

Article

A Prognostic Algorithm for Heat-Related Mortality in Older Adults: Development in Milan

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Abstract

Climate change is increasing the frequency and intensity of heatwaves, with substantial health impacts and higher mortality among vulnerable groups including older adults and individuals with chronic diseases. Risk stratification tools may support public health systems in identifying high-risk individuals and implementing targeted preventive interventions. This population-based study included Milan residents aged ≥ 75 years during the summers of 2022–2023 and aimed to test an algorithm for stratifying heat-related health risk. By combining individuals' classification as ill, treated, and deprived, four heat-related risk levels were defined. The algorithm was developed on the 2022 cohort and validated on the 2023 cohort. A logistic regression model with cross-validation was used, and performance was assessed using AUC, calibration, and Brier score. A total of 192,063 (2022) and 181,509 (2023) residents aged ≥ 75 years were included. Approximately 56% were classified as high or very high risk, with slightly higher proportions in 2023. Mortality increased with risk level and multimorbidity. The model showed good overall accuracy, fair discrimination, and good calibration in the development cohort. Higher mortality was associated with male, older age (≥ 85 years), and higher risk strata, while living alone showed inconsistent associations. This prognostic algorithm may contribute to the stratification of heat-related mortality risk among older adults and could support targeted prevention and timely responses to heatwave.

Keywords: heatwaves; risk stratification; mortality prediction

1. Introduction

Europe is experiencing rapid warming, and rising temperatures are expected to increase the frequency and intensity of heatwaves and related health risks [1]. The increase in the probability of heatwaves in large urban areas in the Region is of particular concern. A recent study estimated heatwave probability increases for the major of European capitals and found that all the European metropolitan areas investigated will be more vulnerable to extreme heat in the coming decades [1–7]. Heatwaves are a threat to human health and are associated with increased mortality, particularly among the most vulnerable segments of the population [8–12]. Risk stratification is an increasingly used tool in environmental health surveillance. It can reveal meaningful disparities in both exposure and health outcomes and help public health agencies target interventions [13,14]. Within heat–health action plans across Europe, forecasting health impacts before hot-weather periods is a key component. In Italy, the Heat Health Watch Warning System (HHWWS), in place since 2004 in regional capitals and other cities with populations > 250,000, monitors heat-related



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health impacts by using observed temperature–mortality relationships and air-mass classifications to identify meteorological conditions associated with significant increases in daily mortality [15–17]. In Milan, the Local Climate Monitoring System is managed by the Epidemiology Unit of the Agency for Health Protection of the Metropolitan City of Milan (ATS-MI). The Unit disseminates the HHWWS bulletin daily to healthcare and social services, including hospitals and elder-care facilities, to support the implementation of preventive actions. These interventions are tailored either to the warning level or to the vulnerability profiles of the populations served [18–24]. Heatwaves disproportionately affect vulnerable populations, and extreme heat is increasingly recognized as a major contributor to preventable summer mortality [17,25,26]. In Milan, we recently examined individual-level demographic, clinical, and social vulnerability factors in relation to heat exposure. We identified several key determinants across these three domains that were associated with an increased risk of death during heatwave period [27]. We therefore aimed to develop a prediction model with broader applicability and greater practical utility for predicting heat-related mortality. Specifically, our aim was to identify individuals at the highest risk of heat-related mortality who would be most likely to benefit from targeted, locally implemented interventions designed to reduce mortality during heatwave periods.

2. Materials and Methods

2.1. Study Period

This study was carried out during the warmest period of the year (mid-July to mid-September) across two consecutive summers (2022–2023). In Milan, we used data from the 2022 cohort to develop the prognostic model, focusing on the hottest weeks of the season, which included a major heatwave from 15 to 25 July 2022 [26]. That summer was characterized by record-breaking temperatures across Europe [28], with repeated intense heatwaves and extreme heat occurring alongside severe drought and widespread wildfires. As previously reported [29], daily maximum temperatures remained persistently high during this episode, providing a clear contrast between heatwave and non-heatwave conditions. Trends in daily temperature and daily deaths over the study period are shown in Supplementary Figure S1. To evaluate the model’s generalizability, we performed temporal validation using the 2023 cohort, assessing the model’s predictive performance in the same population but during a different summer, which included the major heatwave that lasted from 20 to 25 August 2023 [30]. In this validation, the 2023 data served as an external temporal test set, allowing us to examine the model’s predictive performance under temperature conditions that differed from those in 2022 and to capture the year-to-year variability expected under a changing climate. Trends in daily temperature and daily deaths over the external validation period are shown in Supplementary Figure S2.

2.2. Source of Data

Older adults are disproportionately affected by heat (>80% of excess heat-related deaths) [28,30,31] so we restricted the analysis to individuals aged ≥ 75 years. Through the Local Climate Monitoring System run by the Epidemiology Unit of ATS-MI, we identified all deaths occurring during the study period (Supplementary Figure S3). Individual-level demographic, clinical and social factors considered key indicators of vulnerability to heatwaves, were retrieved from the Lombardy Region Health Information System via record linkage (anonymized fiscal code) across six administrative sources: the Nominative Register of Causes of Death (ReNCaM), to extract individual-level mortality data coded according to the International Classification of Diseases, Tenth Revision (ICD-10); the New Regional Registry (NAR), to identify individuals with a valid tax code and assigned to a general practitioner; Hospital Discharge Sheets (HDS), to collect information on

hospitalizations of subjects discharged from all public and private inpatient institutions and coded according to the International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM); Pharmaceutical Flows (all outpatient prescription records), for all pharmaceutical prescriptions; the Exemption Information Flow, including valid and active exemptions; and Social and Health Flows, to identify all service centers to which individuals were linked. To best reflect health status at the time of death, we considered records documented within the 2 years preceding inclusion [32,33] and, when multiple records were available, retained the one closest to the date of inclusion. The list of diagnoses, pharmaceutical groups, exemptions, and social assistance services considered is reported in the Supplementary Materials (Tables S1–S4).

In line with the National Plan for the Prevention of Health Effects of Heat [34], and the Ministry of Health's Heatwave Campaign [35], the indicators were selected a priori based on previous evidence on heat-related vulnerability, biological and clinical plausibility, routine availability in administrative health and social care databases, and their potential operational use for targeted public health prevention.

Specifically, gender (female/male) and age (75–84/ ≥ 85) were included as demographic determinants; pre-existing medical conditions (yes/no), treatment (yes/no) and disability (yes/no) as indicators of clinical vulnerability; deprivation (yes/no) as indicator of socioeconomic vulnerability; and living alone (yes/no) as an indicator of household composition potentially related to social vulnerability, although not as a direct proxy for social isolation. All variables were included in the model as categorical variables. Accordingly, subjects were classified as: Ill, if they had evidence of relevant conditions in HDS (Supplementary Table S1) and/or in the Exemption Information Flow (Supplementary Table S4); Treated, if they appeared in the Pharmaceutical Flows (Supplementary Table S2); and Deprived, if their residence was located in a census section classified as the most deprived according to the 2011 Italian deprivation index [36], which is categorized into five levels, with level 5 indicating the highest deprivation, or if they were entitled to an income-based exemption.

Temperature data were obtained as continuous variables from open-access datasets provided by the Regional Environmental Protection Agency (ARPA) [37]. Tmax was defined as the daily maximum ambient temperature, calculated as the average of the daily maximum temperature records across six urban background monitoring sites.

2.3. Individual-Level Prediction Algorithm: Development

The prognostic tool aims to stratify the population according to increasing vulnerability to extreme heat. Accordingly, death (binary: yes/no) was the primary outcome, used to assess the model's ability to identify heatwave-related adverse impacts and to examine how well its risk classification corresponds to established vulnerability indicators. The study population included all Milan residents aged ≥ 75 years on 1 January 2022 who were alive on 14 July 2022 and were followed until 15 September 2022. In accordance with the Italian Ministry of Health guidelines, the coexistence of chronic illnesses, pharmacological treatments, and socio-economic deprivation identifies population subgroups at progressively higher risk of adverse health effects during heatwaves.

By combining the Ill, Treated, and Deprived conditions, four risk categories for heatwave-related effects were identified [34].

Subjects who were not ill, not treated, and not deprived were classified as Baseline risk. Intermediate risk was assigned to subjects meeting any of the following criteria: (i) deprived or ill but not treated; (ii) treated but not ill and not deprived; or (iii) treated and deprived but not ill. High risk included subjects who were: (i) treated, not ill, and exempt from pharmaceutical charges for chronic or rare conditions, irrespective of economic status;

(ii) treated and ill; or (iii) ill and deprived. Very high risk was defined as being ill, treated, and deprived.

2.4. Individual-Level Prediction Algorithm: Validation

The validation strategy was designed to minimize bias and ensure robust, reproducible performance across datasets. Internal validation was conducted using five-fold cross-validation ($k = 5$). The dataset was randomly partitioned into five mutually exclusive folds of approximately equal size. Across five iterations, four folds were used to develop (train) the prediction model, and the remaining fold served as the validation (test) set. Performance metrics were then averaged across folds to obtain overall internal validation estimates [38,39]. To evaluate generalizability, we additionally performed temporal validation in the external validation cohort [40,41]. The study population included all Milan residents aged ≥ 75 years on 1 January 2023 who were alive on 14 July 2023 and were followed until 15 September 2023 (Supplementary Figure S3). Deaths from natural causes (ICD-10: A00–R99), excluding external causes, occurring between mid-July and mid-September 2023 were recorded as events, while individuals alive on 15 September 2023 were considered non-events. To better capture health status at the time of death, predictor information was considered valid if recorded within the two years preceding inclusion. Based on the predictors selected a priori, we classified subjects into four baseline risk strata, as reported previously: Baseline risk, Intermediate risk, High, and Very high risk.

2.5. Statistical Analysis

Subject characteristics were summarized as counts and percentages. The model's predictive performance was assessed using a logistic regression model including age, gender, risk level and living alone as categorical regressors. Only subjects with complete information on all predictors were included in the analysis.

Overall accuracy was quantified using the Brier score, which ranges from 0 (perfect prediction) to 1 (worst possible prediction) [42,43]. Discrimination was evaluated using the C-index/area under the ROC curve (AUC), where 1 indicates perfect discrimination and 0.5 indicates performance no better than chance; values of 0.7–0.8 are typically considered fair and 0.8–0.9 good [39]. Calibration was assessed using calibration intercept and slope, the Hosmer–Lemeshow test and visualized with a calibration plot [44–46]. In logistic calibration, perfect calibration occurs when the intercept $a = 0$ and the slope $bL = 1$, which appears as a 45° diagonal line in the calibration plot where observed event rates match predicted risks. Miscalibration is indicated by a slope $bL < 1$ (overfitting; predictions too extreme) or $bL > 1$ (underfitting; predictions not extreme enough), and/or by a negative intercept significantly different from 0, meaning that the model overestimates risk on average. In these cases, calibration can be improved through logistic recalibration by fitting: $\text{logit}(Y) = a + bL \times L$, where L is the model's linear predictor [47]. Model performance across risk strata was assessed in the External Validation Cohort (2023) by comparing predicted probabilities with observed deaths, using regression coefficients estimated in the Development Cohort (2022).

Finally, we then examined the relationship between mortality and risk strata (baseline risk as reference), using a log-linear Poisson model adjusted for gender (female as reference) and age (75–84 as reference), and living alone (not living alone as reference) [33] [48–52], with a population offset representing the population exposed to the risk of death from May to September. Results are presented as Relative Risks (RRs) with 95% CIs and estimated model parameters are reported in the Section 3, after checking for overdispersion, by comparing the mean and variance of the count data.

All analyses were preformed in SAS software, version 9.4 (SAS Institute Inc., Cary, NC, USA).

3. Results

3.1. Population Description and Stratification

In Milan, 192,063 (Development Cohort) and 181,509 (External Validation Cohort) residents aged ≥ 75 years were included (Supplementary Figure S3). From mid-July to mid-September, 2203 deaths (1.15%) occurred in the Development Cohort and 1711 (0.94%) in the External Validation Cohort. Table 1 summarizes the characteristics of subjects classified in the highest-risk strata (high and very high risk), who represent the main targets of public health interventions aimed at mitigating heat-related emergencies and preventing excess summer mortality. Overall, in the development cohort, approximately 34% of subjects were classified as high risk and 22% as very high risk. Similar proportions, slightly higher, were observed in the external validation cohort.

Table 1. Descriptive statistics for demographic, clinical, and social characteristics of the Development and External Validation Cohorts, and deaths occurring during the two-month summer period (mid-July to mid-September), in the highest-risk strata.

Characteristic	Development Cohort, 2022 (<i>n</i> = 192,063)			External Validation Cohort, 2023 (<i>n</i> = 181,509)		
	High Risk (N, %)	Very High Risk (N, %)	Deaths from All Causes * (N, %)	High Risk (N, %)	Very High Risk (N, %)	Deaths from All Causes * (N, %)
Gender						
Female	38,719 (58.66)	26,996 (64.76)	1286 (1.08)	37,921 (58.37)	28,020 (64.49)	994 (0.88)
Male	27,289 (41.34)	14,689 (35.24)	917 (1.25)	27,049 (41.63)	15,430 (35.51)	717 (1.04)
Age						
75–84	42,917 (65.02)	24,663 (59.17)	675 (0.55)	41,335 (63.62)	24,601 (56.62)	529 (0.46)
≥ 85	23,091 (34.98)	17,022 (40.83)	1528 (2.21)	23,635 (36.38)	18,849 (43.38)	1182 (1.80)
Ill	57,834 (87.62)	41,542 (99.66)	1411 (1.17)	58,103 (89.43)	43,278 (99.60)	1168 (0.95)
Treated	53,783 (81.48)	39,421 (94.57)	1394 (1.25)	51,307 (78.97)	40,679 (93.62)	1032 (0.96)
Deprived	7856 (11.90)	24,904 (59.74)	395 (0.88)	7838 (12.06)	25,516 (58.72)	314 (0.72)
Disabled	12,833 (19.44)	26,108 (62.63)	1317 (3.09)	12,817 (19.73)	28,311 (65.16)	1042 (2.33)
Chronic condition(s)						
0	2806 (4.25)	903 (2.17)	242 (0.78)	2803 (4.31)	912 (2.10)	162 (0.56)
1	13,203 (20.00)	5660 (13.58)	388 (0.93)	12,610 (19.41)	5570 (12.82)	281 (0.81)
2–3	30,924 (46.83)	17,803 (42.71)	790 (1.26)	30,549 (47.02)	18,582 (42.77)	634 (0.99)
3+	19,075 (28.90)	17,319 (41.55)	783 (2.46)	19,008 (29.26)	18,386 (42.32)	634 (1.84)
Living alone						
Yes	25,248 (38.25)	19,000 (45.58)	962 (1.26)	25,128 (38.68)	19,999 (46.03)	713 (0.95)
No	40,760 (61.75)	22,685 (54.42)	1241 (1.07)	39,842 (61.32)	23,451 (53.97)	998 (0.93)
Total	66,008 (34.37)	41,685 (21.70)	2203 (1.15)	64,970 (35.79)	43,450 (23.94)	1711 (0.94)

* Daily deaths from all causes based on the International Classification of Diseases, 10th Revision (ICD-10; A00-R99).

Across datasets, the proportion of males was slightly lower and variability increased within the very high-risk stratum. During the study period, deaths were more frequent among females than among males only in the Development Cohort, whereas they were approximately evenly distributed by sex in the External Validation Cohort. Full risk profiles for the Development (2022) and External Validation (2023) Cohorts are provided in Supplementary Tables S5 and S6. Within this elderly population, the prevalence of illness, treatment, deprivation, disability, and having two or more chronic conditions increased with higher risk strata. Mortality likewise increased with both risk level and the number of

chronic diseases. Overall, deaths occurred more frequently among subjects not living alone (1.26% in the development cohort and 0.95% in the external validation cohort%) than among those living alone (1.07% in development cohort and 0.93% in external validation cohort).

3.2. Algorithm Predictive Performance

Table 2 shows the measures of the algorithm's predictive performance. The Brier score showed very good overall prediction accuracy; regarding discrimination, the prediction model showed fair discriminatory power, meaning that it can distinguish between individuals who died during the summer period and those who did not. Regarding calibration, the Development Cohort demonstrated good performance, with a calibration intercept close to 0 and a slope equal to 1. In the External Validation Cohort, however, the observed event rate was 9.43 per 1000 individuals, whereas the mean predicted risk was approximately 12.0 per 1000, indicating miscalibration (calibration intercept = -0.55 ; calibration slope = 0.93). Given this systematic deviation, the model was recalibrated, resulting in a marked improvement in calibration. After recalibration, the observed event rate closely matched the mean predicted risk (both approximately 9.43 per 1000 individuals), with a calibration intercept near 0 and a calibration slope close to 1. The Hosmer–Lemeshow goodness-of-fit test was statistically significant overall. Calibration plots are shown in Supplementary Figure S4.

Table 2. Measures of predictive performance for the Development and External Validation Cohorts.

Measures of Predictive Performance	Cross-Validation, 2022 ($n = 192,063$)	External Validation, 2023 ($n = 181,509$)
Overall accuracy		
Brier score	0.01	0.009
Discrimination		
C-index/area under the curve (AUC)	0.71	0.70
	(95% CI: 0.69–0.72)	(95% CI: 0.69–0.71)
Calibration		
Calibration intercept	-0.0242	0
Calibration slope	1	1
Hosmer–Lemeshow test	<0.0001	<0.0001

Table 3 reports the risk ratios (RRs) and corresponding 95% confidence intervals (CIs) from the log-linear Poisson model estimating the daily incidence rate of deaths in the Development Cohort and External Validation Cohort, after confirming the absence of overdispersion (see Supplementary Tables S7 and S8 for details on the preliminary analysis of sample means and variances). The daily incidence rate in the very high-risk stratum was highest in the Development Cohort (3.63; 95% CI: 3.04–4.35); however, the wider confidence intervals reflect the smaller sample size within this stratum. Compared with females, males showed a statistically significantly higher daily incidence rate of death, with an increase of approximately 33% in both cohorts. In addition, older age was associated with a statistically significant increase in the daily incidence rate of death, approximately fourfold higher than that observed in the reference age group (75–84 years) in both cohorts. In the Development Cohort, the daily incidence rate of death was approximately 2% higher among older adults living alone than among those not living alone. In the External Validation Cohort, however, living alone did not appear to be an independent predictor of heat-related mortality.

In both cohorts (Supplementary Table S9), mortality rates generally increased from the baseline to the very high-risk stratum across thermal periods, although this pattern was

not strictly monotonic in all strata. Mortality rates during heatwave periods were generally higher than those observed during non-heatwave periods across risk strata.

Table 3. Risk Ratios for the adjusted model prediction in both the training and validation sets.

Prediction Model	Cross-Validation, 2022 (<i>n</i> = 192,063)		External Validation, 2023 (<i>n</i> = 181,509)	
	RR ^a (95% CI) ^b	<i>p</i> -Value	RR ^a (95% CI) ^b	<i>p</i> -Value
Baseline Risk	Ref ^c		Ref ^c	
Intermediate Risk	2.31 (1.92–2.77)	<0.0001	1.97 (1.57–2.46)	<0.0001
High Risk	2.54 (2.13–3.03)	<0.0001	2.33 (1.88–2.89)	<0.0001
Very High Risk	3.63 (3.04–4.35)	<0.0001	2.82 (2.26–3.50)	<0.0001
Gender				
Female	Ref ^c		Ref ^c	
Male	1.33 (1.22–1.45)	<0.0001	1.27 (1.14–1.40)	<0.0001
Age				
75–84	Ref ^c		Ref ^c	
≥85	3.98 (3.63–4.36)	<0.0001	3.90 (3.51–4.33)	<0.0001
Living alone				
No	Ref ^c		Ref ^c	
Yes	1.02 (0.93–1.11)	0.73	0.86 (0.78–0.96)	0.0057

^a: RR: risk ratio; ^b: RR and corresponding 95% CI; ^c: Reference category in the Prediction Model.

4. Discussion

4.1. Principal Findings

In this study, we developed a multivariable prediction algorithm for heat-related mortality based on administrative data. The algorithm incorporated key vulnerability indicators across demographic, clinical, and social domains, reflecting conditions associated with impaired thermoregulation and/or a reduced capacity to adopt protective behaviors.

Overall, the model demonstrated fair discrimination for summer mortality (C-index $\approx$ 0.71), indicating a reasonable ability to distinguish individuals who experienced heat-related death from those who did not. The Brier score was close to zero, reflecting good overall predictive accuracy and predicted risks that were, on average, close to the observed event rates. Assessment of global calibration further supported good agreement between predicted and observed risks, with the calibration intercept and slope indicating appropriate calibration-in-the-large. These results were also confirmed in the External Validation Cohort after model recalibration.

By contrast, the Hosmer–Lemeshow test was statistically significant, which could be interpreted as evidence of imperfect calibration. However, this test is well known to be highly sensitive to sample size and to the choice of grouping, such that even negligible departures from perfect fit may yield statistical significance in large cohorts [44,53]. Accordingly, we place greater emphasis on global calibration metrics, which are more informative for practical use, concluding that the model exhibits acceptable calibration for the intended risk stratification and population-level applications.

Subsequently, using a log-linear Poisson regression model, we identified a statistically significant risk gradient in heat-related mortality across the predefined strata, with progressively higher risk from the baseline to the very-high-risk group. In addition to risk strata, male sex (vs. female) and older age were independently associated with increased heat-related mortality. These associations were consistent in both the development and external

validation cohorts, supporting the robustness and transportability of the stratification. In summary, the results support the ability of the implemented stratification algorithm for individuals aged ≥ 75 years to distinguish those at higher risk, with consistently higher risk estimates in the upper risk strata. The algorithm integrates and summarizes multiple individual-level dimensions, including health status (i.e., ill, treated, chronic conditions) and socioeconomic deprivation.

The observed excess mortality among older adults classified in the high and very high-risk strata, confirms that the heat-related mortality is associated with underlying vulnerability. More than 60,000 heat-attributable deaths were estimated across Europe in 2022 [28], with Italy among the most affected countries and the majority of deaths occurred in individuals aged 80 years and older. The higher excess mortality observed in our development cohort is therefore epidemiologically coherent with continent-wide estimates for that year. In particular, estimates for the high and very high-risk strata and older adults living alone were higher in 2022 than in 2023, likely reflecting the exceptionally hot summer experienced in Italy in 2022, during which more vulnerable individuals were at increased risk of death on extremely hot days. The observed increase in risk among older adults and among subjects living alone is consistent with evidence from population-based epidemiological studies [54]. In the External Validation Cohort, however, living alone did not appear to be an independent predictor of heat-related mortality. Living alone, as measured through administrative data, captures household composition but may not adequately reflect social isolation or lack of support. Indeed, it may identify a selected group of older adults who are relatively healthier and more autonomous; therefore, it should not be interpreted as a direct proxy for social isolation. Residual confounding, misclassification, statistical instability, and the specific characteristics of the 2023 summer, which was characterized by less exceptional temperatures than 2022, may also have contributed to this counterintuitive finding. With regard to sex, in contrast to most previous studies [28,55], we observed a higher risk among males compared with females, however, our estimates were adjusted for vulnerability, as defined by proposed stratification algorithm. Moreover, the observed pattern was coherent with the summary of results for summers 2022 and 2023 reported in the National Operational Plan for the Prevention of the Effects of Heat on Health, reinforcing the public health relevance of the identified vulnerability gradient.

Given the large population-based sample, statistical significance should be interpreted with caution, as small p -values may also reflect the high statistical power of the study. Therefore, the interpretation of the findings was based primarily on the direction and magnitude of the effect estimates, and on their public health relevance, rather than on statistical significance alone.

4.2. Strengths and Limitations

Key strengths of this study include the large, population-based design: we captured all deaths among individuals aged ≥ 75 years, with no additional selection criteria, thereby minimizing selection bias and enhancing external validity. Moreover, individual-level record linkage across multiple administrative sources enabled the inclusion of a broad set of personal indicators, including demographic, clinical, and social factors, covering conditions associated with increased vulnerability to heat-related mortality, consistent with the National Plan for the Prevention of Health Effects of Heat and the Ministry of Health Heat Wave Campaign. With respect to model development and validation, we selected 2022 to reflect a climate change scenario in which extreme temperatures are becoming more frequent and may increasingly represent the “new normal.” We also performed external validation using data from the subsequent year in the same city to assess the algorithm’s potential implementation as an operational approach in future years within the local setting.

Several limitations should be acknowledged. First, the model was developed in the Milan population and, although the approach may be generalizable to other high-income settings with comparable demographic structures and patterns of access to healthcare services, model performance and applicability may vary across countries due to differences in healthcare organization, baseline population health, and broader social determinants of health. Second, the tool is representative only of individuals with a valid tax identification code and who are registered with a general practitioner, potentially limiting applicability to marginalized groups or individuals not fully captured by administrative systems.

Finally, the study included selected risk factors for heat-related mortality that were routinely available from administrative health and social care databases. Nevertheless, several potentially relevant individual, behavioral, environmental, and contextual factors could not be captured. These include, for example, overweight and obesity, dietary habits and daily fluid intake, smoking and alcohol consumption, other lifestyle-related behaviors, the severity of pre-existing clinical conditions, air pollution and other environmental co-exposures, housing conditions, access to cooling systems, social support networks, mobility limitations, and whether individuals spent part of the summer period outside the city. In particular, we lacked a more granular assessment of other social determinants and contextual determinants of vulnerability (e.g., neighborhood deprivation, and access to cooling), which may influence heat vulnerability. Nevertheless, the included predictors were routinely available and consistently recorded in administrative datasets, supporting the feasibility of implementation. Future work should evaluate whether incorporating richer social and contextual information can further improve predictive performance and the equity of risk stratification.

With regard to the exposure considered in this study, maximum temperature alone may not fully capture the complexity of heat exposure. Future studies should therefore assess whether incorporating minimum temperature or cumulative heat exposure metrics improve model performance and risk stratification.

Model validation was based on a temporal split, which allowed performance to be assessed in a subsequent period not used for model development. Further validation strategies, such as internal–external cross-validation across years or geographic subareas, could provide additional evidence on the robustness and transportability of the model.

Future studies should further estimate mortality rates across different levels of thermal stress and assess how these associations vary across specific population subgroups. Previous evidence from Milan using a similar administrative data-based stratification [29] has already shown the relevance of evaluating heatwave-related mortality risks across demographic, clinical, and social vulnerability profiles.

5. Conclusions

In conclusion, we developed and implemented a prognostic algorithm to predict heat-related mortality in older adults, and the resulting risk stratification provided a clinically interpretable framework for identifying individuals with greater vulnerability. From a public health perspective, this approach may support local health authorities, healthcare administrators, and policymakers in planning and prioritizing heat health prevention strategies before and during the summer period. By using routinely collected administrative health and social care data, the algorithm can help identify high-risk individuals who may benefit from early targeted support and surveillance measures. If adopted systematically, this tool could complement population-wide prevention measures by supporting timely and targeted heatwave responses and more efficient allocation of resources at both local and national levels. Future developments should integrate clinical, social, environmental, and contextual information to better capture heat-related vulnerability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/environments13070370/s1>, Table S1: List of diagnoses recorded in hospital discharge records; Table S2: List of the Anatomical Therapeutic Chemical (ATC) codes; Table S3: List of exemptions; Table S4: List of service centres; Table S5: Full risk profiles across four risk strata in the Development Cohort, 2022; Table S6: A full risk profile for all risk categories in the External Validation Cohort, 2023; Table S7: Mortality rates and rate ratios for the 2022 and 2023 cohorts during the overall period (15 July–15 September), heatwave days, and the remaining non-heatwave period; Table S8: Preliminary analysis of sample means and variances for Development Cohort; Table S9: Preliminary analysis of sample means and variances for External Validation Cohort; Figure S1: Daily deaths and daily ambient temperature during summer 2022; Figure S2: Daily deaths and daily ambient temperature during summer 2023; Figure S3: Flow chart Development Cohort, 2022 ($n = 192,063$) and External Validation Cohort, 2023 ($n = 181,509$); Figure S4: Calibration plot of the multivariable logistic regression model predicting heat-mortality risk, in the Development Cohort (A) and in the External Validation Cohort (B).

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Institutional Review Board Statement: Ethics approval was not required because evaluating residents’ use of health services and the population’s health status is a statutory function of the Agency for Health Protection (ATS) of Milan (Lombardy Regional Laws nos. 23/2015 and 22/2021) and constitutes a key component of surveillance and monitoring within the National Healthcare System (NHS).

Informed Consent Statement: In accordance with national legislation and institutional requirements, written informed consent for participation was not required because the study was based on routinely collected administrative data.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy reason.

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

Abbreviations

The following abbreviations are used in this manuscript:

AUC	Area Under Curve
EURO-CORDEX	European branch of the World Climate Research Programme’s Coordinated Regional Climate Downscaling Experiment
HHWWS	Heat Health Watch Warning System
ATS-MI	Agency for Health Protection of the Metropolitan City of Milan
ReNCaM	Nominative Register of Causes of Death
NAR	New Regional Registry
HDS	Hospital discharge sheets
ICD-9-CM	International Classification of Diseases, 9th Revision, Clinical Modification
ARPA	Regional Environmental Protection Agency
ICD-10	International Classification of Diseases, Tenth Revision
RRs	Relative Risk
CI	Confidence Interval

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