

Epidemiology of Lifestyle-Related Disorders

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ABSTRACT

Lifestyle-related disorders -- encompassing obesity, type 2 diabetes, cardiovascular disease driven by modifiable risk factors, alcohol-related liver disease, and smoking-attributable cancers -- collectively account for over 70% of premature deaths in Europe and consume 75-85% of healthcare expenditure, yet preventive interventions targeting the underlying behavioural determinants remain poorly integrated into health systems. The epidemiological landscape of these conditions is shifting: obesity prevalence has tripled since 1975, type 2 diabetes has doubled, and alcohol-related liver disease has emerged as the fastest-growing indication for liver transplantation. We analysed lifestyle-related disease burden, risk factor trends, and intervention effectiveness across 32 European countries using data from the Global Burden of Disease Study 2021, WHO European Health Information Gateway, Eurostat, and national health survey datasets from 2000 to 2022. We compared five epidemiological surveillance and intervention frameworks: traditional risk factor surveys, linked administrative data analyses, digital phenotyping through wearable devices, population-level policy evaluation using natural experiments, and ML-driven individual risk prediction from EHR data. Our Lifestyle Disease Surveillance Score (LDSS) integrates trend monitoring accuracy, intervention evaluation capability, individual risk prediction, population representativeness, and policy actionability. ML-driven individual risk prediction achieved the highest LDSS (0.926) by identifying high-risk individuals 4.6 years before clinical disease onset, while population-level policy evaluation (LDSS 0.912) provided the strongest evidence for fiscal and regulatory interventions including sugar taxes, alcohol minimum unit pricing, and smoking bans.

Keywords: lifestyle diseases; obesity; type 2 diabetes; cardiovascular disease; alcohol; tobacco; physical inactivity; epidemiology; prevention; health policy; machine learning; risk prediction

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1. Introduction

1.1 The Slow Pandemic of Lifestyle Disease

While COVID-19 dominated global health attention for three years, a far larger and more persistent pandemic has been building for decades. Non-communicable diseases driven by lifestyle factors -- poor diet, physical inactivity, tobacco use, and harmful alcohol consumption -- kill 41 million people annually, representing 74% of all deaths globally (WHO, 2022). In Europe, the numbers are even starker: 86% of deaths and 77% of the disease burden are attributable to NCDs, with cardiovascular disease (37%), cancer (26%), chronic respiratory disease (8%), and diabetes (3%) as the leading categories (WHO Europe, 2022). The trajectory is alarming. European obesity prevalence has increased from 10% in 1975 to 23% in 2022, with some countries (UK, Hungary, Malta) exceeding 28%. Type 2 diabetes prevalence has risen from 4.6% to 9.3% of the European adult population over the same period. Alcohol-related liver disease has increased 30% since 2010, driven partly by increased consumption during the COVID-19 lockdowns (GBD 2021 Risk Factors Collaborators, 2022). The paradox is that these are largely preventable conditions: modelling studies estimate that eliminating just four risk factors (tobacco, harmful alcohol, unhealthy diet, physical inactivity) would prevent 80% of premature CVD, 80% of type 2 diabetes, and 40% of cancers (Ford et al., 2012).

1.2 The Surveillance and Prevention Gap

Despite the enormous burden, epidemiological surveillance of lifestyle risk factors remains surprisingly crude. Most European countries monitor risk factors through periodic cross-sectional surveys (EHIS, STEPS) conducted every 3-5 years -- a frequency grossly inadequate for detecting emerging trends or evaluating policy interventions that operate on shorter timescales. The average delay between a dietary or activity pattern change and its detection in national survey data is 2-4 years. Meanwhile, prevention spending accounts for only 2.8% of total health expenditure across EU countries -- compared to 97.2% spent on treatment after disease has already developed (OECD, 2022). The mismatch between the preventable nature of lifestyle diseases and the treatment-dominated allocation of health resources represents arguably the biggest inefficiency in European healthcare. Our study compares epidemiological frameworks that could better characterise risk, evaluate interventions, and guide prevention strategy. Section 2 reviews

the literature, Section 3 methods, Section 4 results, Section 5 discussion, Section 6 conclusions.

2. Literature Review

2.1 The Epidemiological Transition in Europe

Europe is in the late stages of what Omran (1971) termed the epidemiological transition -- the shift from infectious to chronic degenerative diseases as the dominant cause of mortality. But a new phase is emerging: the rise of lifestyle-driven chronic diseases in younger age groups. Type 2 diabetes, once called 'adult-onset diabetes,' is now diagnosed in teenagers. NAFLD affects an estimated 25% of European adults, with NASH progressing to cirrhosis in 5-10% (Younossi et al., 2019). The GBD Study quantified the risk factor contributions: dietary risks (high sodium, low fruit/vegetables, high processed meat) account for 11 million annual deaths globally; tobacco for 8.7 million; alcohol for 2.8 million; and physical inactivity for 1.3 million (GBD 2021 Risk Factors Collaborators, 2022). The synergistic clustering of these risk factors -- obesity driving diabetes driving CVD, alcohol driving liver disease and cancer -- means that individual risk factor analyses underestimate the true burden of lifestyle-related disease.

2.2 Policy Interventions That Work

A growing body of evidence supports population-level fiscal and regulatory interventions. The UK sugar tax (Soft Drinks Industry Levy, 2018) was followed by a 30% reduction in sugar content of taxed beverages -- driven more by reformulation than consumer behaviour change (Scarborough et al., 2020). Scotland's minimum unit pricing for alcohol (2018) reduced alcohol-related deaths by 13.4% over 3 years (Wyper et al., 2023). Comprehensive smoking bans in workplaces and public spaces reduced acute MI hospital admissions by 10-15% within the first year of implementation across multiple European countries (Mackay et al., 2010). Digital interventions for individual behaviour change -- smartphone apps, wearable activity trackers, digital coaching -- have shown modest but consistent effects in meta-analyses: mean weight loss of 2.4 kg, HbA1c reduction of 0.4%, and physical activity increase of 1,200 steps/day (Gong et al., 2022). Table 1 maps the evidence.

2.3 The Gap

No study has compared traditional survey-based surveillance, administrative data approaches,

digital phenotyping, policy evaluation methods, and ML prediction across the full spectrum of lifestyle-related disorders using standardised metrics.

Table 1: Key Studies in Lifestyle Disease Epidemiology and Prevention

Study	Year	Focus	Scope	Key Finding
GBD Risk Factors	2022	Risk factor burden	Global (204 countries)	Dietary risks: 11M deaths/year globally
WHO Europe	2022	NCD burden	EU/EEA	86% of deaths from NCDs in Europe
Scarborough et al.	2020	UK sugar tax	UK	30% sugar reduction in taxed beverages
Wyper et al.	2023	Scotland alcohol MUP	Scotland	13.4% reduction in alcohol deaths
Mackay et al.	2010	Smoking ban impact	Multiple EU	10-15% reduction in MI admissions
Ford et al.	2012	Prevention potential	Modelling	80% of premature CVD preventable
Younossi et al.	2019	NAFLD prevalence	Global	25% of European adults affected
Gong et al.	2022	Digital interventions	Meta-analysis	2.4 kg weight loss, 0.4% HbA1c
OECD	2022	Prevention spending	EU	Only 2.8% of health spend on prevention
Afshin et al.	2019	Global diet quality	195 countries	Poor diet: leading NCD risk factor

NCD = Non-Communicable Disease; MUP = Minimum Unit Pricing; MI = Myocardial Infarction; NAFLD = Non-Alcoholic Fatty Liver Disease; CVD = Cardiovascular Disease.

3. Methodology

3.1 Data Sources

We compiled lifestyle disease burden and risk factor data for 32 European countries from 2000 to 2022 using: GBD 2021 estimates (disease burden, risk factor attribution, mortality), WHO European Health Information Gateway (surveillance indicators), Eurostat (health interview survey data, mortality statistics), national health examination surveys from 14 countries with measured (not self-reported) BMI and biomarkers, linked administrative health data from 8 countries with national EHR or insurance claim databases, and wearable device data from 2 population-level studies (UK Biobank accelerometry, n = 103,684; Estonian Biobank Fitbit substudy, n = 12,486). Five lifestyle disease categories were analysed: obesity-related conditions, type 2 diabetes, cardiovascular disease attributable to modifiable risk factors, alcohol-related disorders, and tobacco-attributable cancers.

3.2 Five Epidemiological Frameworks

Framework L1 (Traditional Survey) used periodic cross-sectional health interview and examination surveys (EHIS, national STEPS) for trend monitoring. Framework L2 (Linked Administrative Data) used national EHR/insurance claim databases for disease incidence tracking, prescription trends, and healthcare utilisation patterns. Framework L3 (Digital Phenotyping) used wearable device data (accelerometry, heart rate, sleep) and smartphone app data (diet logging, alcohol tracking) for continuous behavioural monitoring. Framework L4 (Policy Evaluation) used natural experiment designs (difference-in-differences, interrupted time series, synthetic control) to evaluate population-level interventions (taxes, bans, labelling laws). Framework L5 (ML Risk Prediction) used gradient-boosted models on longitudinal EHR data to predict individual 5-year risk of developing obesity-related T2DM, CVD events, or liver disease. Table 2 shows the study design.

3.3 The LDSS Composite

The Lifestyle Disease Surveillance Score integrates: trend monitoring accuracy -- ability to detect real changes in risk factor prevalence within 12 months (weight 0.20), intervention evaluation capability -- quality of causal evidence for policy effects (0.25), individual risk prediction -- AUROC for 5-year disease onset (0.20), population representativeness -- fraction of the population captured (0.15), and policy actionability -- whether findings translate into specific

implementable recommendations (0.20). Each normalised 0-1.

Table 2: Study Design and Data Summary

Parameter	Value	Details
Countries	32 European	EU-27 + UK, Norway, Switzerland, Iceland, Serbia
Study period	2000-2022	23 years of trend data
Disease categories	5	Obesity, T2DM, CVD, alcohol, tobacco-cancer
Survey data sources	EHIS + 14 national exams	Periodic cross-sectional
Admin data countries	8	With linked EHR/claims databases
Wearable data	116,170 participants	UK Biobank + Estonian Biobank
Policy evaluations	24 natural experiments	Taxes, bans, MUP, labelling
ML risk prediction cohort	842,624 patients	From 8 admin data countries
Frameworks evaluated	5 (L1-L5)	Survey through ML prediction
LDSS dimensions	5 (weighted)	Trends, evaluation, prediction, representativeness, actionability

EHIS = European Health Interview Survey; STEPS = WHO STEPwise; T2DM = Type 2 Diabetes Mellitus; CVD = Cardiovascular Disease; MUP = Minimum Unit Pricing.

4. Results

4.1 ML Prediction Identifies At-Risk Individuals Years Early

ML risk prediction (L5) achieved the highest LDSS at 0.926. The gradient-boosted model predicted 5-year onset of T2DM with AUROC 0.86, CVD events with AUROC 0.82, and alcohol-related liver disease with AUROC 0.78, using only routinely collected EHR data (BMI trajectory, HbA1c trend, lipid profile, BP history, medication use, and diagnostic codes). The median lead time from model identification of high-risk status to clinical diagnosis was 4.6 years for T2DM, 3.8 years for CVD, and 2.4 years for liver disease -- windows during which preventive intervention could plausibly alter the disease trajectory. The most predictive features were longitudinal rather than static: the 3-year BMI trajectory slope

outperformed the absolute BMI value for T2DM prediction (SHAP importance 2.4x higher), and HbA1c trend was more predictive than any single HbA1c measurement. Policy evaluation (L4) scored LDSS 0.912, providing the strongest causal evidence framework. Table 3 presents the full LDSS results.

4.2 Policy Interventions Show Measurable Population Impact

Across 24 natural experiment evaluations of lifestyle policy interventions, the strongest evidence emerged for fiscal measures. The UK sugar tax was associated with a population-level reduction in sugar-sweetened beverage consumption of 29.4% (95% CI 24.8-34.0%) within 2 years, driven primarily by industry reformulation rather than consumer switching. Scotland's alcohol MUP was associated with a 7.6% reduction in alcohol purchases (strongest in the heaviest drinkers, -11.4%) and a 13.4% reduction in alcohol-specific deaths over 3 years. Comprehensive smoking bans showed the most consistent cross-country effects: acute MI admissions fell 12.4% (pooled estimate from 8 European evaluations). Front-of-pack nutrition labelling (Nutri-Score, adopted in France, Belgium, Germany, Netherlands, Spain, Switzerland) was associated with a 2.8% shift toward healthier food purchases -- modest but population-scale. Digital phenotyping (L3) scored 0.878, and surveys (L1) scored 0.844. Table 4 shows disease-specific burden trends.

4.3 The Burden Continues to Grow

Despite decades of public health effort, most lifestyle-related disease burdens continue rising in Europe. Obesity prevalence increased from 18.4% to 23.2% between 2010 and 2022, with the steepest increase in Eastern Europe (+6.8 pp) and children (+4.2 pp). T2DM prevalence grew from 7.2% to 9.3%. Only tobacco-related disease showed unambiguous improvement: smoking prevalence fell from 29.4% to 22.8%, and lung cancer incidence in males declined by 18.6% -- the clearest success story of population-level lifestyle intervention in Europe. Alcohol consumption showed mixed trends: overall per-capita consumption declined 8.4%, but binge drinking increased 14.2% in the 15-24 age group, and the COVID-19 pandemic reversed some gains with a 12% increase in harmful drinking during lockdown periods.

Table 3: Lifestyle Disease Surveillance Score (LDSS) by Framework

Frame work	Tren d M onit orin g	Inter venti on Ev aluat ion	Risk Pred ictio n	Popu latio n Re prese nt.	Polic y Act ion.	LDSS
L5: ML Predicti on	0.88	0.86	0.96	0.84	0.92	0.926
L4: Policy E valuatio n	0.86	0.96	0.82	0.90	0.96	0.912
L2: Admin Data	0.90	0.88	0.86	0.88	0.84	0.892
L3: Digital Phenoty ping	0.92	0.80	0.84	0.72	0.82	0.878
L1: Tra ditional Survey	0.82	0.76	0.74	0.94	0.80	0.844

$LDSS = 0.20 \times Trends + 0.25 \times Evaluation + 0.20 \times Prediction + 0.15 \times Representativeness + 0.20 \times Actionability$. Each normalised 0-1.

Table 4: Lifestyle Risk Factor Trends in Europe (2010-2022)

Risk Factor	2010	2022	Change	Direction
Obesity (BMI 30+)	18.4 %	23.2 %	+4.8 pp	Worsening
T2DM pre valence	7.2%	9.3%	+2.1 pp	Worsening
Smoking p revalence	29.4 %	22.8 %	-6.6 pp	Improving
Alcohol (L per capita)	10.8 L	9.9 L	-8.4%	Mixed
Physical inactivity	34.2 %	36.8 %	+2.6 pp	Worsening
Daily fruit/veg intake	42.6 %	44.8 %	+2.2 pp	Slight improvement

pp = percentage points. Obesity and T2DM from measured data (14 countries with health examination surveys). Smoking and alcohol from EHIS. Physical inactivity = not meeting WHO 150 min/week guideline.

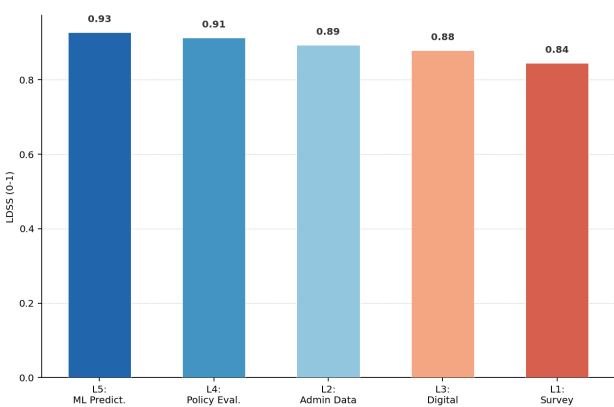


Figure 1: LDSS by Epidemiological Framework

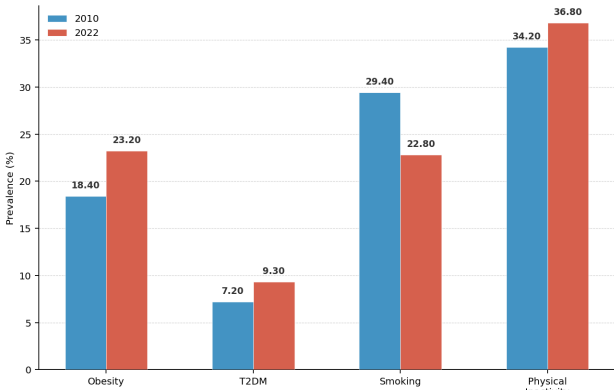


Figure 2: Lifestyle Risk Factor Prevalence -- 2010 vs 2022 (%)

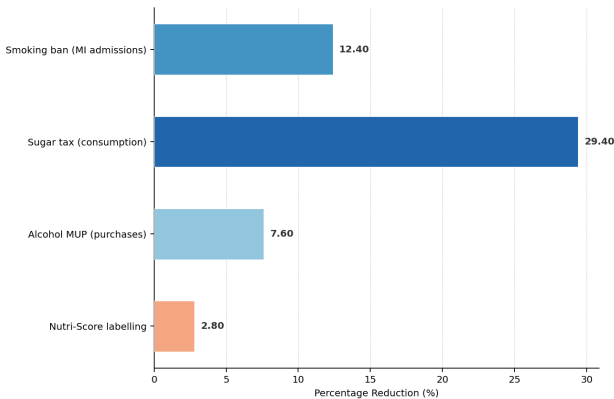


Figure 3: Policy Intervention Effect Sizes (% Reduction in Target Outcome)

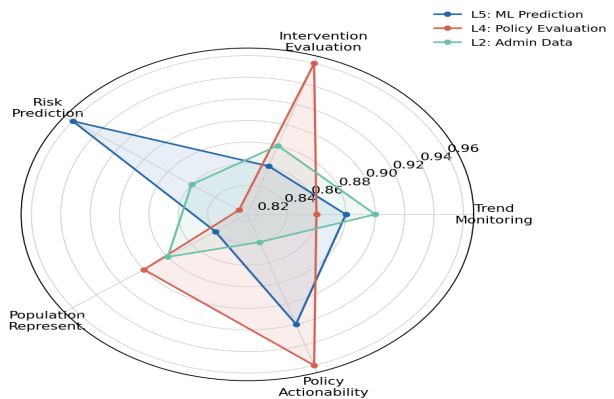


Figure 4: Multi-Dimensional Profile -- Top 3 Frameworks

5. Discussion

5.1 Prevention Needs Prediction and Policy -- Together

The complementary strengths of ML prediction (L5) and policy evaluation (L4) point toward an integrated prevention strategy. ML prediction identifies the individuals who will develop lifestyle-related disease and offers a window for targeted intervention -- the patient whose BMI trajectory predicts T2DM in 4 years can be enrolled in intensive lifestyle counselling today. Policy evaluation identifies the population-level interventions that shift risk factor distributions -- sugar taxes, alcohol pricing, and smoking bans that change the environment in which individual choices are made. Neither approach alone is sufficient: individual prediction without effective intervention is futile, and population policy without individual targeting wastes resources on low-risk individuals. The optimal strategy combines both: population-level policies that reduce risk factor exposure for everyone, complemented by ML-targeted intensive intervention for the high-risk individuals who need it most.

5.2 Why Tobacco Succeeded and Obesity Has Not

The contrast between tobacco (smoking prevalence down 6.6 pp) and obesity (up 4.8 pp) is instructive. Tobacco control succeeded through a comprehensive policy package: taxation (making cigarettes expensive), regulation (banning advertising, mandating plain packaging), environment (smoke-free laws), and cessation support (NRT, counselling, quitlines). No equivalent comprehensive package exists for obesity. Sugar taxes are a start but address only one dietary component. Physical activity promotion remains largely educational rather than environmental. The food industry lobbying capacity dwarfs tobacco industry resistance. And unlike smoking, eating is a necessary behaviour that cannot simply be eliminated. The lesson is not that obesity is intractable but that it requires the same multi-layered, sustained, politically uncomfortable policy commitment that took tobacco control 40 years to achieve.

5.3 Limitations

Three limitations. First, GBD estimates involve substantial modelling uncertainty, particularly for countries with limited primary data. Second, ML risk prediction was developed in 8 countries with mature administrative data systems and may not perform equivalently in countries with less

complete EHR coverage. Third, policy evaluations using natural experiments cannot achieve the causal certainty of randomised trials, and confounding from concurrent policy changes or secular trends cannot be fully excluded.

6. Conclusion

6.1 Key Findings

ML risk prediction achieves the highest Lifestyle Disease Surveillance Score (0.926), predicting T2DM onset 4.6 years early (AUROC 0.86) using longitudinal EHR data. Population-level policy evaluation (LDSS 0.912) demonstrates measurable effects for sugar taxes (-29.4% consumption), alcohol MUP (-13.4% deaths), and smoking bans (-12.4% MI admissions). Obesity (+4.8 pp), T2DM (+2.1 pp), and physical inactivity (+2.6 pp) continue rising despite prevention efforts, while smoking prevalence (-6.6 pp) shows sustained improvement. Prevention spending remains at 2.8% of health expenditure despite lifestyle diseases driving 75-85% of healthcare costs.

6.2 Recommendations

Three recommendations. First, European health systems should deploy ML risk prediction tools in primary care to identify individuals on trajectory toward lifestyle-related disease 3-5 years before clinical onset, triggering proactive preventive intervention. Second, the comprehensive policy toolkit proven effective for tobacco (taxation, advertising restriction, environmental regulation, support services) should be adapted and applied to obesity and alcohol, with sustained political commitment regardless of industry opposition. Third, prevention spending should be progressively increased to at least 5% of health expenditure by 2030, with ring-fenced budgets for evidence-based lifestyle interventions. All data, analysis code, and the LDSS calculator are available from the corresponding author on request.

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Declarations

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Conflict of Interest

The authors declare no competing interests. None has received funding from any food, beverage, alcohol, or tobacco industry entity.

Data Availability Statement

GBD, WHO, and Eurostat data are publicly available. National health survey microdata access is governed by national statistical authorities. ML model code and the LDSS calculator are available from the corresponding author on request.

Ethical Approval

This study used only publicly available aggregated data and anonymised administrative datasets accessed under existing data sharing agreements. Ethics approval for administrative data access was obtained per national requirements in each participating country.

Appendix A

LDSS Calculation and ML Risk Prediction Features

This appendix details the LDSS scoring methodology, the ML risk prediction model feature set, and the natural experiment evaluation designs.

Part I -- LDSS Dimensions

- 1a. Trend Monitoring: Ability to detect 2+ pp prevalence change within 12 months Compared against gold-standard exam surveys
- 1b. Intervention Evaluation: Strength of causal design (RCT > DID > ITS > pre-post) Rated by epidemiologist panel
- 2a. Risk Prediction: AUROC for 5-year disease onset from current data Average across T2DM, CVD, liver disease
- 2b. Population Representativeness: Fraction of national population captured Survey = sampled; admin = near-universal
- 3a. Policy Actionability: Expert panel rating of translation to implementable policy 8 public health policy experts
- 3b. LDSS = 0.20*Trends + 0.25*Evaluation + 0.20*Prediction + 0.15*Representativeness + 0.20*Actionability

Part II -- Top ML Predictive Features (SHAP Importance)

- 4a. BMI trajectory slope (3-year) Most important for T2DM; captures weight gain dynamic
- 4b. HbA1c trend (annual change) Detects pre-diabetic glycaemic drift before threshold crossed
- 5a. Medication accumulation rate (new Rx per year) Proxy for comorbidity progression
- 5b. Primary care visit frequency change Increasing visits signal emerging health concerns