Tobacco control policies predict quit attempts, but household smoking predicts cessation success across 29 countries

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ABSTRACT

Background Tobacco use remains a global public health challenge, leading to over 8 million annual deaths and significant economic burden. Effective tobacco control and cessation interventions are essential to mitigate these impacts.

Methods Using data from the Global Adult Tobacco Surveys (between 2011 and 2021) and WHO reports from 29 countries, this study analysed determinants of quitting behaviour among n=51 196 individuals. Random Forest classification models were employed to identify key predictors for two outcomes: quit attempts and successful cessation. The model incorporated individual characteristics and all MPOWER policies, addressing gaps in the existing literature. Permutation variable importance was used to investigate the predictive power of the features. The Random Forest misclassification rates were 6% and 21%, indicating predictive reliability.

Findings Country-level factors, tobacco control legislation and WHO region significantly influence quit attempts. Individual-level factors, specifically smoking habits and smoking-permissive home environments—more strongly predicted successful cessation.

Interpretation Results highlight the importance of comprehensive tobacco control policies in promoting cessation. To improve cessation rates and reduce the global burden of tobacco-related diseases, public health initiatives must enhance the enforcement and reach of tobacco control measures, provide targeted support for people who smoke heavily and people in smoking-permissive environments and integrate a broader range of population-specific influences. Further research is necessary to understand the impact of actual policy enforcement and the cultural dynamics affecting tobacco use and cessation. These findings are crucial for guiding public health policies and interventions aimed at achieving better tobacco cessation outcomes globally.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Tobacco consumption is a major global health issue extensively studied in terms of smoking behaviour and policy impacts.

WHAT THIS STUDY ADDS

⇒ The evidence-based MPOWER policy package aims to support country-level tobacco control interventions. This study provides value by addressing a key gap in the existing research on MPOWER's impact on smoking cessation, which is either limited to individual countries or specific tobacco control interventions. We integrated data from 29 countries using a Random Forest approach to identify individual and country-level factors that influence smoking cessation attempts and success.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ By examining the interplay between individual behaviour, sociodemographic characteristics and national tobacco control policies, our results emphasise the importance of implementing comprehensive tobacco control policies while also providing tailored support for people who smoke based on their social characteristics.

INTRODUCTION

Tobacco use remains a global public health crisis, causing 8 million deaths annually[1 2] and imposing a staggering economic burden on health systems.[3 4] Globally, smoking prevalence was 17% in 2021,[5] with a significantly varying patterns due to socioeconomic and cultural factors.[6] Understanding these patterns is critical for tailoring cessation interventions and policies to effectively reach and support diverse populations in their endeavour to quit smoking.[7] A multitude of factors influence an individual's decision to quit smoking and their success in doing so[7 8]; where successful quitting is defined as stopping to smoke since a specific period of time, and attempting to quit is defined as being a person who currently smokes but tried to stop for a period of time (detailed definitions are available in the methods section). Identifying and understanding these factors, both at the individual level and at the political level (in terms of tobacco control policies), is crucial for developing effective support and interventions for individuals seeking to quit smoking.

The WHO's MPOWER package comprises six strategies: monitoring tobacco use (M), smoke-free policies (P), cessation support (O), health warnings (W), advertising bans (E) and taxation (R).[5] While these measures have shown varying success in reducing smoking prevalence and encouraging cessation across different regions,[9 10] additional research on population-level and individual-level

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factors among understudied populations remains essential.[11] This study aims to identify the key factors that influence an individual's decision to attempt quitting smoking and their success in cessation, integrating both individual behaviours and country-level tobacco control policies across diverse global populations, overcoming the limitations in current literature that is mostly tackling specific countries or tobacco control policies. This will help to improve the planning of tobacco control interventions considering individual characteristics. The use of Random Forest (RF), a machine learning technique, will help overcome some downsides of the well-known usual regression models, mainly the statistical assumptions of these models.

METHODS

Data source

This study integrated individual-level data from the Global Adult Tobacco Surveys (GATS) with country-level data from the WHO reports on the global tobacco epidemic to conduct analyses on two binary outcome variables (attempting to quit and successful in quitting). GATS are standardised, nationally representative household surveys covering topics such as current smoking, cessation, secondhand exposure to tobacco smoke, exposure to media both antismoking and smoke promotions, economics and knowledge, attitude and perceptions. The purpose of the GATS is to help countries evaluate their tobacco control policies, particularly MPOWER policies.[12] According to the GATS sample design manual: 'GATS uses a geographically clustered multistage sampling methodology to identify the specific households that Field Interviewers will contact. First, a country is divided into Primary Sampling Units, segments within these Primary Sampling Units, and households within the segments. Then, a random sample of households is selected to participate in GATS'.[13] All survey data files were downloaded from the Centers for Disease Control and Prevention (CDC) website. Online supplemental table S1 shows the survey year, WHO region, and response rate for each country.

The WHO reports on the global tobacco epidemic present the countries' levels of legislation adoption of the MPOWER measures. At the time of writing, nine WHO reports have been published, covering the years 2008, 2009, 2011, 2013, 2015, 2017, 2019, 2021 and 2023.[5] These reports report data from the year previous to their publishing year.

Ethics

This work was conducted on publicly available and completely anonymised data and ethical approval was not required.

Study population

Analysis A examined 'attempting to quit smoking among people who currently smoke', and analysis B examined 'being successful in quitting among all those who attempted to quit in the past 12 months'. 51 196 people who currently smoke or previously smoked were included in the final sample (after dropping about 1% with missing data on education and employment) (see figure 1).

Only the latest GATS conducted in the available 29 countries were harmonised and merged into a single dataset. Using the

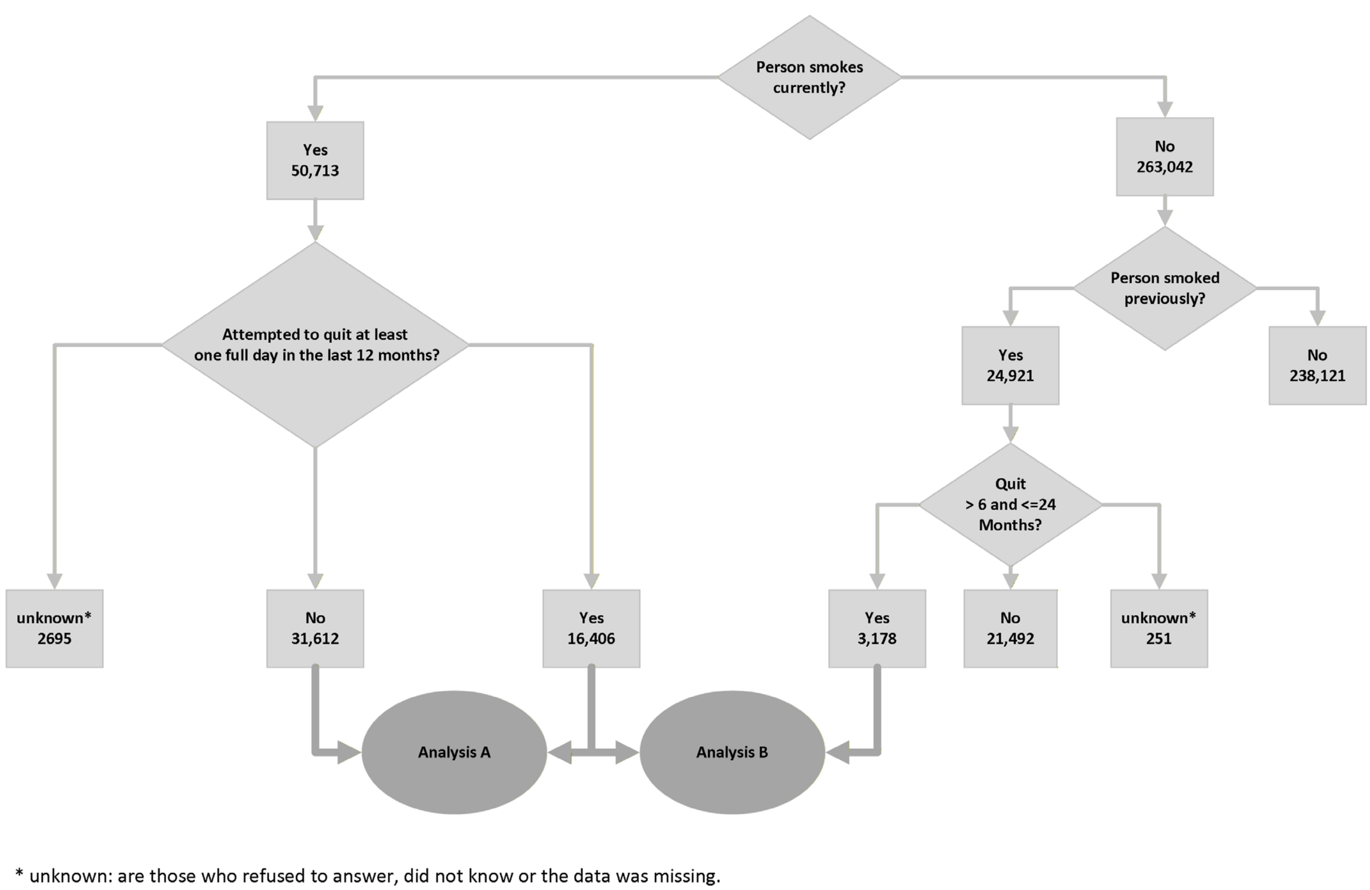

Figure 1 Flowchart depicting how the sample was drawn from GATS datasets, analysis A: attempting to quit, analysis B: successful quitting. GATS, Global Adult Tobacco Surveys.

codebooks for all these 29 surveys, common questions were used to construct the covariates and to ensure that these covariates have the same coding across all surveys. Then, variables with less than 30% of missing data in the overall merged dataset were included, and a separate category was created for these missing data (missing, refused, do not know).

Outcome definition

The binary outcome for analysis A was whether a person who currently smokes attempted to quit or not in the past 12 months. For analysis B, the binary outcome was whether individuals who had attempted to quit smoking were successful or unsuccessful (online supplemental appendix table S2). A precise assignment of the observations to the respective analyses is shown in figure 1. People who previously smoked were not included in the sample of those attempting to quit in analysis A, because data were not available for important potential predictors (time of the day a responder smoked their first cigarette and tobacco smoked per day). The definition of a quit attempt was restricted to being abstinent from smoking for at least 1 day, because there is no data on the period of the day when the quit attempt took place; if a person who smoked heavily smoked his/her first cigarette of the day and then decided to attempt quitting for few hours, then this attempt does really reflect a serious attempt.

Predictors definition

The demographic features encompass age, gender (male vs female), residency (rural vs urban), education (four categories) and employment status (employed, student and unemployed). The behavioural features that also encompass nicotine addiction were the age of smoking initiation, periodicity of smoking (daily vs less than daily), tobacco smoked per day (in analysis A only), the time of the day a responder smoked their first cigarette (in analysis A only), besides others like knowledge of the harmful effects of smoking, the awareness of antismoking advertisements and the awareness of smoking promotions. The environmental features encompass the presence of a person who smokes in the family, secondhand exposure (SHE) to smoke in public places in the last 30 days, and the permissibility of smoking at home.

Indicators of tobacco control policies adoption were mapped from the WHO report corresponding to the GATS year for each country. In instances where a country conducted GATS in a year without a WHO report available, data from the previous year were utilised to assure all countries have data on these indicators. Tobacco control policies adoption indicators are self-reported data by countries, with a validation step by two WHO experts.[14] In the WHO reports, these indicators are grouped in four categories ranging from no or minimum adoption to comprehensive adoption of the evidence-based policy, with two levels in between formed according to the number of adopted measures under each policy type. These policy adoption groups were available for the studied six policies: legislation, cessation support, health warnings, mass media, advertising bans and taxation.[5] In this study, a composite policy indicator was calculated as the aggregation of the 6 indicator groups divided by 18 (the possible maximum), for each country, with the objective of reducing the dimensionality of the policy measures. This was necessary due to the limited availability of data at the country level, acknowledging the fact that interpretation will be harder, as it will not be possible to investigate the individual MPOWER factors any more. Countries were then grouped into tertiles, low, medium or high tobacco control legislation according to their composite indicator. Additionally, the WHO region was incorporated as a further country-level variable. Online supplemental Table S2 in the appendix provides details of the individual and country-level features and explains in detail the calculation of the tobacco control policies variable. Online supplemental Table S1 in the appendix shows the level of the tobacco control legislation by each country.

Statistical analysis

To investigate analyses A and B, the RF was selected as the classification model.[15] The RF was chosen due to its ability to model complex interactions between input features by itself. It was implemented using the ranger package (V.0.16.0) in R (V.4.1.2), applying the algorithm proposed by Breiman[15] with 1000 trees, the gini index as split criteria on a random set of four features per split, a minimal node size of 10, and outcomes as defined in the *Outcome definition* section. First, the models were trained in accordance with the methodology proposed by Malley *et al* to develop Random Forest Probability Machines (RFPM).[16] Subsequently, in order to calculate the adjusted ORs (aORs) from the aforementioned RF classifiers, we applied the two-machine approach, which was shown to lead to the same results as a logistic regression that takes all present interactions into account.[17] Model performance was validated using the out of bag misclassification rate, which serves as an unbiased form of cross-validation. The out of bag misclassification rate is calculated for each tree in the forest individually based on the observations that were not used to train that tree and is aggregated across all trees within the forest afterwards. Permutation variable importance (VIMP) was employed to ascertain the impact of disparate input features on the output. Specifically, permutation importance is the increase in prediction error by randomly permuting one independent feature. Sampling weights were not applied in the analyses due to differences in weighting schemes across countries and the potential for introducing bias when combining data from multiple surveys with different designs. While weighting can increase representativeness within individual countries, it may not be appropriate for pooled analyses of international data. It is important to note that potential data limitations exist at both the individual and country levels. These limitations include heterogeneity in survey timing, policy reporting and missingness. RF models are inherently capable of adjusting for complex non-linear relationships and interactions among predictors; however, the possibility of residual confounding cannot be entirely ruled out without applying computationally extremely expensive adjustments.[18]

RESULTS

Analysis A (attempting to quit) included 48 018 people who currently smoke (40 640 males, 7378 females; online supplemental Table S3). Analysis B (successful quitting) included 19 584 individuals (16 335 males, 3249 females). Survey's size ranged from 9445 (India) to 88 (Russia) for analysis A, and 3347 to 39 for analysis B, respectively. In both analyses, ~46% of participants were aged 25–44; 11.5% and 13% held college degrees, respectively. High tobacco control legislation covered 51% of adults in analysis A and 45% in analysis B (see online supplemental Table S3). The out of bag misclassification rate was 21% for analysis A and 6% for analysis B, respectively, indicating predictive reliability.

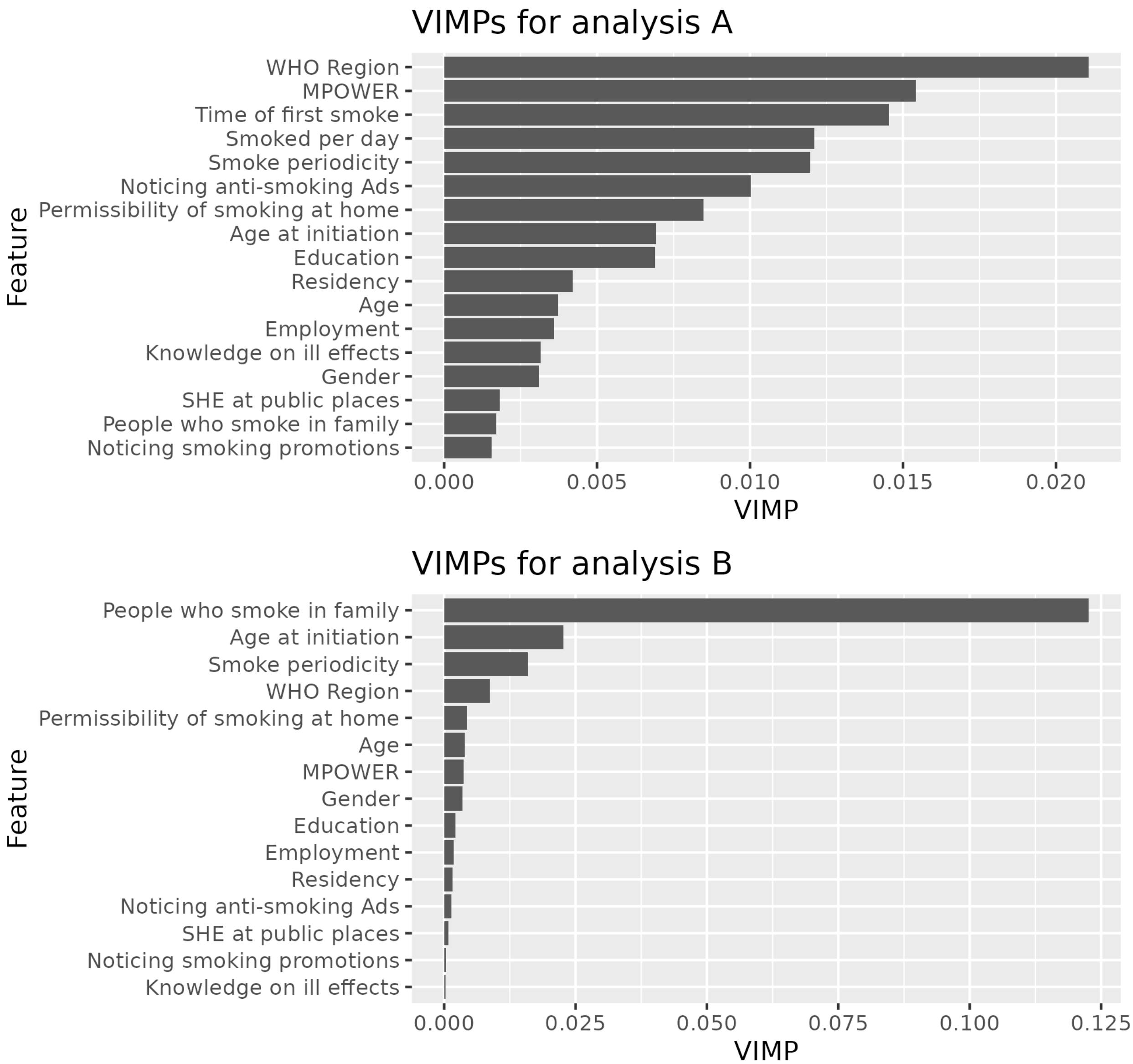

Figure 2 VIMPs for analysis A: attempting to quit and analysis B: successful quitting. The variable importance (VIMP) of a feature is the increase in prediction error, by randomly permuting that specific feature.

Analysis A—attempting to quit

The RF identified the WHO region and tobacco control legislation as the primary predictors for quit attempts. Time to first cigarette and daily tobacco consumption ranked second and third by VIMP values while demographic features ranked in the lower half (see figure 2).

Table 1 presents the aORs for the individual-level features. Adults who smoked their first cigarette within 5 min of waking up had the lowest aOR for attempting to quit compared with those who smoked later in the day. Smoking more than 10 tobacco products daily also reduced attempt likelihood compared with less than 1 (0.91, 95% CI (0.90 to 0.92)). The age of smoking initiation showed a higher aOR for those who started smoking at an age older than 24 years (1.33, 95% CI (1.32 to 1.34)). Noticing a higher number of anti-smoking advertisements as well as more smoking promotion was associated with more attempts to quit. With regard to the environment at home, those with people who smoke in the family exhibited more quitting attempts. Those residing in a house where smoking was prohibited demonstrated similar results.

Table 2 presents the aOR for the country-level features. Individuals living in countries with medium tobacco control legislation adoption showed a high aOR for attempting to quit in comparison to those in low legislation adoption countries (1.66, 95% CI (1.64 to 1.68)). High legislation adoption resulted in an aOR lower than the aOR for medium adoption (1.04, 95% CI (1.03 to 1.06)). People who smoke in Africa, the Americas and Western Pacific were more likely to attempt quitting compared with people who smoke in Southeast Asia, whereas people who smoke in Europe and the Eastern Mediterranean were less likely to attempt quitting.

Table 1 aOR for individual level features

	Analysis A: did not attempt to quit vs attempted to quit	Analysis B: attempted to quit unsuccessfully vs quit successfully
	aOR (95% CI)	aOR (95% CI)
Age		
15–24	Ref	Ref
25–44	1.22 (1.22 to 1.23)	0.83 (0.81 to 0.84)
45–64	1.25 (1.24 to 1.26)	1.08 (1.06 to 1.10)
>65	1.35 (1.34 to 1.36)	1.87 (1.83 to 1.90)
Gender		
Male	Ref	Ref
Female	1.48 (1.47 to 1.49)	5.23 (5.14 to 5.32)
Residency		
Urban	Ref	Ref
Rural	1.36 (1.35 to 1.38)	1.41 (1.38 to 1.43)
Not asked	1.57 (1.55 to 1.59)	3.78 (3.70 to 3.85)
Education		
No formal education	Ref	Ref
Up to primary	1.36 (1.35 to 1.37)	1.56 (1.52 to 1.61)
Up to Secondary	1.26 (1.25 to 1.27)	1.36 (1.34 to 1.39)
Up to College and above	1.32 (1.30 to 1.33)	2.34 (2.30 to 2.38)
Employment		
Employed	Ref	Ref
Student	1.86 (1.84 to 1.88)	4.97 (4.87 to 5.07)
Not employed	1.34 (1.33 to 1.35)	2.64 (2.60 to 2.69)
People who smoke in the family		
None	Ref	Ref
One	1.25 (1.24 to 1.26)	0.03 (0.03 to 0.04)
More than one	1.14 (1.13 to 1.14)	0.02 (0.02 to 0.02)
Permissibility of smoking at home		
Allowed	Ref	Ref
Not allowed, but exceptions	1.87 (1.86 to 1.88)	3.29 (3.23 to 3.37)
Never allowed	2.02 (2.00 to 2.04)	3.83 (3.77 to 3.90)
No rules	1.31 (1.30 to 1.32)	3.35 (3.27 to 3.42)
Do not know/refused	0.75 (0.74 to 0.76)	6.79 (6.60 to 6.98)
Secondhand exposure at public places		
Very rarely	Ref	Ref
Rarely	1.45 (1.44 to 1.47)	1.42 (1.39 to 1.44)
Sometimes	1.76 (1.74 to 1.77)	3.02 (2.94 to 3.09)
Often	1.30 (1.29 to 1.31)	5.37 (5.22 to 5.52)
Age at initiation		
<15	Ref	Ref
15–24	1.13 (1.13 to 1.14)	1.10 (1.08 to 1.12)
>24	1.33 (1.32 to 1.34)	1.02 (1.01 to 1.04)
Not asked*	1.70 (1.68 to 1.71)	9.66 (9.44 to 9.87)
Do not know	0.80 (0.79 to 0.80)	2.38 (2.34 to 2.43)
Periodicity		
Daily	Ref	Ref
Less than daily	3.55 (3.50 to 3.60)	1.08 (1.04 to 1.13)
Noticing anti-smoking advertisement		
Very rarely	Ref	Ref
Rarely	1.80 (1.79 to 1.82)	1.20 (1.18 to 1.21)
Sometimes	2.27 (2.25 to 2.29)	1.20 (1.18 to 1.22)
Often	2.78 (2.76 to 2.80)	0.96 (0.94 to 0.98)
Noticing smoking promotions		
Very rarely	Ref	Ref
Rarely	1.77 (1.76 to 1.79)	1.74 (1.72 to 1.77)
Sometimes	2.16 (2.14 to 2.17)	3.56 (3.50 to 3.62)

Continued

Table 1 Continued

	Analysis A: did not attempt to quit vs attempted to quit	Analysis B: attempted to quit unsuccessfully vs quit successfully
	aOR (95% CI)	aOR (95% CI)
Often	2.36 (2.34 to 2.39)	7.63 (7.48 to 7.78)
Knowledge on the ill effects of smoking tobacco		
Yes	Ref	Ref
No	0.97 (0.96 to 0.98)	2.16 (2.11 to 2.21)
Do not know/refused/missing	0.97 (0.95 to 0.98)	2.34 (2.28 to 2.40)
Time of first smoke		
Within 5 min	Ref	
6–30 min	1.12 (1.12 to 1.13)	
31–60 min	1.23 (1.22 to 1.24)	
More than 60 min	1.57 (1.56 to 1.57)	
Not asked†	2.37 (2.36 to 2.39)	
Tobacco smoked per day		
<1‡	Ref	
1–10	0.99 (0.98 to 1.00)	
>10	0.91 (0.90 to 0.92)	

*People who smoked less than daily and did not smoke daily in the past and people who quitted smoking and did smoked less than daily in the past were not asked about their age of initiation.
†People who smoke less than daily were not asked about the time of first smoke.
‡This category also includes those with no data available.
aOR, adjusted OR.

Analysis B—successful quitting

Analysis B showed that individual-level characteristics were more important predictors of smoking cessation than country-level factors. This is in contrast to the findings of Analysis A.

Presence of people who smoke in the family was the strongest predictor of success, followed by age of initiation and smoking periodicity (daily and less than daily), respectively. Most demographic characteristics studied were ranked of lesser importance regarding successful quitting of smoking, which was a similar finding to that revealed in analysis A. Age was the highest predictor of successful quitting of all the demographic characteristics studied (see figure 2).

Older age at smoking initiation was associated with higher aOR of successful quitting compared with early initiation. Those who smoked less than daily were more likely to succeed in quitting smoking than those who smoked more frequently than that (1.08, 95% CI (1.04 to 1.13)). Similar to analysis A, noticing smoking promotions correlated with quitting, while anti-smoking ads showed an unclear association. The higher the exposure to secondhand smoke at public places, the larger the aOR for quitting smoking. For the variable of people who smoke in the family, identified as the most important feature by the RF, having people who smoke in the family was associated with less success for quitting smoking and showed very low aOR (see table 1).

Tobacco control legislation is associated with higher aOR for successful quitting while medium versus low legislation adoption results in a higher aOR (2.26, 95% CI (2.21 to 2.30)) than high versus low legislation (1.97, 95% CI (1.93 to 2.00)). People who smoke in all other WHO regions were more likely to succeed compared with those in Southeast Asia. The highest aOR was in the Americas (see table 2).

Table 2 aOR for country-level features

	Analysis A: did not attempt to quit vs attempted to quit	Analysis B: attempted to quit unsuccessfully vs quit successfully
	aOR (95% CI)	aOR (95% CI)
Tobacco control legislation		
Low (<0.5)	Ref	Ref
Medium (>0.5 and <0.7)	1.66 (1.64 to 1.68)	2.26 (2.21 to 2.30)
High (>0.7)	1.04 (1.03 to 1.06)	1.97 (1.93 to 2.00)
WHO region		
South East Asia	Ref	Ref
Africa	2.18 (2.17 to 2.20)	3.55 (3.49 to 3.61)
The Americas	1.58 (1.57 to 1.59)	4.01 (3.93 to 4.10)
Eastern Mediterranean	0.81 (0.81 to 0.82)	2.45 (2.41 to 2.49)
Europe	0.79 (0.79 to 0.80)	3.98 (3.88 to 4.07)
Western Pacific	1.61 (1.60 to 1.63)	2.67 (2.62 to 2.71)

aOR, adjusted OR.

DISCUSSION

Our analysis confirmed distinct influences of country-level and individual-level determinants on quitting behaviour. The rankings of VIMPs and aORs derived from the RFPM are not necessarily congruent. While VIMP reflects a variable's contribution to overall predictive performance, capturing also non-linear and interaction effects, aORs quantify marginal directional associations. Consequently, variables may display strong predictive relevance without a corresponding monotonic association. However, although the RF inherently models potential interactions, these are not directly interpretable within this framework and would require additional experiments and methods to get transparent interpretations.[18–21] Consequently, subsequent analyses could explicitly examine how these key predictors interact to shape cessation outcomes. In summary, both metrics describe complementary aspects of the model's structure and should be interpreted jointly.

While research exists on quit attempts, country-specific factors beyond tobacco control policy, such as economic crises, unemployment and policies outside MPOWER, require more attention.[11 22–24] The stage of the tobacco epidemic also influences individual smoking cessation patterns.[25] Interestingly, the overall impact of tobacco control policy also varies between world regions.[26 27] Reasons motivating people to quit can indeed be influenced by the cultural background of the individual and/or the economic situation of the country.[28–30] Social norms about smoking also influence smoking prevalence.[26] A study in Malaysia and Thailand discussed several possible reasons for finding differences in the factors affecting smoking cessation outcomes compared with what is found in western countries. The study identified cultural variations to be influential for smoking cessation, such as religion and collectivism versus individualism features of some societies.[25] Countries worldwide are going through different phases of the tobacco epidemiological transition, and the drivers of their transition from one phase to another vary, with the LMICs being the most affected by the tobacco epidemic, being at earlier stages of the transition. This might help explain the regional differences in cessation outcomes and emphasise the need for better targeted cessation interventions.[31 32] This finding aligns with the results of our current study, as different WHO regions displayed different outcomes regarding attempts to quit smoking and success in quitting smoking.

Policy success depends on actual implementation and cultural variations. However, studying implementation is limited by data availability. Although WHO uses a standardised methodology to validate MPOWER measures,[5] data remain largely self-reported by governments, which could be a limitation.[14 33] Data validation, which is conducted by the two WHO designated experts, might be susceptible to subjective reasoning.[34] Moreover, the reported level of MPOWER shows policy adoption and does not reflect its actual implementation, including enforcement, considering that countries have different capabilities to fully enforce tobacco control legislation.[26 35] Anderson *et al* found a large gap between legislation and enforcement in low-income countries.[36] WHO reports on the global tobacco epidemic provide data only on compliance to bans on advertising, promotions and sponsorship and adherence to smoke-free laws. These compliance scores might also be prone to subjective evaluation according to their collection protocol. In addition, higher quitting relapses in certain settings could be linked to the need for further improvements in the implemented cessation services.[37 38] Another limitation is that the reported MPOWER indicators reflect mainly national level policies.[5] In countries like China, for example, subnational policies can be more comprehensive. This study highlights the importance of better implementation and enforcement of tobacco control policies by countries, suited to reflect the different population characteristics and needs.

Individual characteristics also significantly influence quitting. Indicators of elevated nicotine dependence (eg, smoking the first cigarette earlier or in greater quantities) are associated with diminished success rates.[25 39–42] Our results indicate that awareness of harmful effects alone does not necessarily translate into cessation success. Environmental factors, such as prohibiting smoking at home, were associated with more quit attempts and success, consistent with prior research.[43 44] The quit attempts of people who smoke have also been positively influenced by decreased exposure to second-hand smoke in public places. In our study, living with people that smoke marginally increased quit attempts but substantially reduced the likelihood of successful cessation, identifying household smoking as an important predictor of unsuccessful quitting. This finding is consistent with prior Indian data.[44] Furthermore, the positive correlation between exposure to smoking-related content and motivation to quit may be indicative of heightened awareness or cognitive dissonance rather than genuine promotional effects.

Sociodemographic features impacted cessation, though they were not strong predictors here. Similar to other research, females were more likely than males to successfully stop smoking.[37] Luu *et al* suggested that where smoking is culturally uncommon for women, such as in Vietnam, they may quit more frequently than men.[37] In our sample, 84.6% of people that smoke were male, likely reflecting cultural unacceptance of female smoking. Regarding age, literature indicates that older people who smoke have more attempts[25 37 41 44] and greater success than younger individuals.[37 41 44] The quitting success of seniors may be influenced by the desire to protect health, as seniors may be prone to more illness with increasing age. However, an inverse relationship between age and attempting to quit was found in another study conducted in four western countries; Australia, Canada, USA and UK.[42] The association between education and quitting remains conflicting: Luu *et al* found a positive association,[37] while Hyland *et al* found none.[42] Regarding employment status, unemployment was associated with more quitting. Studies with similar results suggested that this association could be linked to affordability; unemployed people may not be able to afford cigarettes.[41] Raising the price of cigarettes did not lead to a higher quitting rate among people who smoke in some settings. Thus, researchers emphasised the importance of the role of healthcare providers and other factors in assisting patients with smoking cessation endeavours.[44–47]

Limitations

Self-reported data for policy adoption and smoking behaviours may introduce reporting biases. Additionally, aggregating MPOWER measures into one composite indicator may obscure effects of individual policies. Future research should examine each policy component separately to identify their distinct impacts. Geopolitical WHO regions may not represent cultural similarities within. Western European countries are under-represented due to limited GATS dataset availability; therefore, conclusions might not be generalisable for those populations. Missing data prevented including receiving quitting advice by a healthcare provider. Literature shows such advice is crucial for successfully quitting. Interpretation bias might arise due to different timepoints and follow-up periods within GATS surveys. The RF approach has inherent limitations. Despite its robustness, the model remains opaque, precluding causal interpretability. VIMP exhibits bias towards variables with higher variability or more categories. Results may be influenced by data imbalance or correlated predictors. RFPM-derived aORs are post-hoc marginal summaries that may under-represent interaction-driven effects; thus, divergence between VIMP and aORs is plausible.

CONCLUSION

Our findings underscore that comprehensive policies encourage quit attempts, while individual factors are more significant for successful cessation. Tailored interventions considering both policy environment and personal circumstances remain crucial for enhancing global efforts. Policies should target those at high risk of continued addiction or unsuccessful quitting. Robust data on policy implementation and compliance remains essential for refining strategies and should be collected in order to provide a foundation for crafting, implementing and refining tobacco policies to effectively combat addiction and improve public health.

Longitudinal research is needed to develop indicators for the temporal relationship between policy implementation and its measurable effects. Such analysis will provide deeper insights into policy impact.

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