variables with smaller ranges. Therefore, standardizing the three indicators ensures that they are analysed on a comparable metric. Second, transforming the raw data into *z*-scores enhances interpretability of the profiles, allowing for an immediate identification of student clusters that score below, at, or above the sample-average baseline. However, to confirm that this operation did not distort the natural covariance structure of the data, a robustness check was performed by re-running the LPA on unstandardized raw scores. Then, to determine the optimal number of latent profiles, an enumeration process was conducted by systematically evaluating solutions from two to seven classes. To select the best-fitting model, we implemented an analytic hierarchy process (AHP) [38] comparing four distinct model specifications across all class solutions: Model 1 (equal variances, covariances fixed to zero); Model 2 (varying variances, covariances fixed to zero); Model 3 (equal variances, free covariances); and Model 6 (varying variances, free covariances). This multi-criteria approach synthesizes five complementary indices—the Akaike information criterion (AIC), the approximate weight of evidence (AWE), the Bayesian information criteria (BIC), the classification likelihood criterion (CLC), and the Kullback information criterion (KIC)—to mathematically identify the most robust profile configuration. Specifically, since, for all of the information indices considered, a lower raw value indicates a better fit to the data, the raw data vectors were first inverted using a reciprocal transformation (1/(raw index value)) and then normalized, hence mapping the minimum values to the highest local maxima. The global weights assigned to the criteria followed the empirical comparison matrix described in [38], which attributes greater theoretical significance to the indices that are more robust against the risk of overfitting: KIC (weight = 0.310), BIC (weight = 0.253), AIC (weight = 0.232), AWE (weight = 0.113) and CLC (weight = 0.092). The final synthesis of the alternatives was carried out using the simple additive weighting (SAW) procedure, which involves obtaining the final composite score for each model by multiplying the local maximum that the model has achieved in a specific fit index by the global weight assigned to that index and then summing these products across all five criteria considered. The model that achieves the highest normalized overall score represents the solution that represents the best theoretical and statistical balance between parameter parsimony and data fitting. The AHP allowed us to also carry out a post hoc sensitivity analysis regarding the variance–covariance parameterization to account for the inherent dependency among our indicators—particularly between the combined score of the declarative knowledge and reasoning tiers and the normalized average score of the respective confidence tiers, which were derived from the same 10-item instrument. Specifically, by relaxing the local independence assumption (as in Models 3 and 6) we empirically verified whether the emerging class structure was driven by latent participant subgroups or if it merely reflected residual statistical correlations between

the indicators. Then, to support the chosen solution, we also carried out a qualitative analysis by comparing the BIC value, the bootstrapped likelihood ratio test (BLRT), entropy and smallest profile size [37]. We chose the BIC index because it serves as an indicator of model quality, with lower BIC values indicating a better and more parsimonious fit. The BLRT evaluates whether a solution with K profiles provides a statistically significant improvement over a nested model with $K - 1$ profiles. A p-value below 0.05 suggests that the K-profile model should be retained, whereas a p-value greater than 0.05 indicates that the additional profile does not justify the loss of parsimony, favouring the simpler $K - 1$ solution. Classification accuracy was monitored via entropy, which quantifies the separation between the identified classes on a scale from 0 to 1. An entropy value above 0.60 indicates acceptable classification, while values exceeding 0.80 reflect excellent profile separation. Once the optimal model and parametrization were selected based on these converging criteria, each participant was assigned to a specific latent profile using the maximum posterior membership probability framework. Finally, to guarantee the validity of the extracted solution, we evaluated the assumption of intra-class multivariate normality, namely that indicators follow a multivariate normal distribution within each distinct latent profile. To empirically test this assumption, participants' final profile memberships were saved, and Mardia's criteria for multivariate skewness and kurtosis were calculated separately for each extracted profile.

RQ2. To answer RQ2 and investigate the extent to which gender predicted students' membership in the emerging latent psychological–cognitive profiles, we used a classification-error-adjusted maximum-likelihood (ML) three-step approach, inspired by existing correction approaches for mixture models [39,40]. This procedure allowed the relationships between gender and latent profile membership to be estimated while preserving the profile solution identified in the enumeration stage and accounting for uncertainty in profile classification. In the first step, the latent profile model was estimated without including external predictors. In the second step, participants were assigned to their modal profiles on the basis of their posterior membership probabilities. These probabilities were then used to estimate the so-called *classification-error matrix*, D, whose elements represented the conditional probabilities of being assigned to each modal profile given membership in each latent profile. In the third step, the classification-error matrix was held fixed while gender was entered as a predictor of latent profile membership. Specifically, the model estimated the probability of observed modal assignment as a function of the latent profile probabilities conditional on gender and the classification-error matrix. Thus, the likelihood incorporated the distinction between latent profile membership and potentially fallible modal assignment rather than treating the assigned profiles as observed without error. Gender was entered as a binary categorical predictor, with male students as the reference category. The extracted profile with the worst estimates in the three indicators was designated as the baseline reference category. The solution with the lowest negative log-likelihood among those that converged successfully was retained. Standard errors were obtained from the inverse Hessian matrix of the retained solution. The statistical significance of gender was first evaluated through an omnibus Wald test across the two profile contrasts. Profile-specific effects were subsequently examined using unstandardized logit coefficients, standard errors, Wald statistics, odds ratios, and 95% confidence intervals. Statistical significance was evaluated using a two-sided alpha level of 0.05. Mathematical details of the Classification-Error-Adjusted Three-Step Model are reported in Section S6 of the Supplementary Material.

Descriptive analyses were carried out using IBM SPSS v. 30. CFA was carried out with IBM AMOS v.30. LPA was first carried out in Jamovi software v.2.73.8 and then in R version 4.6.1 using the tidyLPA package (v. 2.0.2) with the mclust package (v. 6.1.3) as

the estimation engine using maximum-likelihood estimation. Initial class assignments were obtained through the hierarchical-clustering initialization procedure implemented in mclust, based on Singular Value Decomposition (SVD). The BLRT was computed using 100 parametric bootstrap replications. The ML three-step approach was implemented in R version 4.6.1 using a custom function based on the optim() function from the base R stats package. The Broyden–Fletcher–Goldfarb–Shanno algorithm was used for numerical optimization. To reduce the risk of retaining a local optimum, 100 sets of starting values were evaluated, comprising one zero-value start and 99 randomly generated starts. Mardia's diagnostic test was executed via the *psych* package using the Rj (R Journal) integration within the Jamovi v.2.37.8 program.

5. Results

5.1. Descriptive Statistics of the Content Knowledge Questionnaire

Table 1 reports the item-level descriptive statistics and psychometric indices for the 10-item four-tier energy knowledge questionnaire. For each item, we report the proportion of correct answers for the declarative knowledge tier (*T*1) and the reasoning tier (*T*3), alongside the mean normalized confidence scores for both tiers (T2) and (*T*4), respectively. Additionally, the combined difficulty index (*D*), i.e., the success rate when both *T*1 and *T*3 are correct and the combined discrimination index (Δ) is reported, along with the overall average confidence (*Conf*). At the single-tier level, neither T1 or T3 exhibited extreme difficulty parameters, with success rates remaining within the accepted thresholds of 20% to 80%. To examine the relationships between declarative knowledge and reasoning tiers, a Pearson correlation analysis was performed at the student level. The results show a moderate positive association between the two tiers (r = 0.55, $p < 0.001$), indicating that approximately only 32% of the variance in students' scientific reasoning was accounted for by their declarative content knowledge base. Consistently, when looking at the combined scores of *T*1 and *T*3, results show that the difficulty index decreases for all items. This evidence suggests that students on average were not able to correctly justify their answers, supporting an overall lack of content knowledge about the four energy-related key ideas addressed in the questionnaire. Furthermore, four items were excessively difficult, falling below the acceptable 20% success threshold: *Gymnast 2, Wind turbine 1, Cyclist, and Skater*. These items referred to the key ideas of energy transfers and energy conservation. Note that, among these four items, the *Skater* item also exhibited a negative discrimination index, which signals improper psychometric functioning (i.e., lower-performing students answered it correctly more frequently than higher-performing students). To guarantee the structural validity and reliability of the final indicators, this malfunctioning item was excluded from all subsequent analyses. Consequently, the final indicators used for the LPA were computed based on the remaining nine combined items. This choice was also supported by the reliability analysis. McDonald's omega for the 10 combined items could not be calculated because of negative correlations with other items, while after removing item 10 we obtained a value of ω = 0.62. This modest value of internal consistency should be interpreted cautiously in light of the heterogeneous conceptual content of the inventory.

Table 1. Descriptive statistics for the 10 items of the content knowledge questionnaire.

Item	T1 [a] M ± SE	T2 [b] M ± SE	T3 [c] M ± SE	T4 [d] M ± SE	D [e]	Δ [f]	Conf [g] M ± SE
Gymnast 1	0.72 ± 0.02	0.51 ± 0.01	0.68 ± 0.02	0.48 ± 0.01	0.60	0.24	0.50
Gymnast 2	0.35 ± 0.02	0.37 ± 0.01	0.31 ± 0.02	0.40 ± 0.02	0.10	0.19	0.38
Cars	0.43 ± 0.03	0.51 ± 0.02	0.48 ± 0.03	0.51 ± 0.02	0.36	0.28	0.50

Table 1. *Cont.*

Item	T1 [a] M ± SE	T2 [b] M ± SE	T3 [c] M ± SE	T4 [d] M ± SE	D [e]	Δ [f]	Conf [g] M ± SE
Wind turbine 1	0.34 ± 0.02	0.48 ± 0.02	0.32 ± 0.02	0.46 ± 0.01	0.13	0.24	0.47
Wind turbine 2	0.47 ± 0.03	0.42 ± 0.02	0.39 ± 0.02	0.42 ± 0.02	0.26	0.41	0.42
Arrow 1	0.60 ± 0.03	0.50 ± 0.02	0.51 ± 0.03	0.48 ± 0.02	0.39	0.42	0.49
Arrow 2	0.45 ± 0.03	0.40 ± 0.02	0.32 ± 0.02	0.39 ± 0.01	0.22	0.24	0.40
Cyclist	0.23 ± 0.02	0.48 ± 0.01	0.33 ± 0.02	0.44 ± 0.01	0.08	0.22	0.46
Hydroelectric power station	0.42 ± 0.03	0.45 ± 0.02	0.40 ± 0.02	0.42 ± 0.01	0.24	0.38	0.44
Skater	0.24 ± 0.02	0.42 ± 0.01	0.29 ± 0.02	0.41 ± 0.02	0.07	−0.02	0.41
Total	0.45 ± 0.01	0.45 ± 0.01	0.40 ± 0.01	0.44 ± 0.01	0.24 ± 0.01	0.26 ± 0.04	0.45 ± 0.01

[a] Percentage of correct answers for the declarative knowledge tier. [b] Normalized confidence for the declarative knowledge tier. [c] Percentage of correct answers for the reasoning tier. [d] Normalized confidence for the reasoning tier. [e] Difficulty index of the combined declarative knowledge and reasoning tiers. [f] Discrimination index of the combined declarative knowledge and reasoning tiers. [g] Overall average confidence.

Finally, to investigate students' metacognitive monitoring and calibration, we report in Figure 2 the scatter plot of the average score for the confidence tiers and corresponding combined score of declarative knowledge and reasoning tiers at the item level. The solid diagonal line represents numerical equality between normalized mean confidence and the knowledge success rate and can be used as a reference to evaluate students' calibration. Inspection of the scatter plot shows that nine out of the ten items are positioned within the upper-left quadrant, above the ideal calibration line, thus suggesting the presence of over-confidence bias across the student sample. Moreover, when retaining all 10 items, Pearson correlation between the students' average score for the confidence tiers and corresponding combined score of declarative knowledge and reasoning tiers is r = 0.33 ($p < 0.001$), which slightly increases to a value of r = 0.35 ($p < 0.001$) when removing the misfunctioning item *Skater*. Overall, these results suggest that, on average, students may hold misconceptions about the four key ideas of the energy concept.

5.2. Descriptive Statistics of the Attitudes Towards Energy Questionnaire

The average score of the 12 retained items was 3.38 (SD = 0.69). The zero-order correlations between attitudes scores and the combined conceptual understanding and confidence score are r = 0.29 ($p < 0.001$) and r = 0.18 ($p < 0.001$), respectively. The results of the linear regression using the combined score of the declarative knowledge and reasoning tiers and the average confidence score, after having removed item 10, are reported in Table 2. The results are consistent with the correlational analysis and show that the model accounted for approximately 9.3% of the total variance in students' attitudes towards energy scores and that only the energy conceptual understanding score is a significant predictor.

Table 2. Regression model for *Attitudes towards energy* score.

Predictor	B [a]	95% C.I.	t	*p*
Intercept	3.051	2.091–3.202	39.939	<0.001
Combined knowledge and reasoning	0.832	0.502–1.162	4.962	<0.001
Average confidence	0.246	−0.063–0.556	1.568	0.118

$R^2 = 0.093$, adj $R^2 = 0.088$, $F(2, 360) = 18.425$, and $p < 0.001$. [a] Unstandardized coefficient.

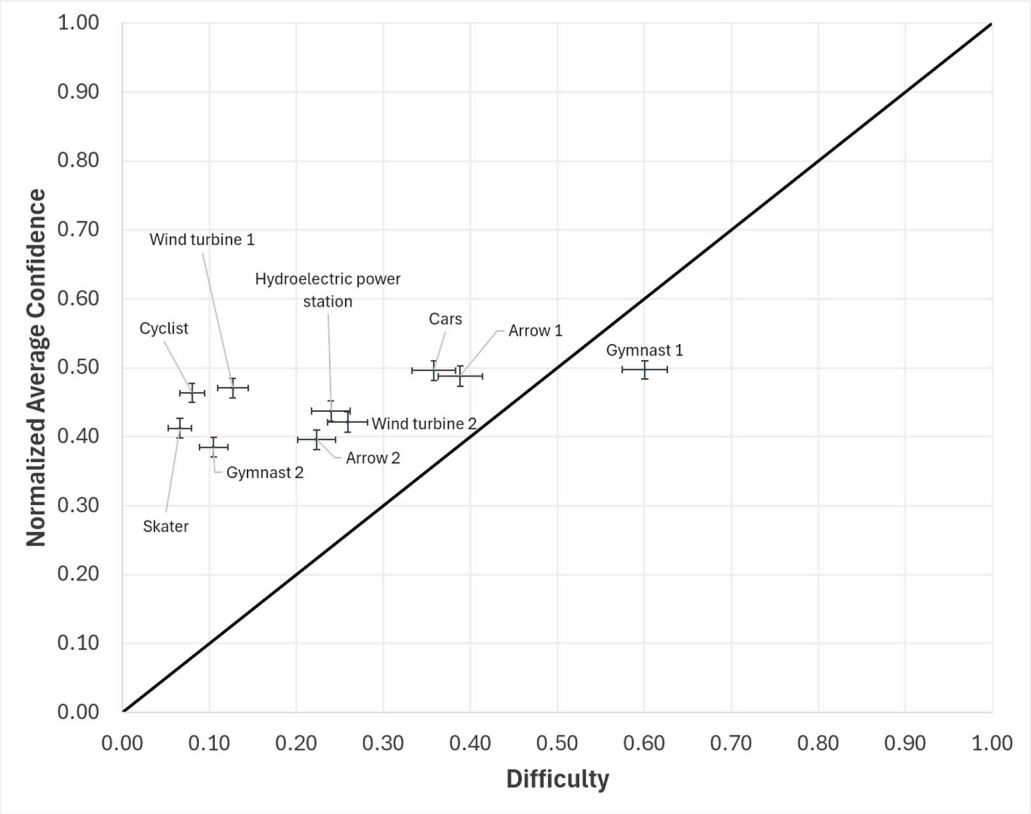


Figure 2. Average normalized confidence score vs. combined declarative knowledge and reasoning success rate (difficulty index) at the item level. The solid diagonal line represents ideal calibration between student confidence judgment and their actual performance. Items above the line indicate an overconfidence bias, while items below indicate an underconfidence bias. Error bars represent standard errors.

5.3. Latent Profile Analysis

The preliminary correlational and regression analyses reported above suggest that each indicator retains a substantial amount of unique variance, justifying their simultaneous inclusion as separate profile indicators in the LPA.

The AHP procedure suggested that Model 1, with three classes, was the best solution. In Section S2 of the Supplementary Materials, we report the table with the fit indices for the four tested models across class solutions from two to seven and the decision table with the ranking of the first ten models. Note also that the sensitivity analysis carried out to empirically test whether the forced equal variances and zero-covariance assumptions of Model 1 introduced classification artifacts due to the residual dependence between indicators showed that relaxing the constraints worsened the BIC values for the equivalent three-profile solutions (Model 2 = 3050; Model 3 = 3029; and Model 6 = 3063). This further empirical evidence suggests that among the parameterizations examined, releasing the specified parameters did not improve model fit according to BIC relative to Model 1 for the three-class solution. The complete sensitivity table as well as average posterior probabilities for the three profiles are also reported in Section S2 of the Supplementary Materials. Then, to qualitatively support the three-profile solution, Model 1 fit indices for the solutions with one to seven profiles were compared (see Table 3). We note that the KIC has a minimum (=2975) for the four-profile solution, while the BIC has a minimum (=3016) for the three-profile solution and the BLRT *p*-value suggests to retain the four-profile solution, being greater than the 0.05 threshold for the five-profile solution. However, classification accuracy is higher for the three-profile solution (entropy = 0.754) with respect to the four-profile solution (entropy = 0.695). The

robustness check performed by re-running the LPA on unstandardized raw scores suggested the same three-profile solution with Model 1. On the basis of the above results, we decided to retain the three-profile solution.

Table 3. Model 1 fit indices for LPAs of students' energy literacy from two to seven profiles.

Number of Profiles	LL	FP [a]	AIC	BIC	KIC	AWE	CLC	Entropy	BLRT	Smallest Profile Size
1	−1543.721	6	3099	3123	3108	3174	3089	1.000	-	-
2	−1484.921	10	2990	3029	3003	3116	2972	0.892	117.564 **	8.81%
3	−1466.836	14	2962	3016	2979	3139	2935	0.754	36.129 **	6.33%
4	−1458.831	18	2954	3024	2975	3183	2919	0.695	15.951 **	6.06%
5	−1454.679	22	2953	3039	2978	3233	2911	0.709	8.3196	6.61%
6	−1451.696	26	2956	3057	2985	3287	2905	0.690	5.9484	6.61%
7	−1447.821	30	2956	3072	2989	3338	2897	0.730	7.8906	1.93%

LL = log likelihood; FP = free parameter; AIC = Akaike information criterion; BIC = Bayesian information criterion; KIC = Kullback information criterion; AWE = approximate weight of evidence; CLC = classification likelihood criterion; BLRT = bootstrapped likelihood ratio test; [a] The number of free parameters is calculated as $2JC - (J-1)(C-1)$ where J is the number of indicators and C is the number of profiles. In our case, $J = 3$. ** $p < 0.01$.

A post-hoc descriptive characterization of differences among previously estimated profiles was then carried out through a Multivariate Analysis of Variance (MANOVA), entering profile membership as the between-subjects factor and the standardized Z-scores of the three indicators as dependent variables. The multivariate omnibus criteria confirmed a highly significant main effect for profile membership, Wilks' $\Lambda = 0.176$, $F(6, 716) = 164.831$, $p < 0.001$, partial $\eta^2 = 0.580$, and subsequent univariate follow-up tests demonstrated that the clusters statistically differed on all three individual dimensions ($p < 0.001$). More details are reported in Section S3 of the Supplementary Materials.

Figure 3 shows the profile plot of the three-profile solution, while Figure 4 shows the profiles' means in the average normalized confidence score vs. combined declarative knowledge and reasoning score plane. When looking at Figure 3, Profile 1 (n = 202; 55.6% of the sample; blue line) is characterized by below-average values in the content knowledge dimension, while response confidence and attitudes towards energy are slightly below the sample mean. From Figure 4, this profile is located well above the calibration line, thus suggesting high overconfidence. Hence, this profile represents students who are overall less interested in sustainability issues related to energy, while being simultaneously unaware of their lack of content knowledge about energy. Thus, we labelled this profile as *Overconfident and with Lower Attitudes*. Profile 2 (n = 23; 6.3%; purple line) is characterized by significantly higher-than-average scores in content knowledge and confidence dimensions, with higher-than-average attitudes scores. This profile is located near the calibration line, suggesting an overall awareness of their own knowledge. Thus, we labelled this profile as *Knowledgeable, Calibrated and with Higher Attitudes*. Finally, Profile 3 (n = 138; 38.0%; yellow line) is characterized by above-sample-average scores in the conceptual dimension and positive attitudes, with their confidence score slightly above the sample mean. The profile is placed near the center of the average normalized confidence score vs. combined declarative knowledge and reasoning score plane, suggesting overall calibration. Thus, we labelled this profile *Calibrated and with Higher Attitudes*. A post hoc analysis aimed at exploring metacognitive calibration at the individual level for each profile using *overconfidence bias* as the response variable is reported in Section S4 of the Supplementary Materials.

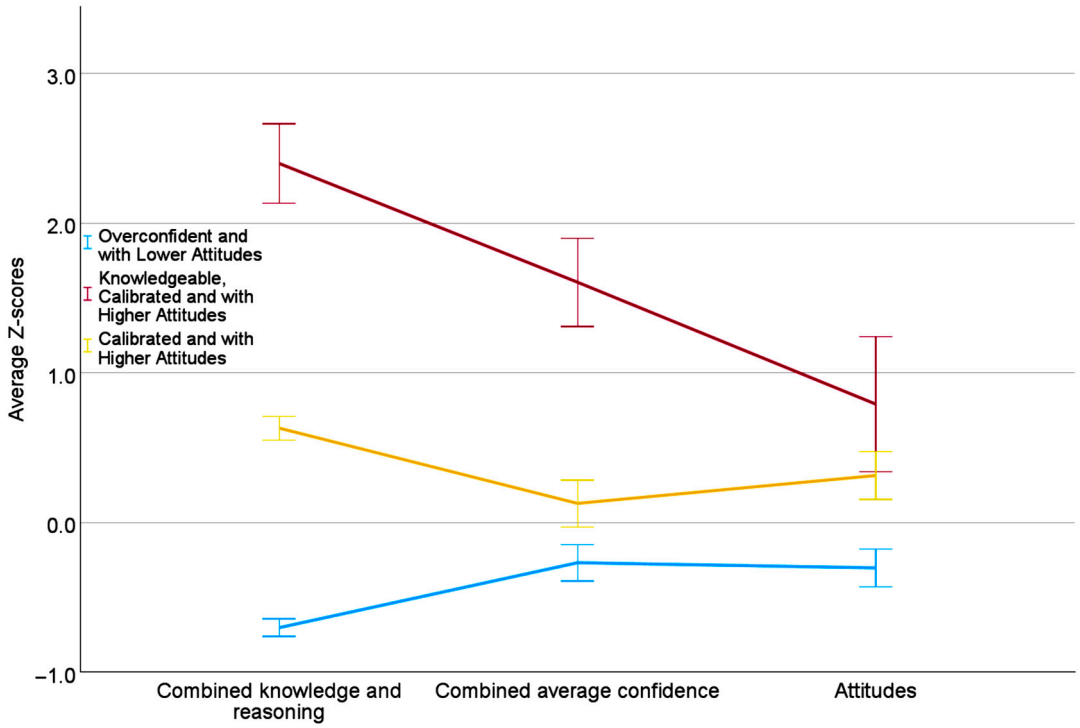


Figure 3. Indicator plot for the three-profile solution. Error bars represent standard errors.

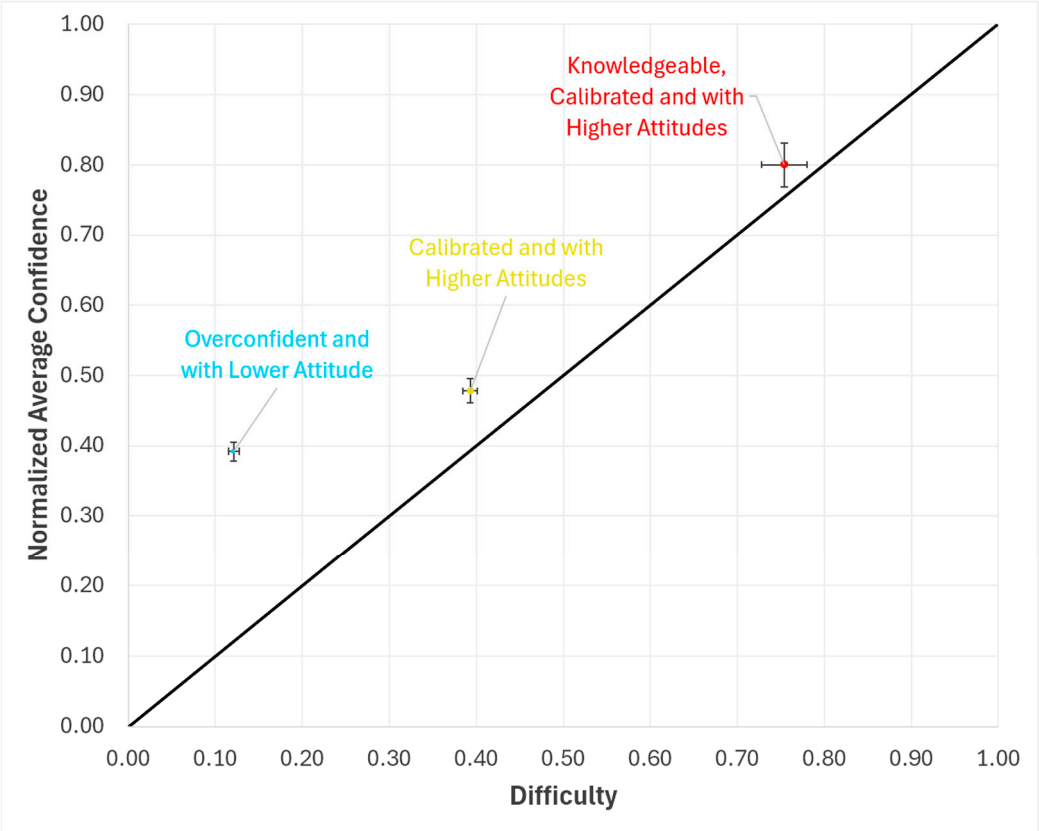


Figure 4. Average normalized confidence score vs. combined declarative knowledge and reasoning success rate (difficulty index) at the profile level. Error bars represent standard errors.

Finally, the Mardia's test performed to confirm the assumption of intra-class multivariate normality for the three-profile solution shows that, for Profile 1, there was no

significant multivariate skewness (b_{1p} = 0.42, χ^2 = 14.27, p = 0.16) or kurtosis (b_{2p} = 14.16, $z = -1.09$, p = 0.27). Moreover, Profile 2 also met the multivariate normality criteria for both dimensions (skewness: b_{1p} = 1.35, small sample χ^2 = 6.24, p = 0.79; *kurtosis*: b_{2p} = 10.90, $z = -1.79$, and p = 0.073). Finally, Profile 3 also exhibited a non-significant multivariate kurtosis close to the theoretical value of 15 (b_{2p} = 14.28, $z = -0.77$, p = 0.44), but a minor statistically significant multivariate skewness (b_{1p} = 0.87), χ^2 = 20.00, p = 0.029). Given the robustness of the maximum likelihood estimation algorithm in LPA against minor skewness deviations in large subgroups, the overall parameters of multivariate normality within the extracted classes were considered acceptable.

For the sake of completeness, we report in Section S5 of the Supplementary Materials the distribution of the students grouped according to the schools attended across the three emerging profiles.

5.4. Association Between Profiles and Gender

To address RQ2, gender was entered as a predictor of latent psychological–cognitive profile membership using the classification-error-adjusted maximum-likelihood three-step model. The *Overconfident and with Lower Attitudes* profile was used as the reference profile, and male students were used as the reference category for gender. The omnibus *Wald* test was not statistically significant, $\chi^2_W(2) = 3.00$, $p = 0.223$, indicating that gender did not significantly predict overall membership across the three latent profiles. The profile-specific contrasts are reported in Table 4. Compared with male students, female students had higher estimated odds of belonging to the *Knowledgeable, Calibrated, and with Higher Attitudes* profile rather than the Overconfident and with Lower Attitudes profile, $B = 0.54$, $SE = 0.47$, $OR = 1.72$, and 95% CI [0.68, 4.32]. However, this contrast was not statistically significant, $p = 0.249$. Female students also had higher estimated odds of belonging to the *Calibrated and with Higher Attitudes* profile rather than the reference profile, $B = 0.44$, $SE = 0.29$, $OR = 1.56$, and 95% CI [0.88, 2.76], but this contrast was also not statistically significant, $p = 0.131$.

Table 4. Classification-error-adjusted maximum-likelihood three-step model predicting latent psychological–cognitive profile membership from gender.

Pairwise Comparison	B [a]	SE	Wald *z*	OR	95% C.I.	*p*
Profile 2 vs. 1	0.542	0.470	1.153	1.720	[0.684–4.320]	0.249
Profile 3 vs. 1	0.442	0.292	1.511	1.555	[0.877–2.757]	0.131

Note. Male (Gender = 0) and Profile 1 *Overconfident and with Lower Attitudes* were taken as the reference category. Profile 2: *Knowledgeable Calibrated and with Higher Attitudes;* Profile 3: *Calibrated and with Higher Attitudes.* [a] Unstandardized coefficient.

6. Discussion

The present study adopted a person-centred approach to investigate energy literacy among Italian secondary school students by adopting a psychological–cognitive oriented operationalization focused on three indicators: energy-related content knowledge, confidence judgments and attitudes. The application of latent profile analysis (LPA) led to the identification of three distinct student subgroups characterized by unique intra-individual configurations of the three indicators. By addressing a significant gap in the energy literacy literature—which has predominantly relied on variable-centred average scores and aggregate associations—this study captures how cognitive, psychological, and metacognitive dimensions dynamically interact within specific profiles of learners.

6.1. Latent Profiles of Energy Knowledge, Confidence, and Attitudes

With regard to RQ1, the analysis identified three latent profiles: *Overconfident and with Lower Attitudes*, *Calibrated and with Higher Attitudes*, and *Knowledgeable, Calibrated and with Higher Attitudes*. The majority of students (55.6%) belong to the *Overconfident and with Lower Attitudes* profile, exhibiting below-average content knowledge, weaker attitudes towards energy-related sustainability issues and a significant overconfidence bias, namely students in this profile seem to be not aware of their lack of knowledge when dealing with familiar energy-related contexts. Such lack of metacognitive awareness may be likely due to energy's "invisibility" in everyday phenomena [41]. The identification of the *Overconfident and with Lower Attitudes* profile is a novel finding since previous research has often reported that secondary school students, while showing partial mastery of fundamental energy concepts, are usually interested in energy and environmental issues [19,25,26]. Moreover, regarding the four key energy ideas—forms, transfers, conservation, and degradation—addressed in our instrument, our findings suggest the existence of robust misconceptions, which should be addressed through targeted instructional interventions aiming to show how energy degradation and transformations can be applied to real-life systems [42]. Similarly, the identification of the *Calibrated and with Higher Attitudes* profile also adds to existing research providing evidence that students may have positive attitudes towards energy-related issues but they can also be realistically aware that their knowledge may not be sufficient to explain basic physical concepts underlying familiar energy-related issues, thus reducing the gap between attitudes and knowledge [43]. Finally, the *Knowledgeable, Calibrated and with Higher Attitudes* profile, characterized by high levels of knowledge, confidence and positive attitudes, represented only 6.3% of the sample. The relatively small size of this group supports the fact that mastering core energy concepts is likely to be challenging for the majority of secondary school students and that students may experience difficulties in achieving a solid understanding of all four energy-related key ideas during their secondary school curriculum [33]. In the Italian physics curriculum, such difficulties may be linked to the fact that energy concepts are mainly addressed in the context of mechanics and thermodynamics, with little attention to how basic principles apply to industrial plants, electrical supplies or everyday phenomena.

6.2. Gender as a Predictor of Profile Membership

With regard to RQ2, the classification-error-adjusted three-step analysis did not identify a statistically significant association between gender and latent energy-literacy profile membership. Although female students showed higher estimated odds than male students belonging to either of the two more calibrated and positively oriented profiles rather than to the *Overconfident and with Lower Attitudes* profile, the omnibus test and profiles contrasts were not statistically significant. However, the directions of the estimates nevertheless remain theoretically relevant. Female students had estimated odds 1.72 times higher of belonging to the *Knowledgeable, Calibrated, and with Higher Attitudes* profile and 1.56 times higher odds of belonging to the *Calibrated and with Higher Attitudes* profile, relative to the *Overconfident and with Lower Attitudes* profile. This trend, although not significant, is broadly compatible with previous research reporting that female students had greater ecological sensitivity, stronger pro-environmental attitudes, and a more pronounced orientation toward environmental issues [32,43], and lower confidence in some science-related domains despite possessing knowledge levels comparable to those of male students and often in the absence of equivalent differences in actual performance [30,44].

7. Limitations and Future Research

In the following, we report the main limitations that should be considered when interpreting the findings of the present study.

First, the sample size (N = 363) was somewhat lower than the threshold of approximately 500 participants commonly recommended in the literature to guarantee maximum statistical power and obtain highly stable latent profile solutions. However, methodological studies [45] show that a minimum of 300 observations is sufficient for information criteria to function adequately, particularly when the model structure yields a small number of well-separated profiles. In our study, the validity of the three-profile solution is strongly supported by an acceptable entropy value (0.754) reflecting clear class demarcation and a multi-criteria analytic hierarchy process that compared different LPA models. Furthermore, our smallest extracted subgroup (n = 23, 6.3%) meets the 5% threshold and the minimum cell size of 20–30 cases recommended to avoid severe estimation biases. Note that, given the study's exploratory nature, the nested nature of our data was not explicitly modelled via multilevel LPA. Preliminary analysis indicated relatively low intraclass correlation coefficients (ICCs) for our indicator variables (0.22 for the combined knowledge and reasoning score, 0.21 for the confidence score, and 0.05 for the attitudes towards energy scale score, respectively), suggesting modest cluster-level variance. However, omitting a formal multilevel framework entirely means we cannot completely rule out the inflation of standard errors or the identification of spurious profiles. Future research is warranted to replicate these findings using MLPA to formally model partition within- and between-cluster variance.

Second, a major conceptual limitation concerns the construct delimitation and the partial operationalization of energy literacy adopted in this work. Due to the known constraints and social desirability biases associated with self-reported behavioural surveys in high school settings, this study deliberately focused on the psychological–cognitive dimensions of energy literacy (knowledge and attitudes) adding a metacognitive dimension (response confidence). Actual energy-related behaviours, agency, participation, or direct contributions to the energy transition were not empirically measured. Consequently, our findings do not describe students' psychological readiness to enact sustainable behaviours, and caution should be used not to infer direct causal links between profile membership and real-world environmental actions. Future research could incorporate objective behavioural metrics to empirically test how the psychological–cognitive profiles translate into concrete energy-saving actions.

Third, from a psychometric perspective, the analysis carried out on the energy attitude scale provides only preliminary within-sample construct-related evidence. The final 12-item structure requires independent replication to confirm construct-related evidence. Moreover, the internal consistency of the refined scale (ω = 0.75) is acceptable but lower than the 0.80 threshold of good reliability. This is likely due to the initial choice of items, which referred to conceptually heterogeneous domains, such as energy-saving views, renewable energy perceptions, and climate anxiety. While acceptable for complex psychological constructs and concept inventories, this moderate reliability must be acknowledged when interpreting the contribution of the attitude indicator to the profiles.

Fourth, we acknowledge that the adopted combined score of the declarative knowledge and reasoning tier and the adopted average score for the corresponding confidence ties may have led to overestimation of the overconfidence bias. Using a less conservative scoring system, e.g., a partial credit scoring, may increase performance and thus reduce overconfidence. Similarly, using a different combination of the confidence ratings or a single confidence rating for both the declarative knowledge and reasoning tiers could have led to a different estimation of the overconfidence bias. We are planning to re-analyse

the data for a subsequent study to investigate how overconfidence changes according to different choices f of the performance scoring.

Fifth, the lack of statistical significance in the association between gender and profile memberships may reflect genuinely modest gender differences, limited statistical power for comparisons involving the smaller profiles, or both. In particular, the precision of a multinomial three-step model depends not only on the total sample size but also on the number of students within each profile and on the quality of classification. Further studies with larger and more representative samples are therefore needed to determine whether the directional patterns observed here are reproducible across educational settings.

Finally, we involved a convenience sample of Italian secondary school students. Because energy literacy is deeply embedded in localized educational experiences, curricular variations, cultural values, and national energy policies, the generalizability of the current three-profile structure remains sample-dependent. Future cross-cultural and longitudinal studies are warranted to investigate the extent to which these specific profiles are replicated across different educational systems, geographic regions, or broader age cohorts.

8. Conclusions

The findings of this study have significant implications for both educational research and instructional practice. First, this work provides strong empirical support for the view that energy literacy cannot be treated as a uniform or unidimensional construct [12,13]. Namely, students vary not only in terms of their levels of knowledge and attitudes, but also in the degree of confidence with which they apply their understanding of energy-related concepts. Consequently, educational interventions designed to foster energy literacy should move away from a "one-size-fits-all" framework and carefully account for these distinct student profiles rather than assuming that all learners share identical educational needs. Specifically, the evidence that the majority of students in our sample, which was constituted by students who voluntarily participated in out-of-school activities focused on energy, belong to the *Overconfident and with Lower Attitudes* profile underscores that traditional, purely informative instruction is insufficient. For these learners, instructional strategies should not merely transmit content and stimulate interest towards sustainability challenges [21,22], but also challenge misconceptions. Conversely, to support students who belong to the *Calibrated and with Higher Attitudes* profile, teachers could focus on strengthening complex conceptual reasoning, promoting systems thinking, and guiding students to connect basic physical principles with real-world energy challenges [46–48]. Activities involving case studies, peer instruction, and inquiry-based learning are also particularly valuable for bridging the documented knowledge–attitude gap and helping students contextualize the "invisibility" of energy in daily routines [49].

Second, although not statistically significant, the association between gender and profile membership provides insights into inclusive STEM and environmental education. The evidence that female students are more likely to belong to calibrated profiles when dealing with energy-related issues suggests that educational interventions could strategically leverage this realistic self-assessment by creating collaborative classroom environments, structured debates, and argumentation tasks that empower female students to communicate their understanding. However, our results do not support the use of gender alone as a basis for differentiated energy-literacy interventions. Instruction should instead respond to students' observed combinations of knowledge, metacognitive calibration, and energy-related attitudes. Although gender-sensitive teaching practices remain valuable for ensuring equitable participation in STEM and sustainability education, the present results suggest that profile-specific educational needs should not be inferred solely from students' gender.

In conclusion, the adopted psychological–cognitive operationalization of energy literacy shows that school curricula require a balanced approach that simultaneously targets energy-related conceptual mastery, value-based attitudinal alignment, and metacognitive monitoring. While future research incorporating reliable behavioural measurement is required to model how the emerging profiles translate into actual sustainable actions, the current person-centred evidence offers educators effective suggestions to design tailored, profile-specific interventions about energy and sustainability that are potentially more aligned with the diverse requirements of secondary school students.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su182110770/s1: CFA of the attitudes towards energy questionnaire (S1), the comparison of the distinct model specifications across all class solutions for the LPA (S2), the post hoc MANOVA on emerging profiles (S3), the post hoc analysis for overconfidence bias at the individual level for the emerging profiles (S4) and the post hoc analysis of associations between profiles and schools (S5). We also report a detailed description of the classification-error-adjusted three-step model specifically developed for the present study (S6). References [50–53] are cited in the Supplementary Materials. Supplementary Figures captions: Figure S1. Initial 3-factor measurement model of the Attitudes towards energy questionnaire; Figure S2. Initial 1-factor measurement model of the Attitudes towards energy questionnaire; Figure S3. Final 1-factor measurement model of the Attitudes towards energy questionnaire; Supplementary Tables captions: Table S1. Standardized Regression weights for the 3-factor measurement model of the Attitudes towards energy questionnaire; Table S2. Standardized Regression weights for the 1-factor measurement model of the Attitudes towards energy questionnaire. Poor fitting items are in italics. Table S3. Fit indices for the four tested models across class solutions from 2 to 7; Table S4. Weighted scores of the fit indices for the first ten ranked models; Table S5. Average posterior probabilities for the three profiles; Table S6. MANOVA results for the 3-profile solution; Table S7. Univariate tests of Between-Subjects Effects for the 3-profile solution; Table S8. Post-hoc tests for profiles' OCB; Table S9. Distribution of schools across the three profiles; Table S10. Classification-error matrix D used in the three-step analysis of the present study.

Author Contributions: Conceptualization, I.T.; methodology, I.T.; formal analysis, C.G. and I.T.; data curation, C.G., F.A. and A.D.G.; writing—original draft preparation, I.T.; writing—review and editing, I.T.; funding acquisition, I.T. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Ethical review and approval were waived for this study by the Institutional Ethics Committee, in accordance with the General Data Protection Regulation (GDPR), Italian Legge n. 189/2012, and Decreto 8 febbraio 2013. In accordance with the Italian national legal framework regarding ethical approval—specifically Legge n. 189/2012 and Decreto 8 febbraio 2013—local institutional ethics committees hold statutory jurisdiction strictly over clinical, medical, and pharmacological trials. Consequently, non-clinical research in the social and educational sciences, such as the present study, falls outside their legal mandate and qualifies for an exemption from clinical ethical approval. However, alternative rigorous ethical protocols were enforced for the current study. Specifically, institutional recruitment was formally approved and authorized by the respective School Principals (Dirigenti Scolastici) following an internal review within the administrative framework of the national *Piano Lauree Scientifiche* project.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study. Institutional authorization for each school's participation was provided by the respective school principal. Because the participating cohorts could include both minors and legal adults, each school was responsible for applying its internal procedures concerning informed consent from adult students, parental or legal guardian authorization for minors, and assent from minor students where applicable. The authors did not administer or retain individual consent, authorization, or assent records.

Data Availability Statement: Data are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LPA	Latent Profile Analysis
CFI	Comparative Fit Index
TLI	Tucker–Lewis Index
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Square Residual
BLRT	Bootstrapped Likelihood Ratio Test
LL	Log Likelihood
FP	Free Parameters
AIC	Akaike Information Criterion
AWE	Approximate Weight of Evidence
BIC	Bayesian Information Criterion
CLC	Classification Likelihood Criterion
KIC	Kullback Information Criterion
STEM	Science Technology Engineering Mathematics

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