Trends in Health Informatics

www.thi.reapress.com

THI. Vol. 2, No. 3 (2025) 142–149.

Paper Type: Original Article

Decision-Oriented Mathematical Modeling for Healthy Longevity: A Conceptual Framework for Personalized Lifestyle Medicine and Clinical Decision Support

Jaleh Shirin Nejad[1,*] , Samad Salehi[2], Davood Darvishi[3]

[1] Department of Mathematics, Institute of Education, Karoon University, Ahvaz, Iran; zhaleshirin@gmail.com.

[2] Artemis Clinic, Ahvaz, Iran; salehisamad83@gmail.com.

[3] Department of Applied Mathematics, Payame Noor University, Tehran, Iran; darvish_davood@gmail.com.

Citation:

Received: 26 February 2024 *Revised: 24 May 2025* *Accepted: 03 July 2025*	Shirin Nejad, J., Salehi, S., & Darvishi, D. (2025). Decision-oriented mathematical modeling for healthy longevity: A conceptual framework for personalized lifestyle medicine and clinical decision support. *Trends in Health Informatics*, 2(3), 142-149.

Abstract

Healthy longevity has emerged as a major goal of modern healthcare, shifting the emphasis from extending lifespan to maximizing healthspan. Although lifestyle interventions effectively prevent chronic diseases and promote healthy ageing, selecting the most appropriate intervention for individual patients remains challenging because of biological heterogeneity, incomplete clinical information, and multiple sources of uncertainty. Existing computational approaches, including artificial intelligence, machine learning, mathematical modeling, and operations research, have shown considerable potential for personalized healthcare; however, they provide limited guidance on selecting the most appropriate method for specific clinical decision-making contexts. This narrative review proposes a decision-oriented conceptual framework for selecting mathematical modeling approaches to support healthy longevity. Evidence from healthy longevity, Precision Lifestyle Medicine, artificial intelligence, mathematical modeling, and operations research was synthesized to classify computational methods according to clinical objectives, dominant sources of uncertainty, and data characteristics. The proposed framework links specific healthcare scenarios with appropriate approaches, including machine learning, Bayesian networks, grey system theory, fuzzy decision models, multi-objective optimization, and digital twins. Unlike previous studies that mainly compare algorithmic performance, the proposed framework emphasizes clinical applicability and decision suitability. It provides practical guidance for selecting computational methods to support personalized lifestyle interventions, improve healthspan, and facilitate the development of intelligent clinical decision-support systems for precision healthcare.

Keywords: Healthy longevity, Mathematical modeling, Uncertainty, Grey system theory.

1 | Introduction

The remarkable increase in human life expectancy over the past century represents one of the greatest achievements of modern medicine and public health. Advances in disease prevention, vaccination, sanitation,

Corresponding Author: zhaleshirin@gmail.com

https://doi.org/10.22105/thi.v2i3.50

and healthcare have substantially reduced premature mortality worldwide. However, increased lifespan has not been accompanied by a proportional increase in years lived in good health. Instead, population ageing has been associated with a growing prevalence of chronic diseases, multimorbidity, frailty, cognitive impairment, disability, and rising healthcare costs. Consequently, the focus of contemporary healthcare has shifted from extending lifespan to promoting healthy longevity, in which healthspan, the period of life spent in good physical, cognitive, psychological, and social health, has become a fundamental objective [1–3].

Although healthspan has emerged as a central concept in geroscience, its definition and measurement remain inconsistent. A recent systematic review identified substantial heterogeneity in its conceptualization and operationalization, limiting comparability across studies and hindering clinical translation. Consequently, developing practical frameworks that translate healthspan into measurable and actionable clinical objectives has become an important research priority [4].

Lifestyle factors play a pivotal role in extending healthspan. Regular physical activity, healthy nutrition, adequate sleep, stress management, smoking cessation, weight control, and social engagement substantially reduce the risk of chronic diseases while preserving physical function, cognitive performance, functional independence, and quality of life. These findings have led to the development of Precision Lifestyle Medicine, which seeks to personalize lifestyle interventions according to each individual's biological, physiological, behavioral, environmental, and psychosocial characteristics [2], [5].

Despite these advances, selecting the optimal lifestyle intervention for an individual patient remains challenging. Patients with apparently similar demographic characteristics or clinical profiles often exhibit markedly different responses to identical interventions because of complex interactions among genetic, metabolic, physiological, behavioral, and environmental factors. Consequently, clinical decision-making in healthy longevity should be viewed as a complex multi-objective process performed under substantial uncertainty [3], [5], [6].

Healthcare professionals must simultaneously balance multiple competing objectives, including disease prevention, preservation of physical and cognitive function, maintenance of functional independence, improvement of quality of life, and efficient use of healthcare resources. These decisions are further complicated by biological variability, incomplete clinical information, measurement errors, behavioral adherence, and temporal [6], [7].

2 | Methodology

This study was conducted as a narrative review with the objective of developing a decision-oriented conceptual framework for selecting mathematical modeling approaches to support healthy longevity. Unlike conventional systematic reviews that primarily summarize existing evidence, this review integrates findings from multiple disciplines, including healthy longevity, healthspan, precision lifestyle medicine, artificial intelligence, mathematical modeling, and operations research.

A comprehensive literature search was performed in PubMed, Scopus, Web of Science, and Google Scholar to identify relevant studies published in English. The search strategy combined keywords related to healthy longevity, healthspan, Precision Lifestyle Medicine, clinical decision-making, artificial intelligence, machine learning, mathematical modeling, operations research, optimization, uncertainty, digital twins, Bayesian networks, grey system theory, and fuzzy systems. Priority was given to recent high-quality review articles, landmark methodological papers, and influential clinical studies published in peer-reviewed journals.

Studies were selected based on their relevance to personalized healthcare, computational decision support, uncertainty modeling, and mathematical approaches applicable to healthy ageing. Rather than comparing algorithmic performance, the extracted evidence was analyzed to identify common decision problems, major sources of uncertainty, data characteristics, and computational strategies used in different healthcare contexts.

Finally, the identified methods were synthesized into a decision-oriented conceptual framework that classifies mathematical modeling approaches according to clinical objectives, uncertainty sources, and data availability.

The proposed framework is intended to provide practical guidance for researchers and healthcare professionals in selecting appropriate computational methods to support personalized interventions aimed at improving healthspan and promoting healthy longevity.

3 | Clinical Challenges in Healthy Longevity Decision-Making

Promoting healthy longevity requires healthcare professionals to make complex clinical decisions that extend beyond disease prevention. The primary objective is to maximize healthspan while preserving physical function, cognitive performance, psychological well-being, functional independence, and quality of life. Achieving these outcomes is challenging because clinical decisions must simultaneously address multiple, and often competing, objectives within highly heterogeneous patient populations.

A major challenge arises from the substantial variability among individuals. Patients with similar demographic characteristics, body mass index, laboratory findings, or disease status frequently exhibit markedly different responses to identical lifestyle interventions. Such variability is influenced by numerous interacting factors, including genetic background, metabolic flexibility, immune function, ageing biology, environmental exposures, behavioral adherence, and socioeconomic conditions. Consequently, personalized lifestyle recommendations cannot rely solely on population-based evidence but require individualized decision-making strategies.

Clinical decision-making is further complicated by multiple sources of uncertainty. Biological variability, incomplete or missing clinical data, measurement errors, temporal changes in physiological status, and unpredictable behavioral responses all contribute to uncertainty regarding intervention outcomes. As a result, deterministic decision-making approaches are often insufficient to capture the dynamic and adaptive nature of human health.

These challenges indicate that healthy longevity should be viewed as a multi-objective clinical decision problem rather than a single disease-management task. Effective decision support therefore requires computational approaches capable of integrating heterogeneous data, managing uncertainty, balancing competing clinical objectives, and generating personalized recommendations. These considerations provide the rationale for examining the mathematical modeling approaches discussed in the following section.

4 | Mathematical Approaches for Healthy Longevity

The complexity of healthy longevity decision-making has stimulated growing interest in computational methods capable of integrating heterogeneous data, addressing uncertainty, and supporting personalized interventions. Various mathematical and artificial intelligence approaches have been applied in healthcare; however, their suitability depends on the characteristics of the clinical problem, data availability, and the nature of uncertainty involved.

4.1 | Machine Learning

Machine learning methods have become widely used for disease prediction, risk stratification, and personalized healthcare. By identifying complex nonlinear relationships within large datasets, these approaches can support the prediction of chronic disease risk, treatment response, and health trajectories. However, many machine learning models require large amounts of high-quality data and often suffer from limited interpretability, which may restrict their application in clinical decision-making [8].

4.2 | Bayesian Networks

Bayesian networks provide a probabilistic framework for representing relationships among clinical variables and updating predictions as new information becomes available. These models are particularly valuable when uncertainty is substantial and causal relationships are important. Their ability to combine expert knowledge with empirical data makes them attractive for personalized lifestyle planning and long-term health risk assessment [9].

4.3 | Grey System Theory

Grey system theory was specifically developed for situations characterized by incomplete, uncertain, or sparse information. Because healthcare data are often limited or partially observed, grey models can provide useful insights when traditional data-intensive methods are not feasible. These approaches may be particularly relevant in early-stage clinical assessments or resource-limited settings [10].

4.4 | Fuzzy Decision Models

Many healthcare decisions involve subjective judgments and imprecise information. Fuzzy approaches enable the incorporation of linguistic concepts such as "high risk," "moderate adherence," or "poor sleep quality" into formal decision-making frameworks. As a result, they can effectively support personalized recommendations when clinical information cannot be expressed precisely [11].

4.5 | Multi-Objective Optimization

Healthy longevity is inherently a multi-objective problem because healthcare professionals must simultaneously consider disease prevention, quality of life, functional independence, and healthcare costs. Multi-objective optimization methods explicitly address these competing goals and identify balanced solutions rather than optimizing a single outcome. Consequently, they are particularly suitable for personalized intervention planning [12].

4.6 | Dynamic Systems and Digital Twins

Human health is a dynamic process that evolves over time. Dynamic systems models and digital twins attempt to represent these temporal changes by simulating physiological processes and predicting future health states. These approaches have considerable potential for proactive and preventive healthcare because they allow intervention strategies to be evaluated before implementation [13].

Collectively, these computational approaches offer complementary strengths. Rather than seeking a universally superior method, the central challenge is selecting the most appropriate modeling approach according to the specific clinical objective, available data, and dominant source of uncertainty. This challenge motivates the decision-oriented framework proposed in the following section.

4.5 | Decision-Oriented Framework for Selecting Mathematical Models in Healthy Longevity

The preceding sections demonstrate that no single computational approach is universally suitable for all healthy longevity decision problems. Instead, the selection of an appropriate mathematical model depends on several interrelated factors, including the clinical objective, the characteristics of the available data, the dominant source of uncertainty, and the complexity of the decision-making process. Therefore, rather than recommending a single superior methodology, we propose a decision-oriented conceptual framework that assists researchers and healthcare professionals in selecting computational approaches according to specific clinical requirements.

The proposed framework is based on four sequential decision dimensions. The first dimension defines the clinical objective, such as disease prevention, healthspan extension, personalized lifestyle planning, functional preservation, or quality-of-life improvement. The second dimension identifies the dominant source of uncertainty, including biological variability, incomplete clinical information, behavioral uncertainty, measurement errors, or temporal physiological changes. The third dimension considers data characteristics, including sample size, data completeness, longitudinal availability, and data heterogeneity. Finally, the fourth dimension matches these characteristics with the computational methodology most capable of addressing the corresponding decision problem.

Within this framework, Bayesian networks are particularly appropriate when probabilistic reasoning and causal relationships are required under uncertain conditions. Grey system models are advantageous when clinical information is incomplete or datasets are relatively small. Fuzzy approaches are suitable for incorporating subjective clinical judgments and linguistic variables into decision-making. Machine learning algorithms perform well when large, high-quality datasets are available for prediction, whereas multi-objective optimization methods are most appropriate when multiple competing clinical goals must be balanced simultaneously. Dynamic systems models and digital twins provide additional value when long-term physiological evolution and personalized intervention trajectories are of primary interest.

Unlike previous reviews that primarily compare computational techniques according to algorithmic performance, the proposed framework emphasizes decision suitability. Its primary objective is not to identify the mathematically optimal algorithm, but to recommend the most appropriate modeling strategy for a specific healthy longevity decision context. Such a decision-oriented perspective may improve methodological selection, enhance clinical interpretability, and facilitate the development of intelligent decision-support systems for personalized healthy ageing.

The classification presented in *Table 1* was synthesized from previous studies on healthspan, Precision Lifestyle Medicine, Bayesian networks, grey system theory, fuzzy systems, machine learning, multi-objective optimization, and digital twins [1], [3], [5], [8–10], [12].

Table 1. Decision-oriented classification of mathematical modeling approaches for healthy longevity. Developed by the authors based on the reviewed literature.

Clinical Objective	Dominant Uncertainty	Data Characteristics	Recommended Model	Main Rationale
Disease risk prediction	Biological variability	Large structured datasets	Machine learning	Learns complex nonlinear relationships
Personalized lifestyle planning	Behavioral uncertainty	Mixed clinical and lifestyle data	Bayesian network	Updates recommendations as new evidence becomes available
Early clinical assessment	Incomplete data	Small or sparse datasets	Grey system theory	Performs well with limited information
Patient-centered decision-making	Linguistic uncertainty	Qualitative and quantitative data	Fuzzy models	Incorporates subjective clinical judgments
Healthspan optimization	Multiple competing objectives	Multimodal longitudinal data	Multi-objective optimization	Balances competing health outcomes
Long-term health monitoring	Temporal dynamics	Longitudinal physiological data	Dynamic systems/Digital twins	Models' disease progression and intervention trajectories

The proposed framework is summarized in *Fig. 1*. Rather than recommending a universally superior computational method, the framework guides model selection according to the clinical objective, dominant sources of uncertainty, and data characteristics, thereby facilitating personalized decision-making for healthy longevity.

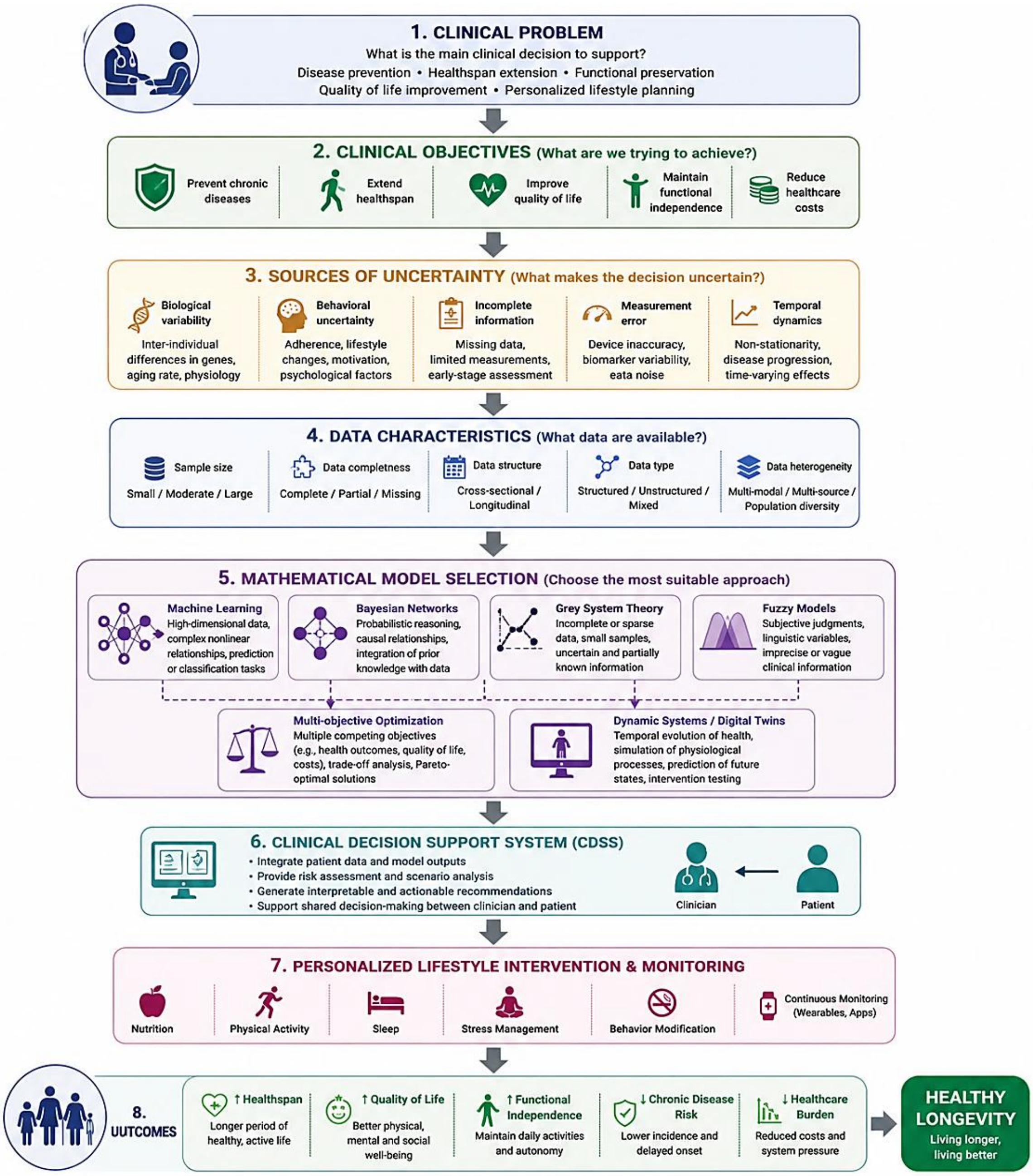

Fig. 1. Decision-oriented framework for selecting mathematical modeling approaches to support healthy longevity.

The framework was developed by the authors based on concepts from Geroscience, healthspan research, precision lifestyle medicine, mathematical modeling, and operations research. The expected outcomes (healthspan, quality of life, functional independence, chronic disease prevention, and healthcare burden reduction) are supported by previous evidence [1], [2], [4], [5].

6 | Discussion

The growing emphasis on healthy longevity has fundamentally changed the focus of healthcare from treating individual diseases to preserving long-term health, functional independence, and quality of life. This shift requires clinical decision-making strategies that can simultaneously consider multiple health objectives while addressing the substantial uncertainty inherent in human physiology. The findings of this review indicate that no single computational approach is universally applicable to all healthy longevity decision problems. Instead, the effectiveness of a mathematical model depends on the specific clinical objective, the characteristics of the available data, and the dominant sources of uncertainty.

A major contribution of the proposed framework is its transition from an algorithm-centered perspective to a decision-centered perspective. Previous reviews have primarily compared computational methods according to predictive accuracy or methodological characteristics. In contrast, the present framework emphasizes selecting mathematical models based on clinical requirements. This distinction is particularly important in healthy longevity because different clinical scenarios require different analytical strategies. For example, probabilistic approaches may be more suitable for uncertain causal reasoning, whereas multi-objective optimization is better suited to balancing competing health outcomes. Likewise, grey system models may outperform data-intensive approaches when clinical information is limited or incomplete.

Another important implication is the integration of Precision Lifestyle Medicine with computational decision support. Lifestyle interventions are inherently personalized, and identical recommendations often produce markedly different outcomes among individuals because of biological, behavioral, and environmental heterogeneity. By explicitly considering uncertainty, data characteristics, and clinical objectives, the proposed framework may facilitate more personalized and clinically meaningful decision-making, ultimately supporting interventions that improve healthspan rather than merely extending lifespan.

Despite these strengths, several limitations should be acknowledged. First, the proposed framework is conceptual and has not yet been prospectively validated in clinical settings. Second, the recommendations are based on evidence synthesized from diverse disciplines, which may introduce methodological heterogeneity. Third, rapid advances in artificial intelligence and digital health technologies may continuously reshape the relative advantages of different computational approaches.

Future research should focus on validating the proposed framework using real-world clinical datasets, integrating wearable sensor data and electronic health records, and incorporating emerging technologies such as digital twins, multimodal artificial intelligence, and explainable AI. Such developments may enable the creation of next-generation clinical decision-support systems capable of delivering adaptive, personalized interventions that maximize healthspan while improving quality of life and reducing the burden of age-related diseases.

7 | Conclusion

Healthy longevity represents one of the most important goals of modern healthcare, requiring a transition from disease-centered management to personalized strategies that maximize healthspan, preserve functional independence, and improve quality of life. Achieving these objectives is inherently challenging because clinical decision-making must address biological heterogeneity, multiple competing health outcomes, and diverse sources of uncertainty.

This review demonstrates that no single computational methodology is universally appropriate for all healthy longevity decision problems. Instead, the selection of mathematical models should be guided by the clinical objective, the characteristics of the available data, and the dominant sources of uncertainty. By integrating evidence from healthy longevity, Precision Lifestyle Medicine, artificial intelligence, mathematical modeling, and operations research, we proposed a decision-oriented conceptual framework that supports the selection of appropriate computational approaches for specific clinical contexts.

Unlike previous reviews that primarily compare algorithms according to methodological performance, the proposed framework emphasizes clinical applicability and decision suitability. This perspective provides a practical bridge between computational methodology and clinical practice, facilitating the development of intelligent decision-support systems capable of delivering personalized lifestyle interventions.

Future studies should validate the proposed framework using real-world clinical data, wearable technologies, digital health platforms, and longitudinal cohort studies. Integrating emerging technologies, including explainable artificial intelligence, digital twins, and multimodal data analytics, may further enhance personalized healthcare and contribute to extending healthspan while improving quality of life. Ultimately, adopting decision-oriented computational strategies has the potential to transform healthy longevity from a conceptual objective into a practical and evidence-based component of precision healthcare.

Acknowledgments

ChatGPT version 3.5 was used for grammar and language checks.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability

All data are included in the text.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Kennedy, B. K., Berger, S. L., Brunet, A., Campisi, J., Cuervo, A. M., Epel, E. S., ... & Sierra, F. (2014). Geroscience: Linking aging to chronic disease. *Cell*, *159*(4), 709–713. https://doi.org/10.1016/j.cell.2014.10.039

[2] Beard, J. R., Officer, A., De Carvalho, I. A., Sadana, R., Pot, A. M., Michel, J. P., ... & Chatterji, S. (2016). The world report on ageing and health: A policy framework for healthy ageing. *The lancet*, *387*(10033), 2145–2154. https://doi.org/10.1016/S0140-6736(15)00516-4

[3] López-Otín, C., Blasco, M. A., Partridge, L., Serrano, M., & Kroemer, G. (2013). The hallmarks of aging. *Cell*, *153*(6), 1194–1217. https://doi.org/10.1016/j.cell.2013.05.039

[4] López-Otín, C., Blasco, M. A., Partridge, L., Serrano, M., & Kroemer, G. (2023). Hallmarks of aging: An expanding universe. *Cell*, *186*(2), 243–278. https://doi.org/10.1016/j.cell.2022.11.001

[5] Masfiah, S., Kurnialandi, A., Meij, J. J., & Maier, A. B. (2025). Definitions of healthspan: A systematic review. *Ageing research reviews*, *111*, 102806. https://doi.org/10.1016/j.arr.2025.102806

[6] Steyerberg, E. W. (2019). Study design for prediction modeling. In *Clinical prediction models: a practical approach to development, validation, and updating* (pp. 37–58). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-16399-0_3

[7] Ben-Tal, A., Nemirovski, A., & El Ghaoui, L. (2009). *Robust optimization*. Princeton University Press. https://doi.org/10.1515/9781400831050

[8] Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature medicine*, *25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

[9] Koller, D., & Friedman, N. (2009). *Probabilistic graphical models: principles and techniques*. MIT press. https://www.amazon.com/Probabilistic-Graphical-Models-Principles-Computation/dp/0262013193

[10] Julong, D. (1989). Introduction to grey system theory. *The journal of grey system*, *1*(1), 1–24. https://uranos.ch/research/references/Julong_1989/10.1.1.678.3477.pdf

[11] Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, *8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

[12] Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons. https://www.wiley.com/en-us/Multi-Objective+Optimization+using+Evolutionary+Algorithms-p-9780471873396

[13] Corral-Acero, J., Margara, F., Marciniak, M., Rodero, C., Loncaric, F., Feng, Y., ... & Lamata, P. (2020). The 'Digital Twin'to enable the vision of precision cardiology. *European heart journal*, *41*(48), 4556–4564. https://doi.org/10.1093/eurheartj/ehaa159