

DANSKE KRÆFTFORSKNINGSDAGE 2023

Earlier palliative care using AI: A national implementation

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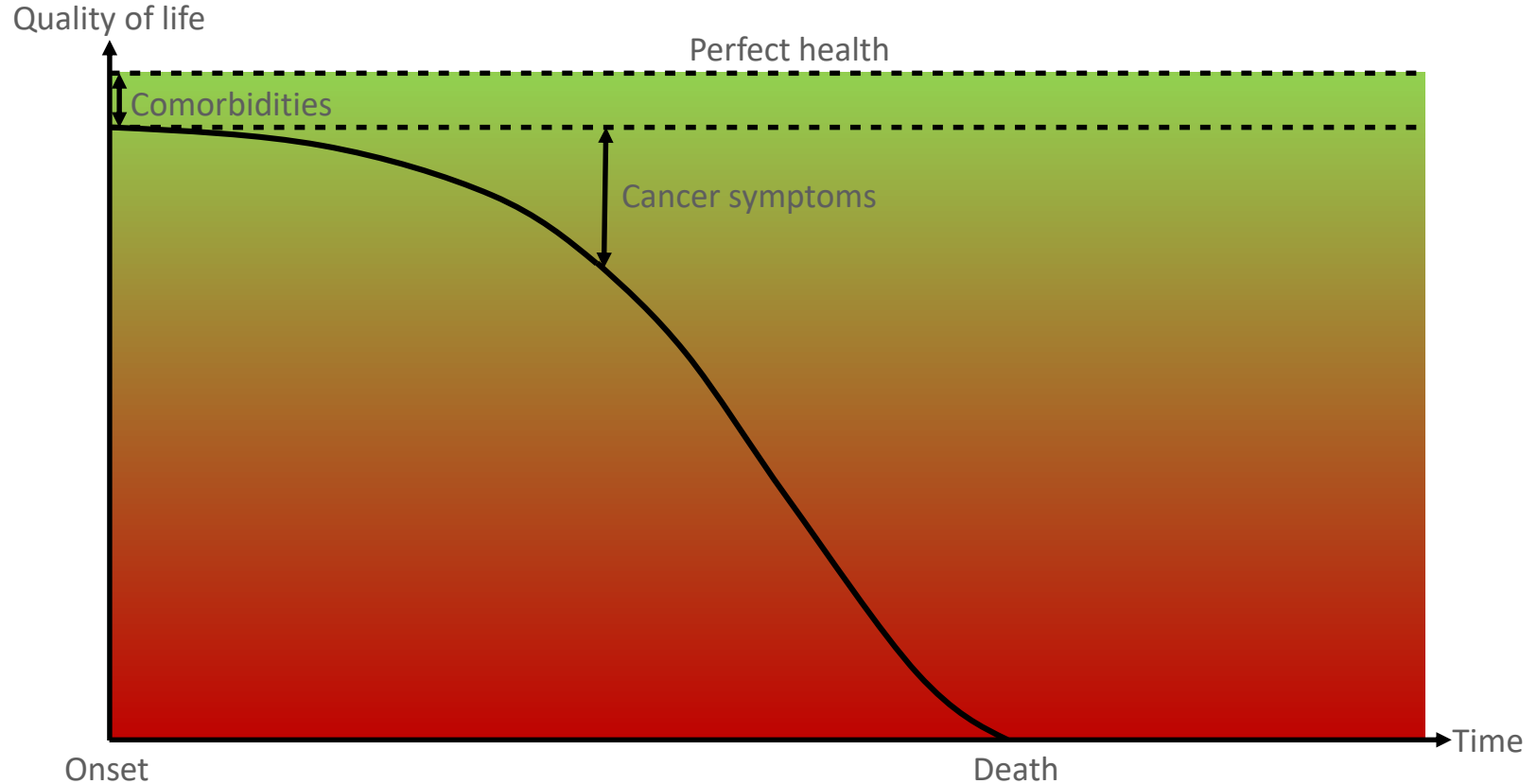
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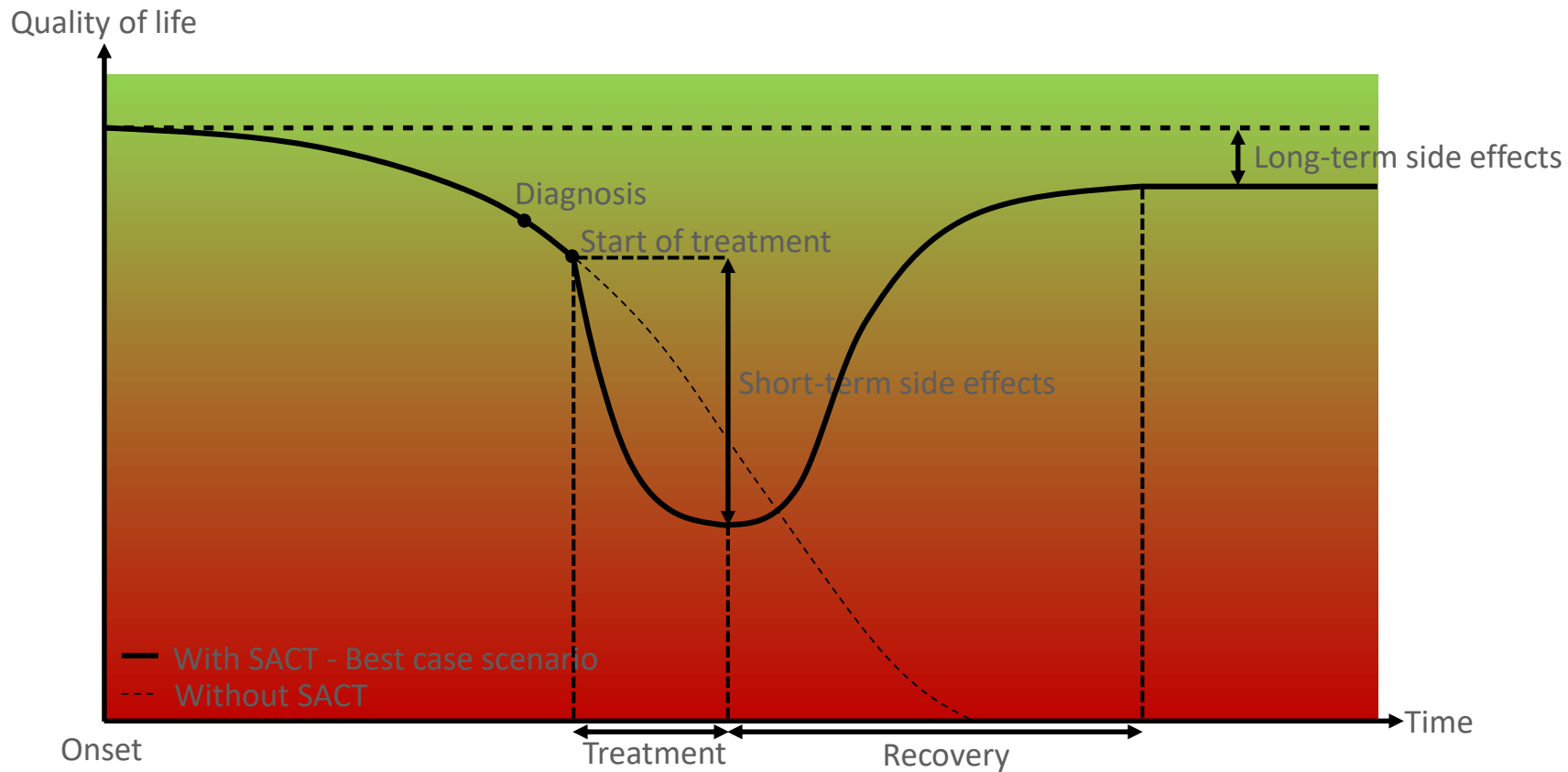
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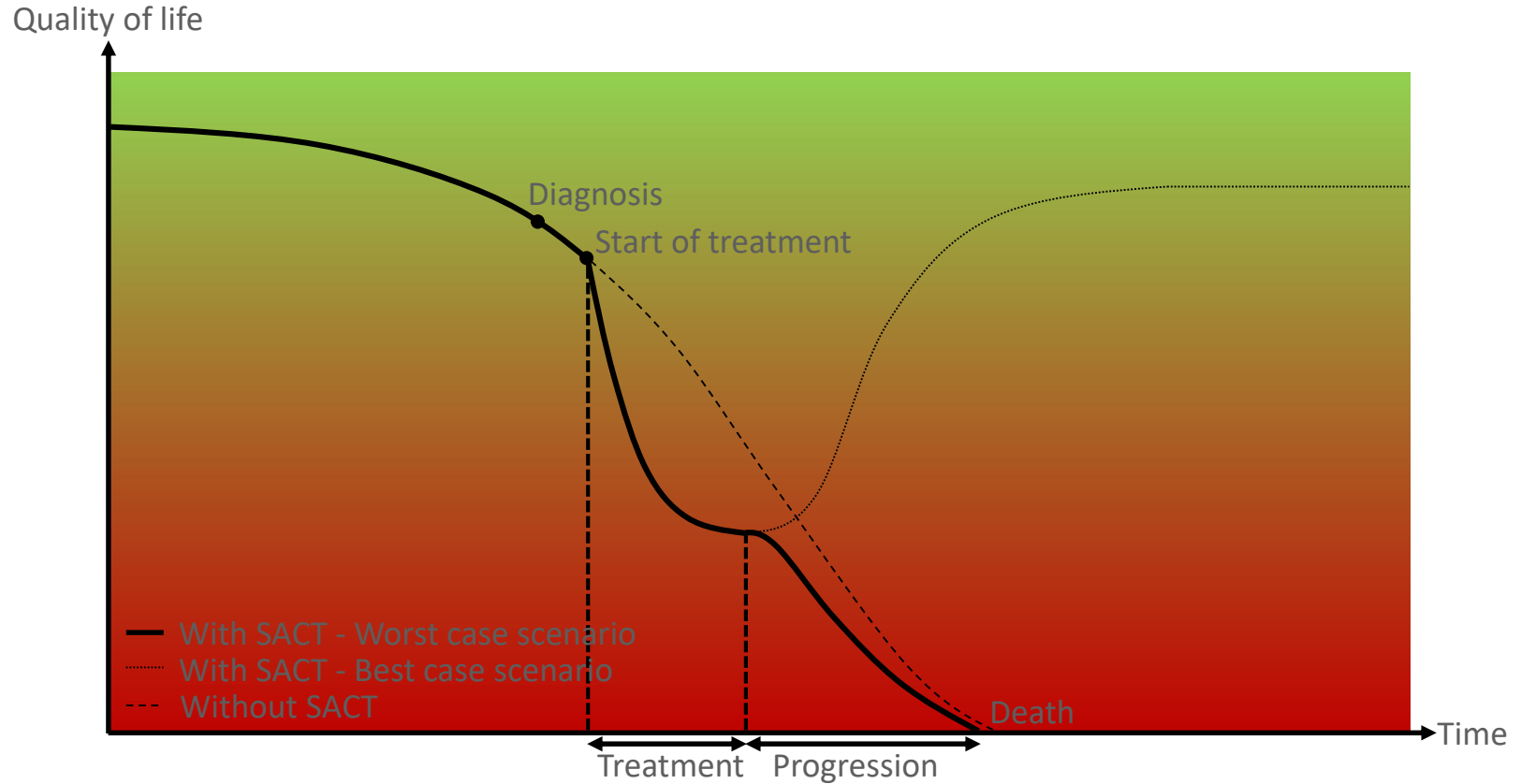
Motivation



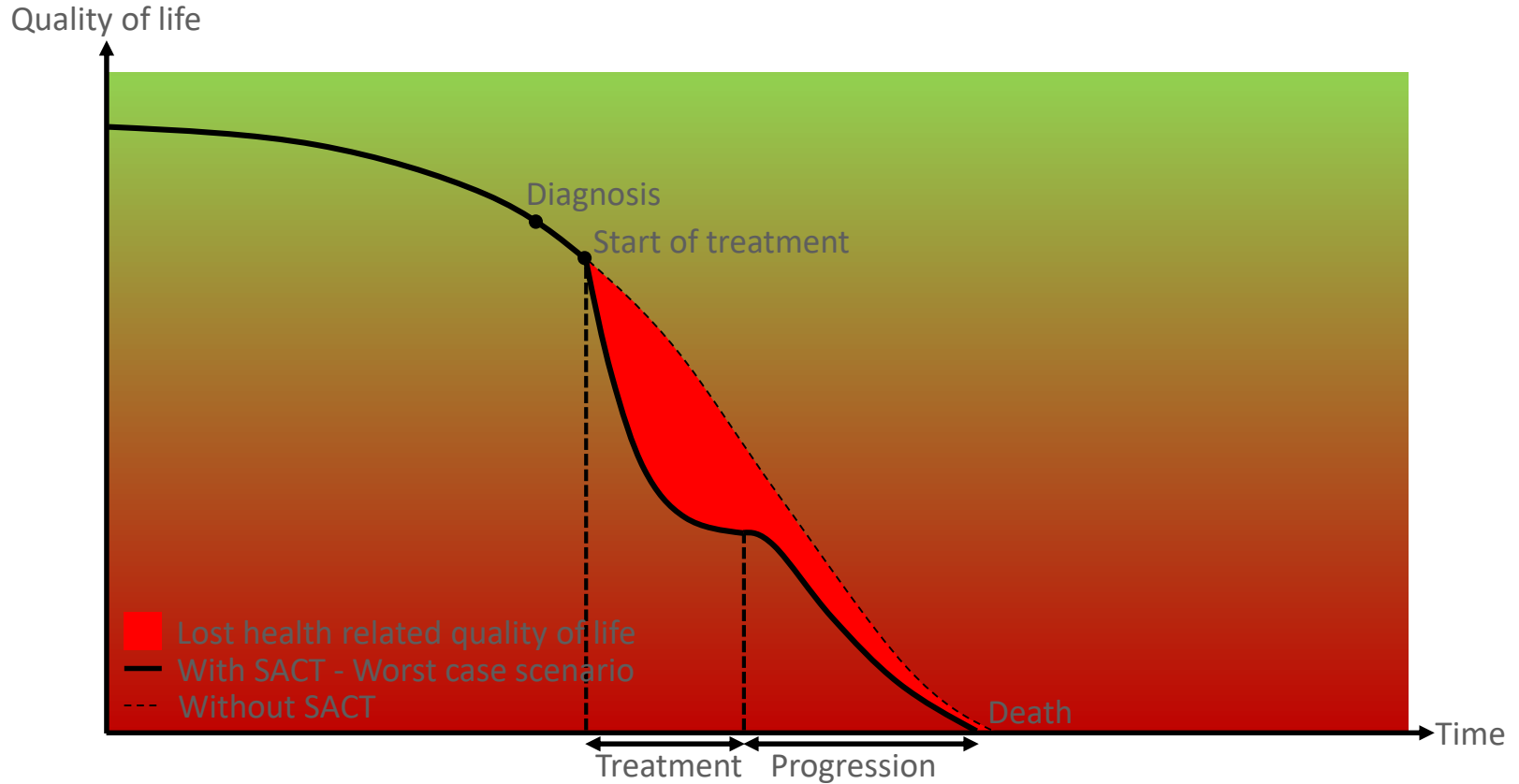
Motivation



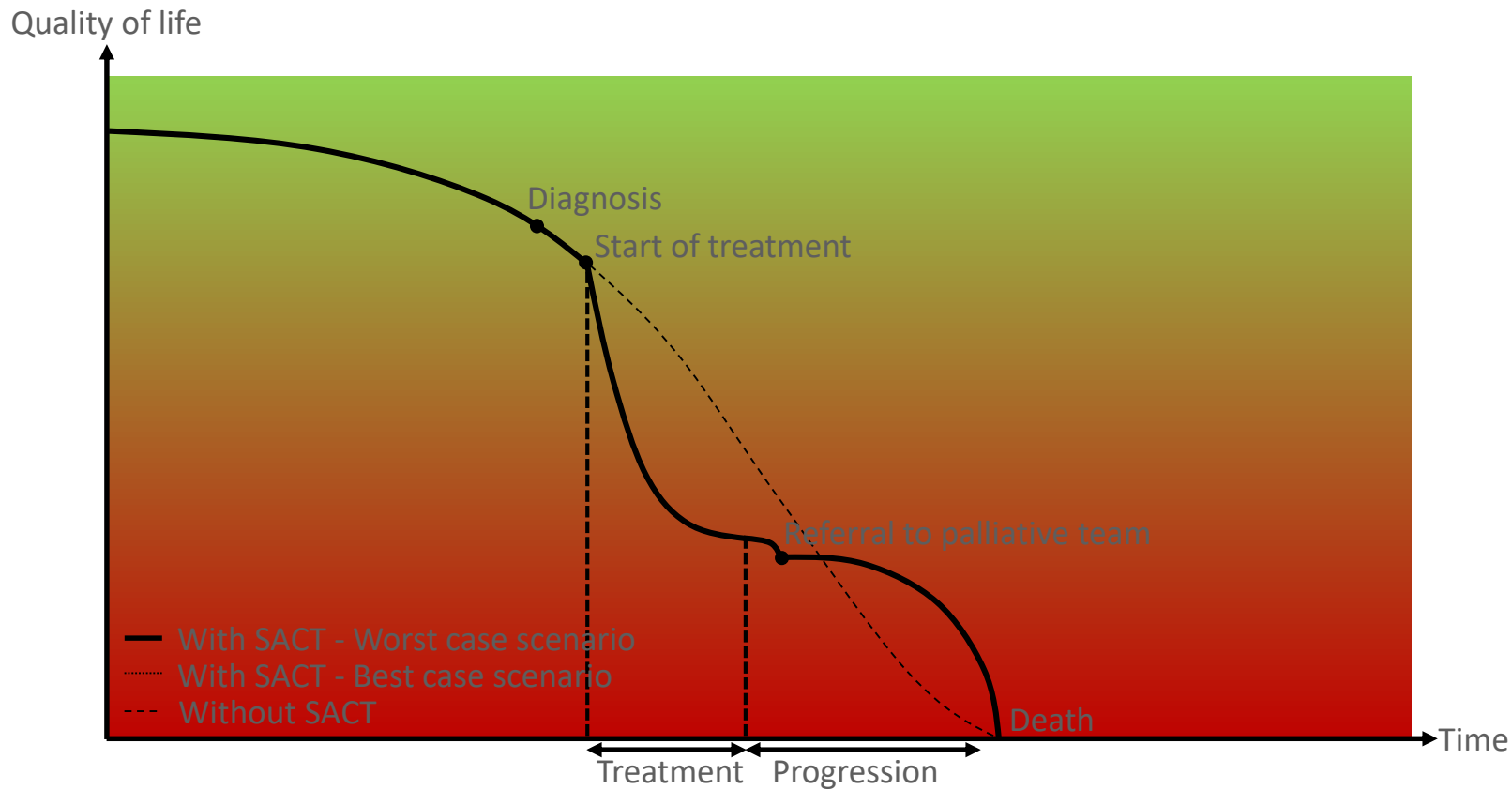
Motivation



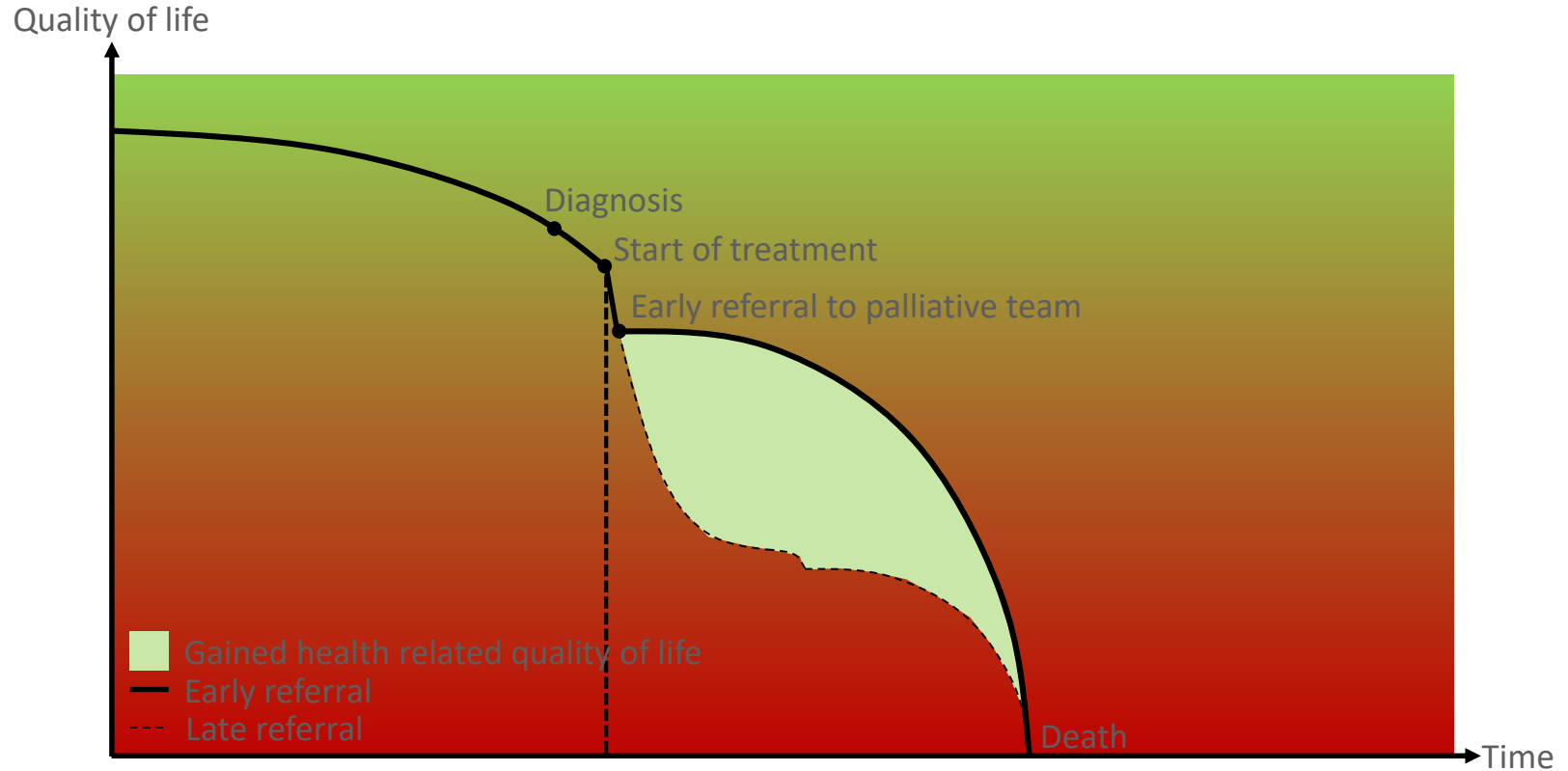
Motivation



Motivation



Motivation



Current situation

- **Guidelines (ESMO 2023)**
 - Clinician Prediction of Survival
 - Clinically validated metrics
 - Univariate: Performance Status
 - Multivariate: Glasgow Prognostic Score
- **Challenges**
 - Requires personal experience
 - Based on subjective criteria
 - Many parameters could play a role

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SPECIAL ARTICLE

Prognostic evaluation in patients with advanced cancer in the last months of life: ESMO Clinical Practice Guideline[☆]

P. Stone^{1,2}, P. Buckle³, R. Dolan⁴, J. Fellu⁵, D. Hul^{6,7}, B. J. A. Laird^{8,9}, M. Maltoni^{10,11}, S. Moine¹², T. Morita¹³, M. Nabal¹⁴, V. Vickerstaff¹⁵, N. White², D. Santini¹⁶ & C. I. Ripamonti¹⁷, on behalf of the ESMO Guidelines Committee

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Available online 11 April 2023

Key words: advanced cancer, ESMO Clinical Practice Guideline, palliative care, prognostic factors, risk prediction models

INTRODUCTION

Patients with cancer may have potentially curable disease or may live for many years despite incurable cancer. However, these guidelines specifically relate to patients with advanced incurable cancer who are expected to live for a few months or less. Distinction is made between patients with a few months to live, who may or may not be receiving anticancer therapies, and those thought to be imminently dying (i.e. within days or weeks). This guideline focuses on the prediction of death or length of survival and not other clinically-important outcomes such as response to treatment, preferred place of death or length of inpatient stay. Recommendations are provided to health care professionals (HCPs) who care for patients with advanced cancer in the last months of life regarding the best way to prognosticate and to communicate prognoses to patients and their families or caregivers. A proposed algorithm for prognostication and communication is shown in Figure 1.

Importance of prognosis

Prognostic information is important to patients, their families and HCPs. Prognoses help to inform future care and

provide opportunities for patients and their families to focus on the things that are most important to them when time is short. Prognostic information can also facilitate access to services and benefits. At an organisational level, prognoses can be helpful for describing the case mix of services or for summarising the health status of patients in different arms of a clinical trial. At an individual level, prognoses can provide information about when a particular patient is likely to die.

Prognostic research methodology

The PROGNosis REsearch Strategy (PROGRESS) partnership describes a four-stage hierarchy of prognostic research.¹ In the context of cancer care, fundamental prognosis research employs epidemiological methods to understand the natural history of cancers under different conditions. Prognostic factor research identifies specific factors associated with length of survival. Statistical models use a combination of prognostic factors to predict an individual's survival risk and such models need to undergo development, validation and assessment for impact. Finally, stratified medicine research uses prognostic information to tailor treatments to individuals or groups with specific prognostic features. Most research in cancer palliative care has been at the level of identifying and validating individual prognostic factors or developing and validating multivariable prognostic models. There have not yet been any studies to evaluate the impact of prognostic models on clinical care. Prognostication in advanced cancer is also somewhat unusual in that, in

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[†]Note: Approved by the ESMO Guidelines Committee: February 2023, 2023-7029/© 2023 The Author(s). Published by Elsevier Ltd on behalf of European Society for Medical Oncology. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

AI to optimize referral

- **Better prediction**
 - Big data approach
 - Can handle complex interactions
- **But ...**
 - Technical and organisational challenges
 - Lack of clinical validation

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DOI: 10.1200/CCI.22.00054

ARTIFICIAL INTELLIGENCE

original reports abstract

Dynamic Risk Prediction of 30-Day Mortality in Patients With Advanced Lung Cancer: Comparing Five Machine Learning Approaches

Charles Vestergaard, PhD^{1,2,3}, Veronika M. Szepiaki, MD, PhD^{1,3,4}, Rasmus F. Brundum, PhD^{2,3}, Ursula G. Faller, MD, PhD^{1,3,4}, Christa Agathe Asmest, PhD^{5,7}, and Martin Dapkin, PhD^{1,2,3}

PURPOSE Administering systemic anticancer treatment (SACT) to patients near death can negatively affect their health-related quality of life. Late SACT administrations should be avoided in these cases. Machine learning techniques could be used to build decision support tools leveraging registry data for clinicians to limit late SACT administration.

MATERIALS AND METHODS Patients with advanced lung cancer who were treated at the Department of Oncology, Aalborg University Hospital and died between 2010 and 2019 were included (N = 2,368). Diagnoses, treatments, biochemical data, and histopathologic results were used to train predictive models of 30-day mortality using logistic regression with elastic net penalty, random forest, gradient tree boosting, multikernel perceptron, and long short-term memory network. The importance of the variables and the clinical utility of the models were evaluated.

RESULTS The random forest and gradient tree boosting models outperformed other models, whereas the artificial neural network-based models underperformed. Adding summary variables had a modest effect on performance with an increase in average precision from 0.500 to 0.505 and from 0.498 to 0.509 for the gradient tree boosting and random forest models, respectively. Biochemical results alone contained most of the information with a limited degradation of the performances when fitting models with only these variables. The utility analysis showed that by applying a simple threshold to the predicted risk of 30-day mortality, 40% of late SACT administrations could have been prevented at the cost of 2% of patients stopping their treatment 90 days before death.

CONCLUSION This study demonstrates the potential of a decision support tool to limit late SACT administration in patients with cancer. Further work is warranted to refine the model, build an easy-to-use prototype, and conduct a prospective validation study.

JCO Clin Oncol Inform 0:e2200054. © 2022 by American Society of Clinical Oncology

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PURPOSE

Systemic anticancer treatments (SACTs) includes chemotherapy, targeted therapy, immunotherapy, and hormonal therapy treatments. A SACT should only be considered in patients with an adequate benefit from the treatment since SACTs often have a short-term negative impact on health-related quality of life.^{1,2} An accepted threshold for late SACT administration is 30 days before death.³ However, clinicians' experience in predicting the remaining lifetime of patients may be inadequate,⁴ leading to prescription of SACT too late to achieve a clinical benefit.⁵ Furthermore, death from advanced cancer often has a multifactorial background where acute complications could lead to patient death.

Lung cancer is a frequently occurring cancer type with poor prognosis and high mortality, particularly in advanced stages. Thus, patients with lung cancer are at

higher risk of receiving SACT close to death than other cancer types with a better prognosis.

There is a need for decision support tools to assist the work of clinicians to minimize the risk of decreasing health-related quality of life because of SACT of patients with lung cancer receiving palliative treatment in advanced stages. Patient health might promptly deteriorate during treatment, requiring frequent use of dynamic predictive tools to assess their situation. To the best of our knowledge, existing studies addressing this issue (1) are based on a limited number of clinical variables; (2) do not consider artificial neural network-based models; (3) are based on different end points, for example, 6-month mortality, or (4) are not suitable for dynamic risk prediction.⁶⁻¹⁷

The aim of this study was to investigate the potential use of machine learning approaches on electronic

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COMMENT

Data Supplement

Author affiliations and support information (if applicable) appear at the end of this article.

Accepted on September 29, 2022 and published on November 15, 2022. DOI: <https://doi.org/10.1200/CCI.22.00054>

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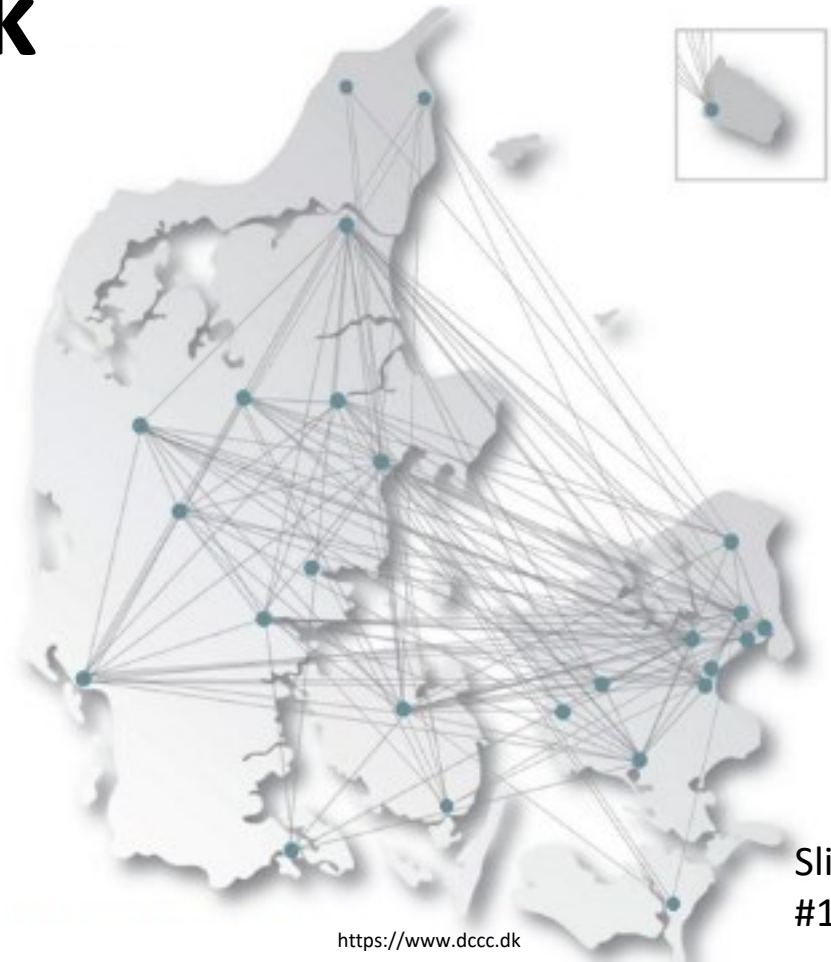
JCO Clinical Cancer Informatics

National implementation

- National network
- Technical implementation
- Prospective validation
- Regulatory aspects

National network

- **Departments of Oncology**
- **Region IT Departments**
- **Palliative Teams & Hospices**



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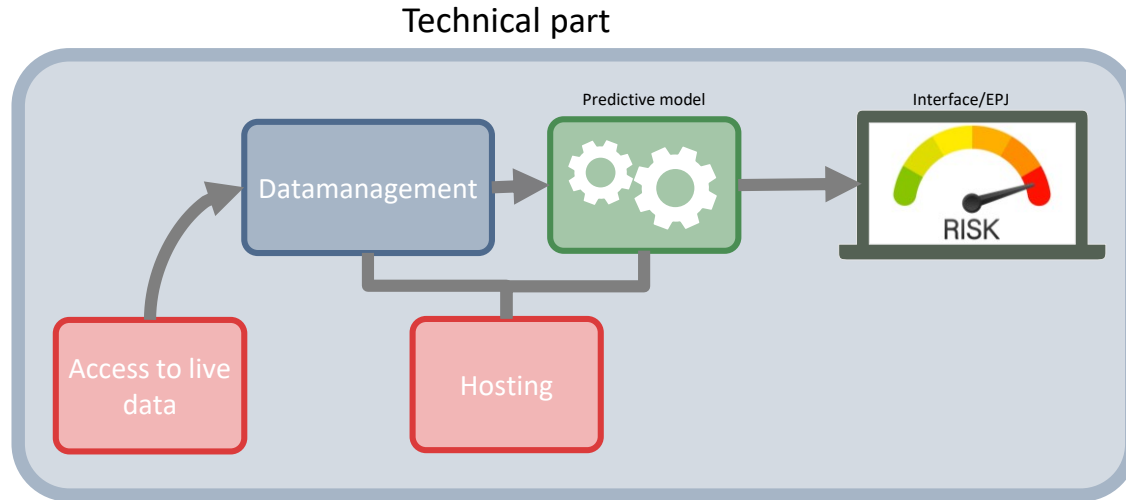
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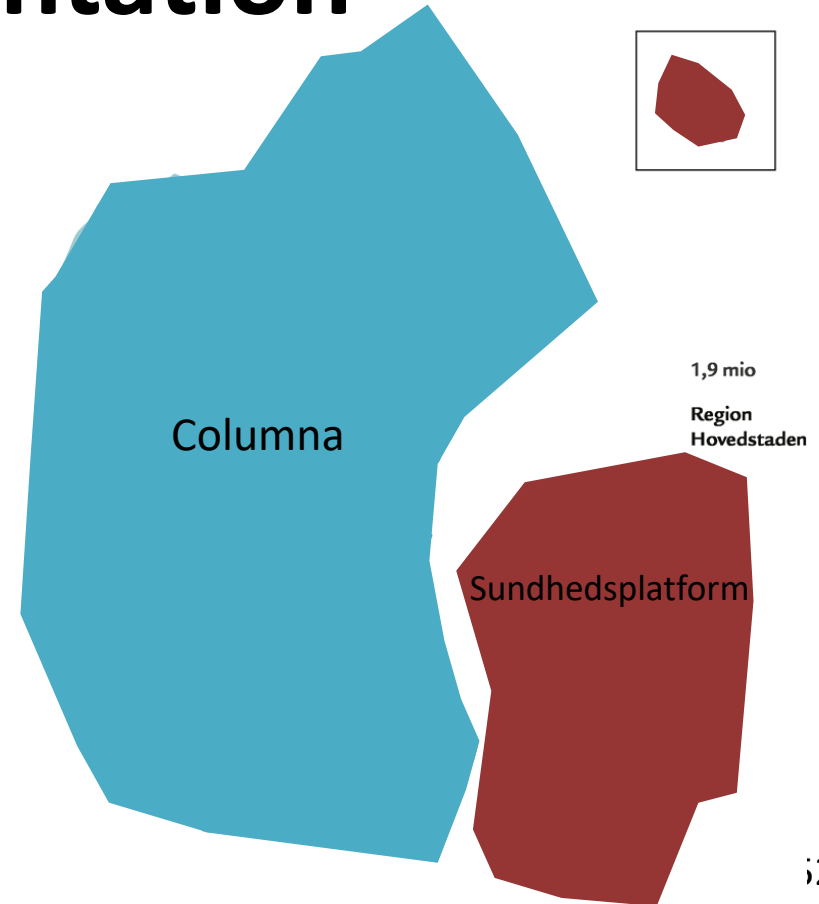
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Technical implementation



Technical implementation

- **Access to live data:**
 - 5 independent regions
 - 2 journal systems



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Technical implementation

- **Interface:**
 - Decision support tool for oncologists
 - Design best practices
 - Integration with patient journals

The screenshot displays a web application titled "Decision Support Tools" for "30-day mortality - Lung cancer". The interface includes a search bar, patient selection fields (Patient ID: 3579193, Days to death: 21), and patient information (Female, DOB: 195, Diagnosis date: 201, Death date: 201). It presents model results: Logistic regression (AP: 0.287, Probability: 18.1%, Baseline: 3.9%) and Random forest (AP: 0.466, Probability: 27.4%, Baseline: 2.0%). Below are tables for detrimental and protective factors.

30-day mortality for metastatic lung cancer patients

Select patient ID and day

Patient ID: 3579193 Days to death: 21

Patient info

Sex	DOB	Diagnosis date	First tx date	First palliative tx date	Death date
Female	195	201			201

Logistic regression AP: 0.287
Probability: 18.1% overall effect:
Baseline: 3.9%

Random forest AP: 0.466
Probability: 27.4%
Baseline: 2.0%

Detrimental factors Logistic regression model

Label	Value	Mean	Effect
Albumin i g/L	2.90	35.01	0.0842
Leukocytes i × 10 ⁹ /L	9.94	9.01	0.6776
Neutrophilocytes i × 10 ⁹ /L (difference)	5.89	0.26	0.4109
Leukocytes i × 10 ⁹ /L (difference)	5.42	0.15	0.3514
Neutrophilocytes i × 10 ⁹ /L	3.95	6.93	0.2934

Protective factors Logistic regression model

Label	Value	Mean	Effect
Glomerular filtration i ml/min	.00	77.60	-0.2825
Kræft i bronkier og lunge (cumulated overall)	.00	2.86	-0.2146
Metamyelocytes+Myelocytes+Promyelocytes i × 10 ⁹ /L (difference)	.60	0.05	-0.2046
Radikal mastektomi (cumulated overall)	.00	0.02	-0.1864
C-reactive protein i mg/L (difference)	107.98	-9.19	-0.1845

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Prospective validation

- **To ensure the performance**
- **Challenges with protocol:**
 - Randomisation
 - How to measure success

Regulatory aspects

- **Ethical approval**
- **Data processing agreements**
- **EU Medical Device Regulation**

Take home message

- **AI can help improve patient care**
- **Implementation is challenging**
- **We are looking for collaborations across Denmark to make it happen**

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Contact us
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