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Survival beyond the hazard: Fine-gray methods for public health: A narrative review

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Abstract

Competing risks are frequently encountered in epidemiological and clinical research, where individuals may experience one of the several mutually exclusive outcomes. Traditional survival analysis methods, including the Kaplan-Meier estimator and Cox proportional hazards regression, assume non-informative censoring and may therefore produce biased risk estimates when competing events are present [1-3]. The Fine-Gray subdistribution hazard model was developed to address this limitation by directly modeling the cumulative incidence function (CIF), thereby providing accurate estimates of absolute event probability in competing risks settings [1]. This narrative review summarizes the theoretical principles, epidemiological applications, healthcare relevance, strengths, limitations, methodology, and future directions of the Fine-Gray model. Current applications in oncology, infectious diseases, cardiovascular epidemiology, nephrology, and critical care are discussed. The review also highlights emerging integration with machine learning and precision public health. The Fine-Gray model remains an important methodological approach for modern epidemiological healthcare research.

Keywords: Fine-gray model; competing risks; cumulative incidence function; survival analysis; epidemiology; public health; healthcare analytics

Introduction

Survival analysis is widely used in epidemiology and clinical research to evaluate time-to-event outcomes such as mortality, recurrence, disease progression, and recovery. However, many clinical and public health scenarios involve competing risks, where the occurrence of one event prevents the occurrence of another event of interest [2, 4]. For example, in cancer epidemiology, patients may die from non-cancer causes before experiencing cancer-specific mortality. Similarly, in intensive care unit (ICU) research, discharge from the hospital competes with in-hospital death. Traditional survival analysis approaches, such as the Kaplan-Meier estimator and Cox proportional hazards model, assume non-informative censoring and treat competing events as censored observations [3]. This assumption is violated in competing risks settings and leads to overestimation of event probabilities [5]. To address this methodological limitation, Fine and Gray introduced the subdistribution hazard model in 1999 [1]. Unlike cause-specific hazard models, the Fine-Gray model directly estimates the cumulative incidence function (CIF), which represents the probability of experiencing a particular event over time in the presence of competing risks [1, 4]. The Fine-Gray model has become increasingly important in epidemiology, public health, oncology, nephrology, infectious disease research, and healthcare analytics. This narrative review summarizes the theoretical background, methodological concepts, current applications, advantages, limitations, and future directions of the Fine-Gray model in public health and epidemiological research.

Methodology

Study design

This study was conducted as a narrative review focusing on the application of the Fine-Gray competing risks model in survival analysis, epidemiology, public health, and healthcare research. Keywords and Medical Subject Headings (MeSH) terms were selected based on

methodological relevance and previous competing risk literature. The primary search terms included “Fine-Gray model,” “competing risks,” “subdistribution hazard,” “cumulative incidence function,” and “survival analysis.” Additional public health and clinical research terms such as “epidemiology,” “healthcare analytics,” “oncology,” “cardiovascular epidemiology,” “infectious diseases,” “critical care,” and “nephrology” were combined using Boolean operators (“AND” and “OR”) to optimize database retrieval. Synonymous methodological terms including “time-to-event analysis,” “cause-specific hazard,” “Kaplan-Meier,” and “Cox proportional hazards model” were also incorporated to ensure comprehensive coverage of competing risk methodology studies. The search strategy was adapted appropriately for each electronic database, including PubMed, Scopus, Web of Science, and Embase.

Eligibility criteria

Studies were included if they applied the Fine-Gray competing risks model in epidemiological, clinical, or public

health research involving survival or time-to-event outcomes. Only peer-reviewed English-language articles published between 1999 and 2025 were considered. Studies focusing on healthcare analytics, oncology, nephrology, cardiovascular epidemiology, infectious diseases, and critical care were prioritized because these areas commonly involve competing risk outcomes. Editorials, conference abstracts without complete data, non-English publications, studies lacking adequate statistical methodology, and articles unrelated to competing risk analysis were excluded from the review. Relevant articles were identified through electronic database searches and manual screening of reference lists.

Study selection process

Titles and abstracts identified during the search were screened independently based on eligibility criteria. Relevant full-text articles were then assessed for inclusion. Duplicate records were removed before screening. The final included studies were narratively synthesized according to methodological relevance and thematic applicability.

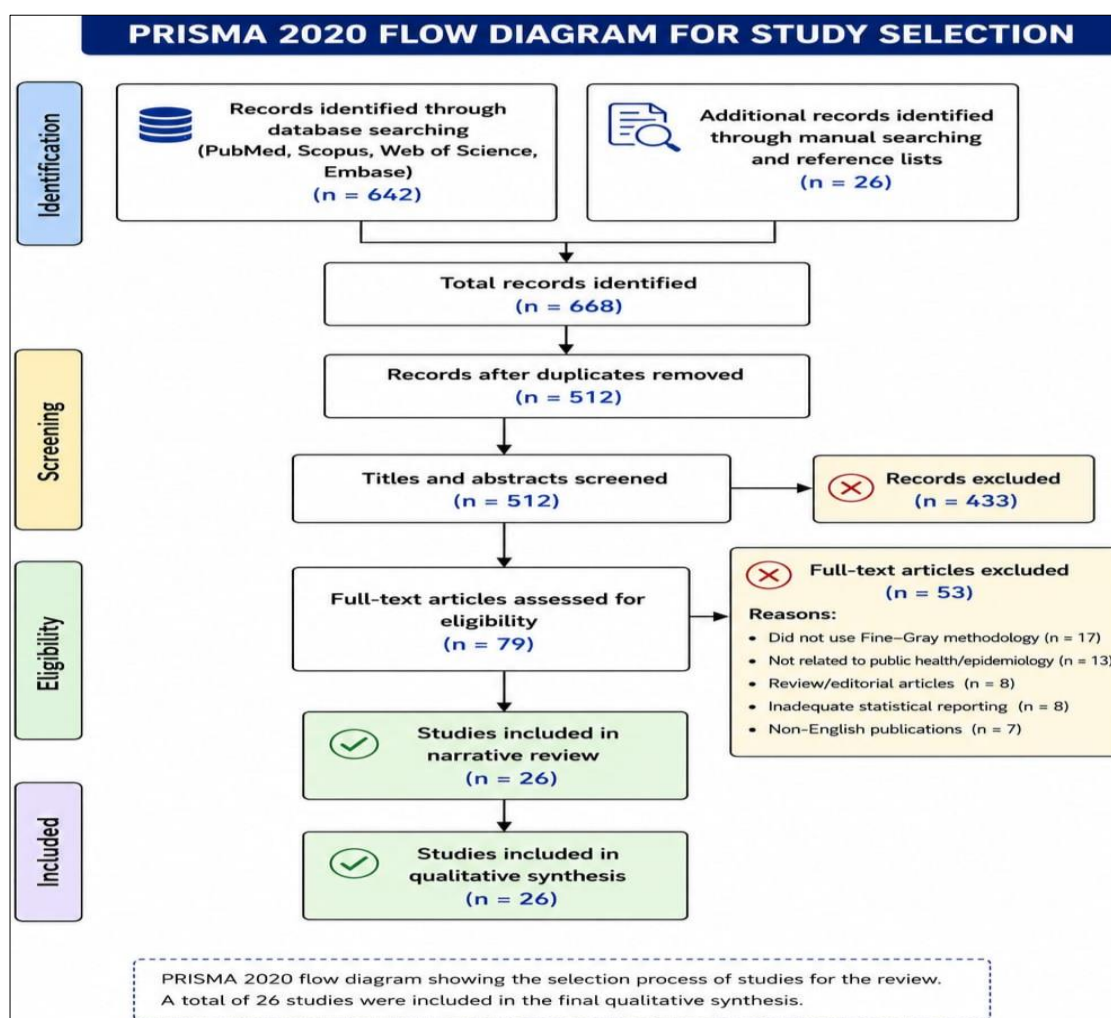


Fig 1: PRISMA 2020 flow diagram illustrating the literature search and study selection process for the narrative review

Theoretical background

Competing risks arise when individuals are at risk of multiple mutually exclusive outcomes [4]. In conventional survival analysis, censoring assumes that censored individuals have the same future risk as those remaining under observation. However, competing events fundamentally alter this assumption because the competing event prevents the event of interest from occurring [2].

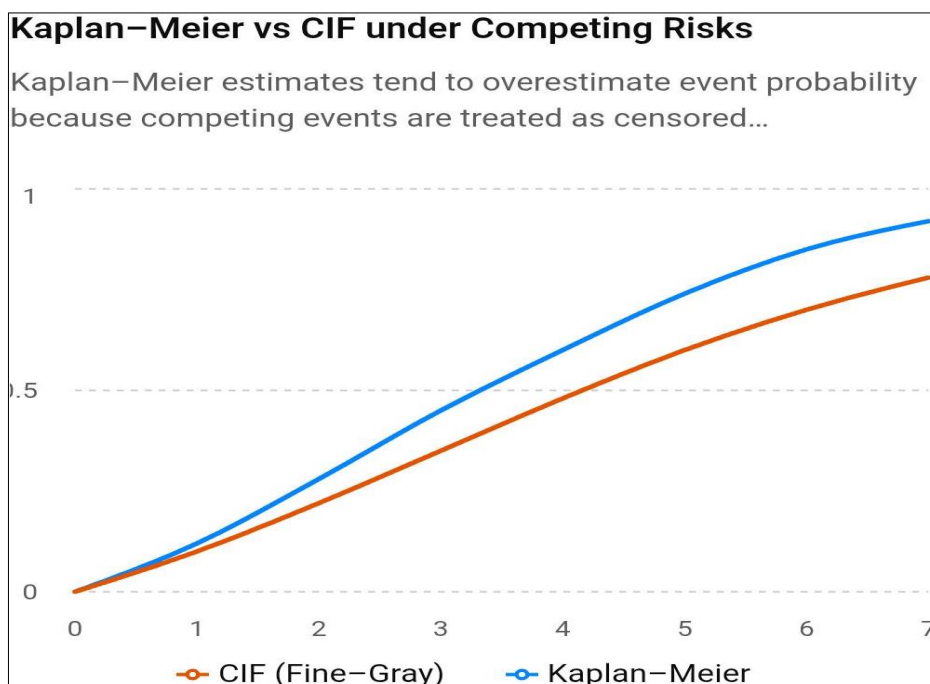
The cumulative incidence function (CIF) estimates the probability of occurrence of a specific event while accounting

for competing risks [4, 5]. The Fine-Gray model directly models the sub distribution hazard associated with the CIF. Unlike cause-specific hazard models, individuals who experience competing events remain in the risk set using weighted approaches, enabling direct estimation of cumulative incidence [1].

The Fine-Gray model is particularly useful when the primary interest is prediction or estimation of real-world event probability rather than understanding etiological mechanisms [2].

Table 1: Comparison Between Cause-Specific Hazard and Fine-Gray Models

Feature	Cause-Specific Hazard Model	Fine-Gray Model
Primary focus	Instantaneous hazard	Absolute cumulative risk
Competing events	Treated as censored	Included in analysis
Interpretation	Etiological	Predictive/Public health
Clinical relevance	Mechanistic understanding	Prognosis and risk prediction
Main outcome	Hazard ratio	Subdistribution hazard ratio

**Fig 2:** Kaplan-Meier methods overestimate event probability because competing events are treated as censored observations, whereas the cumulative incidence function provides unbiased estimates accounting for competing risks

Applications in public health and epidemiology

The Fine-Gray model has extensive applications across epidemiological disciplines. In oncology, it is widely used to estimate cancer-specific mortality while accounting for competing non-cancer deaths^[6]. This is especially relevant in elderly populations where competing causes of death are common.

In infectious disease epidemiology, competing risks arise when recovery competes with mortality. During the COVID-19 pandemic, Fine-Gray models were increasingly used to estimate mortality risk while accounting for discharge and recovery outcomes^[7].

Cardiovascular epidemiology also frequently uses competing risk methods. Studies evaluating cardiovascular mortality must account for competing non-cardiovascular deaths, particularly in aging populations^[8]. Similarly, nephrology research applies Fine-Gray methods to evaluate kidney failure outcomes while accounting for death as a competing event^[9]. In critical care and ICU research, discharge and mortality represent competing outcomes. Fine-Gray models improve prediction accuracy and provide clinically meaningful cumulative incidence estimates^[10].

The increasing availability of electronic health records (EHRs) and healthcare databases has expanded the use of Fine-Gray models in healthcare analytics^[11]. The model supports individualized prognosis, clinical decision-making, and risk prediction systems.

In oncology, Fine-Gray models are integrated into prognostic nomograms for predicting cancer-specific survival^[12]. In cardiovascular medicine, they assist in estimating long-term cumulative incidence of cardiovascular events^[8]. Healthcare systems also use competing risk methodology to evaluate

hospital readmission, ICU discharge outcomes, and transplantation success rates^[13].

Public health agencies increasingly rely on competing risk analyses to estimate disease burden and evaluate intervention effectiveness in real-world settings^[14].

Discussion

The Fine-Gray model represents a major advancement in survival analysis because it directly estimates cumulative incidence in the presence of competing risks. This feature is particularly important in Clinical research, where clinicians and policymakers are often more interested in absolute event probability than instantaneous hazard^[2]. One of the major strengths of the Fine-Gray model is its interpretability in clinical practice. Unlike cause-specific hazard models, which primarily focus on etiological mechanisms, Fine-Gray models may better reflect patient prognosis in the presence of competing events^[1]. Consequently, they are widely applicable in public health planning, healthcare resource allocation, and individualized risk prediction.

Traditional Kaplan-Meier analysis estimates the probability of an event by treating competing events as censored observations. As a result, Kaplan-Meier estimators frequently overestimate the actual incidence of the event of interest when competing risks are present^[4, 10]. Methodological studies comparing “1 – Kaplan-Meier estimation” with cumulative incidence methods have shown that Kaplan-Meier analysis may substantially overestimate event probability when competing events are common^[20, 24]. In contrast, the cumulative incidence function (CIF) appropriately accounts for competing events and therefore provides more realistic and clinically interpretable estimates of absolute risk. Fine-Gray regression directly models the subdistribution hazard

associated with CIF, making it particularly suitable for prognosis-oriented research and healthcare decision-making. Comparative evaluations of cause-specific hazard models and Fine-Gray subdistribution hazard models have further shown that Fine-Gray regression is more informative when the research objective involves estimation of cumulative event probability rather than investigation of etiological mechanisms^[20, 21]. This distinction is especially important in public health and epidemiological investigations where clinicians and policymakers require accurate prediction of disease burden, mortality, and healthcare outcomes over time. Applications of competing risk methods have expanded substantially across oncology, cardiovascular medicine, nephrology, infectious diseases, and intensive care research^[6-10]. In oncology, Fine-Gray models improve estimation of cancer-specific mortality by accounting for deaths from non-cancer causes, which is particularly important among elderly patients with multiple comorbidities^[6]. Cardiovascular epidemiology studies have similarly demonstrated the importance of accounting for competing non-cardiovascular deaths when estimating long-term cardiovascular event probability^[8]. In nephrology research, death frequently competes with progression to kidney failure, and Fine-Gray approaches have therefore become increasingly recommended for cumulative incidence estimation^[9].

Methodological developments in infectious disease survival analysis have also highlighted the importance of selecting appropriate models for censored and competing event data^[7, 25, 26]. Studies evaluating tuberculosis outcomes and longitudinal infectious disease cohorts demonstrated that conventional survival models may inadequately account for multiple mutually exclusive outcomes such as cure, relapse, treatment failure, and death^[25, 26]. These findings support the broader application of competing risk methods in public health surveillance and healthcare outcome research.

Despite its advantages, the Fine-Gray approach also has limitations. Subdistribution hazard ratios should not be interpreted as direct causal effects because they reflect cumulative incidence rather than instantaneous biological risk^[2]. Misinterpretation of these estimates remains relatively common in epidemiological literature. Furthermore, Fine-Gray models can become computationally complex when handling time-dependent covariates, recurrent events, high-dimensional healthcare datasets, or longitudinal repeated measurements^[15].

Recent developments have expanded Fine-Gray methodology into machine learning and artificial intelligence frameworks, including neural survival analysis, random survival forests, and dynamic prediction systems^[16-18]. These approaches have shown promise for handling large electronic health record datasets and improving individualized risk prediction in precision medicine. Integration of competing risk methodology with healthcare analytics platforms may substantially improve future clinical decision support systems and population health monitoring strategies.

The Fine-Gray model is also becoming increasingly important in aging populations where competing causes of mortality frequently. As life expectancy continues to rise globally, accurate estimation of cumulative disease incidence and competing mortality outcomes will remain essential for healthcare planning, epidemiological inference, and evidence-based public health policy development.

Future directions

Future research is expected to focus on integrating Fine-Gray models with advanced computational approaches such as deep learning, neural survival analysis, and dynamic prediction models^[16-18]. Improved handling of time-varying covariates and longitudinal data structures will further enhance predictive accuracy.

Applications in precision medicine and precision public health are also expected to expand significantly. Personalized cumulative incidence prediction may improve treatment stratification, healthcare planning, and population health interventions.

Another important direction involves development of user-friendly software and reporting standards to improve methodological transparency and reproducibility in competing risks research.

Conclusion

The Fine-Gray model is a powerful and clinically relevant approach for analyzing competing risks data in epidemiology and healthcare research. Its ability to provide accurate cumulative incidence estimates makes it highly valuable for clinical prognosis, healthcare analytics, and public health policy. As healthcare datasets continue to expand and precision medicine evolves, the importance of Fine-Gray methodology is expected to increase substantially.

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