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PHD THESIS

OSISP, a new digital colleague in the ambulance team

Have you had any injuries? Perhaps you know of others that have been injured?

Injuries can happen due to many reasons, for instance sport activities, traffic incidents or violent encounters. It may happen at any time and place, both at night and day, as well as in urban and rural locations. The broad spectrum of situations makes injuries a shared experience by many, and it is a common cause of both death and lifelong disabilities.

For injured patients, time to care should be minimized. As injuries are typically sudden incidents, ambulance teams often represent the first healthcare contact. Their task is to assess the patient and decide on a transport destination where the injuries can be treated – which may not be the closest hospital. To enable rapid and accurate selection of destination, the ambulance teams need access to good supporting tools during patient assessment. However, current tools function as checklists with limited accuracy.

This thesis has explored the development of a tool named OSISP that uses artificial intelligence to analyse patients' conditions. We developed and evaluated OSISP with Swedish and Norwegian data. We investigated when and how OSISP can be used, and what its interface should look like. Lastly, we tested a prototype of OSISP with ambulance teams to receive feedback on its usability. The results indicate that OSISP can function as a valuable digital colleague in the ambulance, providing a more accurate support compared to current checklists.

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ANNA BAKIDOU Towards Intelligent Clinical Decision Support Systems for Prehospital Trauma Triage 2025

Towards Intelligent Clinical Decision Support Systems for Prehospital Trauma Triage

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THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Towards Intelligent Clinical Decision Support Systems for Prehospital Trauma Triage

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Cover:
Emergency Medical Service personnel assessing the care need and optimal transport destination for a patient, with support from the On Scene Injury Severity Prediction (OSISP) clinical decision support system. (Created with Copilot, 2025)

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Towards Intelligent Clinical Decision Support Systems for Prehospital Trauma Triage
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Abstract

For severely injured patients, minimizing time to definitive care is crucial to increase the chance of survival and to reduce the risk of lifelong disabilities. The ambulance team is therefore key to providing optimal care to injured patients, as the remaining flow of care depends on the accuracy in the patient assessment and the decision on transport destination. However, current tools used for patient assessment of injured patients function as checklists with limited accuracy. It is hypothesized that Artificial Intelligence (AI) is needed to find more valuable patterns in patient data and thereby improve the support for the ambulance team. This work therefore explores a prehospital Clinical Decision Support System (CDSS) that utilizes AI to predict the risk of a patient being severely injured at the incident scene.

First, an AI model named On Scene Injury Severity Prediction (OSISP) was developed and evaluated on Swedish trauma data. Next, the OSISP model was applied and evaluated on Norwegian trauma data to estimate performance and triage accuracy on future patients. Following model development, packaging OSISP as a CDSS was studied by exploring workflow integration in a workshop together with clinical and industrial representatives. Scientific literature was reviewed to find inspiration for how to communicate OSISP's predictions to the ambulance team. Lastly, a tablet prototype was built and tested together with ambulance teams. The findings of this work demonstrate that OSISP has a theoretical value as a CDSS for ambulance teams during patient assessment of injured patients, both during model development and CDSS building, and offers a promising solution for future work to continue design refinement and initiate prospective evaluations.

Keywords: Artificial Intelligence (AI), Clinical Decision Support System (CDSS), Digital Health, eXplainable Artificial Intelligence (XAI), Field Triage, On Scene Injury Severity Prediction (OSISP), Prehospital Care, Trauma, User Interface (UI).

To my family.

List of Publications

Included publications

This thesis is based on the work contained in the following publications, with author contributions shown in Table 1 following the Contributor Roles Taxonomy (CRediT) system [1] with exception of the supervision item:

[A] **Anna Bakidou**, Eva-Corina Caragounis, Magnus Andersson Hagiwara, Anders Jonsson, Bengt Arne Sjöqvist, Stefan Candefjord, "On Scene Injury Severity Prediction (OSISP) model for trauma developed using the Swedish Trauma Registry," *BMC Medical Informatics and Decision Making*, vol. 23, no. 206, pp. 1–19, Oct. 2023, doi: https://doi.org/10.1186/s12911-023-02290-5.

[B] **Anna Bakidou**, Eva-Corina Caragounis, Magnus Andersson Hagiwara, Olav Røise, Anders Jonsson, Bengt Arne Sjöqvist, Stefan Candefjord, "Evaluating Performance and Potential Clinical Benefit of the Swedish On-Scene Injury Severity Prediction (OSISP) Model for Prehospital Field Triage on Norwegian Trauma Data". Submitted.

[C] **Anna Bakidou**, Magnus Andersson Hagiwara, Eunji Lee, Eva-Corina Caragounis, Bengt Arne Sjöqvist, Mattias Seth, Anders Jonsson, Stefan Candefjord, "Human-AI Collaboration in Emergency Trauma Care: Breathing Life into the On Scene Injury Severity Prediction (OSISP) Model," *Digital Health*, vol. 11, pp. 1–20, Dec. 2025, doi: 10.1177/20552076251403207.

[D] **Anna Bakidou**, Mattias Seth, Magnus Andersson Hagiwara, Hoor Jalo, Eva-Corina Caragounis, Bengt Arne Sjöqvist, Anders Jonsson, Stefan Candefjord, "Usability of a Prehospital Clinical Decision Support System Based on Artificial Intelligence: A case study of EMS personnel's experience of using On-Scene Injury Severity Prediction (OSISP)". Manuscript in writing.

[1] A. Brand, L. Allen, M. Altman, M. Hlava, and J. Scott, "Beyond authorship: Attribution, contribution, collaboration, and credit," *Learned Publishing*, vol. 28, no. 2, pp. 151–155, Apr. 2015, doi: https://doi.org/10.1087/20150211.

Table 1: Author contributions to Papers A–D. - No contribution, ▲ Contributed, ● Contributed to high extent, ■ Main responsible.

Part	**A**	**B**	**C**	**D**
Conceptualization	-	▲	▲	●
Methodology	●	■	■	●
Software	■	■	-	▲
Validation	●	■	■	■
Formal analysis	▲	●	■	■
Investigation	●	■	■	■
Resources	●	●	■	■
Data curation	●	■	■	■
Writing - Original draft	■	■	■	■
Writing - Review & editing	■	■	■	■
Visualization	■	■	■	■
Project administration	▲	●	■	■
Funding acquisition	-	●	●	●

Other publications
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[F] D. Wallstén, G. Axton, **A. Bakidou**, E. Lee, B. Sjöqvist, S. Candefjord, "Design for Integrating Explainable AI for Dynamic Risk Prediction in Prehospital IT Systems," in *Artificial Intelligence, Social Computing and Wearable Technologies: Proceedings of the AHFE International Conference on Human Factors in Design, Engineering, and Computing (AHFE 2023 Hawaii Edition)*, 2023, pp. 268–278, doi: 10.54941/ahfe1004199.

[G] M. Seth, H. Jalo, E. Lee, **A. Bakidou**, O. Medin, U. Björner, BA. Sjöqvist, S. Candefjord, "Reviewing challenges in specifying interoperability requirement in procurement of health information systems," in *MEDINFO 2023 – The Future Is Accessible: Proceedings of the 19th World Congress on Medical and Health Informatics*, 2024, pp. 8–12, doi: 10.3233/SHTI230917.

[H] H. Jalo, E. Lee, M. Seth, **A. Bakidou**, M. Pikkarainen, K. Jood, B. Sjöqvist, S. Candefjord, "Stroke Prehospital Decision Support Systems Based on Artificial Intelligence: Grey Literature Scoping Review," in *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies - HEALTHINF*, 2024, pp. 458–465, doi: 10.5220/0012380400003657.

Supervised projects

Supervised projects by the author, not included in this thesis, are:

[I] J. Jardebrand, "Talk2me, a voice controlled user interface used in the initial ambulance care process". MSc thesis, Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden, 2022. [Online]. Available: `https://hdl.handle.net/20.500.12380/304537`.
Role: Co-supervisor.

[J] A. Kemppainen, "VISAC - Towards a Voice Interface for Swedish Ambulance Care". MSc thesis, Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden, 2022. [Online]. Available: `https://hdl.handle.net/20.500.12380/305366`.
Role: Co-supervisor.

[K] L. Westberg, R. Johansson, J. Ekener, L. Dahlin, A. Thornander, K. Homann, "Towards a dictatable, digitized emergency medical record for the ambulance". BSc thesis, Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden, 2023. [Online]. Available: `http://hdl.handle.net/20.500.12380/306165`.
Role: Main supervisor.

[L] H. Denell, T. Johannesson, S. Nyberg, K. Reimertz, M. Sternhufvud, "EENX16-VT24-40: Ökad patientdelaktighet på akutmottagningen - Användarcentrerad utveckling av mobila gränssnitt för tillgängliggörande av individanpassad information om vårdbesök vid Akutmottagning Sahlgrenska". BSc thesis, Department of Electrical Engineering, Chalmers University of Technology, Gothenburg, Sweden, 2024. [Online]. Available: `http://hdl.handle.net/20.500.12380/309184`.
Role: Shared main supervisor.

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Anna, December 2025, Gothenburg

Acronyms

ACS-COT	American College of Surgeons Committee on Trauma
AI	Artificial Intelligence
AIS	Abbreviated Injury Scale
ANN	Artificial Neural Network
AmbuReg	Swedish Ambulance Registry
ASAP	Acute Support Assessment and Prioritizing
CDSS	Clinical Decision Support System
DHS	Digital Health Sandbox
ECRU	Early Critical-Resource Use
EMS	Emergency Medicine Service
FAIT	Field Artificial Intelligence Triage
FHIR	Fast Healthcare Interoperability Resources
FN	False Negative
FP	False Positive
FTDS	Field Triage Decision Scheme
GCS	Glasgow Coma Scale
ISS	Injury Severity Score
LR	Logistic Regression
ML	Machine Learning
NISS	New Injury Severity Score

NPAS	National Protocol of Ambulance Services
NTC	Non Trauma Center
NTR	Norwegian Trauma Registry
OSISP	On-Scene Injury Severity Prediction
PHI	Prehospital Index
PICTA	Prehospital Information Communication Technology Arena
PoC	Point of Care
PR curve	Precision Recall Curve
RETTS	Rapid Emergency Triage and Treatment System
RF	Random Forest
ROC curve	Receiver Operating Characteristic curve
RTS	Revised Trauma Score
S	Symbol
START	Simple Triage and Rapid Treatment
SUS	System Usability Scale
SVM	Supprt Vector Machine
SweTrau	Swedish Trauma Registry
TC	Trauma Center
TN	True Negative
TP	True Positive
TTA	Trauma Team Activation
TTApp	Trauma Triage App

UI	User Interface
VIPHS	Verified Innovation Process for Healthcare Solutions
VTC	Vittel Triage Criteria
XABCDE	Exsanguinating bleeding, Airway, Breathing, Circulation, Disability/consciousness, and External exposure
XAI	eXplainable Artificial Intelligence
XGBoost	Extreme Gradient Boosting

Part I

Overview

CHAPTER 1

Thesis outline

The thesis is outlined into two parts. Part I presents an overview of the thesis, distributed across nine chapters. Chapter 1 outlines the thesis. Chapter 2 and 3 introduce the research area, aim, and research questions. Chapter 4 presents an overview of current field triage systems and available IT platforms. Chapter 5 describes the frameworks and concepts that have have guided the research conducted in this thesis. Chapter 6 introduces the area of model development, which relates to the methods used in Paper A and B. Chapter 7 introduces the area of building Clinical Decision Support Systems (CDSS), which relates to the methods used in Paper C and D. Chapter 8 summarizes the main work and contributions of the included publications of this thesis. Next, chapter 9 discusses and concludes the results. Lastly, a future outlook is given in chapter 10. Part II presents the four research papers on which this thesis is based upon.

CHAPTER 2

Introduction

Imagine yourself at the beach. It's finally summer, the heat has arrived, and you're relaxing on the cliffs with your friends. You look around. On the far left, you can't see the parking lot, but you know it's there by the stream of people appearing on the small path, walking towards the beach with bags and belongings. Closer, a few families have chosen some flat cliffs to set up their picnic, while the kids run around. On the right, several groups of adults are relaxing and having barbecues on the rockier side of the beach. What a summer day! As you're about to start a conversation with one of your friends, you notice that two people near the water seem to have finished sunbathing. They get up and start walking down the cliff to swim. Suddenly, the person walking first slips and falls backwards. The head hits the cliff, and you see the person loose consciousness and slide towards the water. Screams rise in the air. The second person, who is closest, rushes forward to pull the first person out of the water. But in the rush, the second person makes the same mistake and slips on the cliff, falls backwards, hits the head, becomes unconscious and starts sliding towards the water. People around have started to react and run towards the scene to pull them up from the water. Families are trying to keep the children out of the way. A few people close by, perhaps friends to the victims, are crying and screaming without a stop. Someone shouts that they have called the ambulance. The first person regains consciousness quite quickly, but is a little dazed and with blood starting to appear on the side of the head. It seems to be a struggle to get the second person conscious. People are standing around, lost as to what to do. You head towards the parking lot to be ready to guide the ambulance team when they come. As you arrive, you notice that the road leading to the parking lot, as well as the parking lot itself, are almost blocked by parked cars everywhere.

You start to think for yourself: "How will the ambulance even get to the victims? What will they do? Will they take care of both, or just the unconscious one? How will they deal with all the bystanders? How can they stay calm in a situation like this? How will they know what to do? Will they take both to the hospital? Which hospital is the closest from here?".

For a person not medically trained, this scenario is most likely experienced as quite intimidating. On the contrast, ambulance teams - referred to as Emergency Medical Service (EMS) personnel in the remaining part of this thesis - are educated to handle this and any medical situation effectively and systematically. They are one of our everyday heroes, trained to remain calm during crisis. However, due to changes in society, the role of the EMS personnel is expanding. This leads to new demands on the care provided by EMS personnel and an increased need for tools to support their work. In the following sections, backgrounds on the role of the EMS personnel and the clinical focus of this thesis are presented, followed by the identified problem and the initial efforts towards a solution.

2.1 Prehospital care and the role as Emergency Medical Service (EMS) personnel

Prehospital care describes the care provided outside of hospitals in case of emergency medical incidents [1], [2]. These incidents are characterized by a variation in location (urban, rural, accessibility, site risks), circumstances (weather, lighting conditions, presence of bystanders, friends, family) and medical condition (type of condition, urgency, care need) [1]–[3]. Compared to care provided at hospitals, the variation in situations that could arise increases the difficulty for prehospital care providers to achieve the goal of providing optimal care in all situations.

The EMS personnel are one of the actors that provides prehospital care. They staff ambulances, which are mostly vehicles on the ground, but ambulance helicopters, planes and boats may also be a part of the ambulance fleet [3]. The level of education of those working in the ambulance differs internationally, where examples of titles that can be found in a team are general practice physicians, emergency specialist physicians, nurses, specialized ambulance nurses, and paramedics [1]. The workflow of a typical assignment for the EMS personnel can be described by six phases [3], initiated when receiving the call and completed when handing over the patient to the appropriate destination as presented in Figure 2.1. At each step, the following activities are conducted:

- **Step 1** The EMS personnel use available information for mental preparation [3].
- **Step 2** The EMS personnel assess safety risks at the scene for both the team and the patient [1], [4].
- **Step 3** Assessment of the trauma patient is initiated with the primary survey, which aims to identify and treat life-threatening conditions. The survey follows the XABCDE structure, where X checks for severe external bleeding, A for airway, B for breathing quality, C for circulation, D for disability/consciousness, and E for external exposure or injuries on body and protection from environment [3], [4]. If the condition allows, a secondary survey may be conducted to obtained more detailed information of the incident and patient, for instance asking about the medical history, checking the main symptom and conducting a detailed examination from top to toe [3]. Based on information from the patient assessment, the EMS personnel evaluates the patient's physiology and apparent injuries and decide on a diagnosis, which in turn decides the urgency [3], [4]. Next, the patient is given a priority based on available resources, the patient's condition and the identified care need [3]. This prioritization is called field triaging and often follows a systematic protocol [3].
- **Step 4** The EMS personnel decides on a transport destination to achieve optimal care. Generally, the decision can be to transfer the patient directly to the ambulance for immediate transport (load and go), stabilize the patient before transport (stabilize and go), or treat

and stabilize the patient before transport (stay and play) [3].

- **Step 5-6** The EMS personnel repeats the XABCDE assessment, or conduct the secondary survey if time allows and not completed earlier, until the patient is handed over to the receiving care unit [3].

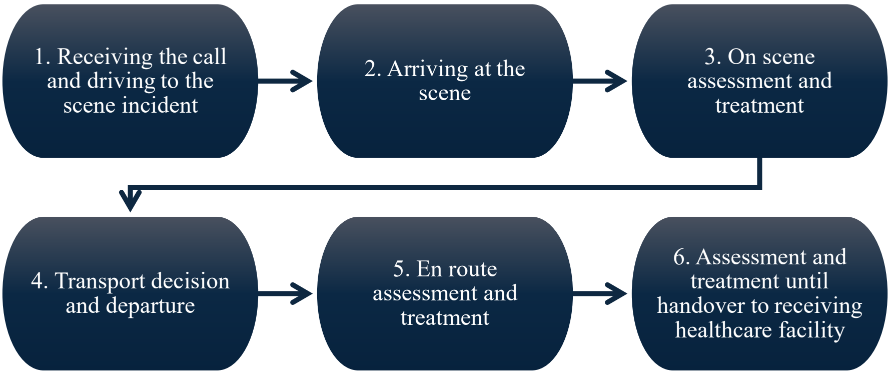

Figure 2.1: EMS personnel's workflow.

In addition to the general practice of caring for acute patients, EMS personnel are also affected by changes in the society. By now, it is well reported that the world's population is increasing and becoming older [5]. This puts stress on the healthcare systems. Zooming in on Sweden, a response to this demographic change was to transition the Swedish healthcare to "Good and close care" (*swe: God och nära vård*) [6]. This transition was initiated in 2018 and intends for the primary care units to become the main actor in healthcare, bringing the care closer to the patients [6]. Note that in parallel, specialist care is being centralized in Sweden [7]. The centralization means that specialized care for defined care areas will be conducted at maximum five hospitals in Sweden and account for 5% of the care [7]. These factors impact the EMS personnel in the following ways: 1) patient assessment becomes more difficult as elderly have complex care needs, and 2) decision-making on transport destination becomes more difficult as more alternatives need to be evaluated, including leaving the patient at home [3]. The increased complexity of the task expands the role of the EMS personnel, while resources remain unchanged.

The EMS personnel is a key actor to achieve the goal of providing optimal care as their ability to correctly identify the condition and urgency and determine appropriate transport destination greatly impacts the remaining course of the patients care journey. Thus, patient safety in prehospital care is important to consider. Patient safety refers to the protection against harm in healthcare and may be viewed from two perspectives called Safety I and Safety II [3]. Safety I defines a system as safe when there is an absence of risks and harmful events, while Safety II defines a system as safe if it has the ability to detect and correct for both expected and unexpected events [3]. For the prehospital care, the patient assessment has been found to be one of the largest threat to patient safety [3]. Other examples of threats are prescribing and medication errors, and diagnostic errors [8]. In the light of threats to patient safety in prehospital care, the expanding role of the EMS personnel coupled with limited resources poses an increased threat to patient safety. There is therefore a need for tools that can support the EMS personnel in their new role, ensure patient safety and increase the precision in the prehospital assessments and decisions.

2.2 Clinical focus: trauma

The EMS personnel encounter all kinds of conditions in the prehospital care but in this thesis we focus on trauma. The formal definition is "*a harmful event that arises from the release of specific forms of physical energy or barriers to the normal flow of energy*" [4]. Reflecting on the definition, it is clear that trauma can be caused by a variety of external factors. The trauma community refers to these factors as mechanisms of injury, which can be reported at different levels of detail. On a general level, the mechanism of injury is often binary classified as penetrating or blunt, where penetrating mechanisms define injuries caused by forces applied on small contact areas and that penetrates the skin and blunt mechanisms define injuries caused by forces applied on large contact areas without penetrating the skin [4], [9]. This binary classification can also be used to describe the main type of injury caused by the trauma, referred to as the dominating type of injury [10]. On a detailed level, subgroups of penetrating and blunt mechanisms can be reported, with common examples visualized in Figure 2.2 [10]. In addition to mechanisms of injury, trauma may also be described based on if it was caused intentionally or not [4], [10].

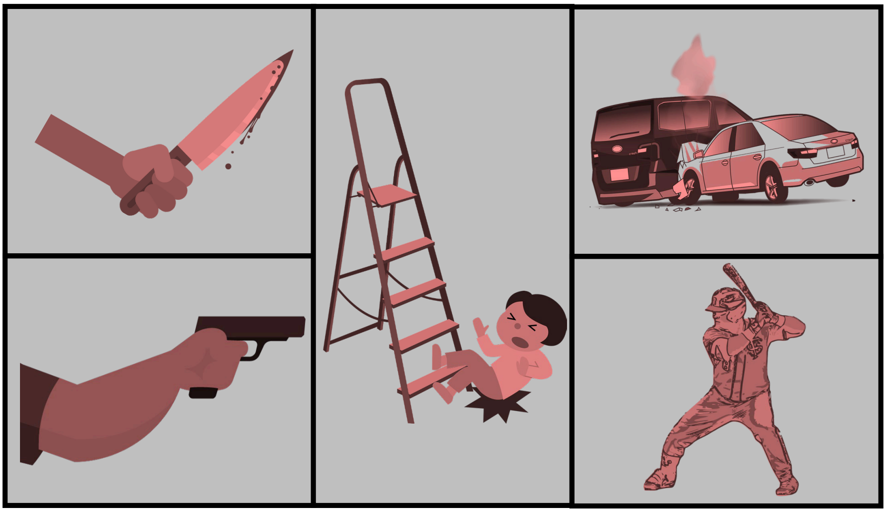

Figure 2.2: Examples of injury mechanisms that can cause injuries, including stabbings by sharp objects, gunshots, falls, traffic incidents, and hits from blunt objects [10]. All sub-figures adapted from [11], licensed under CC0.

Trauma is a condition that causes a lot of pain for the victims and also economic burden on society. It has a high degree of mortality internationally, with reports stating it represents 5 million deaths per year [4] and one of every ten deaths per year [9]. It has been found to be the leading cause of death for people 1 to 44 years of age in the U.S., accounting for about 200 000 deaths in total per year [4], and a report from Australia estimated that about 10% of severely injured died during the year of study, corresponding to about 900 deaths primarily among adults [12]. Although mortality is arguably the worst outcome, the impact on society goes even deeper, with a large number of hospitalizations and visits to emergency departments increasing the pressure on the healthcare system [4]. Furthermore, trauma often leads to permanent disabilities for the patients, as well high costs since there is a loss of productivity, wages, and additional costs of insurances [4], [9]. The risk groups of trauma are often hard to generalize on an international level as it depends on economical, social and developmental aspects [4]. Yet, young adults are a risk group commonly reported [4], [9]. In the future, however, this may change since the ageing population is increasing. In fact, it is estimated that older adults will represent up to 40% of the trauma incidents in 2050 [4]. In Sweden, trauma is also a common cause of death, especially for young adults [3], [9]. It accounts for between 14–17% of all EMS assignments, [3], [13], 25% of all the emergency department visits [9], and about 17% of patients being hospitalized [3]. About 3 000 persons die per year and the estimated societal cost is 60 billion SEK [9].

For trauma patients that are severely injured, time from the trauma to definitive care (surgery, intensive care, or continued care) is important to increase the chance of survival and reduce the risk of disabilities [4], [9]. It is described that a trauma patient has a "Golden period", which refers to a time period in which definitive care must be provided to avoid irreversible injuries and thereby increase the chance of survival [4]. The length of this time period depends on the patient's characteristics and injuries, and can be both shorter and longer than an hour [4]. As a reference, about 60% of trauma patients that die do so within four hours, but many trauma deaths could be prevented by quicker interventions and more efficient treatments [9]. Because EMS personnel often represent the first healthcare contact that trauma patients meet, it is important to optimize the prehospital care so that time to definitive care is minimized and within the Golden Period. One approach working towards this goal is to establish a trauma system, where Trauma Centers (TC) and non-Trauma Centers (NTC) are established. TC are hospitals with special routines, resources and preparedness to receive and care for severely injured patients, while NTC have less resources and follow more general routines for these patients [4]. As an extension of this system, EMS personnel are often prompted to transport severely injured patients to TC, which could lead to the bypass of a closer hospital in case it has inadequate capabilities to meet the care need of the patient [4]. With this system established, several studies have found an increased survival for severely injured when treated at TC compared to NTC [4], [14]–[16]. Although often demonstrating improved outcomes, opposing results have also been indicated in some settings [17] and it should be noted that this type of trauma system has received critique as it is expensive and may cause centralization of specialist care, which may lead to reduced access to care [18].

2.3 Problem statement and technology proposal

It is important to evaluate the quality of care provided by the healthcare system. For prehospital trauma care it is valuable to evaluate the field triage and study if patients are transported to the correct destination depending on their care need. This is often reflected by calculating undertriage and overtriage, commonly calculated according to the definitions by the American College of Surgeons Committee on Trauma (ACS-COT), where TC and NTC are used as transport destination [19]. With this method, undertriage is defined as "severely injured patients transported to lower-level trauma centers or other acute care facilities" and should not exceed 5%, and overtriage as "minimally injured patients transported to higher-level trauma centers" and should be within the interval 25–35% [19]. When reviewing reports on the evaluation of field triage, the recommended levels are difficult to achieve [20]–[22]. Identified factors explaining the exceeded levels of under- and overtriage include distance and time to TC, and underestimation of a patient's care need [4], [20], [23]. The clinical consequences are increased risk of mortality and disability for severely injured patients, and increased risk of overcrowding at TC, where patients with minor injuries occupies resources needed by severely injured patients [4].

The EMS personnel uses tools to support the clinical decision-making during patient assessment and selection of transport destinations, for instance guidelines, local policies and protocols. These tools are commonly referred to as CDSS and often functions as a checklist [24]. The reported under- and overtriage rates in current trauma systems indicate that the CDSS used today for patient assessment and selection of transport destination have a limited ability to identify severely injured at the scene incident. It is therefore hypothesized that a more advanced functionality is needed to analyze the patient's injuries to increase the precision in detecting severely injured. An example of a technology that can perform advanced analysis is Artificial Intelligence (AI), which may be defined as intelligence entities, "machines that can compute how to act effectively and safely in a wide variety of novel situations" [25]. AI is often used as a technology to find more complex pattern in data and has shown promising performance in the prehospital setting [26], [27]. Utilization of AI as a CDSS is therefore considered an interesting technology to support EMS personnel in their clinical decision-making process during field triage, and thereby reduce under- and overtriage.

2.4 Formation of a dedicated digital health research group

Chalmers University of Technology has a rich history of conducting research within the field of biomedical engineering to improve healthcare, including digital health. One example is the work on developing and introducing the MobiMed system [28], a telemedicine, decision support and management system for ambulances still actively used on the market and offered internationally by Ortivus. Other examples include projects integrating and evaluating computerized CDSS in the EMS workflow in collaboration with University of Borås, Sweden [29]–[31].

One outcome from the rich portfolio of digital health projects is the formation of the research group Care@Distance - Remote and Prehospital Digital Health. The group's story began in 2011 when postdoc Candefjord and adjunct Professor Sjöqvist formed a team in the biomedical engineering group, which today belongs to the Department of Electrical Engineering. Back then, Candefjord had completed his thesis on improved detection of prostate cancer and joined the group to work on traffic safety, while Sjöqvist, whose resume summarized over 35 years of academic and industrial work in biomedical engineering, digital health, and prehospital care, combined an academic position in digital health with industrial commitments.

In 2012, Sjöqvist became manager of the post-crash research area at SAFER, the Vehicle and Traffic Safety Centre, a research platform at Chalmers University of Technology. SAFER involved partners from society, academia and industry and worked towards Sweden's Vision Zero, where no one should be killed or seriously injured in a road incident. The post-crash group focused on challenges related to when a motor vehicle crash has occurred and on how to minimize the effects in general and for victims. Within SAFER, Sjöqvist and Candefjord started to explore how digital health and biomedical engineering could support the prehospital care post-crash activities in primarily two areas. Firstly, point of care CDSS for predicting the risk of being severely injured. Initially, the efforts focused on patients with unclear signs and symptoms of severe injury e.g., head trauma with internal bleedings, and over time, more general trauma risk prediction became part of the activities. Secondly, inspired by the eCall initiative in Europe, automatic transmission and at call centers receival of information relevant to predict risk of severe injuries from connected vehicles involved in a crash. Initial efforts introduced the concept of risk prediction of severely injured at the dispatch, which was then further developed into a complete system approach utilizing data fusion from multiple sources for improved call handling, assessment and prioritizing for first responders (dispatch, EMS personnel, police, and fire services) in case of motor vehicle crashes.

Starting from around 2015, a dedicated research group started to emerge through recruitment of postdocs and PhD students. During this growth phase, the group was named Care@Distance, targeting the business area remote and prehospital digital health with the motto “increase decision precision”. The group utilizes digital technology to support prehospital care, from the time a need for care arises after an incident until arrival at a medical facility where the need for care can be managed. Essential for establishment of today’s Care@Distance group was the multidisciplinary network within prehospital research, development and innovation formed during the early years. Apart from Chalmers University of Technology and SAFER, key actors and collaboration partners where PreHospen at University of Borås, the ambulance services within the region of Västra Götaland, Sahlgrenska University Hospital, and the collaboration platform Prehospital ICT Arena (PICTA).

2.5 Care@Distance’s first efforts to tackle the problem

The Care@Distance’s initial efforts to tackle the difficulties in achieving acceptable under- and overtriage levels are connected to the exploratory work at SAFER that started in 2012. Zooming in on these particular activities, the research agenda was mainly guided by international scientific findings: 1) reduced time to correct treatment increases the chance of survival [32], and 2) severely injured should be treated at TC with resources to manage the injuries [15], [32]. The team evaluated different solutions to reduce the time to correct treatment of severely injured, including microwave technology for earlier detection of typical traffic injuries, utilization of data collected from the European Union’s eCall system in case of serious traffic incidents, and a smartphone-based system for data collection in case of a road incidents.

A few years later, the constellation started to focus on prehospital triage systems, and found that the international scientific literature presented large proportions of undertriage in case of traffic incidents. As a result, the On Scene Injury Severity Prediction (OSISP) concept was introduced to describe more efficient injury severity prediction tools to be used by clinicians during the triaging process on site. Initially, an OSISP model based on Logistic Regression (LR) was developed for motor vehicle crashes using Swedish accident data and indicated an improved ability of triaging this patient group [33]. Motivated by the positive indication, a similar OSISP model was developed for Swedish truck incidents and demonstrated similar performance [34]. Later, Machine Learning (ML)-based OSISP models were developed based on U.S. motor vehicle crash data, also showing an indication of improved triage ability [35].

At this point, post-crash had become an established research field within the Care@Distance group and more detailed research questions were targeted. Moving forward, the collaboration started to explore transportation destinations more closely. The scientific literature motivating transport to TC was international and there was a gap of similar evidence in the Swedish setting. Therefore, an investigation of the Swedish setting was initiated. Using university hospitals as a correspondence to TC, the results aligned with the findings from the international literature. In the case of road incidents, a large proportion was incorrectly triaged [36], [37] and the distance to the nearest TC influenced transport destination rather than the type of injuries [37]. When studying the overall Swedish trauma population, it was found that there was an increased chance of survival if treated at TC [38]. Moreover, geographical challenges were identified, such as long distances and exposed regions not covered by one hour of ground or air ambulance [38].

2.6 Solution proposal

Based on the work conducted within the post-crash field, the Care@Distance research group could show that the problems identified for post-crash trauma were applicable to the trauma population as a whole. Moreover, it could be concluded that the OSISP concept showed potential to improve the triage precision in several studies on traffic incidents. Thus, an idea of a solution to increase precision in the field triage of the general trauma population was proposed: to apply and develop the OSISP concept as a CDSS for the general trauma population.

The solution proposal is the starting point of this thesis.

CHAPTER 3

Aim and research questions

The aim of this thesis was to study if an expansion of the OSISP concept, from having focused on patients involved in traffic incidents to including a general trauma population, is feasible and how to develop the OSISP as a CDSS. To achieve the aims, the following research questions were explored in the included publications of this thesis:

RQ 1: *How does OSISP perform when developed to predict the risk of a patient being severely injured for a general trauma population?*
Paper A: proof-of-concept

RQ 2: *How does OSISP developed on data from a general trauma population perform on future patients?*
Paper B: external validation and clinical impact evaluation

RQ 3: *How should OSISP be packaged as a CDSS to fit the prehospital workflow?*
Paper C: workflow integration and interface design

RQ 4: *How do EMS personnel perceive the usability of OSISP as a CDSS?*
Paper D: usability evaluation

RQ 5: *What clinical benefits can OSISP as a CDSS contribute to?*
Paper A-D

The hierarchical relationships of the four research papers on which this thesis is based upon are shown in Figure 3.1, and the distribution of data across the studies are illustrated in the Venn diagram in Figure 3.2.

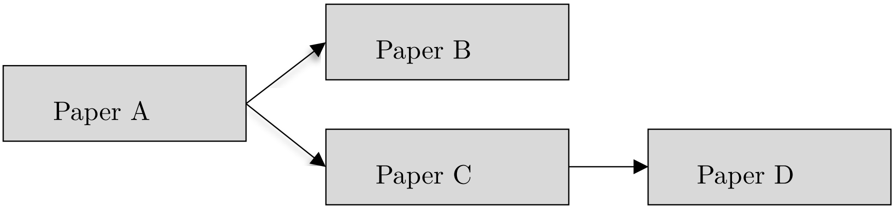

Figure 3.1: Hierarchical relationship of the included publications.

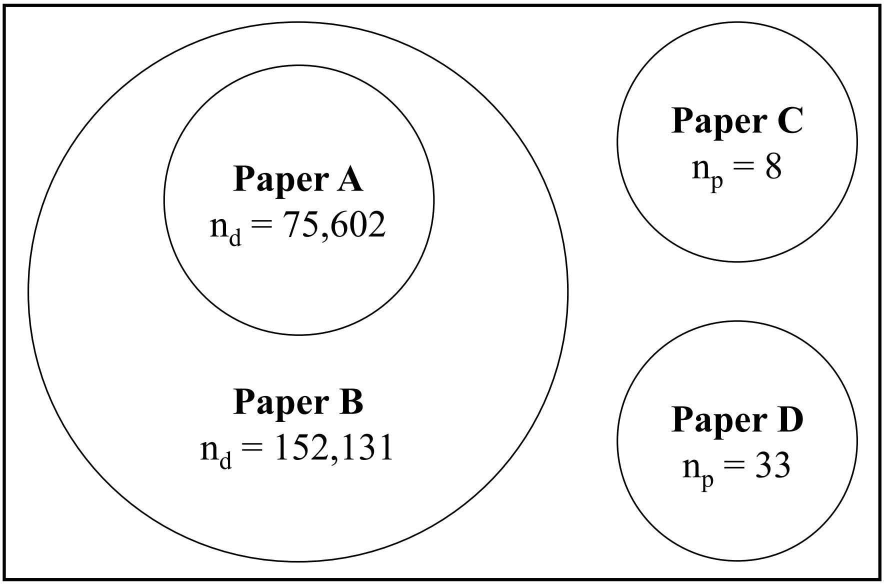

Figure 3.2: Venn diagram showing the distribution of raw registry data (n_d) and workshop participants (n_p) in the studies presented in Paper A-D.

CHAPTER 4

Triage history and overview of triage tools

Triage has its roots in the military, tracing back to the Greek and Roman empire and the care provided to their armies [39]. However, the surgeon Baron Dominique-Jean Larre is often referred to as the official origin of modern triage as a recognition of his systematic approach to sort and prioritize soldiers' care need in the French Napoleonic Army (beginning of 1800) [39], [40]. The soldiers were triaged for most urgent care need and potential to survive, given initial treatment and then loaded on horse transports to hospitals [39], [40]. The benefits of this triage approach gained attention and resulted in further development, and in World War I (beginning of 1900) triaging focused on soldiers expected to survive and was performed at multiple strategically selected locations, and with the technical advancements, soldiers were now being transported by motorized ambulances instead of horses [39]. In World War II (1930s–1940s), triaging had developed further and portable hospitals were offered as intermediate stops at the field to enable earlier treatment [39]. In addition, increased availability of antibiotics, improved surgical techniques coupled with the equipping of basic medical supplies for each soldier improved survivability [40]. In following wars in Korea (1950s) and Vietnam (1950s–1970s), survival was further improved by increased medical knowledge about shock and reduced transportation time, from hours to minutes, to medical facilities by helicopters [39], [40]. The triage knowledge derived from the military experiences was transferred to the civilian setting and forms the shape of modern prehospital care, with medically trained staffing ambulances and providing more advanced triaging and care at the scene incident [40].

4.1 Knowledge-based triage tools

Up until the 1970s, patients were mostly transported to the closest hospital [39]. Around this time, reports of increased survival for certain trauma patients transported to dedicated medical centers started to emerge, raising the need for tools to support the decision-making on appropriate transport destination [39]. Many tools have been proposed over the years.

The majority of triage tools are knowledge-based, which describes tools that are constructed with a set of rules in the format "If x, then y", i.e., if a predefined criteria is fulfilled, the tool states an outcome or action for the user to follow [41]. The rules are constructed by experts based on existing knowledge, which can be collected from for instance the scientific literature and current practices [41]. Multiple knowledge-based triage tools have been studied in the scientific literature, both for general trauma cohorts [42], [43] as well as subgroups, e.g., traumatic brain injuries in adults, mass casualty incidents, and identification of severely injured in elderly [44]–[46].

Examples of early triage tools are the Trauma Index and the Prehospital Index (PHI) [39]. Both use rules that are simple and quick to check, the Trauma Index detects the severity of the injury by checking the body region, type of injury, cardiovascular status, central nervous system status and respiratory status [47], while the PHI consists of four rules to detect patients in need of general surgery or neurosurgery using systolic blood pressure, pulse, respiratory status and consciousness [48]. In general, the early triage tools incorporated rules using variables like body region, type of injury, cardiovascular status, central nervous system status, respiratory status, capillary refill, eye opening, verbal response, motor response, systolic blood pressure, pulse, and level of consciousness [39].

Frequently reported triage tools in current scientific literature is the American Field Triage Decision Scheme (FTDS), the French Vittel Triage Criteria (VTC) and the Dutch National Protocol of Ambulance Services (NPAS). The FTDS was first published by ACS-COT in 1986 and has since then been updated and revised on several occasions (1986, 1990, 1993, 1999, 2006, 2011), with the latest version dated 2021 [49], [50]. The latest version of FTDS defines high risk patients with rules on injury patterns and mental status and vital signs, and moderate risk patients with rules on mechanism of injury and EMS judgment [50]. The VTC guides direct admission to TC with rules distributed across five categories: physiological signs, speed and mechanism, anatomical injuries, resuscitation, and medical history [51]. The NPAS divides patients in three groups based on recommended transport destination: 1) Level I TC, 2) Level I or II TC, and 3) Level I, II or III TC [52]. For the Level I TC group, rules check airway/breathing/circulation instability, consciousness, pupil difference, neurological deficit, body temperature, risk scores, and specific injuries [52]. For the Level I or II TC group, rules check for risk scores, mechanism of injury and pregnancy [52]. For the last group, Level I, II or III TC, the rules check risk scores for trauma and pediatric patients [52].

As triage has its roots in military conflicts with a large number of patients, there are also several examples of triage tools for mass casualty incidents. In the literature, the Simple Triage and Rapid Treatment (START) and the Triage Sieve are examples frequently mentioned [45]. START starts by checking patients that can move and follow commands, and then focus on sorting remaining patients into the categories dead (black), immediate need of care (red) and delayed care (yellow) in three steps: 1) check breathing (respiration), 2) check circulation (pulse), and 3) check mental status [4]. Triage Sieve also asks patients to walk, and then categorizes the patients as dead (white and black) or priority 1–5 (immediate/red, urgent/yellow, delayed/green, walking, expectant/blue) based on rules checking respiratory rate, capillary refill, and also heart rate in case of cold or dark conditions [53]. In Sweden, a recent publication by the Swedish National Board of Health and Welfare presented a national method for mass casualty triage [54], where patients not responding will be assessed first, patients that moves assessed second, and patients that can walk last [54]. The protocol assessment is designed to take one minute per patient and categorizes a patient as dead (black), immediate need of care (red), urgent need of care (yellow), not urgent need of care (green), or await (blue and white) [54].

4.2 Non-knowledge-based triage tools

Although many knowledge-based triage tools exist, as described earlier, management of trauma depends on several factors and the continued reporting of suboptimal performance (high proportions of under- and overtriage) shows that it is difficult to create a set of rules that efficiently identifies severely injured at the scene incident. Arguably as a response, proposals of triage tools based on AI have become more common in the scientific literature in recent years. These tools are non-knowledge based, meaning that the underlying mathematical algorithm on its own can create rules by learning from a data source [41]. Examples can be found for both civilian and military trauma.

For civilian trauma, the Dutch Trauma Triage (TT) App [55], the American pTEST [56], and the Danish triAGe [57] are examples of models proposed for adults (TTApp and pTEST), and for 3–90 years old (triAGe). No AI-based triage tool solely for pediatric patients has been identified. For military trauma, the Dutch Early Critical-Resource Use (ECRU) [58] has been proposed, targeting adults between 16–50 years. The American Field Artificial Intelligence Triage (FAIT) [59], [60] is a model applicable for both civilian and military gunshot trauma for adults aged 16–60 years. The triage tools utilize different techniques, e.g., LR, gradient boosting decision trees, extreme gradient boosting (XGBoost), deep neural network, and hybrid neural network combining time series and tabular data, to predict the outcomes "need of intensive care unit", "need of mechanical ventilation", "early critical-resource use", "critical injuries", "severe head injury", "severe thoracic injury", "severe internal bleeding", "need for major surgery", "shock", "need for early major hemorrhage control procedures", and "need for early massive transfusion" [55]–[60]. The models often use several sources of information about the trauma incident to make the predictions, for instance age, vital signs (e.g., systolic blood pressure, respiratory rate and oxygen saturation), mechanism of injury (e.g., fall incidents and motor vehicle crashes), and specific type of injures (e.g., pelvic fractures and head injuries) [55]–[60]. Indications of good predictive performance have been reported for all AI-based triage tools, yet, the majority remain at the development phase except for the

TTApp, which has been prospectively tested in the Netherlands [61].

4.3 Digital platforms

The use of digital platforms for documentation and support within the prehospital care context differ. At some locations, paper and pen are used. In others, EMS personnel are assisted by digital IT systems for patient journaling with functionalities such as CDSS [2]. There are several companies delivering IT platforms and with installations in both Europe and US, including Ortivus, Bliksund, OMDA, ZOLL, and Dedalus. Based on information from each suppliers websites, a brief description of each solution is described in Table 4.1.

Table 4.1: Prehospital IT platforms.

Company	Solution	Features	Ref.
Bliksund	EWA (Emergency Worker Assistant)	Remote consultation, tablet, touch, horizontal scrolling, hardware agnostic	[62]
Dedalus	amPHI	Live streaming, patient history, data sharing, Fast Healthcare Interoperability Resources (FHIR)	[63]
OMDA	Omda Paratus, Omda Predicare, and Omda Aweria Prehospital	Patient records, medical equipment integration, free text input, Rapid Emergency Triage and Treatment System (RETTS), care documentation, decision support, collaboration, communication, tablet, OS agnostic,	[64]
Ortivus	MobiMed ePR	Decision support, patient history, treatment guidelines, data sharing, remote consultation, FHIR	[65]
ZOLL	ZOLL emsCharts and ZOLL emsCharts NOW	Online/offline mode, device agnostic, HL7 bi-directional, on site mobile solution	[66]

CHAPTER 5

Projects, frameworks and concepts guiding the research

The Care@Distance research group has defined a Vision Zero, similar to the Swedish Vision Zero for traffic safety (no one should be killed or seriously injured within the road transport system) to guide their work: no errors in assessment, prioritizing and handling. The core of this vision is to increase decision precision. To work towards this vision, the group applies data fusion, CDSS, AI, telemedicine and user interaction technologies. The strive for utilization has been a key pillar since the start, demonstrated through multidisciplinary triple helix collaborations with academia, industry and healthcare in a range of projects. Both action and transition research are applied research methods, where structural changes are considered in the simultaneous analysis of the problem and solution. The research conducted within the Care@Distance group is also guided by defined frameworks and concepts.

5.1 Care@Distance's project portfolio

The Care@Distance distance group have been and are involved in several projects. In addition to the OSISP related projects, the group has for instance worked on projects to address interoperability, stroke, sepsis, and drowsiness among drivers. An overview of the project portfolio is given in Table 5.1, accompanied with the year each project started, from which experience and results have been used to guide the development of OSISP as a CDSS in this thesis.

Table 5.1: The Care@Distance group's project portfolio.

Year	Project	Description
2014	Via Appia/ TEAPaN	Traffic event assessment, prioritizing and notification
2015	PrehospIT	Clinical decision support and IT interoperability in the prehospital stroke chain
2015	ViPHS	Video support in the prehospital stroke chain
2016	PreSISe	Prehospital decision support utilizing AI/ML for identification of increased risk for sepsis
2017	COPE, Driver and SynCOPE	Driver disease and drowsiness detection
2018	PreTest	Prehospital test ambulance
2019	Autumn Leaves	Automatic fall detection, assessment, prioritization and prehospital management in the elderly population
2021	Talk2Me	Voice interaction with prehospital IT applications and platforms
2021	When care moves home	Hospital at home care
2021/2024	Kon-tiki 1/2	AI in prehospital care
2022	ASAP PoC trauma and stroke	Acute support assessment and prioritizing (ASAP) concept applied to prehospital stroke and trauma
2022/2024	Virtuality	Digital health sandbox and synthetic data
2023	MAIN	Model for AI utilization

5.2 VIPHS: Verified Innovation Process for Healthcare Solutions

Development of tools for healthcare requires commitment, work effort, navigation of complex regulations, and financial support over a long period of time [67], [68]. To reach utilization, it is therefore important to have a strategy that maximizes the outcome at each step of the development process, from idea to deployment, to ensure the developed tool is usable and wanted by the intended clinicians, integrable with the intended operating environment, compliant with regulatory requirements, and can be funded and maintained by the intended organization. Because the Care@Distance research group strive for utilization, using such a strategy for planning research projects is vital.

The strategy used by the Care@Distance research group is called the Verified Innovation Process for Healthcare Solutions (VIPHS) [69], developed by the group itself based on experience of developing innovations for healthcare. VIPHS is a stepwise framework for the design, testing, utilization and implementation of digital health tools and innovations. It is human-centered, meaning it focuses on the needs of the human user, and consists of four steps to reach operational implementation. Each step generates detailed descriptions of the innovation called blueprints, which serves as official documentation of the development process. The first step generates a holistic description of the innovation. The remaining steps test the innovation iteratively with increasing levels of operational environment. The second step tests the innovation in simulations, the third steps tests the innovation in a limited operational environment, and the fourth step tests the innovation at an extended operational environment. The content of the blueprints generated from each step of VIPHS is presented in Figure 5.1. In this thesis, the development of OSISP as a CDSS for the general trauma population was initiated. Therefore, the research activities in this thesis were guided by the first step of VIPHS.

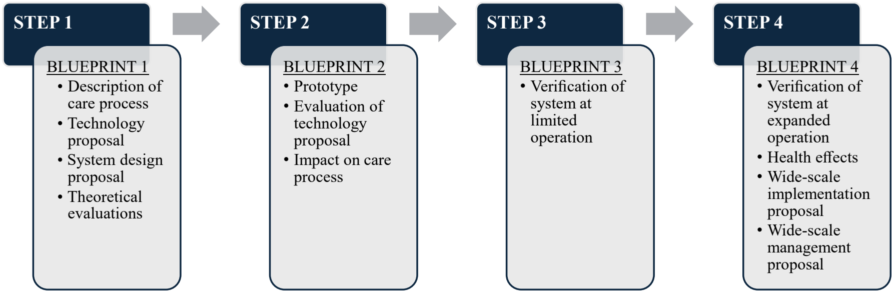

Figure 5.1: Outcome from each step of the Verified Innovation Process for Healthcare Solutions (VIPHS) [69].

5.3 ASAP: Acute Support Assessment and Prioritizing

To increase the decision precision during assessment, prioritizing and handling, the Care@Distance research group has a technology focus categorized in three parts: data aggregation techniques, digital health techniques, and user interaction techniques. Data aggregation, also commonly referred to as data fusion, describes techniques that collect and combine data from different sources to obtain a more complete and richer understanding of the patient at hand. This could for instance be data from home monitoring equipment, data collected on site from EMS personnel or data from the electronic health record at the hospital. Digital health techniques includes methods for processing or using the data, such as statistical methods, AI, CDSS and telemedicine. User interaction techniques are different forms of interfaces that enables data and outcomes from the digital health techniques to be presented to users, as well as the users being able to interact with the data and digital health techniques.

These parts forms the Care@Distance research group's technology focus and supports assessment and prioritizing in acute situations, summarized as the concept ASAP and visualized in Figure 5.2. To the left, data providers transfer data to the system, forming the various sources of data for data aggregation. In the middle (marked in green), ASAP core receives the data, formats the data so that it can be used by software modules using different digital health techniques, and transmits the data and outcomes to the users for presentation.

To the right, the users, also called the consumers, can interact with the data and outcomes through the selected interface.

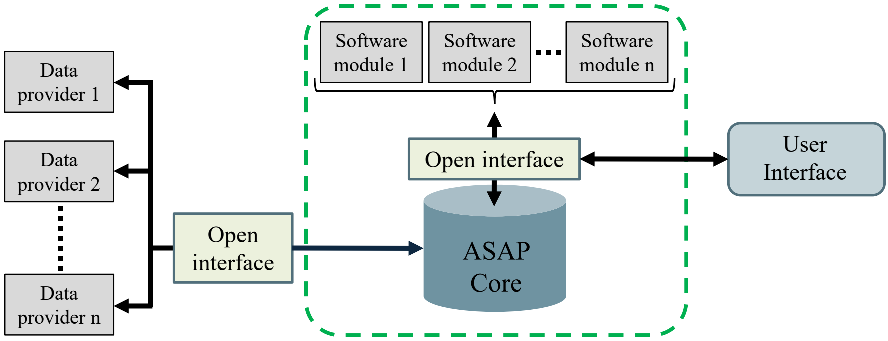

Figure 5.2: The Acute Support Assessment and Prioritizing (ASAP) concept. [70]. Adapted and reprinted with permission.

ASAP is adapted for the project at hand. In this thesis, it was therefore adapted for the context of prehosital trauma and referred to as ASAP Point of Care (PoC) Trauma. PoC describes the context of EMS personnel being available at the scene incident, in contrast to for instance remote care when no healthcare personnel is with the patient. For ASAP PoC Trauma, the data providers are represented by the different sources of data that may arise from the ambulance and EMS personnel, for instance vital measurements, observations, checklists, triage results, and medical history surveys. The digital health technique is OSISP, a CDSS that will generate a risk prediction of the patient being severely injured. Lastly, the user interaction is intended to be facilitated through a tablet.

5.4 Virtuality: a virtual care process simulator

As described earlier, researchers developing innovations for healthcare face several challenges when striving for utilization. Being effective in each step of VIPHS is a way to tackle these challenges, and the Care@Distance group is therefore developing a virtual care process simulator called Virtuality to streamline the tests conducted at step one and two of VIPHS [71]. The purpose of Virtuality is to enable safe testing of digital innovations in a simulated environment that mimics the intended operational environment.

An overview of Virtuality 's main components, the Digital Health Sandbox (DHS) and Synthetic data mechanism, is displayed in Figure 5.3 [71]. As can be seen, the DHS is based on the ASAP concept, where *Providers* represent devices and providers sending data, *Services* represent the software modules that processes the data, and *Consumers* represent the interface towards the users. On top of these, the Scenario Engine is added with the purpose to define and execute a simulation of a scenario that mimics the care processes of interest, with the selected providers, services and consumers. If real healthcare data is difficult to access, the Synthetic data mechanism can be connected to the DHS as a *Provider*. It's purpose is to generate artificial versions of the real healthcare data. Combined, the components of Virtuality makes up a flexible simulation concept that facilitates testing.

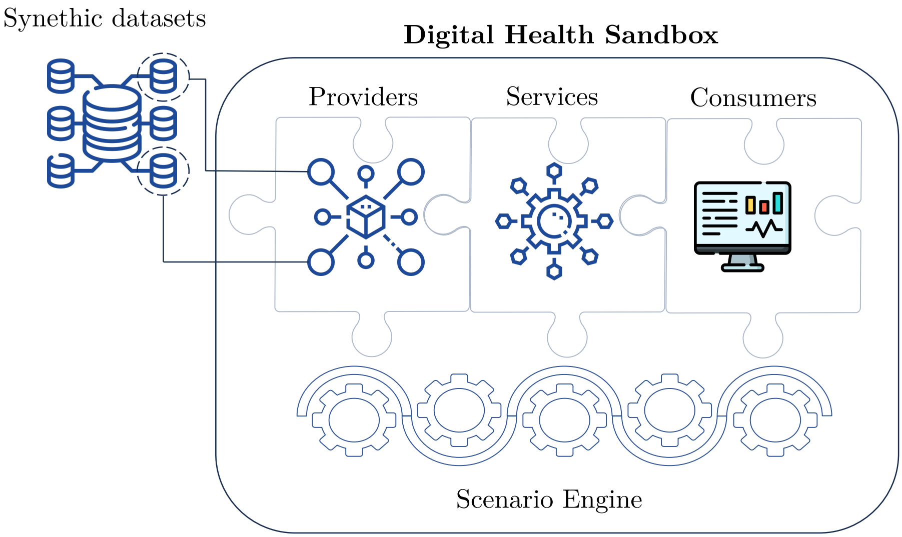

Figure 5.3: Overview of Virtuality components. [71]. Reprinted with permission.

Similar to ASAP, the setup of Virtuality is adapted to the project at hand. Because the DHS is largely based on ASAP, the data providers, software modules and User Interface (UI) from ASAP PoC Trauma are transferable to the *Providers*, *Services* and *Consumers* components of Virtuality. To run simulations, an artificial data mimicking the trauma data used for developing

OSISP should be generated by the Synthetic data mechanism. The Scenario Engine will be configured to define and execute trauma scenarios of interest.

CHAPTER 6

Building the OSISP model

It is time to dive into the work conducted in this thesis, starting with the development of the OSISP model. In line with the technology focus of the Care@Distance research group, AI techniques and data fusion are used in the development process. The term AI has become a buzzword used to describe a wide range of applications, which may make it difficult to distinguish its actual meaning [72]. In its core, AI is about building intelligent computers that can act on their own in an environment [25]. The key word here is *intelligent*. This may be defined in various ways, often based on the assumption of human intelligence being the ultimate level, for instance acting as a human, thinking as a human, thinking rationally, or acting rationally [25]. Depending on the definition and the problem to be solved, a diversity of techniques can be described as AI. Details on the technique and the development process to build the OSISP model are elaborated on in the following sections.

6.1 Machine learning (ML) models

In this thesis, we have focused on ML techniques for OSISP. ML defines computers with the capability of learning from the environment to improve the performance [25]. Learning can be achieved in different ways. One common approach is to learn rules based on observations in the environment [25]. The observations depend on the context and what type of information the computer can observe from the environment. By studying a collection of observations, it is possible to learn which rule best describes the connection between the factors and the impact in the environment. Using a mathematical language, the factors in the environment is denoted as the input x and the impact as the output y [25]. Learning is then about finding a general mathematical function f that can describe the relationship between the input and output as $y = f(x)$ [25]. ML based on input and output observations is called supervised learning [25], and the relationship between AI, ML and supervised learning is displayed in Figure 6.1.

There are various types of mathematical models falling under the category of supervised learning techniques. Which type of model to select is often a process of trying different types and selecting the one that fulfills the requirements the best. In turn, each type of model has an underlying mathematical algorithm (instruction) on how to process data, with a set of parameters that can be tuned. The goal is to find a version of the model, meaning a set of parameters, that approximates the function f well [25]. This process is commonly known as training the model, and is accomplished by entering the input to different versions of the model. For each version, the model uses the mathematical algorithm and the defined parameters to generate estimated outputs, called predictions. The predictions can then be compared to the actual observed output to evaluate the performance. By comparing the result of all versions, the one that performs the best can be selected.

In this thesis, the context is trauma patients encountered at the scene of incident. The input is the observations that the EMS personnel collect from the situation and patient assessment, for instance the injury mechanism, the patient's age, and measured vitals. This input is transformed to a digital format that can be entered and processed by a computer. The output is if the patient is severely injured or not, a binary classification. Five supervised learning techniques were explored to see if a rule between the input and output

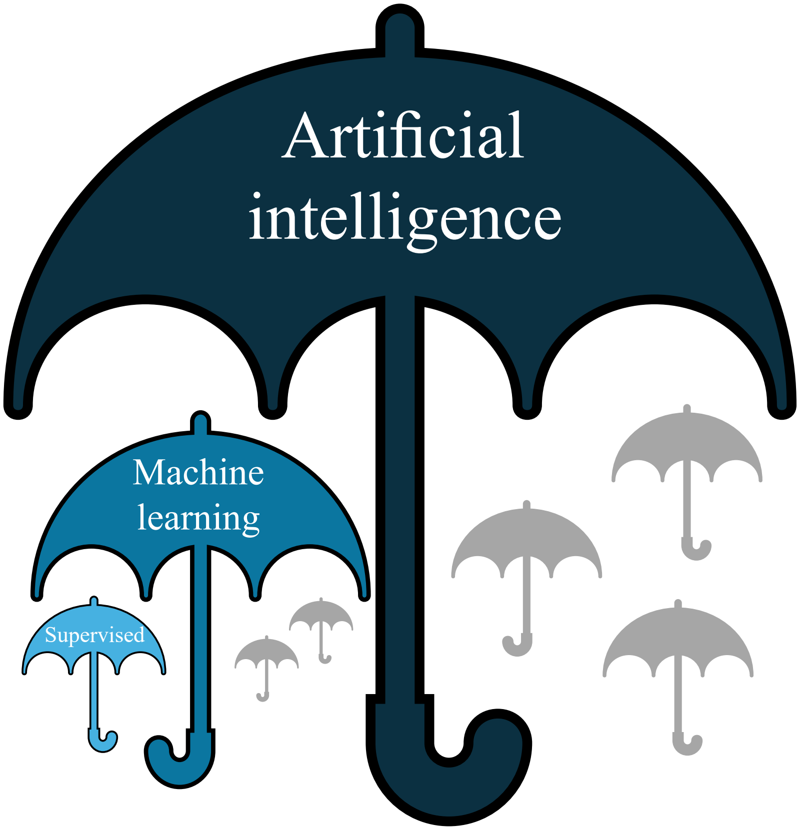

Figure 6.1: Umbrella terms used in the Artificial Intelligence (AI) field.

could be found: LR [73], Random Forest (RF) [74], XGBoost [75], Support Vector Machine (SVM) [76], and Artificial Neural Networks (ANN) [77]. These techniques are well documented in the literature and the work conducted in this thesis applied the techniques without any modifications to their algorithms, the curious reader is therefore referred to the publication on each model for details.

6.2 Data source for model development

The data used to train ML models is arguable the most important aspect of developing a model. This is reflected by the phrase *"Garbage in - Garbage out"* commonly used by the ML community [78], meaning that if the data used to train a model is of poor quality, the output generated by the trained models will be unreliable. It is therefore essential that the data selected to train ML models represent the targeted population well, in this case the general trauma population, and that the registrations have been collected with high accuracy.

A valuable source of quality data are national quality registries. These are often used by healthcare to analyze and improve processes, and are also accessible for research [79]. In this thesis, we used data from one such registry in Sweden called the Swedish Trauma Registry (SweTrau), which focus on registering data for severely injured patients [80]. SweTrau collects data from the whole care chain, from the prehospital encounter until discharge from the hospital, and the variables being registered are based on a recommended set of variables proposed in the Utstein template for uniform reporting [10]. The registration of data to SweTrau is retrospective, where trained personnel at each connected hospital reviews patient records to identify the required information to be entered [80]. Injuries are registered according to the coding framework Abbreviated Injury Scale (AIS), which describes injuries with a code of seven digits in the format "xxxxxx.x" [81]. The first six digits describes the location (head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and external) and injury type, and the final digit describes the severity from minor (1) to maximal (6) severity [81].

6.3 Missing data

Another aspect to consider is the completeness of the data. For the prehospital care, data are rarely complete due to the dynamical situation. Variables relevant for one patient may not be relevant for another patient, and time-critical situations may require EMS personnel to care for the patient with no time to document measurements, which leaves varying data fields empty. Figure 6.2 illustrate the difference of having complete data and data with missing values. Especially for trauma, high proportions of missing data are reported for trauma registries [82]. Because most ML model require complete data to function, it is important to consider the underlying reasons of why the fields are missing to enable conclusions if patient registrations with missing data should be deleted, or if it can be approximated.

Patient	Age	Sex	Airway management	…	Variable N
Emil	25	Male	No	…	Value 1
Emilia	19	Female	Yes	…	Value 3
…	…	…	…	…	…
Patient N	45	Male	No	…	Value 2

a)

Patient	Age	Sex	Airway management	…	Variable N
Emil	25	Male	No	…	Value 1
Emilia	19	Female		…	Value 3
…	…	…	…	…	…
Patient N	45		No	…	Value 2

b)

Figure 6.2: Visualization of what missing values looks like in the data. a) Complete data without missing data. b) Missing airway management data for patient Emilia and missing sex data for Patient N.

For trauma data, there is usually a reason why data is missing [83], and deletion of patient registrations with missing values may therefore remove important information. The reason for missing values often depends on the variable and registry, and a specific investigations for each registry is therefore often needed. To our knowledge, no investigation on why variables have missing data has been conducted for the data in SweTrau. We therefore applied a two-step approach to handle missing data in Paper A. First, predictors with a large number of missing values were removed, as their inclusion would have resulted in a dataset too small for any reasonable analysis to be conducted. Next, we conducted a sensitivity analysis where missing data were handled with four different methods commonly used in the literature. First, we tested to delete all registrations with missing data in predictors (dataset A). Secondly, missing values were marked as an unknown variable level, for instance allowing sex to be registered as male, female or unknown (dataset B). Thirdly, we replaced missing values in predictors with corresponding variables registered from the hospital care (dataset C). Fourthly, missing values were predicted based on the variable's data type and its known values (dataset D).

6.4 Model input: predictors

Based on the data collected by SweTrau, we selected a set of potential predictors. Predictors are a set of variables that together form the input on which the ML models are trained. The potential predictors were selected based on the ability for EMS personnel to access such information at the scene incident and are shown in Figure 6.3. All predictors were used in a categorical format.

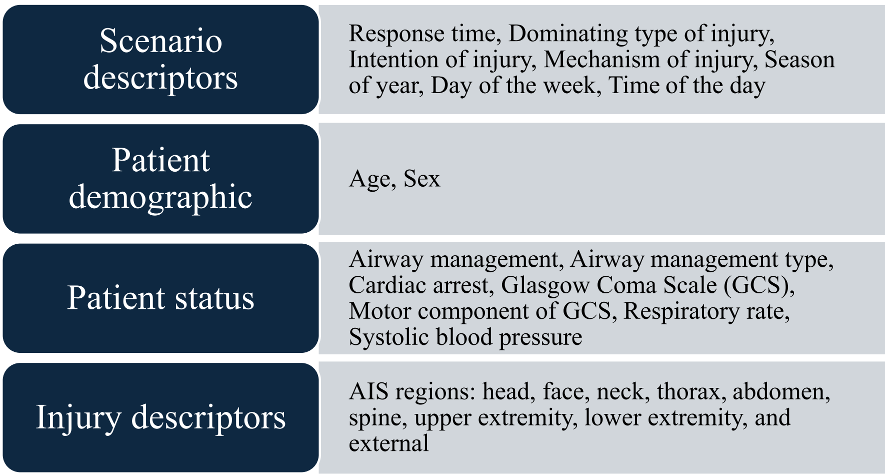

Figure 6.3: Initial set of predictors, categorized based on their content.

6.5 Model output: severely injured

The purpose of OSISP is to predict the risk of a person being severely injured, on which there are several definitions for. One common definition is by using Injury Severity Score (ISS) and the New Injury Severity Score (NISS), a successor of the ISS. The ISS is based on the AIS coding and divides the body into six regions (head or neck, face, chest, abdominal or pelvic, extremities or pelvic girdle, and external) and with a severity scale ranging from minor (1) to critical (5), from which the ISS score is calculated as the "sum of the squares of the highest AIS grades in each of the three most severely injured areas" [84]. The NISS is calculated similar to ISS, with the difference that the three most severe injuries may be located in the same region [85]. Both ISS and NISS have values within the interval 0–75, and the literature uses different thresholds to define severely injured patients. In this thesis, a NISS greater than 15 was selected as the primary definition for severely injured. To enable comparison with the literature, the analysis was repeated for the additional definitions ISS greater than 12, ISS greater than 15 and NISS greater than 12.

6.6 Model development

The model development consisted of two main parts: selection of predictors and model development. To select the final set of predictors, the connection between each potential predictor presented in Figure 6.3 and the output of severely injured were evaluated using a Chi-square univariate test of independence and a LR analysis. In both tests, a so called p-value is being calculated, which is interpreted as the probability that an observed effect happened by chance [73]. Starting from the assumption that there is no connection between two sets of categorical variables, the p-value can be used to evaluate the probability that the connection between the data is observed by chance (p-value above selected threshold) or not (p-value below selected threshold) [73]. In the former case, the variables are not deemed connected, whereas in the latter they are. In this thesis, a predictor was selected if a p-value lower than 0.05 was observed either in the Chi-square test or LR analysis.

Next, the OSISP model was developed according to the procedure visualized in Figure 6.4. The selected predictors formed the model input used to train the model. For each registration, there is a true value of the output informing the model if each patient is severely injured or not. After training, OSISP models based on LR, RF, XGBoost, SVM and ANN were obtained.

Model input | Model output

Patient	Age	Sex	Airway management	…	Variable N
Emil	25	Male	No	…	Value 1
Emilia	19	Female	Yes	…	Value 3
…	…	…	…	…	…
Patient N	45	Male	No	…	Value 2

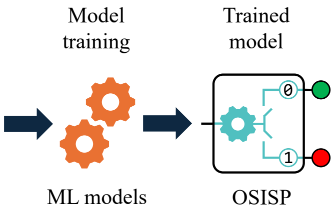

Figure 6.4: Model development.

6.7 Model evaluation

To evaluate the performance of a model, the model is applied on a so called test set, which is data that the model has not yet analyzed. Testing on data that has not yet been processed is important to understand if the model is underfitting or overfitting [25]. Underfitting means that the model has not been able to find a valuable pattern in the training data (it cannot accurately model the data due to being too simple), which leads to the model making large errors both in the training and test data [25]. Overfitting means that the model has considered too many details in the training data (it is an expert on that particular data), which yields a model that will not perform well on new data and have a large degree of variance [25]. The goal is to achieve a balance, and evaluating the model performance can be done in different ways:

- Hold-out analysis: The data is split in two: training data and test data. The model development described in the previous section is conducted using the training data, and the resulting model is then applied on the test data to evaluate how it performs on new data.

- K-fold cross-validation: The data is split in k parts/folds. K combinations of the data are formed. In each combination, one fold is separated as test data while the k-1 remaining folders serves as training data. The model development described in the previous section is conducted using the training data, and the resulting model is then applied on the test data to evaluate how it performs on new data. The result for current combination is then stored. This process is repeated for all combinations of the data. At the end, the model performance across all combinations is averaged. The process for 10 folders is visualized in Figure 6.5.

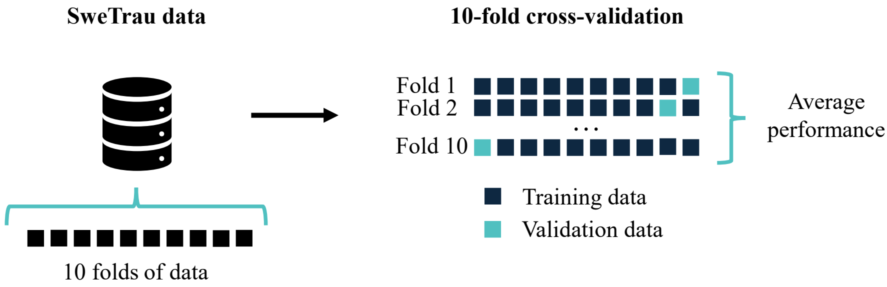

Figure 6.5: Process during 10-fold cross-validation.

Metrics to evaluate performance are often based on a so called confusion matrix and is often used as visualized in Figure 6.6. The columns of the matrix correspond to the true outputs, where positive means the patient was severely injured and negative means the patient was not severely injured. The rows of the matrix correspond to the predicted outputs by OSISP, where positive means the patient was predicted as severely injured and negative means the patient was predicted as not severely injured. If the predictions align with the truth, we obtain True Positives (TP) and True Negatives (TN). If the predictions are incorrect and do not correspond to the truth, we obtain False Positives (FP, patient predicted as severely injured when patient was not severely injured) and False Negatives (FN, patient predicted as not severely injured when patient was severely injured). These are used to calculate technical performance metrics such as accuracy, sensitivity/recall, F-measure, positive predictive value/precision, negative predictive value, observed/expected ratio.

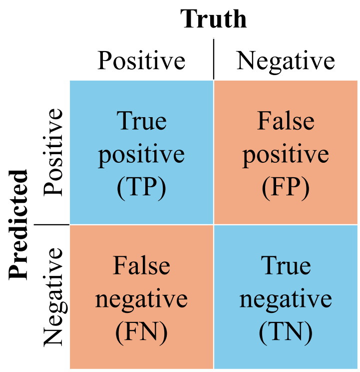

Figure 6.6: Confusion matrix.

It is important to note that the actual output from the model itself is the probability of a patient being severely injured. We as developers then determine a probability threshold where all predictions with probabilities above the threshold are classified as severely injured and all above as not severely injured. Typically, it is interesting to study the model's overall performance by evaluating the model at different probability thresholds. This is often visualized with three graphs: the Receiver Operating Characteristic (ROC) curve, the Precision-Recall (PR) curve, and the calibration curve. Illustrative examples of each curve is presented in Figure 6.7. A good model has a ROC curve reaching towards the top left corner, a PR-curve reaching towards the top right corner and a calibration curve aligned with the diagonal. Each curve yields metrics that can be used to compare and evaluate the overall performance, and these are summarized in Table 6.1.

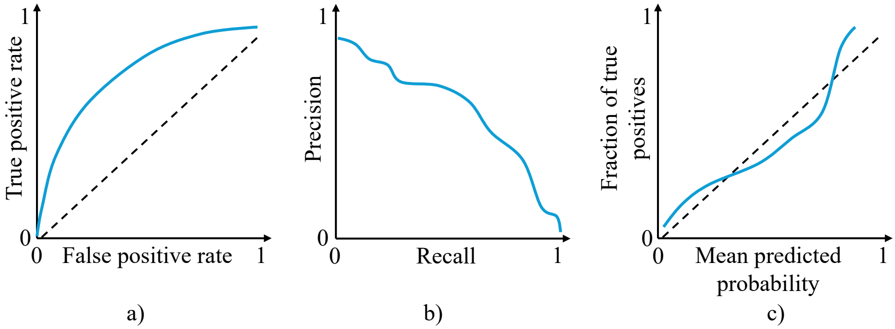

Figure 6.7: Model visualizations. a) ROC curve, b) PR curve, c) Calibration curve.

Table 6.1: Overall performance metrics.

Graph	**Metric**
ROC curve	Area Under the ROC curve (AUC ROC)
PR curve	Area Under the PR curve (AUC PR)
Calibration curve	Calibration slope
	Calibration in the large

In addition to the technical performance it is crucial to evaluate the clinical performance of the model as well, as it is aimed to be used as a CDSS. Because the underlying reason for developing OSISP is to increase the number of patients correctly transported, under- and overtriage becomes metrics of interest. As stated in the introduction, ACS-COT recommends that undertriage should not exceed 5%, and overtriage should be within the interval 25–35% [19]. These metrics has a direct connection to the ROC curve, where the y-axis corresponds to 1-undertriage, and the x-axis to overtriage. Thus, the ROC-curve can be used to evaluate the OSISP model for specific levels of under- and overtriage, where for instance a model achieving 5% undertriage is obtained by selecting the model corresponding to a y-value of 0.95, 25% overtriage at 0.25 of the x-axis and 35% overtriage at 0.35 of the x-axis. The proportion of under- and overtriage may then be compared to the under- and overtriage in the data to evaluate the clinical impact.

6.8 Model validation

Validation is about understanding the model's behavior on new patient data, both from the same population as the development data (internal) but also a similar but new population (external) [86]. The hold-out analysis and k-fold cross-validation described earlier are common approaches for conducting internal validation. External validation applies a developed model on data that has a structural difference compared to the development data, for instance different collected from other countries or care phases [87].

Similar to Sweden, Norway also has a quality registry for trauma, the Norwegian Trauma Registry (NTR) [88], in which the collected data is also based on the Utstein template for uniform reporting [10]. Data from NTR was therefore selected for external validation to estimate OSISP's performance on future patients. Predictors and outcomes as defined during the development were extracted and OSISP was then applied to predict the risk of patients being severely injured. To estimate the clinical benefit, we studied how many of the under- and ovetriaged patients in the NTR data that OSISP could find. This evaluation was done with two methods. First, the under- and overtriage in the NTR data were calculated based on ACS-COT's definitions [19]. Secondly, under- and overtriage were calculated with Trauma Team Activation (TTA) definitions, where under- and overtriage were defined based on if a trauma team was activated or not at the receiving hospital, instead of checking for transportation to a TC or NTC [89].

6.9 Points of attention

It is important that the data used to develop the model represents the population of interest. In this thesis, we focus on the general trauma population. The prevalence in a typical trauma population is not balanced, rather, the severely injured patients constitute the minority. Both SweTrau and NTR are registries with inclusion criteria focused on identifying severely injured. Although a small number of not severely injured have been reported in the registries, the focus on capturing severely injured consequently leads to a large proportion of not severely injured not being registered. In fact, when reviewing the EMS missions related to trauma in Sweden during 2019, it was estimated that only about 4% were registered in SweTrau, in which only

25% (n = 572) were severely injured [13]. Thus, the prevalence of severely injured in SweTrau is reasonably much larger compared to the prevalence in reality, which may impact how OSISP performs if deployed. At the same time, no other data sources are currently available with better representation. The Swedish ambulance registry (AmbuReg), a national quality registry that collects data for all EMS missions [90], is a future candidate but as of now, no variables specific to trauma are collected, which limits its current use for trauma purposes.

Another point is that this thesis builds on work relating to trauma systems and classifications of TC. It is a topic of debate. This thesis builds on the work reasoning that such trauma system would be beneficial to reduce mortality and morbidity. However, understanding its influence on the work conducted in this thesis is relevant. In Sweden, there is no trauma system that classifies hospitals as TC or NTC. The closest resemblance to TC are the seven university hospitals. Some university hospitals consist of several buildings, such as Karolinska university hospital, Sahlgrenska university hospital and Skåne University hospital. When considering the university hospitals as whole entities, encompassing all buildings, each is close to corresponding to the ACS definition of a level I or II TC, however, some differences are still present such as limited interventions for burn injuries to two hospitals. When utilizing the whole entities of the university hospitals as TC, a reduced 30-day mortality has been demonstrated when considering all steps during the patient journey, including field triage, in-house triage, and interventions [38]. For this thesis, focusing on transporting the right patient to the right place, this becomes important to distinguish. Even though a university hospital consists of several bodies, it does not mean that the patient could be transported to all hospital bodies. Instead, there are protocols to which hospital's emergency room a patient should be taken. Thus, there is a limitation of working with the TC definition. If classifying each body of a university hospital as a TC/NTC, the under- and overtriage may reflect clinical practice more correctly. However, if separating the university hospitals into several bodies, they no longer have the resources themselves to reach the capacity of a level I or II TC according to ACS-COT's definition. The reversed reasoning applies if the university bodies are grouped. This is important to consider when evaluating the potential impact of OSISP.

6.10 Summarizing example of the OSISP model

Beach scenario revisited with the OSISP model

In the beach scenario introduced in Chapter 2, two persons fall and hit their head on the cliffs. With the OSISP model, data from each person may be entered to generate a prediction that estimates the risk of each person being severely injured.

For instance, for the person not regaining consciousness the predictor data could be the following: response time = $\geq$ 8 minutes, dominating type of injury = blunt trauma, intention of injury = accident, mechanism of injury = low energy fall, season of year = summer, age = $\leq$ 55 years, sex = male, airway management = depends on EMS personnel's actions (yes or no), cardiac arrest = no, GCS motor = no motor response, respiratory rate = 6—9 breaths/minute, systolic blood pressure = 76—89 mmHg, and AIS region = head.

Based on this data, OSISP will generate a prediction that is either "severely injured" or "not severely injured", based on similar patterns found in the training data. OSISP can then be cleared and re-applied to generate a prediction relevant to the second person.

CHAPTER 7

Building the OSISP Clinical Decision Support System

The second part of the thesis has explored how to build the actual CDSS. Up until now we have covered the development of the OSISP model and in its current shape, OSISP is an algorithm, a set of coded instructions, that can be executed on a developer's computer - it has no housing platform from which clinical users can interact with it. This is as far as the majority of AI research projects go before pursuing the next quest. Yet, it should be pointed out that there are efforts on realizing AI models as CDSS [26], [55].

Assuming access to an AI model, a CDSS can be said to consist of two main components: an interface engine and a communication mechanism. The interface engine is responsible for transforming data to a digital format interpretable by the model, and for applying the model on this data so that an output is generated [41]. The communication mechanism enables data to be entered to the interface engine as well as being transferable back to the user [41]. Examples of formats are computerized alerts and computerized guidelines [41]. In comparison to other tools, the design of a CDSS needs be constructed with special care and with a holistic perspective of its intended use and deployment, as it may otherwise disturb clinicians instead of supporting them. The design and functionalities must fit the workflow, have alerts adapted to the context, be accurate but not cause over-reliance, be easy to use, be able to handle data from different organizations, and have a plan for maintenance and financial support [41]. This part of the thesis addresses the building of OSISP as a CDSS, which we refer to as packaging the model.

7.1 Adding qualitative methods to the toolbox

When exploring how to build OSISP as a CDSS, a large part of the work was done by applying qualitative research approaches. In qualitative research, data based on text, speech, images or artefacts are analyzed, compared to quantitative research where numerical data are analyzed [91] (for instance the analysis conducted during model development as described in Chapter 6). Examples of sources to qualitative data are interviews, surveys, observations, and documents [91], [92]. The data are often rich in details, anchored in reality, and expressive of uncertainties in opinions and explanations, which enables analyses of complex situations [91]. Because the decision-making process in prehospital care is complex, where multiple factors (like scene situation and safety, injury mechanism and severity, care need, traffic situation, transportation time, and provision of care) are considered [4], a qualitative approach was deemed appropriate to study the workflow integration.

7.2 Workflow description and need

To be able to understand how OSISP as a CDSS fits to the prehospital workflow, the care process needs to be documented with enough details. One approach is to derive the documentation through service design methods. Service design is a mindset, process, toolset, cross-disciplinary language, and management approach all at once [93]. It encompasses approaches to create products based on the principles that the design process is human-centered, collaborative, iterative, sequential, real and holistic [93]. As these principles resonates with the requirements for CDSS, service design was adapted to document and analyze the prehospital trauma care process in this thesis. One such powerful method is customer journey mapping. With this approach, users divide the care process into steps and activities for a journey, based on the perspective of a selected main actor [94]. They then add perspectives and emotions that may arise during each activity in each step [94]. The map creates a detailed base for analysis of where new tools can be introduced.

To study the workflow integration of OSISP, a customer journey map was therefore created in a workshop together with participants representing EMS personnel, emergency and trauma surgery, as well as industrial developers of CDSS. An inductive design approach was applied [92], meaning that no information specifically about OSISP had been given to allow participants to reason about the EMS workflow and the need for CDSS in general. As a basis for the analysis, the six steps of the EMS workflow presented in Figure 2.1 in the introduction were used to define the journey, and EMS personnel were selected as the actors. For each step of the workflow, the participants were asked to reflect on five perspectives to gain a detailed understanding of the EMS personnel's reasoning and work: channels, "what if", job to be done, tools and data availability. The perspectives channels, "what if" and job to be were perspectives recommended in the literature [94], while the tools and data availability were added to capture information relevant to the integration of a digital tool in the workflow. A description of each perspective is given below.

- **Channels**: Captures any mean the EMS personnel might use to communicate, for instance phone or radio. It was selected as a perspective to understand from what sources the EMS personnel can receive and transmit information.
- **"What if"**: Defined as any part that may go wrong during an EMS assignment and was selected to understand the variability of considerations the EMS personnel must process across assignments.
- **Job to be done**: Described the actions the EMS personnel need to take at each step. It was selected to gain insights of appropriate integration and possible workflow disruptions.
- **Tools**: Defined as any equipment or protocols the EMS personnel might use, selected to identify possible data sources to generate the predictors and integration options for the CDSS.
- **Data availability**: Defined what data are available at each step, for instance vitals, and how data are collected or measured. It was selected to identify what and when predictors are available and when predictions could be generated.

Following the procedure, a detailed map of the EMS trauma workflow was captured, based on both clinical and industrial experiences. In addition, the discussions and reflections during the creation of the map were audio recorded to ensure all reflections were documented. The process of generating the map is illustrated in Figure 7.1.

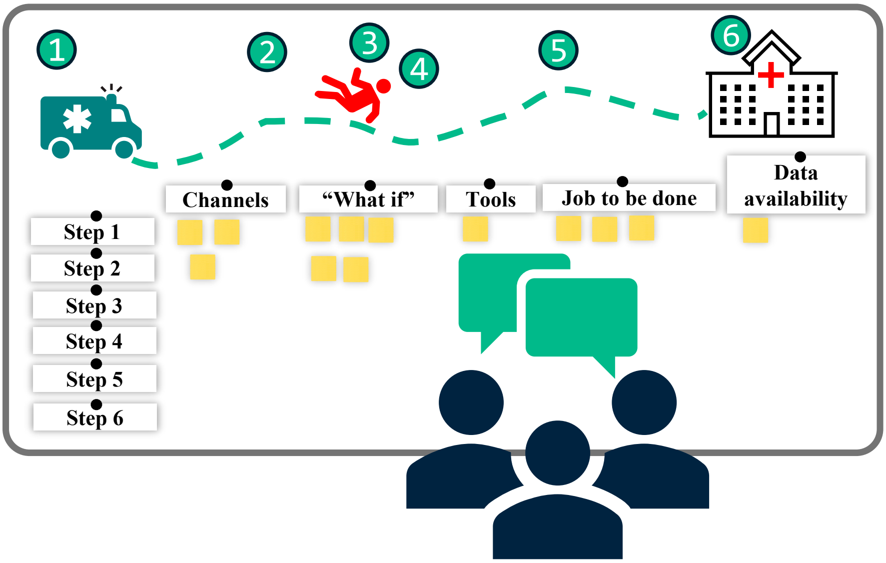

Figure 7.1: Illustration of a group creating a journey map. The numbered circles represent the steps of the EMS workflow.

Next, further group discussions were held to reflect on emotions that can be perceived at each step of the workflow, additional perspectives that may influence the map (for instance years of experience and team work), and to identify critical information points ("where information is lacking or competing with the user's attention") and critical decision points ("where the user must make an important decision"). Based on the discussions, a deeper understanding of the general need for CDSS was obtained.

7.3 Workflow integration

Appropriate workflow integration of OSISP as a CDSS was also studied in the same workshop where the journey map was created. For this part, a deductive design approach [92] was applied, where participants were informed on the concept of OSISP. Based on the created journey map and the derived general need for CDSS, participants were asked to reflect as a group on the need for OSISP, how OSISP fits the workflow and when predictor data are available. Based on the discussions, a preliminary workflow integration of OSISP as a CDSS in the workflow was proposed. Audio recordings from the workshop were collected and transcribed to document the workshop discussions, control the items included in the journey map and preliminary workflow integration, and clarify unclear text from the workshop as these were handwritten on a whiteboard and post-its.

Throughout the workshop, multiple reflections had been given on OSISP as a CDSS, but not all were captured in the preliminary proposal of the workflow integration. A content analysis was therefore applied to the workshop transcriptions to identify and document complementary participant feedback. Content analysis is a process where qualitative data, often text in documents, are grouped into themes to enable easier interpretation [95]. The grouping are based on codes, which may be created either deductively by using prior knowledge or inductively by finding patterns in the text [95]. To promote the finding of new perspectives on the OSISP concept, an inductive content analysis was conducted when analyzing the workshop transcriptions. The generated themes were added as complementary aspects to the journey map and workshop documentation, and the proposed workflow integration was then updated and finalized based on the new themes.

7.4 Initial work on platform integration

Integration of OSISP as an UI in digital platforms was explored next. As stated earlier, a CDSS should be easy to use, accurate, and not cause over-reliance [41]. These aspects are interesting to consider when working on creating the UI for OSISP. One central issue of accomplishing these requirements is that the exact functionality of ML models is often difficult to explain and they are commonly described as "black boxes", from which data is entered and an output generated [96]. Not being able to explain a prediction becomes a usability problem for users working in healthcare, as their decisions must be informed and evidenced-based [96]. The response to this issue is eXplainable AI (XAI), a field that aims to provides explanations and interpretations of how ML models work [97]. Traditionally, this area has been focused on explaining and interpreting ML algorithms, typically creating explanations useful for developers [98]. More modern efforts have acknowledge the need for XAI methods to also study the communication with end users, applying a human-centered perspective [98]. The development of an UI that integrates OSISP in digital platforms must therefore be based on a holistic system design that generates and communicates OSISP predictions in a way that is usable by the end users. The work on developing the OSISP UI was initiated in a master's thesis project [99], where the students Wallstén and Axton proposed a UI with functionalities inspired by existing IT platforms, for instance a journal page and ABCDE assessment page. In addition, a scenario page was added where predictors to the OSISP model are entered, and an output page where the OSISP prediction is displayed [99].

The structure of the scenario page is visualized in Figure 7.2. The page can be considered to consist of two columns, where the first displays a body where the location of the patient's injures can be marked, and the second displays the remaining predictors with clickable buttons to select the values. A selected value is marked in blue, and each predictor value has a symbol to clarify the content it represents, for instance in case of a motorcycle incident a symbol of a motorcycle would be used.

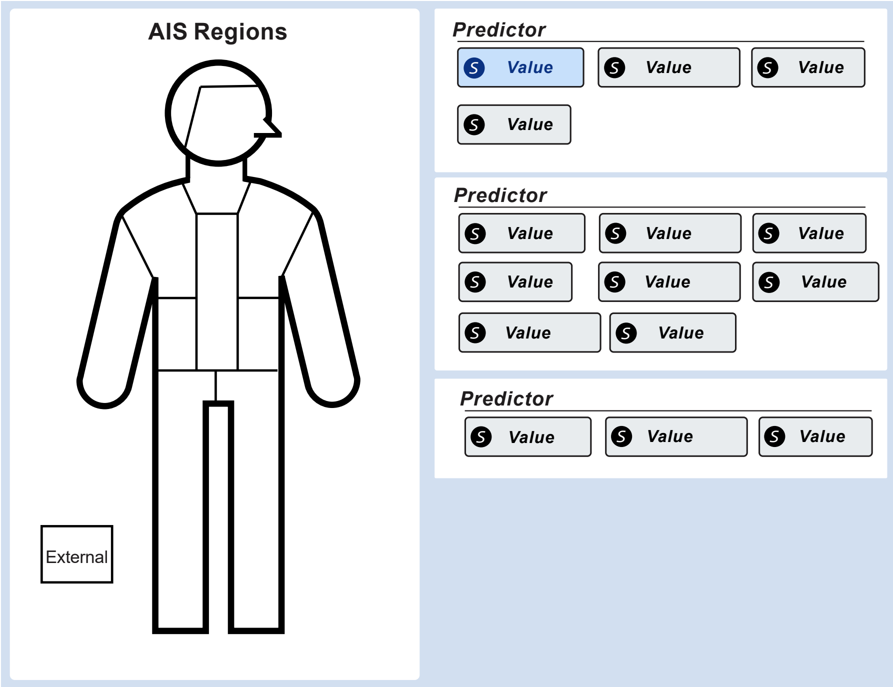

Figure 7.2: First version of OSISP UI: predictor page. AIS = Abbreviated Injury Scale, S = Symbol.

The structure of the output page is visualized in Figure 7.3 and consists of three blocks: risk prediction, entered predictors, and missing predictors. At the risk prediction block, the OSISP prediction is displayed as a color to resemble the color-coded prioritizes used in today's triage protocols. It is accompanied with a integer confidence score in the range 1 to 5, and a clarifying text if the prediction is confident enough to act on and a reminder for the clinician to follow their own clinical judgment. The entered predictor block displays entered predictors in two rows, where the first row ranks predictors that are for a serious condition, and the second row ranks predictors that are against a serious condition. Each predictor card contains the name of the predictor, a symbol of its content (as described for the predictor page), the selected predictor value, the entry time, and a color-coded ranking number, where a darker box corresponds to a higher ranking and thereby a bigger influence on the prediction that has been made. The user can also select to filter the entered predictors so that only the three most important ones are displayed. The missing predictor block displays predictors that have not been entered, displayed by the predictor name and its symbol.

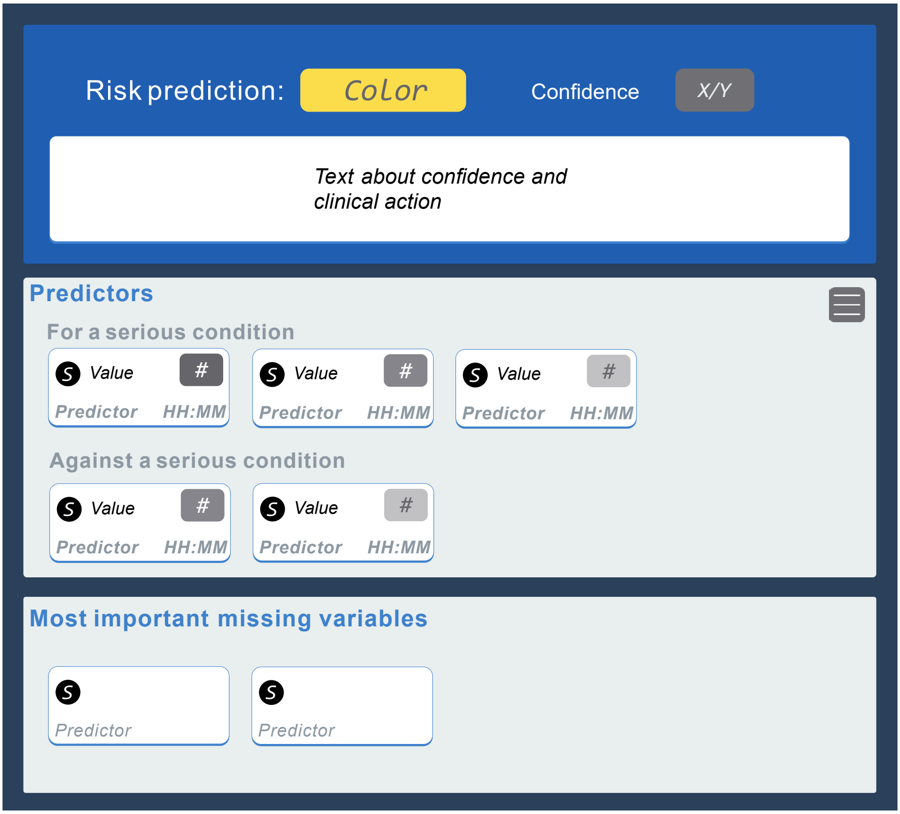

Figure 7.3: First version of OSISP UI: output page. X/Y = confidence score ranging from 1 to 5, S = Symbol, # = ranking number, HH:MM = entry time.

7.5 Refinement of the output page

The first version of the OSISP UI was based on a student project. Although the work was considered to be of high value, the rapid development of the XAI research field and the importance of XAI in healthcare motivated an updated review of current practices and recommendations for the collaboration between humans and AI to inform a refinement of the output page. To learn about current practices and recommendations, the scientific XAI literature was explored.

Reviewing literature is a cornerstone in research to understand what has previously been done, what are the current knowledge gaps, and to find sources for result comparison [91], [92]. Because reproducibility is highly valued in research, reviews often follow a structured method to identify, analyze and summarize literature [92]. First a search string is defined, which contains words selected to capture the topic of interest [92]. Depending on the topic, the search string may need to contain words that captures both broad and narrow perspectives. The search string is then applied on databases where scientific literature is indexed [92]. There are multiple databases to select from, often focusing on different fields, for instance PubMed that contains scientific literature on biomedicine and health, and the ACM Digital Library that focuses on research related to the field of computing. For increased reproducibility, selection of relevant literature may be based on predefined inclusion and exclusion criteria that are applied on titles, abstracts and full-texts [91]. The result from the search become a body of text documents, on which for instance content analysis can be applied as described earlier to create themes that describes the topic.

The exploration of the XAI literature for refining OSISP's output page was conducted in two steps. First, publications on general XAI applications and XAI in healthcare were searched for in a selection of electronic databases with a search string including words selected to describe AI, interfaces, and XAI. The included collected body of publications were analyzed using content analysis with both a deductive and inductive approach. For the deductive part, the publication content were matched to the themes terminology, taxonomy, and techniques. For the inductive part, themes describing additional aspects of XAI were created. The results formed a basis on which key contents and characteristics of prediction communication were identified. To inform the refinement of the OSISP output page, a complementary literature search and inductive content analysis were conducted to learn more about the key contents and characteristics, as well as concrete methods to realize the findings as UI components and functionalities. These findings were then used to refine the OSISP UI for the output page, hereafter referred to as the prediction information page.

7.6 Usability evaluation

In the final part of the thesis, EMS personnel were invited to evaluate the usability of the developed OSISP CDSS. Usability evaluation may be conducted in various ways, both using qualitative and quantitative methods, for instance through "Think-Aloud" protocols while performing a task, interviews, task completion, questionnaires, user testing, and heuristic principle/heuristic evaluations [100], [101]. The evaluation procedure is often designed to incorporate multiple methods, preferably a mixed method of both qualitative and quantitative, to increase the chance of gaining a holistic understanding of the usability [101]. In mixed research science, the the term triangulation is often used to describe the collection and use of data from multiple sources, enabling that a research question or problem can be studied from different perspectives [91].

Because EMS personnel work in a complex environment influenced by many factors, a mixed method was deemed appropriate for the usability evaluation of OSISP. The evaluation procedure was designed as an individual session to be completed within 75 minutes and contained seven steps, illustrated in Figure 7.4. A description of each step is given below:

- **Step 1**: Invited EMS personnel were informed about the project, evaluation procedure, recording equipment, and management of data, followed by the EMS personnel signing a voluntary informed consent to confirm their participation.
- **Step 2**: The participant filled in a questionnaire on personal data so that the characteristics of all participants could be described.
- **Step 3**: Participants were given a brief introduction to the OSISP UI, incorporating the scenario page described in section 7.4 and the refined prediction information page from the method described in section 7.5. The participant was also instructed to think out load during the whole

session.

- **Step 4**: Participants performed the task of determining if a patient was critically ill or not. A written description of a patient scenario was provided, containing information until the first XABCDE assessment. The participants filled in their assessment, as well as their confidence in their assessment on a discrete scale ranging from 1 to 5.
- **Step 5**: The complete patient scenario was provided and the participant was asked to repeat the task of assessing if the patient was critically ill or not, and their assessment score. At this step, the participants had access to the OSISP CDSS as a frontend prototype accessed from the web on a tablet.
- **Step 6**: The participants were asked to fill in a System Usability Scale (SUS) form. SUS is a frequently used questionnaire in usability evaluations [100], [101] and consists of ten questions rated on a discrete scale from 1 to 5 corresponding to a scale from “strongly disagree” to “strongly agree” [102]. The ratings on each question are used to calculated a score ranging from 0 to 100, where higher numbers correspond to increased usability [102].
- **Step 7**: A follow-up interview were conducted last to collect additional qualitative data with feedback and reflections regarding OSISP’s usability. The interview was semi-structured, meaning that a base of questions was predefined, with the flexibility for the interviewer to change the order and ask freely formulated follow-up questions [91].

Step 4 and 5 were repeated for three patient scenarios: A, B, and C. Scenario A, describing a pedestrian hit by a car, was always the first scenario and designed to be easy to allow the participants to familiarize themselves with the task procedure and the OSISP UI. Scenario B, an elderly women that had fallen, and scenario C, an adult skier injured in the ski slope, were designed to be more challenging to assess.

From the procedure, both quantitative and qualitative data were collected. The task completion and SUS score were collected as filled in papers and summarized as quantitative results, while the "think aloud" thoughts and interviews were collected through screen recordings and transcriptions from video and audio recordings and analyzed with a content analysis. In combination, the results provided a holistic understanding of OSISP’s usability, strengths and areas of improvements.

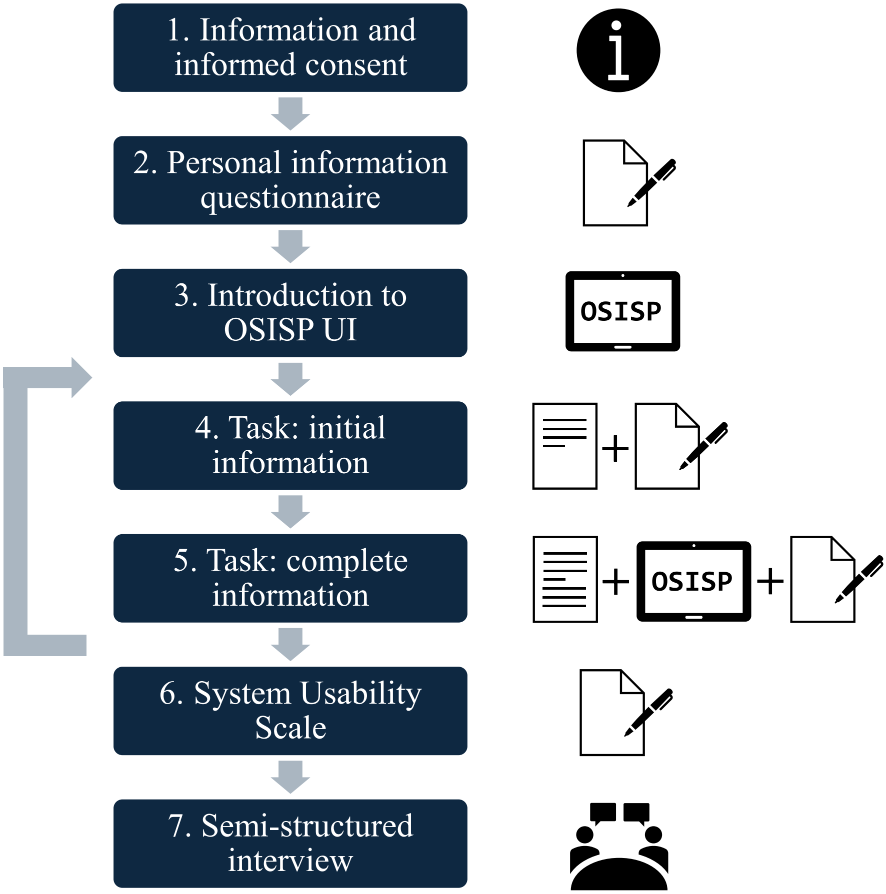

Figure 7.4: Process during usability testing.

7.7 Points of attention

The refined prediction information page is based on participant feedback on workflow integration and scientific literature, but design requirements from existing IT platforms could not be studied within the scope of this thesis. This could potentially cause conflicts between design limitations in existing IT platforms and the prediction information page's UI components and functionalities. When reviewing Table 4.1 on features in existing prehospital IT platforms, the prediction information page's UI components and functionalities may be deployable. Close collaboration with industry representatives to ensure the UI components and functionalities can be implemented will therefore be important moving forward with the development of OSISP as a CDSS.

A central question when conducting the usability evaluation is how many participants that are needed in order to make conclusions on OSISP's usability. The number of participants is commonly referred to as the sample size [92]. In quantitative research, statistics can be used to estimate a suitable sample size [73], however, since thoughts and experiences are usually the focus in qualitative research sample sizes are more commonly estimated based on saturation in themes or other qualitative results [103]. How quickly a qualitative study can reach saturation depends on several factors, for instance the definition of saturation, saturation goals, number of participants in the session, and analysis method [103]. A sample size in the range of 9 to 17 participants have been found to reach saturation for interviews when reviewing qualitative literature [103]. In this thesis, we used this guiding interval to estimate that data from about 20 participants would be needed to reach saturation, and to account for the new experience in conducting usability evaluations the aim was to collect data from about 30 participants to ensure saturation. It should also be noted that the usability evaluation was conducted as part of VIPHS step 1 and thereby part of early development. The priority was therefore to obtain early feedback from participants to inform the next step of the development process. If instead the project would have been closer to deployment, a larger sample size may be beneficial to ensure regulations on usability can be met.

Lastly, the usability evaluation was a new type of study for involved and method refinement is therefore natural to consider. One part of the study in need of refinement is the descriptions of the scenarios and their usage during the task step. Both scenario B and C were designed to be more challenging to assess, however, almost all participants found them easy to assess solely based on the scenario description. Thus, the usability of having access to OSISP in medical conditions difficult to assess could not be evaluated as planned. Piloting scenario descriptions and validating them with a few representatives from the EMS personnel prior to the usability evaluation sessions would increase the chance that participants perceive the intended level of difficulty for the task.

7.8 Summarizing example of the OSISP CDSS

Beach scenario revisited with the OSISP CDSS

Recall the beach scenario introduced in Chapter 2, where an ambulance has been assigned to an incident where two persons have fallen and hit their head on the cliffs. The OSISP CDSS, integrated as a portable tablet, can be used in this scenario to support the EMS personnel in assessing the care need and where to transport the patients.

For instance, if the EMS personnel are confident in their assessment of the patients' care need, they may enter the predictor data on the scenario page to confirm their assessment. This can be of support both if deciding to leave the patients at the scene if they are deemed to not be severely injured, or if deciding on transport destination where an agreement on severely injured could strengthen the argument to bypass the closest hospital for direct transportation to a TC. If the EMS personnels' are insecure about the patients' conditions, the OSISP prediction and ranking of predictors may provide guidance on additional factors and measures to consider. Similarly, if the OSISP prediction has a different opinion than the EMS personnel, the prediction and predictors may encourage the EMS personnel to control and re-evaluate their assessments.

In the future, OSISP as a CDSS may also be used as mental preparation already when the ambulance is on its way to the scene by entering data provided by the dispatch. Furthermore, connection to electronic journals could enable quicker and more accurate documentation of the prehospital care.

CHAPTER 8

Summary of included papers

This chapter provides a summary of the included papers.

8.1 Paper A

Anna Bakidou, Eva-Corina Caragounis, Magnus Andersson Hagiwara, Anders Jonsson, Bengt Arne Sjöqvist, Stefan Candefjord
On Scene Injury Severity Prediction (OSISP) model for trauma developed using the Swedish Trauma Registry
Published in BMC Medical Informatics and Decision Making
Vol. 23, No. 206, PP. 1–19, Oct. 2023.
DOI: https://doi.org/10.1186/s12911-023-02290-5

Summary
Injured patients, especially those that are severely injured, have an increased chance of survival if treated at trauma centers. Optimization of field triage is therefore crucial to ensure that the condition of injured patients is accurately assessed so that an optimal transport destination can be selected. Previous research has introduced the AI-based OSISP model to support EMS personnel with patient assessment during field triage in case of traffic incidents, demonstrating potential to increase the precision in detecting severely injured patients. In this paper, a proof-of-concept study is presented for the expansion of OSISP for the general trauma population. Data from SweTrau were used to train five OSISP models (LR, RF, XGBoost, SVM, and ANN) to classify adult patients as severely injured or not, based on a set of predictors deemed collectable at the scene incident. The performance of all OSISP models, validated in a 10-fold cross-validation setting and hold-out analysis, showed potential to increase the precision in detecting severely injured patients (see Figure 8.1). OSISP also showed potential to reduce the undertriage when evaluated at different operating points compared to current triage rates (see Figure 8.2). The findings support the expansion of using OSISP for the general trauma population and that OSISP has potential to support EMS personnel during field triage.

Contributions
AB, SC, ECC and BAS conceived the study. AB, SC and ECC were the main authors responsible for data acquisition. AB was the main author responsible for the design and analysis of the study, and drafting the manuscript, with support from SC. All authors (AB, ECC, MAH, AJ, BAS, and SC) contributed to the interpretation of the results and revised the manuscript critically for important intellectual content, approved the submitted version and agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work.

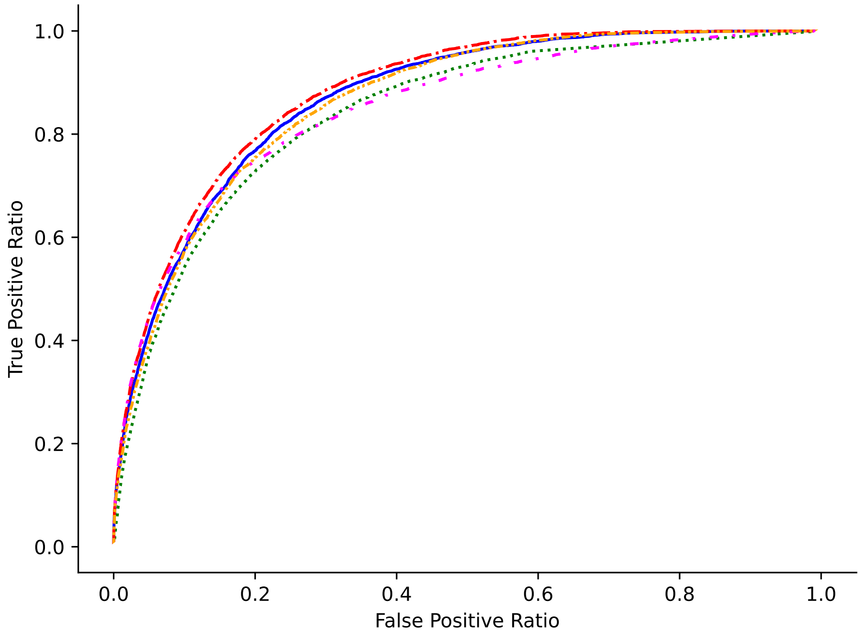

Figure 8.1: ROC curve for OSISP models trained to predict severely injured in Paper A. Model coloring: LR blue, RF green, XGBoost red, SVM purple, and ANN orange. [104], CC BY 4.0. Adapted with permission.

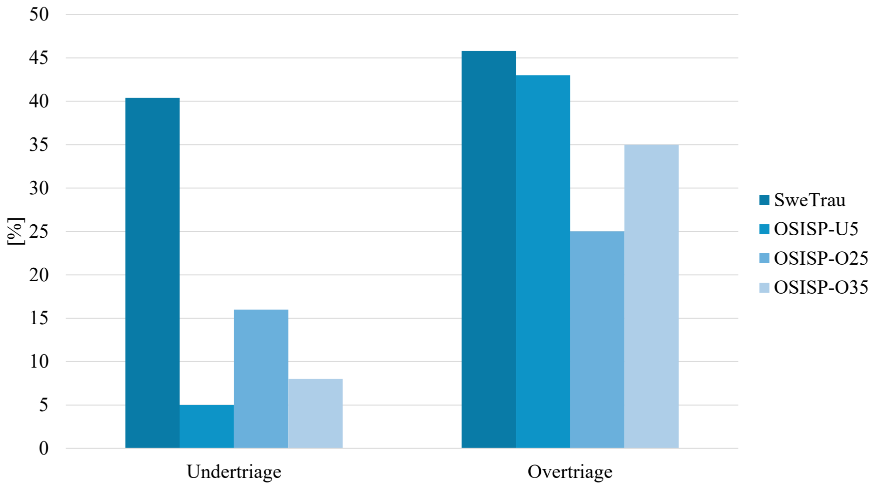

Figure 8.2: Triage accuracy reported in study A. SweTrau: current triaging, OSISP-U5: OSISP's triaging when evaluated at 5% undertriage, OSISP-O25: OSISP's triaging when evaluated at 25% overtriage, and OSISP-O35: OSISP's triaging when evaluated at 35% overtriage.

8.2 Paper B

Anna Bakidou, Eva-Corina Caragounis, Magnus Andersson Hagiwara, Olav Røise, Anders Jonsson, Bengt Arne Sjöqvist, Stefan Candefjord
Evaluating Performance and Potential Clinical Benefit of the Swedish On-Scene Injury Severity Prediction (OSISP) Model for Prehospital Field Triage on Norwegian Trauma Data
Submitted.

Summary
Although there is a large body of research demonstrating promising theoretical performance when utilizing AI to improve healthcare, few solutions reach implementation. It is therefore vital that researchers stay committed and complete activities needed to enable utilization. One such activity is external validation, where developed models are applied on new data to estimate the performance on new and unseen patients, representing an approximation of future patients. This paper therefore conducts an external validation of OSISP. The extreme gradient boosting OSISP model was applied on adult trauma data from NTR. The Swedish and Norwegian trauma data showed statistically significant differences in both predictors and outcome distributions. When applied on Norwegian trauma data, OSISP continued to demonstrate the ability to improve the precision in detecting severely injured and reduce undertriage (see Figure 8.3 and 8.4). The findings indicate that OSISP has theoretical potential to perform well on future patients, motivating future work to initiate prospective evaluations to confirm the performance in clinical practice.

Contributions
AB, BAS, ECC, and SC contributed to the conception; AB, ECC, OR, and SC contributed to the analysis; AB and SC contributed to the creation of new software used in the work; all authors contributed to the design of the work and acquisition. AB, ECC, MAH, OR, BAS and SC contributed to the interpretation of data. All authors have drafted the work, read and approved the submitted version (and any substantially modified version that involves the author's contribution to the study), and have agreed both to be personally accountable for the author's own contributions and to ensure that questions related to the accuracy or integrity of any part of the work, even ones in which the author was not personally involved, are appropriately

investigated, resolved, and the resolution documented in the literature.

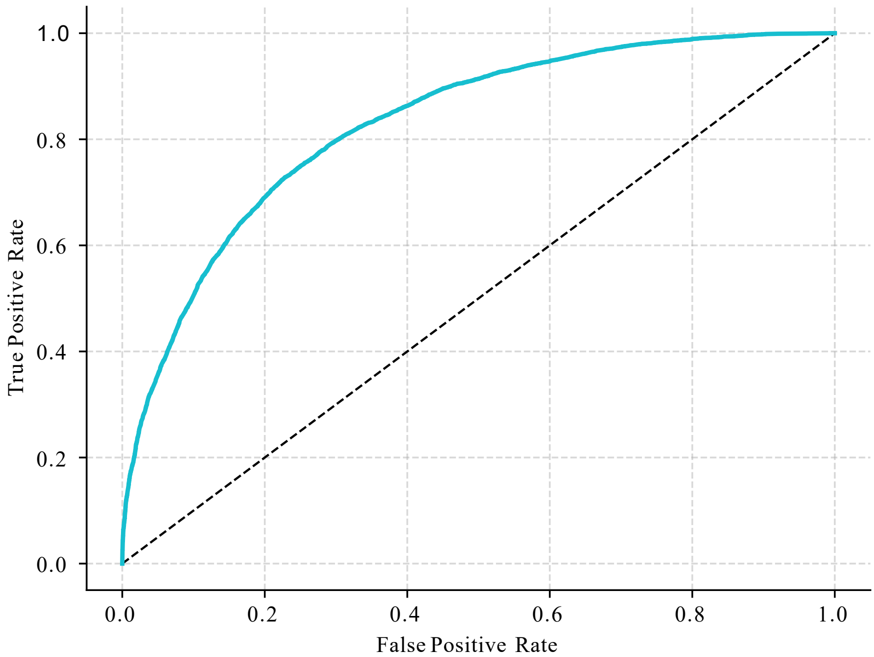

Figure 8.3: ROC curve for OSISP models trained to predict severely injured in Paper B.

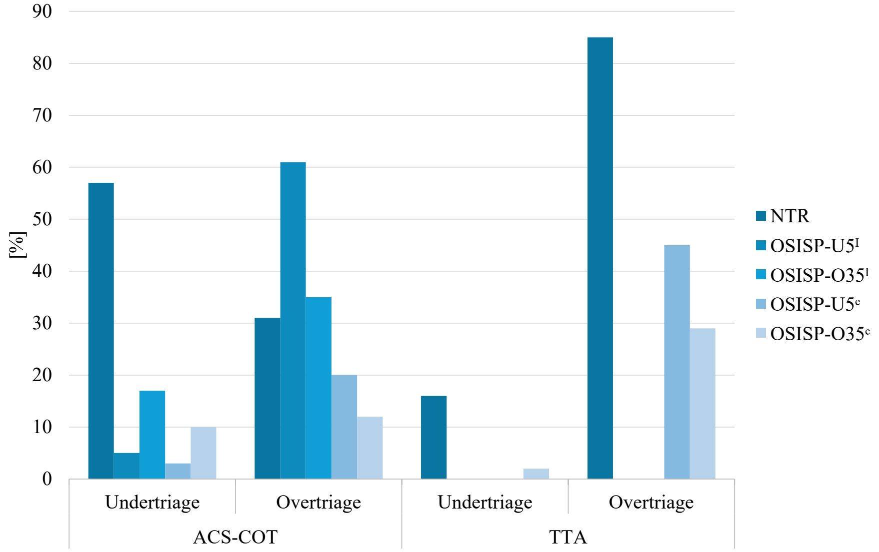

Figure 8.4: Triage accuracy reported in study B, calculated with 1) ACS-COT definitions and 2) Trauma Team Activation (TTA) definitions. NTR: current triaging, OSISP-U5^I/OSISP-U5^C: OSISP's triaging when evaluated at 5% undertriage as an independent/complementary tool, OSISP-O35^I/OSISP-O35^C: OSISP's triaging when evaluated at 35% overtriage as an independent/complementary tool.

8.3 Paper C

Anna Bakidou, Magnus Andersson Hagiwara, Eunji Lee,
Eva-Corina Caragounis, Bengt Arne Sjöqvist, Mattias Seth,
Anders Jonsson, Stefan Candefjord
Human-AI Collaboration in Emergency Trauma Care: Breathing Life into the On Scene Injury Severity Prediction (OSISP) Model
Accepted in Digital Health
Vol. 11, PP. 1–20, Dec. 2025.
DOI: 10.1177/20552076251403207

Summary
A basic requirement to conduct prospective studies is that there is a product to test. A CDSS must integrate well to the clinical workflow and have an interface that enables efficient communication of information. In this paper, packaging of OSISP as a CDSS was therefore studied to enable prospective testing. First, a workshop was conducted with clinical and industrial representatives to identify where OSISP could be used within the workflow. Next, the scientific literature was reviewed to explore XAI approaches for communicating predictions to clinical users. Lastly, a refinement of the OSISP interface was proposed. The findings showed that OSISP can be used as an additional colleague in the ambulance during patient assessment at the scene incident and during transport, both to confirm the assessment by the EMS personnel and to motive a re-assessment in case of different opinions. The workflow integration is summarized in Figure 8.5. The review on recommended XAI approaches for the prehospital setting revealed a research gap, the refined interface was therefore based on general recommendations, resulting in an interactive interface that communicates the predictions with joint information on entered predictors against the condition, for the condition and also missing predictors. The refined prediction information page is displayed in Figure 8.6. The proposed packaging of OSISP as a CDSS holds potential to support the EMS personnel during field triage, but its usability must be validated in tests with EMS personnel. The results may in addition inspire similar work for other acute conditions, for instance stroke or sepsis.

Contributions

AB, AJ, BAS, ECC, MAH, MS, and SC contributed to the conceptualization. AB contributed to data curation, formal analysis, and software. AB, AJ, BAS, and SC contributed to funding acquisition. AB, BAS, ECC, and MAH contributed to the investigation. All authors contributed to the methodology. AB and SC contributed to project administration. AB, BAS, ECC, MAH, and SC contributed to resources. AJ, BAS, ECC, MAH, and SC contributed with supervision. BAS, ECC, and MAH contributed to validation. AB contributed to visualization and writing of the original draft. All authors contributed the reviewing and editing of the writing.

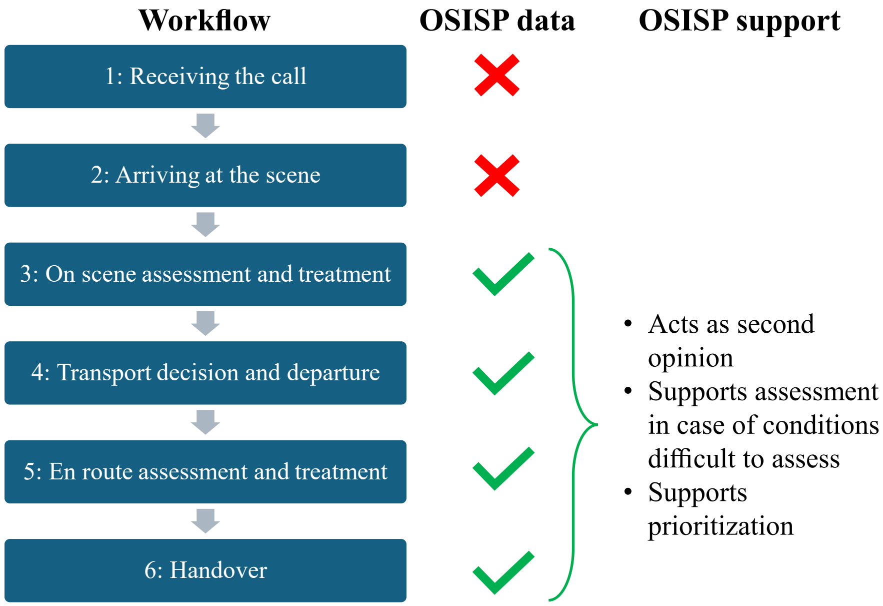

Figure 8.5: Summary of workflow integration derived in Paper C, with predictor availability and available OSISP support stated for each phase of the workflow.

Figure 8.6: Refined OSISP UI based on results from Paper C. The view displays the initial information, and extended information is accessible by clicking on the different card. [105], CC BY 4.0. Adapted with permission.

8.4 Paper D

Anna Bakidou, Mattias Seth, Magnus Andersson Hagiwara, Hoor Jalo, Eva-Corina Caragounis, Bengt Arne Sjöqvist, Anders Jonsson, Stefan Candefjord
Usability of a Prehospital Clinical Decision Support System Based on Artificial Intelligence: A case study of EMS personnel's experience of using On-Scene Injury Severity Prediction (OSISP)
Manuscript in writing.

Summary
For severely injured patients, the EMS personnel provide care for life-threatening conditions. New tools introduced for field triage must therefore be rigorously tested prior to prospective evaluations to ensure patient safety. The previously proposed packaging of OSISP as a CDSS is based on theoretical recommendations for workflow integration and communication of predictions. This paper therefore addressed the need for practical validation and conducted usability testing of an OSISP prototype with EMS personnel. First, a prototype was built that integrated the OSISP model as a web-based application executed on a tablet. Next, EMS personnel from an ambulance station in Sweden were invited. The test session started by asking the tester to assess if a patient was critically ill for three prepared scenarios, based on a) limited scenario description, b) full scenario description, and c) full scenario description with access to OSISP. Thereafter, the testers filled in a SUS, and a semi-structured interviewed concluded the test session. In total, 34 tests were conducted. All participants assessed the correct conditions during the tasks with a few exceptions. OSISP received an average SUS score of 76, indicating good usability with room for improvement. The interviews resulted in scattered opinions on the design and the ability to understand the communicated predictions, as well as recommendations for improvement, summarized in Table 8.1. The findings support the value of OSISP as a CDSS during field triage, but additional refinement and testing with higher degree of complexity are needed to make conclusions on the usability.

Contributions

AB, MAH, ECC, BAS, AJ and SC contributed to the conceptualization. All authors contributed to the methodology. AB, MS and SC contributed to the software. AB, MS and SC contributed to the validation. All authors contributed to the formal analysis. AB, MS, MAH and SC contributed to the investigation. AB, MS, MAH, BAS and SC contributed to the resources. AB, MS, HJ and SC contributed to data curation. AB contributed to the visualization and writing of the original draft. All authors contributed to the reviewing and editing of the writing. MAH, ECC, AJ and SC contributed to the supervision. AB and SC contributed to project administration. AB, AJ, BAS, and SC contributed to the funding acquisition.

Table 8.1: Qualitative findings from the usability evaluations.

Theme	**Findings**
Tasks	Conditions were easily assessed.
Scenario page	The body to mark locations of injuries was often missed it and an increased level of details were desired.
	The naming and structure could be improved grouping predictors and use locally used terminology.
	For the injury mechanism, a second tab containing additional mechanisms was not easily detectable.
Prediction information page	Perceived as easy to use and was used to confirm assessments.
	Participants tended to only use the prediction or the entered predictors, not both.
	The colored bars were often used correctly and confirmed their own reasoning about risk factors.
	The extended information was not used.

CHAPTER 9

Conclusions

In this thesis, an overview of the work towards expanding the OSISP concept has been provided, from focusing on the subgroup of traffic incidents to include the general trauma population. The research activities have targeted the blueprint of step 1 in the VIPHS framework, including technology proposal, description of the care process, a proposal for system design and theoretical evaluations. Based on the findings from these activities, the posed research questions can be answered.

RQ1: How does OSISP perform when developed to predict the risk of a patient being severely injured for a general trauma population? The initial work explored the expansion of the OSISP model. Paper A showed that the combination of data fusion and AI seem to provide a solid technology proposal that performs well and with potential to improve the precision in field triage. Because all models performed well independent on the outcome definition, the key seems to be that the models are able to find valuable patterns in the aggregated data of age, airway management, AIS regions, cardiac arrest, dominating type of injury, motor component of the GCS, sex, intention of injury, mechanism of injury respiratory rate, response time, season of year and systolic blood pressure.

RQ2: How does OSISP developed on data from a general trauma population perform on future patients?
New tools should never be tested prospectively on patients with possible life-threatening injuries without prior validation of its performance, a similar but different dataset compared to the development data was therefore used to estimate the performance for future patients. Paper B showed that when applying an OSISP model on Norwegian trauma data, the overall performance remains at a good level, with a small need for re-calibration. Notably, although having similar geographical challenges and demographical populations, almost all data from Sweden and Norway were found significantly different. This is deemed to be a valid difference, as health data tends to change over time (referred to as a distributional shift), most likely causing changes in Swedish trauma population too. The indications of a continued overall performance therefore continues to support the technology proposal and good performance for future patients.

RQ3: How should OSISP be packaged as a CDSS to fit the prehospital workflow?
The next phase focused on realizing OSISP as a CDSS. Paper C became a comprehensive study identifying both workflow integration and XAI approaches to efficiently communicate the predictions to the end users. Based on knowledge and experience from clinicians and developers, OSISP should be packaged as a service that can be used on portable IT platforms. Based on recommendations in the scientific literature on XAI, the service should support the EMS personnel as a second opinion during both patient assessment and prioritization, and its interface should be interactive, support customization, and incorporate key information items like entered predictors, missing predictors, and model details.

RQ4: How do EMS personnel perceive the usability of OSISP as a CDSS?
Tools will not be used if not appreciated by the users. In Paper D, EMS personnel were able to use the CDSS fairly independent after an introduction of about five minutes and completion of the first scenario, indicating that the interface is intuitive and easily understood. Overall, most testers acknowledged the need for a better CDSS during field triage. However, based on preliminary results, the feedback received during the testing were inconclusive regarding the usability, as the CDSS received a fairly high

score from the SUS while scattered opinions on design features were voiced, with no clear connection to neither age, experience or educational level. The inconclusive results may be due to too simple scenarios. Therefore, an indication of a positive response to the usability has been shown, but additional testing with more challenging scenarios is considered needed for confirmation.

RQ5: What clinical benefits can OSISP as a CDSS contribute to?
The purpose of OSISP is to contribute with clinical benefits compared to current tools. All included papers offer insights to various potential clinical benefits. Paper A and B demonstrated the potential to reduce under and overtriage, leading to the potential to increase the survival among severely injured not detected today as well as freeing up care resources as patients with minor injuries are transported elsewhere. Paper C showed the different use areas where EMS personnel can receive support. In addition, the study showed the importance of mental preparation, opening up for earlier use. Paper C also holds the potential to inspire more work on XAI for the prehospital setting, opening the door for more research on developing CDSS for the EMS personnel. Finally, Paper D confirmed the use cases identified in Paper C.

Concluding remarks
Collectively, the findings of indicated improved field triage support the expansion of OSISP for the general trauma population. As a CDSS, the findings points to using OSISP as an interactive tablet-based application during patient assessment on site and during transport. Yet, although OSISP has been shown to be a promising solution, it is essential with a long-term commitment to continue the innovation process so that its potential can be transferred to actual clinical benefit.

CHAPTER 10

Future Outlook

Although being at the end of this thesis, there are several interesting ideas to explore for the continued work of developing and deploying OSISP as a CDSS. These can primarily be divided into four areas as shown in Figure 10.1: advancing OSISP as a CDSS, recommending transport destination, exploring new UI platforms, and expanding to new applications.

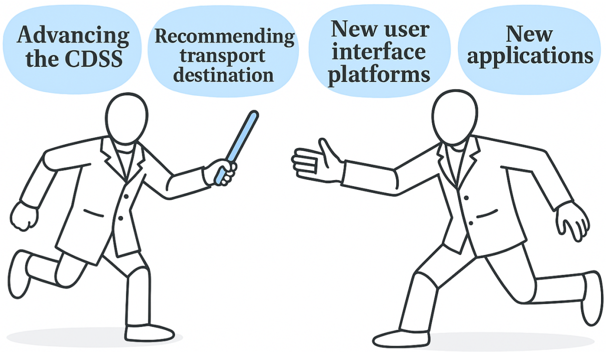

Figure 10.1: Recommended future work for the development and deployment of OSISP. (Created with Copilot, 2025)

10.1 Advancing OSISP as a CDSS

As stated earlier, committing to the innovation process, from idea to deployment, is essential to reach clinical benefit. The work in this thesis has targeted the first step of the VIPHS framework. Overall, OSISP as a CDSS is starting to mature and is expected to soon initiate step 2 of VIPHS, after completing refinement of the system proposal. The blueprint of step 2 involves activities to build a high-fidelity prototype of the OSISP CDSS that can be integrated to existing IT-platforms and evaluated in simulations with increased complexity with the EMS personnel. The simulations should be conducted both as a web-based environment utilizing Virtuality and as physical simulations, to enable evaluation of both the technology proposal and the impact on the care process. For physical simulations to be valuable, it is important to increase the complexity so that all phases of a mission are represented, and that the scenarios are realistic [106]. It may also be valuable to include economical reasoning when moving forward with advancing OSISP as a CDSS and to clarify its potential economic benefits, for instance as shown with TC in [107].

Although not explicitly stated, working towards a prototype compliant with regulations is included in step 2 of VIPHS. The reason is that in step 3, the CDSS is expected to be verified by testing in clinical operation, which requires patient safety aspects to be fulfilled and thereby also regulatory compliance. Being prepared to work on regulatory compliance is therefore important for researchers aiming to utilize their research. In the projects enabling the research conducted in this thesis, parallel activities have investigated the regulatory process for utilization of AI [108]. This work defined OSISP as an AI-enabled medical device and outlined a complex regulatory landscape for AI and medical device software, including the Medical Device Regulation, the General Data Protection Regulation, the Data Act and Data Governance Act, as well as regulations for cybersecurity. It is recommended to establish a data management process, have contracts for intellectual properties, and to create a clinical evaluation plan that describes the work to be able to show the needed clinical performance. As a medical device software, clinical evaluation consisting of valid clinical association, technical validation, and clinical validation must be completed. To make it more concrete, the following performance metrics have been proposed to be collected: accuracy, robustness, generalization, stability, efficiency, scalability, interpretability, bias and fairness, safety and reliability, and consistency. By incorporation regulatory requirements into the research activities stated for step 2 of the VIPHS framework, the innovation process is believed to become more efficient.

10.2 Recommending transport destination

The background on trauma care in the introduction emphasizes the need to transport patients to appropriate transport destinations. In this thesis, the output from OSISP is a prediction whether the patient is severely injured or not. This output was selected as an objective measurement of severity that healthcare organizations can use to formulate transport policies fitting their circumstances. However, the prediction of a patient being severely injured itself is not directly related to actions used by EMS personnel today, which may cause confusion on how to use it. As an alternative, the prediction could be accompanied with a recommendation on transport destination, which could be generated for instance based on policies, or be a predictions from a new model that uses the prediction of severely injured combined with routing optimization [109]. The Dutch trauma model has this feature, where a prediction of a patient being severely injured is mapped to a TC transportation recommendation, and not severely injured to NTC [55]. Adding this functionality may therefore increase the usability of OSISP.

10.3 New UI platforms

The proposed OSISP CDSS is dependent on data being entered to the system. In this thesis, the main work has focused on a touch UI requiring data to be entered by hand, possibly also using a keyboard. This requirement can cause difficulties in the prehospital setting if the EMS personnel needs to care for the patient. An alternative with potential to free the hands of the EMS personnel is to use a speech recognition interface to enter the information to OSISP. The Care@Distance research group has made initial efforts within this field, where speech recognition was explored in student projects with demonstrated potential to enter data structurally and hands-free, and found that such system must be accurate and quicker than hand-typing to be of interest. When reviewing the literature, speech recognition has shown several benefits for the prehospital setting, for instance a reduced need to recall information, quicker documentation compared to hand-typing, and more complete and accurate prehospital documentation [110]. Yet, the reliability of such system must be rigorously tested. For instance, a voice recognition software has been implemented in a Swedish healthcare region for hospital documentation, causing frustration among users due to frequent errors and increased documentation time [111]. In the prehospital setting, time may be limited and ensuring a robust speech recognition system is essential.

Furthermore, other physical platforms may also be explored. The EMS personnel work with a mix of technologies, including applications for computers, tablets, smart phones and wearable devices [112]. The work conducted in this thesis focused on a tablet interface since this is the most common platform among the companies delivering IT platforms for the prehospital care, as seen in Table 4.1. Exploring alternative platforms may increase access to the CDSS, for instance smart phones may be available at all times. However, a reduced screen size may make the proposed OSISP interface and its communication components cluttered and difficult to navigate. Adaption of the findings of this thesis will therefore be likely.

10.4 New applications of OSISP

The OSISP concept is about predicting the risk of a patient being severely injured to support assessment of a patient's condition. In this thesis, the concept was applied on adult trauma patients encountered prehospitally. However, the concept may also be relevant to consider for additional patient groups, for instance patients already at the hospital, and pediatric or geriatric patients. For patients already at the hospital, a transfer from one hospital to another may be needed due to the severity of the patient's injury not matching the resources at the current hospital. These situations could arise if patients transport themselves to the hospital, if EMS personnel makes an error and transports a patient to a hospital with inadequate resources, or if the condition of the patient becomes worse. Future studies should investigate if the developed OSISP model can be directly applied for these patients with good performance, or if retraining of the model on data representing transferred patients is needed.

Similarly, certain age groups may benefit from dedicated CDSS. For instance, pediatric patients is a patient group with a high risk of trauma [113]. Pediatric and adult trauma is often separated due to the difference in responses to trauma and assessment. However, due to the high mortality, developing a version of OSISP to predict if a child is severely injured may also have a high clinical value as current assessments are challenging to complete, especially vital signs assessment of young children [113]. From the work conducted in this thesis, it was also found that EMS personnel often experience child trauma more challenging to mentally prepare for, further supporting the need for such tool. Because the characteristics of pediatric and adult trauma patients are often substantially different, it would be expected that OSISP needs to be retrained on pediatric trauma data to result in clinical benefit. Likewise, the need for a dedicated CDSS is also present for elderly, as this group has an indicated increased risk of mortality in Sweden [114] and is often reported to be undertriaged in the literature [115].

Another interesting area where OSISP may hold potential is for military trauma. AI-based triage for military applications has received more attention, with one example being the European project Nightingale focusing on mass casualty incidents [116]. In this context, OSISP is needed to support end users, possibly with reduced medically knowledge, with information on which patients to prioritize when there are multiple patients, possibly leaving patients uncared for depending on the circumstances. Furthermore, the military setting may be viewed as an extreme and dangerous version of the prehospital care, with a larger degree of lack of resources and longer transportation times [58]. Applying OSISP for this application is therefore expected to require adjustments to the end user profile, the predictors, as well as when to apply the CDSS.

Pursuing the proposed activities for future work increases the chance of realizing OSISP as a deployed and valuable CDSS, with the hope to improve the work situation for EMS personnel and the outcomes of injured patients.

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