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LOGICAL-COMBINATORIAL METHODS FOR CARDIOVASCULAR RISK FACTOR ANALYSIS AND ASSESSMENT

Abstract:

Cardiovascular diseases (CVD) remain the leading cause of mortality and morbidity worldwide, posing significant challenges to healthcare systems and society at large. Despite advancements in prevention and treatment, the prevalence of CVD continues to rise, driven by non-modifiable risk factors such as age, gender, genetic predisposition, and ethnicity (World Health Organization, 2021). Accurate and comprehensive assessment of CVD risk factors is vital for effective prevention and intervention strategies.

Conventional tools for assessing individual CVD risk factors, such as the Framingham Risk Score (FRS), Atherosclerotic Cardiovascular Disease Risk Calculator (ASCVD), QRISK Calculator, and SCORE (Systematic Coronary Risk Evaluation), provide percentage estimates of a 10-year CVD risk based on specific populations and datasets. However, from a Public Health perspective, there is a need for innovative approaches that quantitatively assess, analyze, and predict overall CVD risks on a Global, Regional, or National scale.

This paper proposes the use of logical-combinatorial methods to quantitatively evaluate non-modifiable CVD risk factors, including age, gender, genetic predisposition, and ethnicity, based on global statistical data. The analysis involves estimating the probabilities of the simultaneous presence of two, three, or four non-modifiable risk factors. The study presents key findings from the quantitative assessment of various risk factors combinations and draws actionable conclusions for public health practice.

This method provides a scalable framework for global risk assessment and targeted public health intervention planning. Integrating logical-combinatorial approaches into Public Health research is critical for developing more effective strategies to mitigate the burden of CVD and improve population health outcomes globally.

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JEL Classification: C00, C02, I18

1. Introduction

Cardiovascular diseases (CVD) remain a leading cause of morbidity and mortality worldwide, accounting for an estimated 17.9 million deaths annually (WHO.int, *Cardiovascular diseases*, 2019). Despite advancements in healthcare, the burden of CVD remains high due to incomplete adherence to clinical guidelines, and challenges in securing policy and public support for prevention measures (WHO, HEARTS *technical package for cardiovascular disease management in primary health care: Risk based CVD management*, 2020). The multifactorial nature of CVD necessitates comprehensive methods for risk factors analysis and assessment to enable early detection, prevention, and targeted intervention strategies.

Several well-established models for CVD risk assessment have been developed and widely implemented in the United States and Europe, including the Framingham Risk Score (FRS) (Ko, D. T.; Siveswamy, A.; Sud, M.; Kotrri, G. et al., 2020), the Atherosclerotic Cardiovascular Disease (ASCVD) Risk Calculator, and the QRISK calculator (Gidlow, C. J.; Ellis, N. J.; Cowap, L. et al., 2021). These models primarily rely on conventional risk factors such as age, gender, cholesterol levels, blood pressure, smoking status, diabetes, and socioeconomic factors. However, their applicability may be limited in diverse populations due to regional variations in genetic predisposition, environmental influences, and healthcare accessibility. Very few reports have explored risk-assessment models from a global perspective, highlighting the need for more adaptable and inclusive frameworks (Zhao, D.; Liu, J., Xie, W. Et Al., 2015, Damen J. A. A.; Hoft L.; Schuit E.; Debray T. P. A. et al., 2016).

To address these challenges, artificial intelligence (AI) and machine learning (ML) are being increasingly utilized to enhance risk prediction models. Traditional risk models often rely on linear associations between risk factors, which may oversimplify the true nature of CVD pathophysiology. In contrast, AI-driven models can integrate vast datasets, including genomic, proteomic, and metabolomic information, along with real-world clinical and lifestyle data, to generate highly personalized risk predictions. Advanced computational techniques such as neural networks, clustering algorithms, and ensemble learning methods enable the identification of high-risk subpopulations with greater precision, allowing for earlier and more effective interventions. The growing complexity of cardiovascular risk factors necessitates a paradigm shift in risk assessment methodologies (Zhou, J.; You, D.; Bai, J.; Chen, X., et al., 2023).

The methods discussed above for assessing CVD risk probabilities are personalized and are used to calculate 10-year forecasts for specific patients. Due to public health objectives, it is necessary to make an overall assessment of CVD risk probabilities in the context of the world, regions, countries or administrative units. This paper explores the application of logical-combinatorial methods for cardiovascular risk factors analysis and assessment, aiming to enhance predictive accuracy and optimize prevention strategies (Tsiramua, S.; Meladze, H.; Davitashvili, T.; Zhorzholiani, A., 2025). By leveraging mathematical modeling and AI-driven analytical frameworks, we seek to provide a more holistic, data-driven approach to CVD risk factors assessment, which can be adapted across different healthcare settings.

This study examines non-modifiable risk factors for cardiovascular disease (CVD) and applies logical-combinatorial methods for their quantitative assessment. Logical-Combinatorial Methods are a class of analytical and algorithmic approaches that combine formal logic and combinatorial mathematics to solve complex problems, especially in fields like: System reliability and risk analysis, Decision-making, Optimization, Pattern recognition, Artificial intelligence, Bioinformatics. They are particularly useful where systems are discrete, structured, and require analysis of all possible logical combinations of components, states, or decisions.

Non-modifiable CVD risk factors include four key variables:

x_1 - Age: CVD risk increases with age, particularly after 45 years in men and 55 years in women. Aging contributes to arterial stiffness, endothelial dysfunction, and other physiological changes that elevate cardiovascular risk.

x_2 - Gender: Men generally face a higher risk of developing CVD at an earlier age compared to women. However, after menopause, women experience a significant increase in risk, likely due to hormonal changes that impact lipid metabolism and vascular health.

x_3 - Genetics/Family History: A family history of premature CVD (before 55 years in men and 65 years in women) significantly raises individual risk. Genetic predispositions, such as familial hypercholesterolemia, inherited hypertension, and other hereditary conditions, further contribute to increased susceptibility.

x_4 - Ethnicity: Certain ethnic groups, including individuals of African, South Asian, and Indigenous descent, exhibit higher CVD prevalence due to a combination of genetic, cultural, and socioeconomic factors. Differences in lipid profiles, insulin resistance, and predisposition to hypertension contribute to elevated risk levels in these populations.

This study employs combinatorial analysis to quantify the interplay of these non-modifiable risk factors and assess their cumulative impact on CVD risk. Along with non-modifiable risk factors, we also examined smoking (x_5) as a modifiable risk factor and analyzed its impact in combination with non-modifiable risk factors.

2. Research Method

To perform a general probabilistic assessment, we first considered each individual risk factor and obtained quantitative estimates of their probabilities based on statistical data.

The risk of developing cardiovascular disease (CVD) based solely on non-modifiable risk factors (for example, for age) can be estimated using a weighted average formula, incorporating statistical data:

$$Average\ Risk_i = \sum(Risk_i \times Population_i) \ / \sum Population_i \quad (1)$$

- $Risk_i$ represents the probability of CVD occurrence for a given age group *i*;
- Population refers to the number of individuals in age group *i*.

This approach allows us to estimate the baseline CVD risk associated with non-modifiable factors before incorporating the influence of modifiable risk factors such as smoking. By integrating smoking prevalence into our analysis, we aim to assess its synergistic effect on CVD risk and quantify the overall probability of disease occurrence in different population segments.

Calculation of Weighted Average Risk by age: Age-Specific Statistical Data and CVD Risk Probabilities for Individuals Over 45 in Table 1:

Table 1. CVD Risk By Age Group (45+)

Age Group	Population (millions)	CVD Risk (%)	Weighted Risk
45-54	1080	10	10,800
55-64	800	15	12,000
65-74	720	25	18,000
75+	560	32.5	18,200
Weighted average	**3160**	**18.67**	**59,000**

Source: statistical data of WHO

To estimate the age-specific risk factor of developing CVD based on non-modifiable factors, we analyzed statistical data for individuals aged 45 and above. Table 1 provides the population distribution**,** CVD risk percentage, and the weighted risk calculation for each age group.

Thus, using the weighted average formula (1), the estimated overall CVD risk by age for individuals aged 45 and above is approximately: $p(x_1) \approx 0.1867$ (18.67%)

Calculation of Weighted Average CVD Risk by Gender: To assess the weighted average CVD risk by gender**,** we use the statistical data presented in Table 2**.**

Table 2. CVD Risk Development By Gender

Gender	Population (Millions)	Risk (%)	Weighted Risk
Male 45-70	1000	20	20,000
Female 55-70	600	15	9,000
Male 70+	340	35	11,900
Female 70+	460	30	13,800
Weighted average	**2400**	**22.79**	**54700**

Source: statistical data of WHO

Thus, using the weighted average formula (1), the weighted average probability of CVD risk by gender is approximately: $p(x_2) \approx 0.2279$ (22.79%)

Calculation of Weighted Average CVD Risk by Family History: To estimate the average probability of CVD risk by family history, we use the statistical data presented in Table 3.

Table 3. CVD Risk Development by Family History

Gender	Population (Millions)	Risk (%)	Weighted Risk
Male (CVD 10%)	1,500	15	22,500
Female (CVD 10%)	2,500	17	42,500
Weighted average	**4,000**	**16.25**	**65,000**

Source: statistical data of WHO

Thus, Applying the weighted average formula (1), the average probability of developing CVD based on family history is approximately: $p(x_3) \approx 0.1625$ (16.25%).

This result highlights the significant impact of genetic predisposition on CVD risk with individuals who have a family history of the disease facing a notably higher risk than those without.

Calculation of Weighted Average CVD Risk Based on Ethnicity: To estimate the average probability of CVD risk by ethnicity**,** we use the statistical data presented in Table 4**.**

Table 4. CVD Risk by Ethnicity

Ethnic Group	Global Share (%)	Average CVD Risk (%)	Weighted Risk
Asian	60	15	0.09
African Descent	14	25	0.035

European	12	20	0.024
Latin American	8	18	0.0144
Indigenous / Other	6	22	0.0132
Weighted average	**100**	**17.66**	**0.1766**

Source: INTERHEART, WHO, AHA

Thus, applying the weighted average formula (1), the weighted average probability of developing CVD based on ethnicity is approximately: $p(x_4) \approx 0.1766$ (17.66%).

This result highlights ethnic disparities in CVD risk development, with certain populations (e.g., African ethnicity) exhibiting higher risk levels, which may be influenced by genetic, lifestyle, and socioeconomic factors.

Smoking is a major modifiable risk factor for cardiovascular disease. According to World Health Organization (WHO) data, the prevalence of tobacco use varies by gender and region:

- Men: >35% prevalence;
- Women: ~8% prevalence;
- Global adult population**:** ~22% prevalence.

Thus, the probability of smoking as a risk factor is approximately: $p(x_5) \approx 0.22$ (22%)

Based on the probabilities of individual non-modifiable risk factors, based on logical-combinatorial analysis, we can calculate the probability that a person will develop cardiovascular disease from any of two risk factors, for example, from the non-modifiable risk factors of age (x_1) and gender (x_2) under the influence of either or both risk factors.

Since the sum of probabilities of all possible logical combinations of risks x_1 and x_2 equals 1:

$$p(x_j)\times p(x_k) + [1-p(x_j)]\times p(x_k) + p(x_j)\times[1-p(x_k)] + [1-p(x_j)] \times [1-p(x_k)] = 1 \quad (2)$$

we obtain the probability of having either or both of these risks:

$$P\{Z(x)=1\} = p(x_j)\, p(x_k) + [1-p(x_j)]\, p(x_k) + p(x_j)\, [1-p(x_k)] = 1 - [1-p(x_j)] \times [1-p(x_k)] \quad (3)$$

where, $j \neq k$, $j \in [1, n-1]$, $k \in [j+1, n]$; n – number of risk factors; $(1-p(x))$ denotes the probability of risk x not occurring (Tsiramua, S.; Meladze, H.; Davitashvili, T., 2024).

For general n, formula (3) takes the following form:

$$P_n\{F(x)\} = 1 - \prod_{i=1}^{n}(1 - p(x_i)) \quad (4)$$

We model the conditional probabilities of each risk factor influencing the others. For example, ethnicity may influence both family history and age-related risks.
The Bayesian formula adjusts for prior probability distributions (YASMIN YOUSSEF, 2022):

$$P(CVD|x_1, x_2, x_3, x_4) = \frac{P(CVD)P(x_1|CVD)P(x_2|CVD)P(x_3|CVD)P(x_4|CVD)}{P(x_1,x_2,x_3,x_4)} \quad (5)$$

where:

$P(\text{CVD} \mid x_1,x_2,x_3,x_4)$ - probability of CVD given age (x_1), sex (x_2), family history (x_3) and genetic predisposition (x_4).

$P(x_1,x_2,x_3,x_4 \mid CVD)$ - likelihood of these factors occurring in individuals with CVD.

P(CVD) - baseline probability of CVD in the population.

$P(x_1,x_2,x_3,x_4)$ - overall probability of the factors in the general population.

This approach uses prior probabilities from epidemiological data and updates risk dynamically.

When modeling risk scenarios, we apply De Morgan's laws. The negation of a conjunction of logical variables equals the disjunction of their negations. Conversely, the negation of a disjunction equals the conjunction of their negations (Ryabinin, I. A., 2000).

In the case of double negation, the following equations hold:

$$A \wedge B = (A' \vee B')' \qquad (6)$$
$$A \vee B = (A' \wedge B')'$$

For a general *n* logical variable, the formula will take the following form:

$$\bigwedge_{i=1}^{n} x_i = \left(\bigvee_{i=1}^{n} x_i'\right)' \qquad (7)$$
$$\bigvee_{i=1}^{n} x_i = \left(\bigwedge_{i=1}^{n} x_i'\right)'$$

In addition to applying De Morgan's laws, we use a logical-probabilistic method for modeling risk scenarios—the orthogonalization algorithm. This algorithm is based on the Shannon decomposition formula, which states that any logical function $f(x_1, \dots, x_n)$, depending on n logical variables ($n \geq 1$), can be represented as follows:

$$f(x_1, \dots, x_n) = x_i f_1^{(i)}(x_1, \dots, 1_i, \dots, x_n) \vee x_i' f_0^{(i)}(x_1, \dots, 0_i, \dots, x_n) \qquad (8)$$

The orthogonalization algorithm is described in detail in (RYABININ, I.A., 2000).

3. Assessment of Cardiovascular Disease (CVD) Risk Development Using Logical-Combinatorial Method

3.1. Estimation probabilities of non-modifiable CVD risk factors

Substituting given probabilities from previous calculations (Table 1 & Table 2):

- Age-based CVD risk: $\underline{p}(x_1) = 0.1867$ (18.67%);
- Gender-based CVD risk: $p(x_2) = 0.2279$ (22.79%).

Using the method (3) we obtain the probability of $P\{Z(x_1, x_2)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] = 0.3721$ (37.21%).

Interpretation

- The probability of developing CVD due to age and/or gender is approximately 37.21%;
- This forms the baseline before incorporating additional risk factors (e.g., genetics, ethnicity, smoking).

Using the same method, we can calculate the probabilities of other combinations of any two non-modifiable risk factors:

$P\{Z(x_1, x_2)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] = 0.3721$ (37.21%)

$P\{Z(x_1, x_3)=1\} = 1 - [1-p(x_1)] \times [1-p(x_3)] \approx 0.3189$ (31.89%)

$P\{Z(x_1, x_4)=1\} = 1 - [1-p(x_1)] \times [1-p(x_4)] \approx 0.3303$ (33.03%)

$P\{Z(x_2, x_3)=1\} = 1 - [1-p(x_2)] \times [1-p(x_3)] \approx 0.3534$ (35.34%)

$P\{Z(x_2, x_4)=1\} = 1 - [1-p(x_2)] \times [1-p(x_4)] \approx 0.3643$ (36.43%)

$P\{Z(x_3, x_4)=1\} = 1 - [1-p(x_3)] \times [1-p(x_4)] \approx 0.3104$ (31.04%)

The probability estimates for any three non-modifiable risk factors combinations will be:

$P\{Z(x_1, x_2, x_3)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_3)] \approx 0.4741$ (47.41%)

$P\{Z(x_1, x_2, x_4)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_4)] \approx 0.4829$ (48.29%)

$P\{Z(x_1, x_3, x_4)=1\} = 1 - [1-p(x_1)] \times [1-p(x_3)] \times [1-p(x_4)] \approx 0.4392$ (43.92%)

$P\{Z(x_2, x_3, x_4)=1\} = 1 - [1-p(x_2)] \times [1-p(x_3)] \times [1-p(x_4)] \approx 0.4676$ (46.76%)

The probability estimate of at least one risk factor (one or two or three or all four) out of the four non-modifiable risk factors will be as follows:

$P\{Z(x_1, x_2, x_3, x_4)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_3)] \times [1-p(x_4)] \approx 0.5670$ (56.70%)

The probabilities of combinations of non-modifiable risks $P\{Z(x_1, x_2, x_3, x_4)\}$, the number of which is equal to $N=2^n-1=2^4-1=15$, are shown in the probability matrix (Table 5).

3.2. Estimation probabilities of non-modifiable CVD risk factors taking into account smoking

By logical-combinatorial methods (Tsiramua, S.; Sulkhanishvili S.; Asabashvili E.; Kvirtia L.; Berikashvili, I., 2024) we can calculate the probabilities of combinations of non-modifiable risk factors with x_5 given that the probability estimates of the modifiable risk factor x_5 - smoking is $p(x_5) \approx 0.22$ (22%):

$P\{Z(x_1, x_5)=1\} = p(x_1)\, p(x_5) + [1-p(x_1)]\, p(x_5) + p(x_1)\, [1-p(x_5)] = 1 - [1-p(x_1)] \times [1-p(x_5)] = 0.3656$ (36.56%)

$P\{Z(x_2, x_5)=1\} = 1 - [1-p(x_2)] \times [1-p(x_5)] \approx 0.3978$ (39.78%)

$P\{Z(x_3, x_5)=1\} = 1 - [1-p(x_3)] \times [1-p(x_5)] \approx 0.3468$ (34.68%)

$P\{Z(x_4, x_5)=1\} = 1 - [1-p(x_4)] \times [1-p(x_5)] \approx 0.3577$ (35.77%)

See Figure 1 for a graph of the probabilities of combinations of non-modifiable CVD risk factors with the modifiable smoking risk factor.

The probability estimates of the combination of any two non-modifiable risk factors with modifiable risk factor smoking (x_5) will be:

$P\{Z(x_1, x_2, x_5)=1\} = 1 - [1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_5)] \approx 0.4696$ (46.96%)

$P\{Z(x_1, x_3, x_5)=1\} = 1 - [1-p(x_1)] \times [1-p(x_3)] \times [1-p(x_5)] \approx 0.4687$ (46.87%)

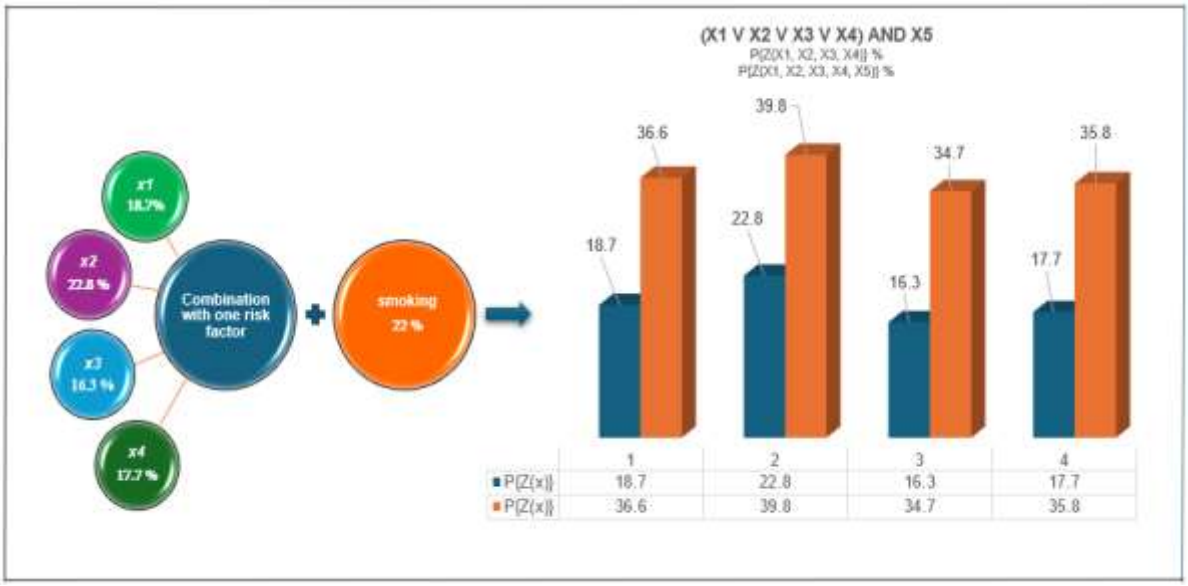
$P\{Z(x_1, x_4, x_5)=1\} = 1 - [1-p(x_1)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.4777$ (47.77%)

$P\{Z(x_2, x_3, x_5)=1\} = 1 - [1-p(x_2)] \times [1-p(x_3)] \times [1-p(x_5)] \approx 0.4956$ (49.56%)

$P\{Z(x_2, x_4, x_5)=1\} = 1 - [1-p(x_2)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.5041$ (50.41%)

$P\{Z(x_3, x_4, x_5)=1\} = 1 - [1-p(x_3)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.4621$ (46.21%)

Figure 1. Probability graph of combinations of non-modifiable risk factors with the risk factor of smoking



Source: The results of our calculations using statistical data of WHO

The probability estimates of the combination of any three non-modifiable risk factors with modifiable risk factor smoking -x_5 will be:

$P\{Z(x_1, x_2, x_3, x_5)=1\} = 1-[1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_3)] \times [1-p(x_5)] \approx 0.5898$ (58.98%)

$P\{Z(x_1, x_2, x_4, x_5)=1\} = 1-[1-p(x_1)] \times [1-p(x_2)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.5967$ (59.67%)

$P\{Z(x_1, x_3, x_4, x_5)=1\} = 1-[1-p(x_1)] \times [1-p(x_3)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.5625$ (56.25%)

$P\{Z(x_2, x_3, x_4, x_5)=1\} = 1-[1-p(x_2)] \times [1-p(x_3)] \times [1-p(x_4)] \times [1-p(x_5)] \approx 0.5847$ (58.47%)

The probability estimates at the same time of the combination of four $\{x_1, x_2, x_3, x_4\}$ non-modifiable risk factors with modifiable risk factor smoking x_5 -will be:

$P\{Z(x)=1\} = 1-[1- p(x_1)] \times [1- p(x_2)] \times [1- p(x_3)] \times [1- p(x_4)] \times [1-p(x_5)] \approx 0.6622$ (66.22%)

See Table 5 for the probabilities of all combinations of non-modifiable risk factors with modifiable risk factor smoking - $P\{Z(x_1, x_2, x_3, x_4, x_5)\}$, and the corresponding graph in Figure 2.

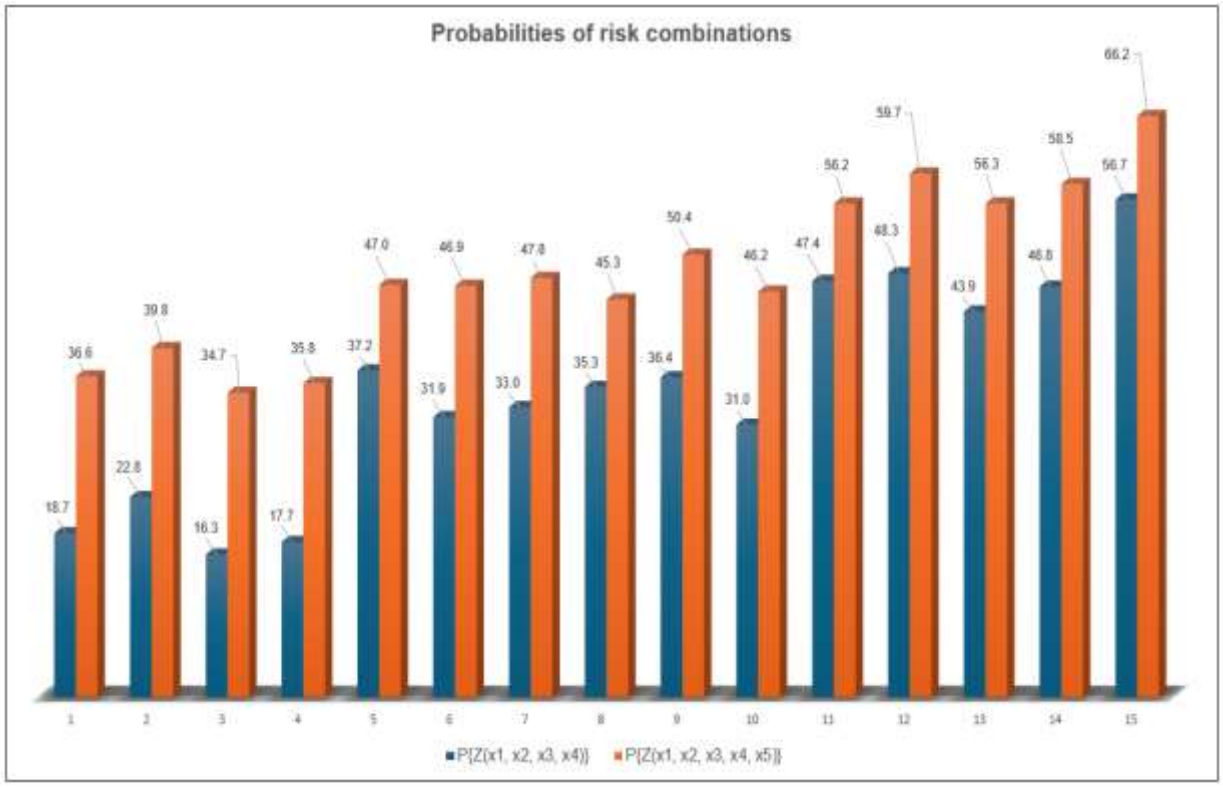
Table 5. Probabilities of combinations of non-modifiable risk factors without smoking and with smoking

№	$p(x_1)$ %	$p(x_2)$ %	$p(x_3)$ %	$p(x_4)$ %	$p(x_5)$ %	$P\{Z(x_1, x_2, x_3, x_4)\}$ %	$P\{Z(x_1, x_2, x_3, x_4, x_5)\}$ %
1	18.7	-	-	-	22.0	18.7	36.6
2	-	22.8	-	-	22.0	22.8	39.8
3	-	-	16.3	-	22.0	16.3	34.7
4	-	-	-	17.7	22.0	17.7	35.8
5	18.7	22.8	-	-	22.0	37.2	47.0
6	18.7	-	16.3	-	22.0	31.9	46.9

7	18.7	-	-	17.7	22.0	33.0	47.8
8	-	22.8	16.3	-	22.0	35.3	45.3
9	-	22.8	-	17.7	22.0	36.4	50.4
10	-	-	16.3	17.7	22.0	31.0	46.2
11	18.7	22.8	16.3	-	22.0	47.4	56.2
12	18.7	22.8	-	17.7	22.0	48.3	59.7
13	18.7	-	16.3	17.7	22.0	43.9	56.3
14	-	22.8	16.3	17.7	22.0	46.8	58.5
15	18.7	22.8	16.3	17.7	22.0	56.7	66.2

Source: The results of our calculations using statistical data of WHO

Figure 2. Graph of probabilities of combinations of non-modifiable risk factors without smoking and with smoking



Source: The results of our calculations using statistical data of WHO

Our study demonstrates that logical-combinatorial methods provide a robust quantitative approach to assessing cardiovascular disease (CVD) development risk. One of the key findings is that the probability of developing CVD increases significantly with the accumulation of non-modifiable risk factors, such as age, gender, family history, and ethnicity. Our results align with established epidemiological data, reaffirming the need for targeted preventive interventions for individuals with multiple non-modifiable risk factors. Additionally, the inclusion of a single modifiable risk factor, smoking, dramatically increases the probability of CVD, underscoring the critical role of smoking cessation programs in cardiovascular risk mitigation.

Conclusion

This study highlights the effectiveness of logical-combinatorial modeling as a quantitative tool for assessing cardiovascular disease (CVD) risk factors within a public health framework. By systematically representing all possible combinations of risk factors through logical functions, this approach offers a realistic simulation of complex health scenarios. The analysis demonstrates that the accumulation of non-modifiable risk factors—namely age, gender, family history, and ethnicity—significantly elevates the probability of developing CVD. Risk escalates further with the addition of a modifiable factor such as smoking, which alone can markedly increase disease likelihood. For example, a smoker over the age of 50 with a family history of CVD has a 47% chance of developing the disease, which decreases to 32% upon smoking cessation—emphasizing the critical role of behavioral interventions.

The validity of these findings is supported by the use of statistical data from the World Health Organization (WHO), rigorous logical combinations of selected risk factors, and the transformation of logical expressions into probabilistic terms using De Morgan's rules. This methodological robustness enhances the credibility and applicability of the model. The results affirm that logical-combinatorial assessment provides a precise and scalable framework for identifying high-risk individuals, informing targeted screening, and shaping early intervention strategies—thereby contributing meaningfully to population-level CVD prevention and control efforts.

References

1. Damen, J. A. A., Hoft, L., Schuit, E., & Debray, T. P. A., et al. (2016). Prediction models for cardiovascular disease risk in the general population: Systematic review. *BMJ, 353*, i2416. https://doi.org/10.1136/bmj.i2416
2. Gidlow, C. J., Ellis, N. J., Cowap, L., et al. (2021). Cardiovascular disease risk communication in NHS Health Checks using QRISK®2 and JBS3 risk calculators: The RICO qualitative and quantitative study. *Health Technology Assessment, 25*(50). https://doi.org/10.3310/hta25500
3. Ko, D. T., Siveswamy, A., Sud, M., Kotrri, G., et al. (2020). Calibration and discrimination of the Framingham Risk Score and the Pooled Cohort Equations. *CMAJ, 192*(17), E442–E449. https://doi.org/10.1503/cmaj.190848
4. Tsiramua, S., Meladze, H., Davitashvili, T., & Zhorzholiani, A. (2025). Risk modeling and assessment with a logical-probabilistic scenario. *Journal of Mathematical Sciences*. https://doi.org/10.1007/s10958-025-07558-x
5. Ryabinin, I. A. (2000). *Reliability and safety of structural complex systems*. St. Petersburg: Politechnika. (*in Russian*)
6. Tsiramua, S., Meladze, H., & Davitashvili, T. (2024). Logical-probabilistic modeling and structural analysis of reconfigurable systems composed of multifunctional elements. *Pattern Recognition and Image Analysis, 34*(*1*), 144–157. https://doi.org/10.1134/S1054661824010218
7. Tsiramua, S., Sulkhanishvili, S., Asabashvili, E., Kvirtia, L., & Berikashvili, I. (2024, May 20–22). Digital transformation of the master's course "Structural Analysis of Systems" [Conference presentation]. *IISES International Academic Conference*, Vienna, Austria. https://iises.net/proceedings/iises-international-academic-conference-vienna-142/table-of-content
8. World Health Organization. (2019). *Cardiovascular diseases*. https://www.who.int/health-topics/cardiovascular-diseases#tab=tab_1

9. World Health Organization. (2020). *HEARTS technical package for cardiovascular disease management in primary health care: Risk-based CVD management* (WHO/UCN/NCD/20.01). https://www.who.int/publications/i/item/9789240001367
10. Zhou, J., You, D., Bai, J., Chen, X., & Wu, Y. (2023). Machine learning methods in real-world studies of cardiovascular disease. *Cardiovascular Innovations and Applications*. https://www.scienceopen.com/hosted-document?doi=10.15212/CVIA.2023.0011
11. Zhao, D., Liu, J., & Xie, W., et al. (2015). Cardiovascular risk assessment: A global perspective. *Nature Reviews Cardiology, 12,* 301–311. https://doi.org/10.1038/nrcardio.2015.28

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