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RESEARCH ARTICLE

Who talks to adolescents about e-cigarettes? Attitudinal profiles among Italian pediatricians

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ABSTRACT

E-cigarette use among adolescents is rising rapidly, yet heterogeneity in pediatricians' knowledge, risk perception, and counselling practices remains poorly characterized. This study aimed to identify distinct attitudinal profiles among Italian pediatricians and to determine the variables that most strongly discriminate between them. A cross-sectional anonymous online survey was distributed between April and October 2025 via the Italian Pediatric Respiratory Society (IPRS/SIMRI) national newsletter. The questionnaire covered demographic characteristics, smoking habits, knowledge of e-cigarettes, risk perception, clinical practices, and counselling behaviors. Latent class analysis (LCA) with an expectation-maximization algorithm was applied to 250 completed responses. Models with two to six classes were compared using AIC, BIC, entropy, and the Lo-Mendell-Rubin likelihood ratio test. The three-class solution provided the best balance between fit and parsimony (lowest BIC); however, entropy values were uniformly low (<0.05), indicating limited separation between classes, so the resulting profiles should be interpreted as broad, partially overlapping tendencies rather than sharply distinct groups. Class 1 (≈25%) tended to include senior pediatricians (mean age >60 years), with a pattern of more conservative attitudes and lower engagement in e-cigarette counselling. Class 2 (≈39%) showed tendencies toward mid-career practitioners reporting greater confidence and openness in discussing e-cigarettes with patients. Class 3 (≈36%) was more frequently composed of early-career pediatricians who tended to underestimate e-cigarette risks and reported lower counselling self-efficacy. Years of practice (importance = 1.00) and age (0.86) were the strongest class discriminators, followed by communication behaviors and risk perception variables. Italian pediatricians appear to cluster along three career-stage-related attitudinal tendencies regarding e-cigarettes, though the low entropy indicates these groupings are partially overlapping rather than rigid categories. These findings support the development of differentiated, career-stage-tailored educational interventions to strengthen counselling capacity across the pediatric workforce.

HIGHLIGHTS BOX

What is already known about this topic? E-cigarette use among adolescents is rising rapidly; pediatricians are expected to counsel on this issue, but their knowledge and attitudes vary substantially by professional setting and career stage. **What does this article add to our knowledge?** Applying latent class analysis to a national survey of 250 Italian pediatricians, this study identifies three career-stage-defined attitudinal profiles; professional experience and age are the strongest discriminators of e-cigarette knowledge and counselling behavior. **How does this study impact current management guidelines?** The three-class structure suggests a single educational intervention is insufficient; differentiated, career-stage-tailored training is needed to align all pediatricians with AAP, EAP, and SIMRI counselling recommendations on e-cigarettes.

INTRODUCTION

The use of electronic cigarettes (e-cigarettes) among adolescents has grown sharply over the past decade, raising serious concerns for public health. Global estimates counted approximately 68 million e-cigarette users in 2020 and around 80 million by 2023, with higher prevalence in high-income countries (1). In Italy, the proportion of adolescents aged 11-17 who reported e-cigarette use more than doubled between 2014 and 2018, rising from 9.1% to 18.3% (2, 3). E-cigarettes are increasingly used alongside conventional cigarettes (CC) and heated tobacco products (HTP), with many adolescent users reporting concurrent use of two or more products (2).

Risk perception is a key driver of this trend. Studies conducted in Europe, North America, and India consistently show that a substantial proportion of adolescents consider e-cigarettes safer than CC, perceive the aerosol as harmless water vapor, and underestimate the addictive potential of nicotine (4-6). This distorted risk perception is reinforced by targeted marketing, social media exposure, and the wide availability of flavored products designed to appeal to young users (7). Available evidence documents associations between e-cigarette use and respiratory symptoms, airway inflammation, nicotine dependence, and, via the gateway effect, subsequent initiation of conventional smoking (4, 8-15). In 2018, the Forum of International Respiratory Societies issued a position statement specifically addressing electronic cigarette use in youths, recommending that these products be regulated as tobacco products and their sale barred to minors worldwide (16).

Pediatricians are well positioned to address this issue. They maintain regular contact with children, adolescents, and their families, and are expected to screen for tobacco and nicotine use, provide counselling, and promote risk awareness (17-19). The American Academy of Pediatrics recommends universal screening and preventive counselling on e-cigarette use for both patients and parents (17); the European Academy of Pediatrics has similarly issued specific guidance for clinical practice (18). More recently, the Italian Pediatric Respiratory Society (SIMRI) published a comprehensive position statement outlining ten recommendations to protect children from vaping exposure (19), whose relevance for clinical practice has been underlined in an accompanying editorial (20).

Yet the international literature documents considerable heterogeneity in pediatricians' knowledge and attitudes towards e-cigarettes. Surveys conducted in Jordan, Poland, Turkey, and the United States report that many physicians lack adequate training on e-cigarettes during their undergraduate education, source information primarily from non-scientific channels, and show ambivalence about whether to recommend e-cigarettes as a harm-reduction strategy (21-23). These knowledge gaps may limit the quality of counselling provided and reduce practitioners' confidence in discussing e-cigarettes with patients (21-23). E-cigarettes are not currently recognized by the FDA or WHO as smoking cessation tools, given insufficient evidence (24-26), and this ambiguity appears to compound clinical uncertainty.

Against this background, characterizing the heterogeneity within the Italian pediatrician workforce is a necessary step towards designing targeted educational interventions. A previous Italian study by Cilluffo *et al.* applied latent class analysis to a nationally distributed survey of pediatricians within the GARD-Italy Demonstration Project, identifying three distinct profiles of barriers and incentives for smoking cessation counselling (27). Building on this methodological approach, the present study used latent class analysis (LCA) to identify distinct knowledge and attitudinal profiles among Italian pediatricians, and to determine which variables most strongly discriminate between groups.

MATERIALS AND METHODS

Study design and objectives

This cross-sectional observational study was conducted via an anonymous online survey to investigate the awareness among Italian pediatricians of the respiratory health risks associated with electronic cigarettes. The primary objective was to identify distinct profiles based on knowledge of e-cigarettes. The secondary objective was to identify the variables that best discriminate between the identified groups.

Survey development and distribution

A 27-item questionnaire was designed and distributed via the SIMRI national newsletter. The questionnaire was organized into three sections. The first collected the pediatrician's professional profile. The second addressed personal smoking habits. The third investigated knowledge, risk perception, awareness of key concepts (*e.g.*, the "gateway" effect), opinions on regulatory policies, perceived training, and how pediatricians discuss e-cigarettes with children, adolescents, and families. The survey was administered on Google Forms from April to October 2025. Participation was voluntary and took about 5 minutes. All responses were collected anonymously and stored securely for analysis.

Data analysis and statistical methods

We used descriptive statistics to summarize the participants' demographic and clinical characteristics. We reported the frequencies and percentages for categorical variables and mean ± standard deviation (SD) for continuous variables. Before the latent class analysis, respondents with more than 30% missing values across the indicator set were excluded from the modelling sample; for the remaining respondents, residual missing values were imputed using the median for ordinal and continuous variables and the mode for categorical variables.

Overview of latent class analysis

Latent class analysis is a form of finite mixture modelling that identifies unobserved subgroups within a population based on patterns of responses to categorical indicators (4). The underlying assumption is that the observed distribution of responses arises from a mixture of a finite number of latent classes, each characterized by distinct conditional response probabilities (4). Unlike traditional cluster analysis, which relies on distance metrics, LCA is model-based and provides statistical fit indices for determining the optimal number of classes (4). Once the model is fitted, posterior probabilities quantify each respondent's likelihood of belonging to each class. Individuals are usually assigned to the class with the highest posterior probability, although membership remains probabilistic (4).

Estimation via the expectation-maximization algorithm

Parameter estimation in LCA was conducted using the Expectation-Maximization (EM) algorithm. The EM algorithm is an iterative procedure designed to find maximum likelihood estimates in models with unobserved variables (5). Starting from random initial values for the class proportions and item-response probabilities, the algorithm alternates between two steps:

1. E-step: Given current parameter estimates, the posterior probability that each respondent belongs to each latent class is computed.
2. M-step: Parameters are updated by maximizing the expected complete-data log-likelihood with respect to the class membership probabilities computed in the E-step (5).

Each iteration increases the likelihood, guaranteeing convergence to a local maximum (5). In this study, the EM algorithm was implemented in Python 3.11 using the numpy and scipy.stats libraries (custom code, available from the corresponding author upon reasonable request). For each candidate model, initial class proportions and class-specific item-response probabilities were drawn at random from a Dirichlet distribution with uniform concentration parameters ($\alpha = 1$). The EM updates continued until the absolute change in the log-likelihood between successive iterations fell below a tolerance of 1×10^{-6} or a maximum of 200 iterations was reached, whichever occurred first. Each candidate K-class model (K = 2-6) was fitted with a single Dirichlet-based random initialization and its log-likelihood, AIC, BIC, entropy and LMR-LRT p-value were stored for subsequent model comparison.

Model specification

Let J be the number of indicators and K the number of latent classes. For individual i, the joint probability of responses x_{ij} and class membership c_i is

$$p\left(x_{i1}, \ldots, x_{iJ}, c_i = k\right) = \pi_k \prod_{j,1}^{I} p_{jk}(x_{ij})$$

where π_k is the prior probability of belonging to class k (with $\sum^{k}_{k,1} \pi_k = 1$) and $p_{jk}(\cdot)$ is the class-specific probability distribution for indicator J. During the E-step, the posterior membership probability for class k is computed via Bayes' rule using current parameters. In the M-step, updated π_k values are obtained by averaging the posterior membership probabilities across individuals, and $p_{jk}(x)$ are updated by the expected relative frequencies of response categories within each class.

Determining the number of latent classes

Models with two to six latent classes were fitted. Model fit and parsimony were compared using several criteria:

1. Bayesian Information Criterion (BIC): as outlined by Nylund-Gibson *et al*., the BIC is one of several information criteria used to evaluate LCA models; it penalizes model complexity and recommends selecting the model with the lowest BIC (28). In practice, researchers may plot BIC values across different class solutions and look for an "elbow" where adding further classes yields diminishing reductions in BIC (28).

2. Entropy: it measures the certainty of classification; values near zero indicate that individuals have similar posterior probabilities across classes, whereas values approaching one denote clear separation. Low entropy across all models suggests overlapping response patterns.
3. Lo-Mendell-Rubin adjusted likelihood-ratio test (LMR-LRT): this test compares a model with *K* classes to a model with *K - 1* classes; a significant P-value suggests that the *K - class* model provides a significantly better fit. Nylund-Gibson *et al*. noted that if the P-value is non-significant, the simpler model is preferred (28).
4. Akaike Information Criterion (AIC): although not explicitly discussed in the document, AIC is another information criterion computed as *-2×log likelihood*+ × *d*, where *d* is the number of estimated parameters. Lower AIC values indicate better trade-off between fit and complexity. Both AIC and BIC were used to rank models.

The BIC indicated that the three-class solution achieved the best balance between fit and parsimony, despite the five-class model having a slightly lower AIC. Entropy values were uniformly low (<0.05), indicating that the classes are not sharply distinct; however, the three-class model still offered interpretable groupings.

Variable importance

To assess the discriminative power of each indicator, a variable importance metric was computed. For each variable *j*, the analysis calculated the maximum difference between the highest and lowest conditional response probabilities across classes. Formally,

$$Importance(j) = max_k \left(max_x p_{jk}(x) - min_x p_{jk}(x) \right)$$

where $p_{jk}(x)$ denotes the probability of responding *x* to indicator *j* given class *k*. Variables with larger importance values exhibit greater variability in response probabilities across classes and thus better discriminate between latent groups. For example, the discretized years of practice variable showed the highest importance (1.00), while age and several items related to discussing electronic cigarette use with patients also ranked highly.

RESULTS

Study population

The survey was completed by 250 Italian pediatricians. The majority of respondents were over 40 years of age (55.2%) and female (80.4%). Most of the sample had been practicing for over 10 years (57.2%), 20.0% had been practicing for 5-10 years, 18.8% had been practicing for less than 5 years, and 4.0% prefer not to answer. Participants were geographically located throughout Italy, with 67.2% working in the North, 19.6% in the South, and 13.2% in Central Italy. Work contexts ranged widely: most of the sample worked as Primary Care Pediatricians (42.0%) or in Pediatric Specialty Hospitals (42.0%), while the remainder worked as Local Pediatricians (2.8%) or in General Hospitals (13.2%), consistent with **Table 1**. In the Italian National Health Service, Primary Care Pediatricians (Pediatri di Famiglia) are individually assigned to children aged 0-14 years and serve as their principal healthcare provider, delivering routine care, preventive visits, and first-line management of acute and chronic conditions. Local Pediatricians (Pediatri Territoriali), by contrast, are employed by the Local Health Authority (ASL) and operate within community health services, where they focus on developmental screening, vaccination programmes, school health activities, and public health interventions rather than individual patient follow-up. The demographic characteristics and smoking lifestyle of the pediatricians are shown in **Table 1** and **Table 2**.

Model selection and fit criteria

The latent class analysis was executed using an expectation-maximization (EM) algorithm that alternated between estimating posterior class membership probabilities for each individual and updating the class-specific item-response probabilities until convergence. Models with two to six latent classes were fitted, and their relative adequacy was assessed using Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), entropy, and the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT). These fit statistics balance model complexity against goodness of fit and can suggest the most plausible number of classes when interpreted jointly.

Table 3 summarizes the model fit indices reported in the document. The BIC reached its minimum with the three-class model, whereas the AIC continued to decrease slightly until the five-class solution. Entropy values were uniformly low (<0.05), signaling that the separation between latent classes was modest. The LMR-LRT P-values were significant for transitions from two to three classes and from four to five classes but not for the other comparisons. Taken together, these criteria led the authors to select the three-class solution, prioritizing parsimony and interpretability over marginal improvements in AIC.

Figure 1 visualizes the AIC and BIC trajectories across the models. The plot shows a pronounced decrease in AIC up to five classes but a sharp inflection in BIC at three classes. The low entropies across all solutions caution that even the selected model likely features overlapping response patterns, and class assignments should be interpreted probabilistically rather than deterministically.

Class proportions and profiles

The chosen three-class model yielded the following class membership proportions: Class 1 – 63 respondents (≈25%), Class 2 – 97 respondents (≈39%) and Class 3 – 90 respondents (≈36 %). These proportions indicate that no single latent class dominates the sample; instead, the distribution is relatively balanced, allowing meaningful comparison across groups. Posterior probabilities of class membership were used to assign individuals to classes for descriptive purposes, though the low entropy implies that some individuals had similar probabilities across multiple classes.

Class 1 tended to include the most senior and experienced pediatricians, with class-conditional probabilities that most strongly distinguished this group from the others on seniority-related indicators. On average, respondents assigned to this class had a mean age exceeding 60 years and had worked in the profession for over three decades. On indicators related to cigarette smoking, the class-conditional probabilities showed a relative concentration of the few respondents who smoked traditional cigarettes. Respondents in this class had a lower probability of reporting exposure to educational material on electronic cigarettes and showed a higher class-conditional probability of being less inclined to initiate discussions about e-cigarette use with adolescent patients. Taken together, the response pattern of this class is consistent with a generally more conservative stance towards reduced-risk nicotine products and potentially more limited exposure to contemporary cessation strategies, though individual members may depart from this overall pattern.

Class 2 was more frequently composed of mid-career pediatricians around their early forties, with approximately 13.5 years of professional experience. On the counselling-related indicators, their class-conditional response probabilities were consistent with greater confidence in discussing electronic cigarettes with patients and reported more frequent engagement in conversations about e-cigarette use during adolescent consultations. On risk-perception items, class-conditional probabilities showed a relatively higher likelihood of viewing electronic cigarettes as potentially useful for smoking cessation, while still acknowledging their risks. This mixed pattern of openness and caution is suggestive, rather than definitive, of more nuanced attitudes within this group and should be read in light of the overall low entropy.

Class 3, the youngest group, showed a relative concentration of early-career pediatricians with a mean age under 40 years and less than a decade of practice. Although they were closer in age to many adolescent patients, they reported lower confidence in discussing electronic cigarette issues and tended to perceive these devices as less harmful than traditional cigarettes. Overall, the response pattern in this class is consistent with a combination of youth, limited experience and lower perceived risk, and points to a possible gap in training rather than to a sharply bounded subgroup; it nevertheless supports the potential value of targeted educational interventions for early-career pediatricians.

The narrative profiles above provide qualitative interpretation of the quantitative findings. They should, however, be viewed in light of the overall low entropy, which signifies that class differences are subtle rather than stark. Individual pediatricians may share characteristics of more than one class, and the classes should be considered as conceptual guides rather than rigid categories.

Model fit indices

Beyond the AIC and BIC, we obtained entropy and LMR-LRT P-values for each model. Entropy measures the certainty with which individuals can be assigned to latent classes, with values close to one indicating clear separation. In this analysis, entropy ranged between 0.0021 and 0.0436 across models with two to six classes (**Table 2**). Such low values suggest that the posterior membership probabilities were diffuse: respondents often had comparable probabilities of belonging to multiple classes. This result emphasizes that the latent structure explains only a small portion of the variability in response patterns and underscores the importance of reporting uncertainty when classifying individuals.

The Lo-Mendell-Rubin (LMR) likelihood ratio test compares models with *k* and *k - 1* classes to determine whether adding another class significantly improves fit. According to **Table 3**, the P-value for the transition from two to three classes was 0.0000, indicating a significant improvement in fit. Conversely, the P-value for the transition from three to four classes was 1.0000, suggesting no meaningful improvement; for the transition from four to five classes the P-value was 0.0000, but the subsequent comparison to six classes yielded 0.9953, indicating again no significant improvement. These alternating results align with the contradictory signals from AIC and BIC, highlighting how the choice of model requires balancing statistical criteria with interpretability. Ultimately, the three-class solution provided a parsimonious representation that captured the major differences in the sample without overfitting.

Variable importance and discriminative power

To identify which variables most strongly differentiated between latent classes, the authors calculated, for the selected three-class model, the maximum difference in conditional response probabilities across classes for each variable. This statistic indicates how much the probability of a given response differs between the class with the highest probability and the class with the lowest probability for that response. Variables with larger differences possess greater discriminative power and thus contribute more to defining the latent structure.

Table 4 lists the nine variables with the highest discriminative importance. The duration of professional practice variable ("How long have you been doing your profession?") achieved the maximum possible importance value (1.00), confirming that seniority is the principal driver of class separation. Age was also highly discriminative (importance = 0.86), consistent with the strong correlation between age and years in practice. Variables related to discussing electronic cigarette use with adolescents and confidence in addressing e-cigarette issues with patients ranked prominently, indicating that communication behaviors and self-efficacy contribute to class differences beyond mere demographics. Perceptions of the relative safety of electronic versus traditional cigarettes and experiences with adverse events also appeared among the top discriminators. Conversely, variables relating to the clinical setting ("What kind of structure do you work in?") had lower, though still meaningful, discriminative values.

These results, visualized in **Figure 2**, show that both demographic variables (age and years of practice) and attitudinal variables (perception of harm and communication practices) shape the latent grouping of pediatricians. The high importance of professional experience underscores how exposure to clinical practice and continuing education shapes practitioners' confidence and behavior regarding electronic cigarette counselling.

DISCUSSION

Before interpreting the three-class solution, it is important to emphasize that entropy values across all models were uniformly low (<0.05). Posterior membership probabilities were therefore diffuse, many respondents had comparable probabilities of belonging to more than one class, and the three classes should be read as broad, partially overlapping attitudinal tendencies rather than as sharply bounded, mutually exclusive subgroups. The class-specific profiles described below and their discussion in terms of age, experience, counselling behavior and risk perception thus refer to differences in class-conditional response probabilities, not to deterministic descriptions of individual pediatricians. The combined evidence from model fit statistics, class profiles and variable importance analysis suggests that latent heterogeneity among the surveyed pediatricians is driven primarily by age and professional experience, with attitudinal and behavioral variables playing secondary but still meaningful roles. The relatively balanced class sizes mean that interventions aimed at improving knowledge and counselling practices could be tailored to specific career stages. For instance, senior pediatricians (Class 1) may benefit from updated training materials and guidance on the evolving evidence around electronic cigarettes to overcome conservative biases. Mid-career practitioners (Class 2) already display a proactive stance but could be supported with formalized communication strategies to ensure consistent messaging. Early-career pediatricians (Class 3) may require foundational education that addresses both the risks and potential cessation benefits of electronic cigarettes and builds confidence in discussing these topics with patients and families.

The low entropy values across all models highlight an important methodological caveat: the latent classes identified are not sharply delineated. This could reflect genuine complexity in pediatricians' attitudes, with many holdings nuanced or ambivalent positions that do not align neatly with distinct categories. It may also indicate that additional variables not captured in the questionnaire (*e.g*. exposure to specific training modules, institutional policies, or personal experiences with nicotine cessation) play a role in shaping attitudes. Future research could incorporate more granular measures of education and training, as well as longitudinal designs, to examine how attitudes towards emerging nicotine products evolve over time.

The findings of the present study align with and extend those reported in the international literature on healthcare providers' knowledge and attitudes towards electronic cigarettes. Surveys conducted in Jordan, Poland, and Turkey consistently documented substantial gaps in physicians' training on e-cigarettes, with many practitioners relying on non-scientific sources of information and holding ambivalent views on the role of these products in smoking cessation (21-23). The profile of Class 1 in our sample, characterized by greater clinical experience, lower engagement in e-cigarette counselling, and a more conservative stance towards reduced-risk nicotine products, is consistent with the pattern observed by Mohammad et al. among Jordanian physicians, where longer time since graduation was associated with lower confidence in discussing e-cigarettes with patients (21). Similarly, the ambivalence towards harm-reduction strategies observed in Class 2 mirrors findings by Tanriover *et al*. among Turkish family physicians, approximately half of whom considered e-cigarettes a viable cessation tool despite limited supporting evidence (23). The relatively higher engagement of mid-career practitioners in e-cigarette counselling in our sample is also broadly consistent with the pattern reported by Zgliczyński *et al*. in Poland, where younger physicians showed greater familiarity with e-cigarettes and greater willingness to discuss them with patients (22). Compared with these international surveys, the present study adds methodological value by applying latent class analysis rather than descriptive comparisons, enabling the identification of distinct attitudinal subgroups rather than aggregate means. This approach reveals heterogeneity that univariate analyses might obscure and provides a basis for profiling physicians in need of targeted educational intervention. The observation that Class 3, the youngest practitioners, reported lower perceived risk from e-cigarettes is consistent with evidence that younger cohorts have greater exposure to industry marketing and social-media content promoting e-cigarettes as safe alternatives (4, 7), and underscores the importance of integrating evidence-based e-cigarette content into undergraduate and postgraduate medical training. The current position statements from the American Academy of Pediatrics, the European Academy of Pediatrics, and the Italian Pediatric Respiratory Society all recommend systematic screening and counselling on tobacco and nicotine use (17-19); our results suggest that achieving this standard will require differentiated educational strategies across career stages.

Limitations

Like any study, this one has limitations worth acknowledging. Distribution through the IPRS/SIMRI newsletter may have introduced self-selection bias, potentially overestimating engagement with e-cigarette issues. The cross-sectional design prevents causal inference between career stage, knowledge, and counselling behavior; longitudinal studies would be needed to assess how attitudes evolve over time. Self-reported data carry an inherent risk of social desirability bias, particularly for items on clinical practice and perceived competence. Low entropy values in the latent class analysis suggest the findings reflect broad tendencies rather than mutually exclusive categories. The overrepresentation of northern Italy (67.2%) limits generalizability across different healthcare contexts. Future research should include general practitioners, adolescent medicine specialists, and school health professionals.

CONCLUSIONS

This study provides a novel characterization of Italian pediatricians' knowledge, attitudes, and counselling practices regarding electronic cigarettes. Applying LCA to a nationally distributed survey of 250 practitioners, we partially overlapping profiles structured primarily along the dimension of professional experience: senior pediatricians with conservative and less engaged stances (Class 1), mid-career practitioners exhibiting greater openness and counselling confidence (Class 2), and early-career pediatricians with lower perceived risk and reduced self-efficacy in discussing e-cigarettes with patients (Class 3). Years of practice and age were the strongest discriminators between classes, followed by communication behaviors and risk perceptions, confirming that career stage is a central axis of heterogeneity in this professional group.

These findings may carry direct implications for the design of continuing medical education programmes. The three-class structure suggests that a single, undifferentiated educational intervention is unlikely to be adequate. Senior pediatricians may require targeted updates on emerging evidence regarding e-cigarette harms and the current regulatory and clinical guidance issued by the American Academy of Pediatrics, the European Academy of Pediatrics, and the Italian Pediatric Respiratory Society (17-19). Early-career practitioners, despite their proximity in age to the adolescent populations they serve, appear to underestimate e-cigarette risks and lack confidence in counselling, a gap that should be addressed through dedicated content in undergraduate and postgraduate medical curricula. Mid-career pediatricians, while more proactive, would benefit from structured communication tools to ensure that the information conveyed to patients and families is consistent, evidence-based, and aligned with current clinical recommendations. Given the continued rise in e-cigarette use among Italian adolescents (2, 6), strengthening the capacity of pediatricians across all career stages to screen, counsel, and refer is an urgent public health priority.

Future research should replicate this profiling approach in larger and more geographically representative samples, incorporate objective measures of knowledge alongside self-reported attitudes, and examine the extent to which targeted educational interventions shift practitioners between attitudinal classes over time. Extending the analysis to general practitioners, school health professionals, and adolescent medicine specialists would broaden the evidence base and support the development of coordinated, multi-professional strategies for reducing youth e-cigarette initiation in Italy.

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COMPLIANCE WITH ETHICAL STANDARDS

Conflicts of interest

The authors declare no conflicts of interest.

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None.

Author contributions

SR, AP, SLG, MG: conceptualization. SR, AP: data curation, visualization, writing – original draft. AP: formal analysis. SR, AP, MEDC: investigation. SR, AP, SLG, MG: methodology. SLG, MG: project administration, supervision. SR, AP, MEDC, SLG, MG: writing – review & editing.

Ethical approval

Human studies and subjects

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. In accordance with Italian law (Legislative Decree 211/2003 and subsequent amendments), studies based exclusively on anonymous questionnaires administered to healthcare professionals, involving no intervention, no collection of biological samples, and no processing of sensitive personal data, are exempt from formal ethical committee review. Participation in the survey was entirely voluntary. No personally identifiable information was collected at any stage of the study. Completion and submission of the questionnaire were considered to constitute implicit informed consent to participate. All data were stored securely and used solely for the purposes of this research.

Data sharing and data accessibility

The data presented in this study are not publicly available due to privacy and confidentiality constraints. The survey was conducted anonymously, and respondents were assured that their responses would not be shared beyond the research team. Data may be made available upon reasonable request to the corresponding author, subject to applicable data protection regulations.

Publication ethics

Plagiarism

Authors declare no potentially overlapping publications with the content of this manuscript and all original studies are cited as appropriate.

Data falsification and fabrication

All the data corresponds to the real.

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Table 1. *Demographic characteristics and lifestyle of the pediatricians.*

	Total (n = 250)
Age, mean (± SD)	45.42 (± 12.32)
Gender	
Female, n (%)	201 (80.4%)
Male, n (%)	49 (19.6%)
Years of professional experience	
< 5 years, n (%)	47 (18.8%)
5 - 10 years, n (%)	50 (20.0%)
10 - 15 years, n (%)	27 (10.8%)
15 - 20 years, n (%)	22 (8.8%)
≥ 20 years, n (%)	94 (37.6%)
Prefer not to answer, n (%)	10 (4.0%)
Region of work	
North of Italy, n (%)	168 (67.2%)
Center of Italy, n (%)	33 (13.2%)
South of Italy, n (%)	49 (19.6%)
Work setting	
Primary care pediatricians, n (%)	105 (42.0%)
Local pediatricians, n (%)	7 (2.8%)
General hospital, n (%)	33 (13.2%)
Pediatric specialty hospital, n (%)	105 (42.0%)
Conventional cigarette smoker	
Yes, n (%)	6 (2.4%)
No, n (%)	217 (86.8%)
Ex-smoker, n (%)	27 (10.8%)
E-cigarette smoker	
Yes, n (%)	9 (3.6%)
No, n (%)	239 (95.6%)
Ex-smoker, n (%)	2 (0.8%)
Both smoker	
Yes, n (%)	0 (0.0%)
No, n (%)	247 (98.8%)
Ex-smoker, n (%)	3 (1.2%)

Table 2. *Demographic characteristics by smoke habits [n (%)].*

	Conventional cigarette smoker	**E-cigarette smoker**	**Both smoker**
Years of professional experience			
< 5 years	1 (16.7%)	1 (11.1%)	0 (0%)
5 - 10 years	1 (16.7%)	2 (22.2%)	0 (0%)
10 - 15 years	0 (0%)	3 (33.3%)	0 (0%)
15 - 20 years	0 (0%)	0 (0%)	0 (0%)

≥ 20 years	4 (66.7%)	2 (22.2%)	0 (0%)
Prefer not to answer	0 (0%)	1 (11.11%)	0 (0%)
Work Setting			
Primary care pediatricians	1 (16.7%)	0 (0%)	0 (0%)
Local pediatricians	0 (0%)	0 (0%)	0 (0%)
General hospital	2 (33.3%)	3 (33.3%)	0 (0%)
Pediatric specialty hospital	3 (50%)	6 (66.7%)	0 (0%)
Region of Work			
North of Italy	4 (66.7%)	4 (44.4%)	0 (0%)
Center of Italy	0 (0%)	0 (0%)	0 (0%)
South of Italy	2 (33.3%)	5 (55.6%)	0 (0%)
Gender			
Female	4 (66.7%)	5 (55.6%)	0 (0%)
Male	2 (33.3%)	4 (44.4%)	0 (0%)

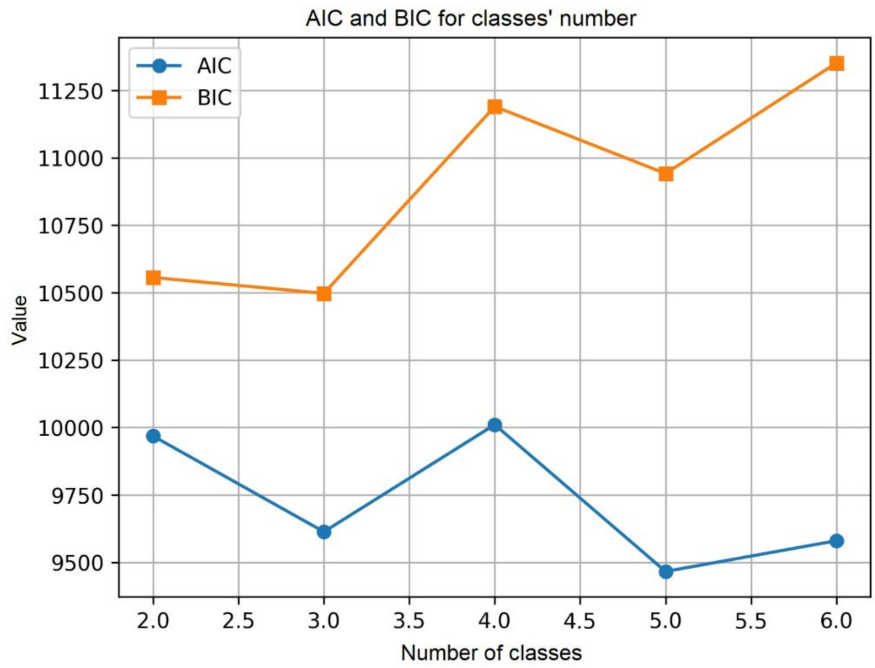
Table 3. *Model fit statistics for latent class solutions.*

Numbers of classes	AIC	BIC	Entropy	P-value LMR-LRT
2	9,968.31	10,556.39	0.0360	-
3	9,613.39	**10,497.28**	0.0373	0.0000
4	10,010.63	11,190.32	0.0021	1.0000
5	**9,466.36**	10,941.85	0.0356	0.0000
6	9,580.17	11,351.47	**0.0436**	0.9953

Table 4. *Top nine discriminative variables in the three-class model.*

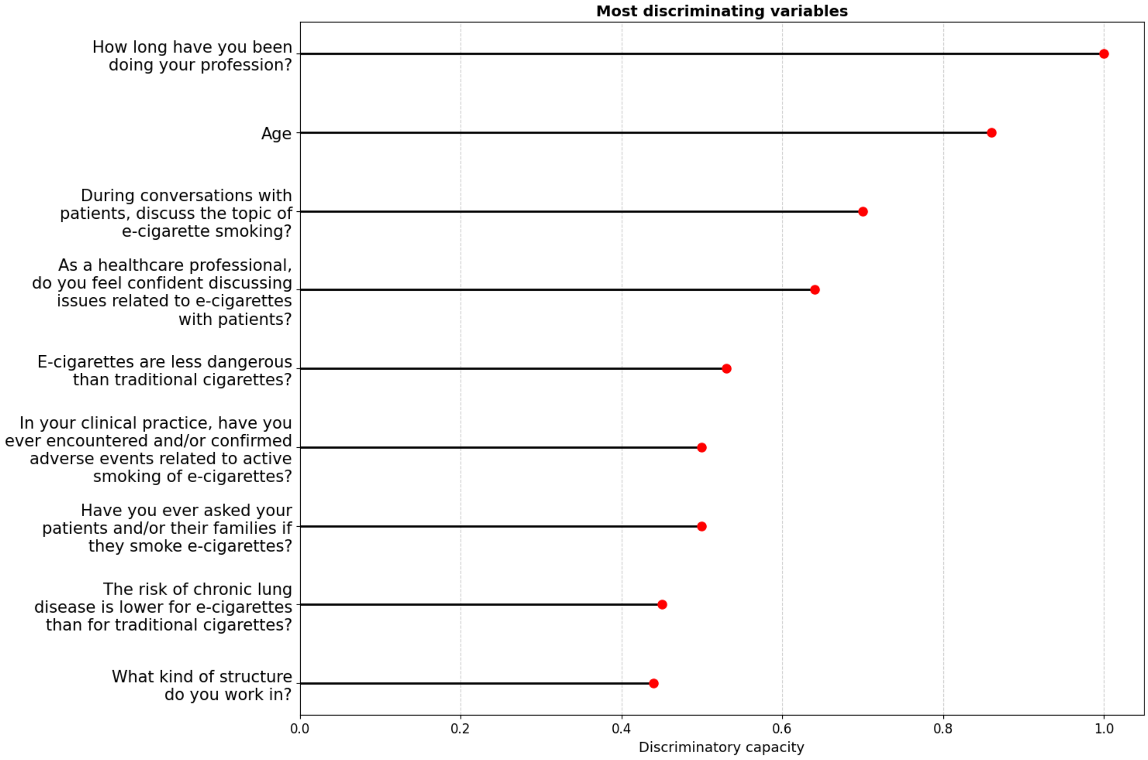
Variable	Importance
How long have you been doing your profession?	1.00
Age	0.86
During conversations with patients, discuss the topic of e-cigarette smoking?	0.70
As a healthcare professional, do you feel confident discussing issues related to e-cigarettes with patients?	0.64
E-cigarettes are less dangerous than traditional cigarettes?	0.53
In your clinical practice, have you ever encountered and/or confirmed adverse events related to active smoking of e-cigarettes?	0.50
Have you ever asked your patients and/or their families if they smoke e-cigarettes?	0.50
The risk of chronic lung disease is lower for e-cigarettes than for traditional cigarettes?	0.45
What kind of structure do you work in?	0.44

__Figure 1.__ AIC and BIC values plotted against the number of latent classes.



While AIC suggests improved fit up to five classes, BIC reaches its minimum at three classes, favoring parsimony.

__Figure 2.__ Plot of the top nine variables contributing to class discrimination.



The horizontal axis displays the discriminative importance, defined as the maximal difference in conditional response probabilities across classes. Larger values indicate greater separation.