A Work Project, presented as part of the requirements for the Award of a Master's degree in Management from the Nova School of Business and Economics.

ARTIFICIAL INTELLIGENCE AS A STRATEGIC TOOL TO CONTRIBUTE TO SUSTAINABLE DEVELOPMENT

-

ARTIFICIAL INTELLIGENCE AS A STRATEGIC TOOL TO REDUCE MARINE POLLUTION – USING EXPERT INTERVIEWS TO IDENTIFY STRENGTHS, WEAKNESSES, OPPORTUNITIES, AND THREATS OF INTEGRATING AI IN THE IN-SITU MANAGEMENT OF MARINE LITTER

YANNIK ROSENLEHNER

Work project carried out under the supervision of:

João Nuno Lopes de Castro

16-12-2021

NOVA SCHOOL OF BUSINESS & ECONOMICS

Table of Contents

Group Abstract

This work aims to provide a new perspective and basis for assessing the potential contribution of AI to sustainable development. This was explored in the context of the SDG targets for health, responsible consumption, sustainable cities, and life below water. The expert interviews, complemented by a selective literature review, identified both internal factors that appear to be quite homogeneous across the different goals and a wide variety of external factors. Researchers, policymakers, and practitioners exploring or using AI in the context of sustainable development should be aware of both its potential and its dependence on external factors.

Individual Abstract

Artificial Intelligence (AI) and Sustainable Development are phenomena disrupting our society. This work analyzes how the breakthrough technology AI can be used as a strategic tool to minimize marine litter and contribute to achieving SDG 14. Expert interviews were conducted, and the results were categorized into the dimensions of a SWOT framework, indicating the factors that affect the potential of AI in the context. The overall results suggest that AI is not a panacea in the world of sustainable development, but it is a great strategic tool for marine litter management that is likely to improve in the future.

1. Introduction

Floods. Draughts. Pandemics. Scarce resources. Today's world is becoming a more and more hostile place. Many of the challenges we face are caused by the mismanagement of our planet, its resources, and the society that is built. Even though this degradation is apparent to an alarming extent already, there is still hope. Hope that comes in the form of innovation, groundbreaking ideas, and disruptive technologies. Especially the latter is said to have the power to transform society, the economy, and consequently, the environment (Herweijer and Waughray 2019). One of the most disruptive technologies that seems to be on everyone's lips today and is expected to vastly transform life as we know it is *Artificial Intelligence* (AI). AI might hold the inconceivable potential to overcome some of the problems caused by unsustainably managing the earth and society – thus, this work centers itself on this intersection: AI and *sustainability development* (SD). Despite the efforts that scholars from multiple fields have already put into this topic, there is room for further investigation of the strategic potential of AI to contribute to SD. This work aims to contribute towards filling this research gap. It is not the intent to close the gap by this work entirely, but it is rather explorative in the realm of this topic: By adding a novel perspective to this pertinent subject, we aim to increase the ability of other scholars, practitioners, and institutional representatives to understand the potential of AI in the context of SD and find and explore new solutions. It is vital to note that, even though this work deals with a highly dynamic and complex technology, due to the expertise of the authors, and the need to reduce complexity for readers with limited technological expertise, this paper only scratches the surface in terms of technology. As technology and strategy are considered as two inseparable parts of an organization (Kantrow 1980), this work views AI as a strategic tool, which organizations can integrate to achieve a desired goal. Viewing AI's implementation in light of technology strategy allows for an assessment of the potential of AI to achieve selected SDGs using the SWOT analysis - a framework borrowed from the field of strategic management. The intention is to illuminate the role of AI as a strategic tool to contribute to the achievement of four different, carefully selected SDGs that jointly cover all three aspects of sustainability (economic, social, environmental) (Vinuesa et al. 2020a). Due to the inherent nature of this work, where an individual component but also a team component is needed, this work's contribution to the research field is two-fold: First, the SWOT framework was used to derive findings of the potential of AI in the selected subfields of the aforementioned four SDGs. Second, the findings were consolidated to gain a holistic view on the subject and derive a conclusion that goes beyond the consideration of the individual SDGs. The components of the first aspect are to be found in the individual works and the latter in Sections 5 and 6.

2. Theoretical Foundation: AI & Sustainable Development

2.1. Definition of AI

There is no universally accepted definition of AI. Existing definitions of AI often do not meet the requirements for a legal definition, which include permanence, precision, comprehensiveness, and practicability (Schuett 2019). It should be kept in mind that this work does not attempt to settle a dispute about the correct definition of AI, but this section is rather used to provide all readers with a common understanding of the technology. Therefore, the authors have defined *AI as a system* (AIS) following Palomares et al. (2021a), which contains three essential elements. A computational system, which has the capacity of processing data through algorithms. Data, which is the representation of the environment, and through which algorithms learn the way to reach their goals. And finally, the goal, which represents the task to be accomplished by the system and is guided by the input data (Palomares et al. 2021a). In this context, it is worth noting that machine learning is considered a branch of AI that uses statistical learning algorithms to develop systems that may learn automatically from experience. Further, deep learning is a machine learning technique inspired by how the human brain filters information and uses neural network architectures (Roy 2020). Having grasped the author's definition and guiding principles of AI, the underlying theoretical definition of the second key building block of this thesis, namely SD, needs to be outlined.

2.2. Definition of Sustainable Development

The concept of sustainability (*German: Nachhaltigkeit*) was first coined in 18th century Germany: the *Sylvicultura Oeconomica* is not only considered to be the first publication on forestry but rather the first publication that was formerly embracing the idea of sustainability managing natural resources such as trees (Grober 1999). Despite its centuries of history, the concept of sustainability has become more prominent than ever lately: With a growing population, it is urgent to the limited number of resources on this planet and minimizing the negative impact that humankind has on earth's climate. Even though experts and the public largely agree about the importance of this concept, there is no clear consensus on a definition, and the term *"sustainability"* remains relatively open and context-specific (Purvis, Mao, and Robinson 2019). A clearer understanding of the concept emerges when looking at the closely related term Sustainable Development (SD). The Brundtland Report defined SD in 1987 as follows: *"Sustainable development seeks to meet the needs and aspirations of the present without compromising the ability to meet those of the future"* (World Commission on Environment and Development 1987). The concept of SD became more defined and actionable in 2015 when the United Nations proposed the 17 Sustainable Development Goals (SDGs) that are covering the most important challenges that our society faces until 2030 (Schönherr and Martinuzzi 2019). With the formulation of the SDGs, all three pillars[1] of sustainability are covered, and the concept was shifted from vague to particular. The framework was refined in 2017 when the UN developed a total of 169 targets and 232 indicators associated with these 17 SDGs to make them even more actionable and measurable (UN General Assembly 2017).

[1] social, economic, environmental

Because of its wide global recognition, this work will use the SDGs as a foundational framework to understand the potential of AI to contribute to SD.

2.3. Selection of SDGs: Reflecting Environmental, Economic, and Social Sustainability

For the purpose of this work, four different SDGs, namely SDG 3, 11, 12 and 14, have been carefully selected to reflect all three pillars of SD. According to Vinuesa et al. (2020a), SDG 3 and 11 relate to social, SDG 12 to economic and SDG 14 to environmental sustainability. This classification logic is applied for the subsequent work.

2.3.1. The Importance of Achieving SDG 3 – Good Health and Well-Being

SDG 3 has pledged to *"[e]nsure health and wellbeing for all, at every stage of life"* and therefore, declared a healthy world population as indispensable to SD (UNOOSA 2021). Health, as defined by the WHO (1995, 1), is *"a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity"* and constitutes a fundamental human right (United Nations 1948). It can be seen as a facilitator for the prosperous and flourishing societies that governments aspire to attain. Good health is vital to ensuring positive family and community life, allowing individuals to participate in, and contribute to, society in various ways (Lovell and Bibby 2018). Furthermore, a healthy population is supporting the economy through better educational outcomes, increased productivity across the workforce, and, consequently, increased prosperity (Lovell and Bibby 2018). Poor health costs around 15% of global real GDP each year, mostly due to premature deaths and lost productive potential among the working-age population (Dash et al. 2020). Hence, good health supports individuals in reaching their *"full potential"* in both their private and professional life. While positive progress has been achieved in ameliorating individuals' health and well-being in recent years, huge disparities in healthcare (HC) access, delivery, and quality continue to persist (WHO 2017). Continued global effort and financial and non-financial investment are inevitable to achieve this vital goal to humanity.

2.3.2. The Importance of Achieving SDG 11 – Sustainable Cities and Communities

Good health is also of great importance for the development of cities and communities and the people living in them. Even though most of the world's population is already living in cities, it is expected that the number of urban residents will increase to an estimated 68% of the world population by 2050 (United Nations - Department of Economic and Social Affairs 2018). This development is already witnessed in Europe, where over 70% of the population is living in urban areas (Eurostat 2020). Consequently, cities are of great importance to the world in many ways: They generate more than 80% of global GDP, and urbanization trends, as well as global population growth, will further increase both consumption and demand for global resources in the future. As promising as the opportunities may seem, the speed and scale of the shift to cities are accompanied by several challenges. First, cities need to provide housing for billions of people. The urgent need for jobs and affordable and accessible public transport so that all residents can reach all parts of the city is of great importance. This is especially true for the 1 billion urban poor who live in underdeveloped and unsafe areas near the cities to be closer to opportunities including access to jobs and HC. Lastly, as cities are the world's largest energy consumer, responsible for more than 70% of greenhouse gas emissions[2], they play a crucial role in combating climate change (World Bank 2020). With that said, there is a big need for inclusive, healthy, resilient, and sustainable cities. Yet, the creation of sustainable urban areas[3] is associated with numerous challenges and requires a holistic view of all relevant factors (World Bank 2020). SDG 11, which intends to create such sustainable cities and communities, provides this comprehensiveness and is thus crucial for all three pillars of the SDGs[4] and for achieving several of them (two-thirds of the 234 SDG indicators contain urban components) (UN Habitat SDG n.d.).

---

[2] There exists a range of available information concerning this factor reaching from 65-80%

[3] In the context of this work, a distinction is only made between urban areas/cities and communities (incl. suburbs), and rural areas (all population, territory and housing are not included in the urban area)

[4] Yet, as the classification logic from above applies: Goal 11 relates to the social sustainability pillar

2.3.3. *The Importance of Achieving SDG 12 – Responsible Consumption and Production*

Ever-increasing amounts of natural resources are needed worldwide to support economic activity (UN, Statistic Division 2021). Considering the consumption and use of natural resources, it is evident that the demand for resources exceeds the earth's regenerative capacity. Annually, 1.3 billion tons of food are wasted (AI for Good 2021), accounting for one-third of the food produced for human consumption (Holm et al. 2021). Further, 35 billion kilograms of clothes are thrown away, of which 85% end up in landfills (Holm et al. 2021). If 20% of those were reused, 139 million tons in CO2 emissions could be saved (Haller, Lee, and Cheug 2020; Van Vugt and Van der Liende 2021). In particular, the global material footprint is a representative indicator of the pressure exerted on the environment to meet people's material needs and achieve economic growth (UN ECOSOC 2021). Both the global material footprint per capita and the domestic material consumption rose nearly by 40% to 12.2 metric tons in 2017, eliciting resource depletion and associated environmental impacts (UN ECOSOC 2021). Thus, it is important to recognize that achieving sustainable consumption and production, decoupling economic growth from resource use and environmental impacts, and the associated impacts on poverty eradication and shared prosperity will contribute to the achievement of almost all other SDGs. SDG 12 should rather be seen as an integral lever and driving force for the achievement of many other goals. Recognizing this impact of consumption on the SDGs overall highlights the importance and responsibility individuals carry to take personal actions (UNEP 2017).

2.3.4. *The Importance of Achieving SDG 14 – Life Below Water*

The ocean is the largest ecosystem on this planet. Covering more than 70% of the earth's surface and containing 97% of the planet's water, researchers estimate that the ocean is home to millions of different animal species (Mora et al. 2011). Beyond that, the ocean is indispensable for humans: With more than a third of the world's population living in coastal communities, the livelihood of more than 3 billion people is dependent on the ocean's resources in the forms of food or other resources (UN DESA 2021). Furthermore, the complex system of the ocean's flora and fauna is acting as a stabilization mechanism that is essential for climate regulation on our planet (Reid et al. 2009, 115). Scientists have further estimated that the plankton from our oceans provides 50-80% of the oxygen we breathe (Witman 2017). Knowing the tremendous importance of the oceanic ecosystem signals the urgency to find solutions to the many challenges that are threatening the stability and resilience of this system. Plastic pollution, depletion of fish stock and endangerment of other species due to overfishing and human activity, and rising sea levels owing to global warming are just a few of the factors threatening the oceans (Greenpeace 2021; National Geographic 2017; UN DESA 2021). To align the activity of organizations and individuals with sustainable management of our ocean resources, the United Nations included SDG 14 – Life Below Water into their 2030 Agenda. With a total of 10 targets and 10 indicators, SDG 14 covers a wide array of problems that the ocean faces.

3. Methodology: Exploratory Research Approach

The present work is designed to uncover the potentials of AI as a strategic tool to achieve the selected set of SDGs. However, the technology still is in its infancy, thus, current literature does not yet offer expedient insights on this matter (Di Vaio et al. 2020). Further, AI is evolving at a fast pace, often causing studies to be outdated. Consequently, the present work intends to enrich the existing literature by exploring valuable insights. To do so, the work's overall design follows a qualitative method (Saunders, Lewis, and Thornhill 2009a). Following the pursued purpose of this work, an exploratory research approach is utilized to gain new inside views (Robson 2002).

3.1. Research Design: Semi-Structured Expert Interviews

To ensure consistency throughout the research objective, question, and method, semi-structured expert interviews are chosen to conduct exploratory research. This data collection method is selected to ensure the collection of unfiltered data and the emergence of novel and rich insights (Saunders, Lewis, and Thornhill 2009a). The literature review serves as guidance to the qualitative part. To enhance the existing understanding and to take rise to the fact that this area has only been scratched on the surface so far, an inductive analysis approach is chosen to examine the interviews. Inductive reasoning is an approach in which *"[...] theory is following the data [...]"* (Saunders, Lewis, and Thornhill 2009a, 129). This is especially helpful to gain innovative insights to investigate the research question (Robson 2002; Saunders, Lewis, and Thornhill 2009a). The research will be carried out through four individual studies with respect to the investigated area. Each study includes expert interviews with relevant industry insiders that help to build an understanding of the potentials of AI in the areas of SDG 3, 11, 12, and 14.

3.1.1. Selection: Expert Interviews

Evidence from expert interviews serves the purpose of gaining valuable knowledge by investigating the topic through inside lenses. In general, an expert is *"[...] a person with a high level of knowledge or skill relating to a particular subject or activity"* (Cambridge Dictionary 2021). Personal interviews were conducted with company representatives and industry experts. Experts were selected based on their competencies in the field of AI and their connection to the specific SDG. In total, 23 experts were interviewed and are referred to under the aliases that can be found in Appendix 1 to 4. Due to the limited scope and to ensure in-depth conversations, the partners were chosen purposively, which is why this work did not cover the comprehensive set of the many innovative solutions nor the entirety of industry experts in the field.

3.1.2. Sample Collection: Primary Data from Semi-Structured Interviews

Interviews allow for the collection of first-hand data on the potentials of AI to promote SD. Further, the open nature of semi-structured interviews offers the possibility to proactively react and to probe for deeper elaborations (Saunders, Lewis, and Thornhill 2009a). Thereby, the interviewees get the opportunity to think out loud, reflect, and explain elusive aspects. Each expert was interviewed individually via video call. It was essential to create a pleasant atmosphere to build trust and, in return, receive open and honest answers (Saunders, Lewis, and Thornhill 2009a). The interviews were conducted between October 10 and November 17, 2021 and lasted between 20 and 60 minutes. All experts participated voluntarily, without any incentives and could freely express their insights, which provided a rich data set.

3.1.3. Data Analysis

The following section discusses the inductive analysis approach to evaluate the interview data. This approach is appropriate when the objective of the research is the development of initial insights based on the gathered qualitative data. In the inductive approach, the investigated categories result from the process of data analysis. Further, the merit of an inductive analysis is the possibility to look for new patterns and critically reflect. The basis of the data analysis is formed by the transcribed interviews. To organize the data, achieve transparency, and develop categories, a three-step coding process is applied. First, *open coding* was used to filter and conceptualize the content-rich quotes into units. Labels are used to form groups of statements. The results are conceptual labels that differ in the level of focus. Next, the relation between the labels is investigated to cluster interrelated labels into categories - *axial coding*. It is essential to continuously challenge the acquired knowledge to ensure the development of rigorous categories (Saunders, Lewis, and Thornhill 2009a). Finally, *selective coding* involves identifying the key categories and establishing relationships (Strauss and Corbin 2008).

3.1.4. Data Reliability

When performing qualitative research, *data reliability* is a crucial factor. Data reliability is concerned with the question of whether other researchers would come to similar results (Easterby-Smith et al. 2008; Silverman 2007). The answer, in the present case, would probably be no. The research method was deliberately chosen to account for this work's purpose, to explore and uncover first-hand expert insights. Thereby, exploratory research is intended to investigate the topic at the moment of the data collection in circumstances that might change (Marshall and Rossman 1999). This reasoning is reinforced by the nature of the explored topic. AI is a fast-evolving technology and is impacted by countless factors. The dynamics and complexity can only be accounted for if the chosen method allows for flexibility. In the case of qualitative interviews, data validity is rather concerned with the comprehensiveness with which insights can be captured than with the generalizability of the results (Saunders, Lewis, and Thornhill 2009a; Yin 2003). During interviews, potential biases result from the interviewers' influences. To prevent such biases, the priorly developed guideline induced a frame to raise objectivity. However, some subjectivity in their perspectives results from the expertise of the authors who come from the area of strategic management. Credibility was ensured by conducting one-to-one interviews to get a sense of the circumstances and the interviewee. The interviews transcripts and the coding process induce transparency of the research process.

3.2. Analytical Framework: SWOT Framework to Assess AI as a Strategic Tool

For this work, the SWOT framework is considered suitable for the analysis of the qualitative research results due to its high recognition and comprehensibility in both research and practice, its simplicity, and the value that it adds through aligning the implementation of AI to contribute towards sustainability (Palomares et al. 2021a). However, to apply this framework in the context of this work, it had to be differentiated between internal factors (strengths and weaknesses) and external factors (opportunities and threats). Internal factors include all company-internal resources, such as capital and workforce. Further, all factors influencing data-processing itself as well as post-processed data count towards internal factors. Conversely, external factors include pre-processed data as well as political, economic, societal, technological, environmental and legal considerations. A visualization of this distinction can be found in Appendix 5.

4. Exploring the Role of AI to Approach a Specific Set of SDG

4.1. AI as a Strategic Tool to Contribute to the Reduction of Premature Mortality from Non-Communicable Diseases - SDG3

4.1.1. Introduction

4.1.1.1. Motivation and Relevance of Research

Non-communicable diseases (NCDs), referred to as the *"world's biggest killers"* (WHO 2013), kill an appalling 41M people each year, equal to 71% of all deaths globally. Even more tragic, 15M of these deaths occur prematurely, between the ages of 30 and 69 (WHO 2021a). These *"big killers"*, also known as chronic diseases, are not caused by acute infections and cannot be transmitted directly from person to person. Instead, they tend to be of long duration and result from a combination of genetic, physiological, environmental, and behavioral factors. Due to their complex and often singular nature, NCDs often constitute a riddle to the medical community, impeding their accurate medical management. The four main types of NCDs are Cardiovascular Diseases (CVDs), Diabetes, Chronic Respiratory Diseases, and Cancer, accounting for over 80% of all premature deaths (WHO 2021a). Especially these four types of diseases are said to become increasingly prevalent in the coming years due to an epidemiological and demographic transition (Varghese 2017). This constitutes a tremendous challenge to healthcare (HC) systems, economies, and communities around the globe, as in most cases, these conditions require lengthy and costly treatment and severely impair the quality of life and ability to work of those affected (WHO 2021a). The severity of their detrimental impact is further manifested in their admission to the SDGs. SDG target 3.4 specifically enshrines the reduction of premature mortality from NCDs until 2030 as a global responsibility. For all these reasons, the author has chosen to provide a theoretical contribution to the combat against NCDs by dedicating the underlying thesis to the exploration and assessment of supporting tools valuable in the abatement of this global health crisis.

4.1.1.2. Detailed Scope Definition

The management process of these chronic diseases in HC systems can be divided into three consecutive steps: prevention, diagnosis, and treatment (I1.2). The WHO (2021a) declared that "*investing in better management of NCDs is critical",* and naturally, the goal shall be to take action as early as possible in the described process. As the scope of the underlying work is limited, the author has chosen to examine AI's role only in one of the presented process steps in detail. While the field of prevention, namely preventing the occurrence of the disease in the first place, may first seem like the most promising choice, the opportunities for and impact of AI solutions in this field are fairly limited (I.2). Diagnosis,*"[t]he process of identifying a disease, condition, or injury from its signs and symptoms*" (NCI 2011a), however, offers a significantly wider spectrum of potential applications for AI (Spatharou et al. 2020). Further, when a diagnosis is accurate and reached in a timely manner, the at-risk patient has the best chance of a positive health outcome, as successive clinical treatment decisions are essentially based on a correct and thorough understanding of the patient's medical condition (National Academies of Sciences 2015). For all these reasons, the field of diagnosis was prioritized over both prevention and treatment by the author.

To reach a diagnosis, a patient suffering from a NCD must pass through various steps in a given HC system. Usually, the diagnostic process is initiated with some form of *"trigger event"*, with the symptoms associated with the event varying in severity. The event may be *"as simple as"* a headache or as extreme as a heart attack. Depending on the severity of the event, the patient either first goes to see a general practitioner, who performs a basic medical examination, potentially including routine diagnostic tests such as a blood or urine test or, is directly referred to a specialist. This specialist may then order a variety of specialized diagnostic tests to ascertain an accurate diagnosis (Biundo et al. 2020). A visualization of this simplified and generalized patient journey may be found in Appendix 6b. In many diagnostic fields, the demand for specialists far exceeds the available supply, at worst leading to diagnostic errors and inaccurate or delayed diagnoses (Biundo et al. 2020). Thus, the author has decided to examine the potential supporting role AI can take in diagnostics for NCDs.

Lastly, the analysis of the underlying work will focus on the application of such solutions in high-income countries (HIC) (see Appendix 6a). Although most premature deaths from NCDs occur in low-to-middle-income countries (LMIC), these countries currently do not provide the adequate infrastructural and institutional context for a reliable development and deployment of such technology (WHO 2021b). Thus, there currently does not exist enough fertile ground to conduct a sound analysis of AI solutions for diagnostics in LMIC. The following section will start with exploring related work that has been published around the field to date.

4.1.2. Related Work

With its rapid pace of development, AI applications for HC services have increasingly become the subject of both academic and professional research. The subsequent section explores the existing, related work of 15 academic and five professional research papers to i) better understand AI's current state of applications in diagnostics for NCDs and ii) grasp the prevailing sentiment of scholars, regulators, professionals, physicians, and the general public towards the development and deployment of such technology.

4.1.2.1. Overview of the Current Use of AI in Diagnostics for NCDs

Existing literature has identified four key driving forces for the increased development and deployment of medical AI solutions for diagnostics: 1) a rising shortage of skilled and experienced radiologists and pathologists across nations and the limitation of global HC resources, 2) the increasing demand for diagnostic modalities, 3) the continuously rising amount of health data, including digital images, omics, clinical records, and patient demographic information, and 4) the increased complexity in having to manage and integrate the elevated volumes of data across different sources to maximize patient care (Robboy et al. 2013; Cui and Zhang 2021; Biundo et al. 2020) (see Appendix 6d). These driving forces are largely influencing the respective quality of the HC systems that patients find themselves in.

At present, diagnostic AI solutions are generally employed for specific tasks in specific domains, for instance, for detecting lung cancer based on a computed tomography (CT) scan (WHO 2021b). Thus, existing AI applications are extensive, especially when considering four different, large groups of diseases. Therefore, the following overview will not be able to cover the vast number of current solutions in diagnostic subspecialties for NCDs but rather give an outline of the most prominent forms of application. These current applications of AI in diagnostics can be divided into two key fields: the support of specialists in imaging-related analysis and in laboratory-related analysis (Biundo et al. 2020).

Medical imaging (MI) refers to several different image-capturing and processing technologies that are employed to look at the human body to diagnose, monitor, or treat medical conditions and are mostly used in radiology and digital pathology (FDA 2018; Biundo et al. 2020). AI-MI applications are among the most widespread, essentially supported by the fact that the diagnostic information is already digitized and thus offers concrete data to train an algorithm (Choy et al. 2018). Examples of such images in radiology are images from CT, Magnetic resonance imaging (MRI), and Positron emission tomography (PET) scans, while in digital pathology, these comprise digital microscopic images, so-called Whole Slide Images (WSI)[5], from biological material such as blood or tissue. Sub-forms of AI can identify complex patterns in imaging data and perform quantitative, rather than qualitative, evaluations of recognized characteristics (Spatharou et al. 2020). Such algorithms may be employed in multiple stages of the workflow. In the early stages in radiology, AI can assist the specialist in determining the

[5] Whole Slide Imaging, also known as virtual microscopy, refers to scanning a complete microscope slide through a whole slide scanner that creates a very high-resolution image of the whole specimen (Kantify 2021)

most appropriate imaging procedure and specify individual radiation doses, alleviating the patient's exposure to radiation based on specific risk factors developed through machine learning processes and population data (Choy et al. 2018). AI can also analyze images during capture and perform relatively simple actions, from rotating the images to checking the quality of the captured field in real-time. Once images are captured, AI can help in triaging images to determine which cases are more urgent and whether a patient requires more comprehensive imaging, such as an MRI scan. Further, among the most popular application is image segmentation and recognition (Beck et al. 2020). These algorithms are often asked to come up with so-called segmentation maps, *"[..] a technique where every single pixel in an image is given a certain meaning, such as [..] 'diseased tissue' versus 'healthy tissue', [..] immediately highlighting and quantifying features and patterns of interest such as biomarkers indicative of certain diseases"* (Kantify 2021, 1). Hence, AI can support the interpretation of results, the detection of disease and already suggest the most likely diagnosis as part of computer-aided diagnosis (CAD). Moreover, AI is nowadays also used in *"double reading"*, essentially operating as a safety net once a diagnosis has been reached by the responsible specialist: the diagnosis and respective radiology or digital pathology slide are entered into the algorithm for additional screening, and the algorithm raises a flag if there is a high probability of a diagnostic error. In addition, AI can also offer support in structured reporting, creating a large portion of the final report, linking words, images, and quantitative data (Beck et al. 2020).

In contrast, laboratory analysis in diagnostics for NCDs usually involves a laboratory assessment of a sample of bodily fluids such as blood and urine or other biological material such as tissue to confirm, exclude, classify or monitor the above-mentioned diseases (Gunčar et al. 2018; NCI 2011b). AI laboratory solutions for diagnostics of NCDs are nowadays mainly employed for data analysis while still being far less common than solutions in the visual area (Beck et al. 2020).

4.1.2.2. Academic and Professional Research View on the Application of AI in Diagnostics

While not all gathered research material focuses on AI's application in diagnostics exclusively, all subsequently depicted arguments also hold for diagnostics specifically. The most striking stances on the application of AI in diagnostics are to be presented in the following.

Overall, AI's potential to be a transformative tool for diagnostics, and HC in general, is being widely acknowledged across existing literature. A recurring and most striking point in literature is that AI can essentially reduce human errors and may assure a more accurate diagnosis

(Cui and Zhang 2021; Kelly et al. 2019). In MI analysis, AI solutions allow for the identification of patterns of disease and imaging associations that are hidden from human sight, providing a more comprehensive view of the underlying pathology (Noguerol et al. 2019). It is further stressed that human error reduction is best achieved when combining the algorithm's predictions with the ones from the responsible physician (D. Wang et al. 2016). Moreover, in specialized disciplines of MI or laboratory analysis, AI algorithms have even demonstrated a similar or ameliorated performance to human physicians (Liu et al. 2019; Noguerol et al. 2019). Therefore, existing literature especially stresses AI's potential in simple, time-consuming tasks, potentially releasing human physicians from, for instance, otherwise extensive manual annotations at the pixel level for each imaging slide (Cui and Zhang 2021). But apart from improvements in diagnostic quality, AI is also said to accelerate diagnostic turnaround times. A study performed by McKinney et al. (2020) revealed that AI was able to interpret mammogram results for breast cancer up to 30 times faster than human physicians, with a striking 99% accuracy. Conversely, this implies a reduction in costs associated with diagnosis, ultimately leading to more efficient as well as effective diagnostic workflows (Paranjape et al. 2021). Thus, existing literature suggests that AI could play a role in closing gaps in the previously mentioned absence of HC services or skilled workforce (WHO 2021b). While AI's potential in diagnostics and HC, in general, is the subject of an impressive array of research studies, real-world deployments in clinical practice are said to be rare (Kelly et al. 2019).

Apart from the previously demonstrated positive apprehensions, the underlying literature also emphasizes several drawbacks to clinical implementation. To begin with, Noguerol et al. (2019) pointed out that AI algorithms are incapable of interpreting the patient's clinical context, restraining their capacity to perform subjective associations as the human brain, but which in some diagnostic tasks, are inevitably relevant. Furthermore, the current predominant form of AI in diagnostics is *"weak AI"*, which is focused on the completion of one narrow task (Noguerol et al. 2019). The underlying literature, therefore, raises the issue of a lack of generalizability, which is limiting AI's safe and accurate deployment for other contexts and datasets outside the training domain due to a sharp decline in the algorithm's performance when exposed to divergent evaluation data, also called a dataset shift (Quiñonero-Candela et al. 2009). Interwoven with the issue of poor generalizability is that of discriminatory bias. The WHO (2021b) argues that AI is biased towards the majority data set, namely the populations for which there is most data. A risk identified from this is the deployment of such technology in unequal societies, where these medical AI solutions could be biased towards the majority and discriminate against the minority population. It further warns that such systematic biases, typically present in any inferential model for pattern recognition, when embedded in medical AI algorithms, are at risk of becoming normative biases, exacerbating existing HC inequities (WHO 2021b). Further, it is stressed that HC workers, like all humans, may be subject to cognitive biases that affect their decision-making. Of special importance is confirmation bias, in which clinicians may give undue weight to evidence that supports a presumed diagnosis and ignore evidence that refutes it (Fernández García et al. 2020). This means that these unjust human decisions that are included in the data and mold the algorithm are potentially at risk of being hidden behind the pledge of neutrality and have the power to wrongfully discriminate at a much larger scale (WHO 2021b). Henceforth, research determined a high dependency of AI algorithms on data, as "*AI is only as good as the data used to generate it"* (Beck et al. 2020, 48). Moreover, several issues around the broad field of data are named, including important datasets not being linked and currently being held in silos, as well as critical data governance, access, and security issues still needing to be specified by international regulatory bodies (Beck et al. 2020). The sensitive nature of individual health data further reinforces these issues as a comprehensive provision of such data imposes a large risk to an individual's data security, potentially resulting in a so-called *"function creep"* that occurs when information is utilized for a purpose other than the one originally specified (WHO 2021b). The current absence of a standard format for the labeling of imaging data is also presented as a potential source of disparate results and a lack of replicability (Noguerol et al. 2019). Beyond that, an issue also named across various studies is the general aversion towards the adoption of new technologies in the medical community (Paranjape et al. 2021). Many physicians complain that there is not enough externally validated evidence available yet that these solutions actually work in clinical practice. *"We are holding lives in our hands. We need proof that it works, and you have to convince people with results."* (Beck et al. 2020, 87). Another fact exacerbating the hampered change management is the general perception of AI algorithms being black-box systems, resulting from the opacity in how these work. AI algorithms are assumed to prevent ideal tracing of the steps required to achieve a given input-algorithm-output and therefore bear ethical and legal challenges (Noguerol et al. 2019). Hence, *"[i]t is very difficult as a regulator to take a leap of faith and trust something that is that difficult to assess."* (Beck et al. 2020, 88). This leads to a *"control problem"* in assigning responsibility, where AI developers may not be held accountable because their algorithms operate autonomously and progress in ways that the developer could not have anticipated (WHO 2021b). Thus, another source of uncertainty for physicians stems from the current responsibility gap for clinical AI solutions which is yet to be defined by regulatory bodies. The requirement for novel training, education, and continuous upskilling constitutes another mentioned pain point (Fernández García et al. 2020). Apart from that, it has been noted that current pricing and reimbursement mechanisms for medical AI are inadequate to compensate for the implementation and use of such technology, representing a lack of a proper business model (Biundo et al. 2020).

4.1.3. Assessment of AI as a Strategic Tool in Diagnostics for NCDs

The analysis of the existing literature yielded expedient insights concerning the general deployment of AI in the HC sector, while some papers specifically addressed diagnostics. However, literature on-hand has shown to widely lack the *"developer's or other stakeholder's*[6] *view"*. The conducted qualitative research specifically includes these voices. The interviewees were carefully chosen, with four of them explicitly working on AI diagnostics solutions for NCDs in both key fields, image-related and laboratory-related analysis. Notably, the expert's solutions are already being employed in routine clinical practice in diverse HIC. The remaining expert is a trained physician who is now a healthcare operating partner at a private equity fund and was chosen to complement the analysis with a more business-oriented perspective while still contributing with a thorough medical understanding on the matter. A more detailed overview of the interview partners and their respective organizations is shown in Appendix 1. The interviews were recorded, transcribed, and coded using a three-step coding process[7]. Thereafter, the coded insights were consolidated and clustered into the four dimensions of the SWOT framework, which will be presented in the following[8].

[6] For example investors, entrepreneurs, practitioners, professionals working on medical AI
[7] Please find the detailed results analysis and interview transcripts from Appendix 6e onwards
[8] For a full overview of the applied research design, please consult section 3 Methodology in the group thesis

4.1.3.1.Strengths (Internal)

Exceeding human capabilities in diagnostics. Interviewees pointed out that AI algorithms, for specific tasks, can extend human capabilities in medical diagnostics (I1.1). For instance, in blood analysis, algorithms are able to see smaller, less apparent patterns and irregularities or abnormalities that are, in some cases, not even visible to their human counterparts (I1.1; I1.3). Further, they can do so much faster, performing the analytical work in real-time and thus reducing turnaround times of diagnostic processes (I1.1). This has been particularly praised for repetitive tasks, *"[..] where lots of numbers, in particular, have to be considered in relation to one another [..]"* (I1.3). Inferentially, affiliated operational costs of diagnostic processes are said to decrease, especially when AI is employed at scale (I1.1; I1.3).

Increased accuracy of diagnosis. Moreover, many interviewees agreed that AI can increase diagnostic accuracy in a two-fold way. First, through the fact that the employment of AI enables physicians to focus on more critical matters. For instance, AI-MI applications may help identify the right areas of cancer, which allows pathologists to focus on what they are best trained for, namely to provide all the characteristics and attributes of the specific form of cancer on-hand that are critical to the subsequent management of that disease (I1.5). Second, diagnostic accuracy may be enhanced through the increased objectivity ensured by impartial screening. For instance, AI can be trained to look at blood samples for all known abnormalities, while physicians usually look at those samples with an initial *"human filter"*, i.e. a hypothesis that they are trying to confirm or refute (I1.1). Intertwined with the fact of impartial screening is AI's ability to reduce (human) error in diagnosis. One of the interviewees' solutions already routinely detects misdiagnosed cancers in digitized pathology slides in clinical practice, guiding pathologists to areas of cancer in support of a prompt review (I1.5).

Earlier detection of chronic conditions. Another vital implication resulting from this is that AI has the ability to detect chronic conditions in patients earlier. Interviewee I1.4 stressed that patients suffering from NCDs are generally being diagnosed too late, meaning that the *"trigger event"* mentioned in section 2.1 is usually initiating the diagnostic process, while at that point, patients have already been suffering from the condition for quite some time. AI has the potential to help remedy that issue through its impartial screening. An example is that CT scans are being performed on a frequent basis in HIC, so someone who had a car accident and is scheduled for a CT scan to look for fractions may find out that they have severe CVD as an AI algorithm may automatically highlight that information in the radiology report. While radiologists may theoretically do that as well, the clinical reality is marked by a lack of interoperability and overarching communication beyond the initially specified order (I1.4).

Enhanced triaging and stratification of patients and improved collaboration across processes. It was further stressed that AI can improve triaging and stratification of patients (I1.3; I1.4). For instance, Interviewee I1.3's solution constitutes an AI-powered blood test that gives a calibrated probability of the individual at hand having cancer. Thus, this may essentially increase the chances of endangered patients for a positive health outcome, as the solution helps send critical cases *"[..] to the front of the queue"* (I1.3). Additionally, it was stressed that AI, therefore, has the potential to improve the collaboration across diagnostic processes within the HC system (I1.3).

Increased accessibility of high-quality diagnostic services. An effect resulting from all these capabilities is that AI may increase the accessibility of high-quality diagnostic services as it can i) bridge the gap between the specialist shortage and the demand for diagnostic services by being able to examine more patients and ii) bridge the gap in diagnostic quality depending on the geographic or clinical context, which is even present in HIC (I1.5). For instance, it can make a huge difference whether individuals receive their cancer diagnosis in a capital city, in a top academic center, or a commercial lab in a small town (I1.5). What is important to note at this point is that it was clearly stressed that, especially in HIC, AI in diagnostics is designed and employed as an aid, with the physician being able to override results or proposals generated through the technology (I1.5).

Thus, the prevailing opinion is that AI solutions can greatly *increase both, efficiency* and *effectiveness* of diagnostic processes for NCDs.

4.1.3.2. Weaknesses (Internal)

Lack of maturity of algorithms. As far as *weaknesses* were concerned, the conducted qualitative analysis yielded relatively sparse results. Only one interviewee (I1.2) questioned the maturity of medical AI solutions, noting that existing solutions on the market may still not be as good as the human doctor.

Resource-intensive implementation of AI. Moreover, the interviewee emphasized the resource-intensiveness of the adoption of such solutions. Many solutions to date would lack real cost-efficiency, as costs for the implementation and integration of the solutions would not compensate for respective productivity gains (I1.2).

4.1.3.3. Opportunities (External)

Strengthened focus on application of AI for earlier detection of chronic conditions. An increased focus on the development and deployment of medical AI for early detection of NCDs was identified, as it not only reduces patients' morbidity but also relieves HC systems from lengthy therapy and costs associated with the management of advanced cases of disease (I1.4).

High potential of increased application of AI in non-visual POC testing. Another expert stressed that while the industry is primarily focused on medical AI solutions for imaging, where images are expensive to get, there exists high potential for an application of AI in the non-visual area. "*Anything that is really easy to administer [such as point-of-care tests, that only require very basic medical training], where you can send data to the cloud that can then be easily analyzed* *because it's just numbers, [..] is particularly benefitting from AI"*, thus holding great scaling and efficiency maximization potential (I1.3).

Progress in regulatory formulation. Apart from that, the comprehensive formation of a well-defined and proactive regulatory framework for medical AI solutions has been named as a huge opportunity as this could essentially facilitate the development process and reduce uncertainty around compliance among developers (I1.1).

Patient data integration from multiple sources in the HC system and *growing access to this data.* Moreover, growing access to large volumes of all-embracing patient data is also widely seen as an enabler to creating a robust and improving system, inter alia, supporting the reduction of bias (I1.1; I1.3; I1.4). An enhancer for this development constitutes the integration of a patient's data from various sub-departments and sub-processes in the HC system, allowing for a holistic view of the patient's condition.

Shift in mindset towards AI technology. Also, a pro-innovation shift in mindset among regulators, health institutions, physicians, and the general population was seen as an opportunity. It is important to highlight that geographical differences in pro-innovation attitudes have been particularly pointed out, with, for instance, the UK being far ahead of the EU (I1.3). Interviewee I1.4 stressed that the promotion of medical AI by a renowned health institution such as the WHO would be of enormous value for the further adoption of AI in diagnostics.

Growing scientific proof for practicability of medical AI. The aforementioned shift in mindset may partly be reinforced through the following opportunity, namely through the increased instigation of clinical validation studies to demonstrate the practicability of medical AI in a clinical context (I1.4).

Further increasing accessibility of diagnostic services. It was mentioned that there is a strong opportunity for AI to further increase the accessibility of diagnostic services through supporting the detection of rare forms of NCDs, such as rare cancers, which are usually too complicated, lengthy or expensive for regular hospitals or laboratories to examine, often requiring further specialist referral or incurring long delays before getting a diagnosis (I1.1).

Lastly, listed external enhancers also include *improvements in computing technology* and *increased funding* for medical AI solutions in diagnostics (I1.1; I1.3; I1.4).

4.1.3.4. Threats (External)

Persistence of poor data quality and fragmentation. The persistence of poor medical data quality, as well as the continued fragmentation of such data, have been identified as external risks to the further development and improvement of AI algorithms (I1.3). However, geographical differences in data access, quality, and availability have been pointed out, with, for instance, Israeli companies not encountering issues in this regard (I1.4; I1.5). Fragmentation of medical data may not only occur at a country level but also within hospital systems, where information of a single patient is siloed in several sub-departments and inhibiting a holistic view on the underlying pathology (I1.4).

Imparting (systemic) biases and potential misuse of patient data. A further threat noted, which is resulting from insufficient data quality and quantity, is the potential of enduring (systemic) biases in medical AI in diagnostics (I1.3). While the access to large volumes of all-embracing patient data has been named as an opportunity to combat this threat, the potential misuse of this sensitive data when made available poses a novel threat itself (I1.3).

Restrictive course of regulations limiting possibilities of AI applications in diagnostics. On top of that, a restrictive course of regulations is said to limit the possibilities of AI applications in diagnostics as well. In some geographies such as Europe, there is currently a lack of a clear, holistic regulatory framework for medical AI, which introduces high uncertainty among developers as it seems obscure whether their product will comply with (future) regulation (I1.1).

Lack of a business model of medical AI solutions. A lack of a business model for AI diagnostics solutions constitutes another raised threat. Interviewee I1.2 argues that the payers, as well as reimbursement mechanisms, have not been identified to date. Besides, the cost-reducing effect on the healthcare system has also yet to be quantified and outlined to responsible institutions and customers (I1.2).

High cost of input data for AI-MI solutions. An interesting threat raised specifically for AI-MI applications is the high cost of the input data. While AI-MI solutions are among the most widespread applications of AI in the medical field, Interviewee I1.3 argues that the drawbacks in this field of application have not yet been sufficiently grasped: Medical images are usually obtained through machines such as a CT scanner. Thus, this process is said to be inherently expensive to perform due to the nature of these physical devices, to have a large carbon footprint and to require lots of well-trained staff to use and manage the devices (I1.3).

Insufficient institutional conditions for optimal adoption of medical AI. It was noted that it is difficult and time-consuming to navigate through the large bureaucracies of the HC system as a small player, as most developers of medical AI tend to be start-ups (I1.3; I1.4). Thus, the alignment within such enormous institutions that currently widely lack interoperability, more specifically interdepartmental communication, from the government down to departments, down to hospitals and care systems, is proving to be difficult and complex. *"AI, generally speaking, joins up things. But if you're joining things up in a system that is not joined up, that's a barrier"* (I1.3). Therefore, HC institutions' current setup and operations could hamper AI's adoption and transformative potential**.** Interviewee I1.3 further elaborated that the non-existence of an overarching institution that is in the position to recognize the benefits from implementing a system that has a joint effect on a multitude of currently siloed HC domains and processes and thus advocating for that change poses a significant threat to the wide adoption of medical AI.

Tedious change management in the HC industry. Lastly, all interviewees have remarked a general change-aversion and skepticism towards new technology in the medical community: *"[..] [E]ven just instituting mammography took years until people really got into it - anything that's new in medicine, it just takes a lot of persistence and a lot of patience because the medical community is just a very conservative community in general [..]"* (I1.4). Physicians' aversion towards AI in clinical contexts is said to being reinforced by a fear of replacement and a lack of thorough education on the matter (I1.4). *"So one of the biggest barriers is people. But also, one of the sort of, biggest advantages. So it's always about people, human systems. As much we are always talking about AI and technologies, it always comes down to: Yes, but can you get the people to do the thing?"* (I1.3).

Subsequently, the gathered insights from both qualitative research and related work will be adduced to assess the potential of AI as a strategic tool to contribute to the reduction of premature mortality.

4.1.4. Discussion

4.1.4.1. Synthesis of Qualitative Results and Related Work

Within the conducted qualitative research, AI in diagnostics has been widely praised as an efficiency-increasing tool, contributing to the closure of two fundamental gaps: the specialist and the quality gap in diagnostics. Of particular importance is the carved-out strength of early detection. AI may significantly contribute to the reduction of premature mortality from NCDs by shifting the initiation of the diagnostic process prior to the *"trigger event"*, essentially increasing the probability of a positive health outcome. Rather than just treating the underlying, well-advanced condition, health personnel may then even work on preventing a more severe progression of the disease. A rather unexpected but expedient outcome is that the conducted qualitative research shed light on applications for laboratory analyses in the non-visual area, greatly stressing its efficiency-maximization potential. Interesting to find was also that there appears to be a high geographical dependency for the success of AI-based diagnostics solutions that traverses through many different subfields. The discussed categories of data, regulation, mindset and institutional context all heavily depend on the country- or region-specific procedures and may greatly influence AI's adoption and blooming. Adding to this, a valuable insight constitutes the importance of the institutional context AI-diagnostic applications are employed in. The developed solution may theoretically be excellent, but it still will not unfold its full potential in HC institutions that predominantly work in silos, suggesting a fundamental reliance on its external conditions. Another intriguing and crucial finding is that AI's adoption and further development in diagnostics, and the HC system as a whole, first and foremost depends on the people working in these systems. They are the gatekeepers to AI's comprehensive adoption in HC systems around the globe. However, while acknowledging threatening external conditions, the interviewees remained confident in being able to cope with these risks and thus showed a very positive stance towards the adoption of AI in diagnostics for NCDs. Important to note is that the presented weaknesses were voiced by the one interviewee that is not working on real-life deployed AI solutions, which is why their impact on the overall conclusion of the author is considered limited.

When setting the gathered results in the context of the findings from academic and professional literature, it becomes evident that attitudes coincide in a significant number of presented arguments. While the presented literature also recognizes the positive disruptive impact AI can have on diagnostics, ultimately leading to more accurate diagnoses in shorter periods of time, it widely remains cautious of actively recommending real-world deployment in clinical practice and puts a strong focus on emphasizing potential drawbacks to an implementation. Central to this are the voiced concerns about a responsibility gap, the amplification of systemic biases and a lack of subjectivity of algorithms to interpret the patient's clinical context. A pivotal observation made is that many of these fears voiced in existing literature around the practicability of AI in medical diagnostics relate to a scenario where AI would be operating fully autonomously. However, the qualitative research has strongly highlighted that, especially in HIC, AI in diagnostics is only used as an aid. The way that current applications in diagnostics for NCDs work is that physicians still have the power to overrule results generated by an algorithm. Thus, AI should be treated as what it is: a *tool* that physicians may avail to improve diagnostic processes for NCDs. This observation further shows that there appears to be a fundamental disconnect between related work and demonstrated real-life practice. This stems from the dynamic nature of the underlying topic: The field of AI is incredibly fast-paced, where developments from a year ago are considered outdated (Spatharou et al. 2020). Thus, it can be assumed that both academic and professional research, due to the nature of developing and publishing such work, is simply unable to keep up with the rapid pace of technological development, leading to disparate viewpoints. Hence, it remains to be said that with its qualitative research approach, the underlying thesis attempted to help alleviate the demonstrated disconnect between literature and real-life practice and showcase the views of *"medical AI practitioners"*. This work can further be used as an introductory, informative synopsis for representatives of the medical community that lack thorough knowledge on the matter and thus may aid in closing the existing knowledge gap on AI in medicine.

4.1.4.2. Managerial Implications

To translate the identified results into an exemplary set of actions to reinforce strengths, exploit opportunities and overcome potential weaknesses and threats, managerial implications have been formulated. These were particularly conceived for AI-diagnostics practitioners for the following reasons: The author essentially aims at advocating for actions to help reduce premature mortality from NCDs, which, as implied in the above, includes the adoption of AI in diagnostics. From the conducted research, it became evident that the further adoption of AI as a strategic tool is more likely to be induced by proactive thrust from those developing and selling AI-diagnostics solutions rather than caused *"intrinsically"* by HC institutions.

To begin with, one of the most critical aspects drawn from this thesis is that, especially in the HC sector, people are central to the development and adoption of technology. Thus, the complementation of humans and machines should be a fundamental principle for both the development and use of AI-based diagnostics solutions for NCDs. Within their marketing and sales strategy, companies developing and selling such solutions should put special emphasis on communicating this complementarity principle to actively counteract skepticism. Further, these companies should inevitably incorporate the geographic context into their strategic planning. Favorable entry markets such as Israel or the UK that offer conducive conditions in terms of data, regulation, institutional context, and mindset should be identified. Ideally, the success generated in these markets should be taken as a foundation to expand to other geographies, further antagonizing potential concerns from customers in less innovation-friendly geographies. Finally, medical AI practitioners are advised to put an even stronger focus on developing solutions enabling early detection of NCDs. Harnessing the presented potential of AI in non-visual, POC tests, one may think about developing a *"silent"* algorithm that runs in the background of standard blood tests that are frequently performed in HIC. This algorithm may then raise a flag if there is a high probability for diabetes and certain forms of CVD and cancer.

4.1.5. Conclusion

After thoroughly evaluating all arguments on-hand, it can be concluded that medical communities in HIC should harness AI as a strategic tool for diagnostics to combat premature mortality from NCDs. The complementation of human physicians and AI shall be fundamental in doing so, alleviating key weaknesses and threats noted within existing literature. Other presented drawbacks shall be carefully considered in the development and implementation process, to warrant a safe, reliable and beneficial deployment of AI as an aid for HC systems.

4.1.6. Limitations and Future Work

The underlying thesis is subject to a multitude of limitations, which will, however, be jointly discussed with the other authors due to remarkable congruence on this matter (see group thesis 6.3 Limitations). Nevertheless, some limitations, mainly resulting from the limited scope of this thesis, provide room for future research on this particular topic, which are to be discussed here.

Future research could specifically examine AI in the field of non-visual applications for laboratory analysis in more detail as it has not been at the center of attention in research despite its great potential. Moreover, there appears to be merit in quantifying the impact AI diagnostics solutions already employed in routine clinical practice have on the reduction of premature mortality from NCDs. With that being said, research around the role of AI in medical diagnostics for NCDs is still at its very beginning and should thus, be further examined.

4.2. AI as a Strategic Tool for Sustainable Transport Systems – SDG 11

4.2.1. Introduction

4.2.1.1. Motivation and Relevance of Research

Cities can be epicenters of health crises. Covid-19 once again has reminded society of this fact. However, cities can also be engines of economic recovery, centers of innovation, and catalysts for social and economic transformation (United Nations - DESA 2021). Public well-being is a significant factor in a city's quality of life. Both health and the sustainable development of cities are a pressing concern, so each is included in a dedicated Sustainable Development Goal (SDG)[9], respectively Goal 3[10] and 11[11] (United Nations - DESA 2021).

Cities are complex. Despite the significance of the SDG´s, there remains a lack of evidence on the usefulness of these goals. The main criticism of the inadequacy of SDG targets and

[9] For list of abbreviations, see Appendix 7a
[10] SDG 3: Good Health and Well-being
[11] SDG11: Sustainable cities and communities

indicators is based on research findings by (Giles-Corti, Lowe, and Arundel 2020, 589–90). It suggests that the metrics for achieving the SDGs may omit critical leading indicators for technical, regulatory, and legislative measures and interventions or investments. According to the author, there is a distinct gap in measuring the legal limits for air pollution. The lack of efforts to improve air quality, such as promoting public transportation, was another omission identified. According to (United Nations - DESA 2021), although 156 countries have developed national urban policies, only half of these plans are in the implementation stage.

Ambitious SDG goals. The International Council for Science (ICSU) coordinated a more comprehensive study in partnership with the International Social Science Council (ISSC). A particular concern of the researchers in the review of Goal 11 on sustainable cities and communities is the fulfillment of the expectations on that goal. The goal is challenging on political and operational levels, and achieving inclusion, safety, resilience, and sustainability is unlikely. One of the more significant issues is the lack of fully comprehensive standardized metrics to measure the objectives. The targets and corresponding indicators introduced with the SDGs can only cover this highly complex issue to a limited extent[12]. Further limits of the indicators concern the absence of fundamental Information and Communications Technology or connectivity objectives and the lack of consideration of the institutional dimension. It is a complicated network of interactions between academia, the states, the private sector, and civil society and must be managed with great foresight (ICSU and ISSC 2015, 55).

4.2.1.2. Important Technological Developments

One of the essential requirements for managing something with great foresight is predicting it. The most important instruments that can help with predictive planning are Artificial Intelligence (AI) systems. Based on the findings of (Nosratabadi et al. 2019, 1), Deep Learning (DL) and

[12] For the NUA specification and further Criticism on the SDG and NUA framework, see Appendix 7b

Machine Learning (ML) methods[13] are among the most critical tools for the prediction, planning, and uncertainty analysis of smart cities and urban development. The main areas for AI applications in smart cities range from more efficient and better-supplied energy, water, and waste infrastructure to feasible, more efficient, and sustainable urban mobility (Policy Department for Economic, Scientific and Quality of Life Policies 2021, 1–2).

Smart city. Several writers and research institutions have vigorously challenged the topic of technologies for sustainable development in recent years. When it comes to digital technologies such as AI enabling the sustainable development of an urban area, the term "smart city" has become a topic of great interest (Urban Innovative Actions 2019; Policy Department for Economic, Scientific and Quality of Life Policies 2021; UITP 2018). The core idea of this concept is to create a city that has access to the correct information at the right place and through the suitable device to make city-related decisions more manageable and help citizens more efficiently and faster (Rathore et al. 2016, 63–65).

Internet of Things. One of the leading technologies that enable and drive a smart city is the Internet of Things (IoT). It is defined as "the interlinking of heterogeneous devices with each other together over the Internet" (Rathore et al. 2016, 65). These intelligent devices provide access to a constantly growing amount of data. With the resulting data available, it is possible to develop intelligent systems such as AI applications for smart cities (Jha et al., 2021, 937).

Mobility and Health. The fact that intelligent algorithms are getting better every day due to continuous development and the daily increase in data volume supports the far-reaching potential of AI for change (Jha et al. 2021, 937). By reducing the need for human labor and boosting scientific and technological progress, AI promises more excellent health, wealth, and happiness (Nikitas et al. 2020, 2). In this context, mobility plays a central role in addressing the

[13] Five methods have been most applied: Artificial Neural Networks; Support vector machines; Decision trees; Ensembles, Bayesians, Hybrids, and neuro-fuzzy; and Deep Learning

problem of traffic congestion and pollutant emissions in cities that prevent the decarbonization of towns. Exposure to air pollution is one of the most critical risk exposures, according to (Giles-Corti et al. 2016, 2914–16) and is primarily caused by motor vehicle traffic both in high-income and low-income countries.

4.2.1.3. Detailed Scope Definition

Given all that has been mentioned so far, it supports the rationale for focusing the following on the potential of AI systems on "providing access to safe, affordable, accessible and sustainable transport systems for all and improving road safety, in particular through the expansion of public transport" as per SDG Goal 11.2 (United Nations - DESA 2016). For this reason, the emphasis of this work is on public administrations and organizations in the development of sustainable urban areas, including and focusing on public transport providers. Privately owned autonomous passenger vehicles are out of scope.

The pandemic of Covid-19 has exacerbated the predicament of slum dwellers and marginalized those already weak. With already over one billion people living in slums, as well as only half of the world's urban population with convenient access to public transport, the need for a drastic shift towards more socially sustainable development is present for both developing and developed countries (United Nations - DESA 2021). However, it is noteworthy that due to the scope of this work, the focus of the transport systems studied is on developed economies. This also stems from the fact that internet connection is an immediate need to participate in society fully. It is essential for education, affordable housing, and critical government services, among other things (UN Habitat Flagship Programme 2020). However, internet use in the least developed countries is around 20% compared to 90% in developed economies. Also, the average internet speed in developed economies is eight times faster compared to the least developed countries (United Nations Conference on Trade and Development 2021, 2). These two conditions are central to IoT, and AI applications, so improving connectivity should be the most immediate concern for the least developed countries (United Nations Conference on Trade and Development 2021, 10).

The expert interviews were conducted explicitly with smart city and urban mobility actors. It is also worth mentioning that the European perspective was explored more in detail based on the interviews conducted with Portuguese and German representatives. Experts included representatives from Carris[14], public mobility provider of Lisbon (Portugal) and governmental representatives from Lisbon[15] (Portugal), Berlin[16] and Munich[17] (Germany).

4.2.2. Related Work

4.2.2.1. Understanding Applications and Areas

The international association of public transport conducted a representative and comprehensive study of the contribution of AI on mass public transport (UITP 2018). The study stated that the main applications of AI currently used are real-time operations management and customer analytics. Predictive maintenance, network planning, and route planning are the possible applications on the horizon for many organizations (UITP 2018).

Main possibilities. The applications have improved employee performance by increasing the quality and efficiency of undertaken tasks, reducing employee workload from mundane tasks, and providing efficient, safer, and cost-effective services to the customer. The most significant positive impact was found on customer service and operational reliability, which form the basis for the uptake of public transport and improving financial efficiency (UITP 2018, 9–10). Following the research of (Abduljabbar et al. 2019, 1), the introduction of AI systems in public

[14] Mr. João Vieira, Innovation & Strategy manager
[15] Pedro Machado, Former Advisor to the Deputy Mayor of Mobility, Safety, Economy and Innovation of the Cjty of Lisbon, from 2017 to 2021
[16] A Policy Advisor and another expert on Transport and Climate for the city of Berlin
[17] A city planner and mobility expert

transportation addresses the challenges posed by increasing transportation demand, CO_2 emissions, safety concerns, and environmental degradation (Jha et al. 2021).

Main challenges. A deeper look into developing an AI-based solution for an efficient transport service reveals that it is highly complicated to create machine intelligence that correctly understands human-based information. Another limitation is the highly complex nature of an artificial neural network, meaning that a system is developed without knowing the internal computations (Abduljabbar et al. 2019, 12). Taking a closer look at the five main challenges of implementing AI systems in mass public transport identified by (UITP 2018, 9), three of those challenges public transport authorities and operators are related to data. Data is collected from multiple sources in transport, ranging from sensors on the road, connected devices, toll gantries, GPS to Cloud applications, and many others. The amount makes the computational process of a specific system complex of data from different transportation features such as traffic flow, speed, and occupancy (Abduljabbar et al. 2019, 13).

Importance of Data. The multidimensionality and dynamic character of cities result in a variety of problems for local authorities to deploy infrastructure enabling data analytics and AI solutions for the benefit of smart cities and urban mobility, as stated by the (Policy Department for Economic, Scientific and Quality of Life Policies 2021, 1–2). The degree of usability for more efficient and sustainable mobility solutions depends heavily on the growth of the associated data economy (Policy Department for Economic, Scientific and Quality of Life Policies 2021, 2).

4.2.2.2. Current Use of AI Systems for the Urban Mobility Sector

An interesting example of an implemented AI system in predictive maintenance that contributes to more efficiency and reduced costs is developed by the German company Konux. The frequency of maintenance requirements for rail networks increases, and manual inspections are insufficient to detect them in time. In this context, switches are among the most critical components of rail infrastructure: they are responsible for around 20% of infrastructure-related delay minutes, and maintenance and replacement incur costs of 12 billion euros worldwide every year. The Konux system offers a solution that uses IoT sensors and AI to improve the availability of rail networks, extend asset life, and reduce costs. The system continuously monitors and analyzes the condition of crucial switch components and makes specific recommendations. Thus, it enables significantly more efficient maintenance because infrastructure managers can anticipate failures early and plan the type and duration of the necessary measures (Konux 2021).

4.2.3. Assessment of AI as a Strategic Tool for Sustainable Transport Systems

This section uses the SWOT framework to analyze the strengths, weaknesses, opportunities, and threats connected to the use of AI as a strategy in the context of sustainable transport systems. As outlined earlier, the insights of this analysis are based on expert interviews. The interviews were recorded, transcribed, and coded using a three-step mechanism (see Section Method)[18]. Subsequently, the coded insights were consolidated and clustered into the four dimensions of the SWOT framework. A differentiation was made between internal factors (Strengths and Weaknesses) and external factors (Opportunities and Threats). The rationale for this distinction can be found in section 3.2. A total of three strength clusters, three weakness clusters, four opportunity clusters, and six threat clusters were extracted. An overview of the clusters can be found in Appendix 7d.

4.2.3.1. Strengths (Internal)

One of the main strengths of implementing AI systems in urban mobility was to improve *the safety and service quality for customers*. It can provide customers with a cost-effective and autonomous service that is better tailored to the needs of citizens, while avoiding disruptions

[18] For Coding Excel, see Appendix 7c

and accidents in cities (I2.1, I2.2, I2.6). For instance, a system has been tested on Lisbon buses that help employees by warning them whenever a pedestrian gets close (I2.1). By using such methods, accidents and fatalities can be prevented, and a better sense of safety can be created for citizens in cities and urban traffic.

AI can *improve operational excellence* by promoting resource-efficient use on the operational side. It is particularly evident in the positive impact of AI on employee quality and efficiency (I2.4). It comprises the ability to use vehicle data from buses, trams, and other vehicles to perform predictive maintenance instead of corrective maintenance and the ability to predict events, understand the demand, and modify the offer accordingly (I2.1, I2.2).

A further strength recognized is AI's ability to *reduce congestion and pollution.* With the ability to optimize and control traffic flow, AI helps to reduce traffic congestion and thus improve air and noise pollution (I2.1, I2.2). Automatic license plate recognition can be enabled and supported, allowing track routes for better planning (I2.1). By reducing greenhouse gas emissions, AI can contribute to the decarbonization of the transport sector and hence to combating climate change. The technology could directly affect the health and well-being of the people living in cities (Giles-Corti et al. 2016, 2914–16).

4.2.3.2. Weaknesses (Internal)

The biggest and most general weakness of an AI system for urban mobility, mentioned in every interview, is *data dependence and resource intensity*. A public transportation provider may have a high level of data availability, but its potential is not yet effectively realized (I2.1). Because even if the raw data tends to be available, it cannot be further processed and ultimately used without resource-intensive pre-work. The existing fragmentation and incompatibility of individual systems must be reduced to increase the availability of high-quality data[19]. Given

[19] High-quality data: data that is cleaned and ready to use for the specific chosen AI application

that mobility can collect data from several sources like sensors on the road, GPS and Cloud applications, and other connected devices, it is imperative to maintain a variety of data sources. Integrating the data from the various data sources into one system requires a significant effort in data preparation. To use the data in the specific application while meeting the high demands on data volume requires further data cleaning, which is time-consuming and labor-intensive. Moreover, this extra work leads to additional direct costs for the organization (I2.1, I2.2, I2.4).

These costs are exacerbated by the subsequent weakness addressed, the *high demand for human resources*. Implementing AI systems requires expertise and continuous employee training to enable and drive the process. Since the broader use of AI is still a relatively young technology, highly skilled workers are scarce, making it difficult to attract talent, especially for a public transportation company (I2.1). Typically, these organizations have little or no experience working with AI, which is why talented professionals tend to take a different path to find a more intriguing opportunity.

Another weakness worth mentioning is the diversity of *implementation difficulties*. The multidimensionality of cities and a large amount of differently formatted data complicates AI systems' inherently complex computational process (I2.1, I2.2, I2.3, I2.4). The problems reach further into technological maturity, limiting AI systems. The current purely task-specific use of AI requires an employee to manage the big picture in many use-cases (I2.4, I2.6).

4.2.3.3. Opportunities (External)

The dimensions of the PESTEL framework[20], considering the opportunities of an implementation of an AI system in the public transport context, are difficult to separate.

In terms of the political, economic, social, and environmental dimensions, the interviews show an increasing awareness of policymakers and government institutions (and individuals,

[20] PESTEL: Political, Economic, Social, Technological, Environmental and Legal Aspects

researchers, and governments) of the importance of implementing AI systems for more sustainable public transport. This increased attention represents a great opportunity, reflected in the strength of *collaboration and commitment* (I2.1, I2.2, I2.3, I2.4, I2.6). The findings indicate good communication between regulators and providers in the transportation sector (I2.1). The extensive network of stakeholders from the academic and private sectors contributing solutions and ideas could foster the possibility of collaborative partnerships that create synergies and form highly qualified multidisciplinary teams (I2.2, I2.4).

Over and above this, the availability of limited yet *supportive legal frameworks* such as the General Data Protection Regulation (GDPR), which represents the first step towards legal clarity and uniformity across Europe, can be a driving force from a legal perspective (I2.1). Nevertheless, this topic can quickly become a challenge, as shown below.

The need for legal certainty and existing data protection rights is also critical to realizing the full potential of AI systems for the next opportunity. In terms of the technological and social dimensions, AI systems can provide a *supportive tool for human interactivity.* As the number of connected devices increases (with the necessity of legal certainty) and people in cities are more likely to be digitally engaged, individuals can contribute to more relevant datasets (I2.1, I2.4). In this context, great importance was attached to transparency regarding the use of data. The city of Munich has already gained experience in this area. For instance, 80% of users of the Oktoberfest app voluntarily disclosed their movement data to answer questions about visitor flows or tent capacities. It shows an excellent example of creating a win-win-win situation for both the provider and the organizer, and the visitors, who derive a direct benefit. It makes the event more efficient and predictable and consequently more visitor-friendly in the end (I2.4).

On the technological and economic dimension, the opportunity of *exponential growth of available data* received attention. It ranges from constantly growing databases and the data acquired from other parties to the increasing availability of open-source data. However, this data's quality, interest, and actuality are always decisive for the potential use case and must be carefully examined (I2.2, I2.3, I2.4).

4.2.3.4. Threats (External)

The importance of data for AI systems is again demonstrated by the fact that data was mentioned as an opportunity and presented as the main threat. First, the experts' primary concerns were *data volume and data protection issues* (I2.3, I2.4, I2.6). Therefore, data protection issues and regulations must be addressed quickly and uniformly because overly stringent data protection can slow progress and innovation. However, AI systems should always ensure people's privacy rights to be implemented in a long-term and sustainable manner (I2.2, I2.4, I2.6).

Closely related to this point is the increasing *shift in power towards organizations and companies* with access to a large amount of data like Google and Facebook. Data volume is crucial as companies with more users and data have a more profound knowledge of their customers' preferences and requirements. In the mobility sector, online mobility platforms have a significant advantage compared to public transport providers because they have more data about where people live, where they go, and which means of transport they use for various purposes. A public transport provider must sometimes buy this external data about its customers from this platform, which results in an additional financial burden (I2.1).

However, as the GDPR is a potential opportunity, legal issues also affect the identified threats. A further problem is *regulations and warranty*. Due to the fast-paced developments in AI technology, it is challenging to constantly keep laws and regulations up to date. It is exacerbated by the fact that rules are slow to adapt because of their highly complicated nature (I2.2). An issue raised in autonomous vehicles was the extraordinarily complex liability issue that has made it challenging to define a comprehensive law so far. The lack of a sophisticated legal framework is noticeable regarding warranties or maintenance contracts with other providers. The undefined nature of AI, which is constantly developed fast, further complicates the ability of public transport providers to test new systems. Warranty terms make it impossible for new vehicles to change and try a new option. As a result, it is even more challenging to use and implement intelligent solutions like AI or autonomous driving in public transportation, which slows down the innovation process considerably (I2.1).

On the other side of the service, the customers themselves are also identified as a critical threat in implementing AI systems. To remedy the *skepticism about the technology*, it must believe in positive change for all in AI applications. The experts have proposed that this can only be achieved by building trust in the technology. However, at least for the next few years, it will still be limited because public transport still requires human interactions to be trustworthy. Furthermore, creating a perception of benefit for the many associated with implementing AI systems. An impeding factor for this process is the rapid changes in the mobility sector and urban transport, such as sharing services, that have occurred within the last few years (I2.1, I2.2).

Another factor that further complicates the process is the *high complexity and uncertainty* that must be managed with utmost foresight. The importance and complexity of public transport for the accessibility of the workplace, the doctor, or other essentials of life around the clock is a crucial factor in the city context. The transition of public transport to a more sustainable transport system is a protracted, diverse, and gradual process, and therefore needs to be rigorously planned. Considering the multi-faceted and complete tasks that public transport needs to address and the variety of different stakeholders and uncertain behaviors in this field, the complexity increases even more (I2.2, 2.3, 2.6). One of these stakeholders in the urban transport sector is workers. The workers' fear of succumbing to the enormous workload of AI and becoming unemployed should also not be ignored. It would significantly reduce employee acceptance and required contribution to the transition (I2.1).

A highly related ubiquitous point mentioned in the *operational focus* of a public transport company on the day-to-day management of operations can lead to difficulties when trying to implement an AI system. As Mr. Vieira noted: *"Our (short-term) goal is to have 700 busses tomorrow at 6:00 a.m. outside with drivers, with passengers, that everything is working."* Moving daily reliable transport needs for all while at the same time innovating and introducing new technologies is a highly complex task. It is compounded that operations cannot be stopped to test new things. Moreover, it was inferred that communications and exchanges between providers and regulators outside the transportation sector, but who are also critical to the transportation sector, such as data and information technology departments, tend to be poor. Regarding the innovation and operations aspect, Mr. Vieira pointed out that "insufficient innovation can lead to irrelevance of public transport operators" (I2.1, I2.2).

One specific but exciting point from an interview concerned the *potential increase in traffic*. It can be attributed to the fact that more autonomous vehicles could be on the road when parking spaces are scarce in cities. The cars can simply drive around relatively effortlessly and without humans (I2.1).

4.2.4. Discussion

As a general observation, the expert interviews identified a total of 16 clusters related to the strengths, weaknesses, opportunities, and threats. These clusters, verified by the literature research, missed only one major opportunity for *technology improvements* that the experts did not mention. It can be explained by the non-technical background of most of the interviewees. As a second observation, it is noteworthy that the experts noted external threats to implementing an AI system most consistently and frequently. External opportunities were addressed slightly less but were considered more significant than the internal factors of strengths and weaknesses. These clusters were considered the least, but equally with a count of three.

4.2.4.1. Synthesis of Qualitative Results and Related Work

The strengths mentioned by the experts were all confirmed or even promoted by the research work carried out. This includes the potential ability of AI systems to deliver greater efficiency and lower costs, lower emissions, lower environmental impact, and fewer accidents (Audenhove et al. 2021; Rathore et al. 2016; Policy Department for Economic, Scientific and Quality of Life Policies 2021; Nikitas et al. 2020; UITP 2018).

The addressed opportunities in the interviews focused mainly on collaboration, the increasing adoption of AI, and the growing availability of data. The researchers confirmed all these, but another focus on technological improvements was further identified during the literature review. Real-time data collection and edge processing are enabled by advances in technology such as AI, IoT, and cloud computing and are also becoming more accessible through lower prices and more efficient implementation possibilities (Shrivastva 2014; Kaplan and Haenlein 2018; Nikitas et al. 2020; Michael L. Littman et al. 2021).

The principal limiting internal factor addressed by all interviewees is the overall complexity resulting from the multidimensional nature of cities. It is highly complicated to determine an urban strategy including public transport that is functional on a day-to-day basis and meets all the basic needs of the citizens while at the same time allowing for innovation and sustainable change in this stringent system. It is further complicated by the high requirements for highly skilled human resources and the need to build trust in the technology. These facts are confirmed and corroborated by many types of research (Jha et al. 2021; Allam and Dhunny 2019; Rathore et al. 2016; United Nations - DESA 2021; UITP 2018).

In the interviews, the main external threats mentioned were data formats that are difficult to integrate due to their origin from different data sources. This is time-consuming and labor-intensive, increasing the cost of such systems. Research on this topic supports statements about the highly complex logic of AI algorithms while taking them even further. To create a mechanical intelligence with the proper understanding of humans, limiting factors such as hybridization to improve the performance of soft computing techniques in multi-scenarios such as cities or the current task-specific nature of AI need to be addressed (Abduljabbar et al. 2019; Nikitas et al. 2020; Rathore et al. 2016). As one of the significant limitations of an AI algorithm, (Abduljabbar et al. 2019) have addressed the issue of Artificial Neural Networks (ANN)[21] being a "black box," meaning that the input-output relationship is developed without knowledge of the system's internal computations. This issue further complicates the development of trust in this technology.

(UITP 2018) also highlights the importance of leadership engagement for organizations to drive cultural change and make the necessary changes. This specific point was not mentioned in the interviews. Only increased interest and awareness were confirmed, but leadership's direct responsibility and importance were not explicitly mentioned. Additionally, the potential traffic increase is highlighted in the literature, creating more occupied and unoccupied trips with connected and autonomous vehicles and a mobility-as-a-service model that could still be primarily car-centric (Ho et al., 2018). The fear from the interviews of job loss could be mitigated, as no AI applications have yet been designed to replace workers, according to (UITP 2018). Digital twins had not received much attention in this context, but there was one pilot project for Munich, conducted by a private company (I2.4). However, significant potential has been identified for this use case and could be further exploited (Ketzler et al. 2020).

4.2.4.2. Managerial Implications

To build up smart cities and urban transport that can leverage their citizen data, the citizens need to become active and engaged citizens to generate the necessary data for a smart city. This includes but is not limited to smart homes and the willingness to participate digitally. The AI

[21] A Method of AI

system must understand and satisfy the human user, markets, and society. To do so, it must operate within a responsible, sustainable, and user-centric architectural framework (Nikitas et al. 2020). Since building trust can only be done in small steps, it is necessary to start slowly and demonstrate to relevant stakeholders the benefits of AI applications that society can leverage meaningfully. It is essential to show and convince all stakeholders in the city that the system works to ultimately establish the necessary trust. As this work has shown, this also depends heavily on transparency whenever data is involved. It is challenging to balance people's rights to privacy and overly strict data protection, which can slow progress and innovation (Palomares et al. 2021b; European Parliament 2020). However, it is critical that this opportunity is fully exploited, which means that the appropriate infrastructure is in place, operations are functioning, and users are shown the benefits. Even if the public sector is reluctant and thus slows things down, it is imperative to push innovation and collaborative working. Recognizing the challenge of having the right, cleaned, non-biased, and updated data critical to the successful implementation of AI, the City of Lisbon launched VoxPop (European Parliament 2020). It should lead to more meaningful use of public and private data, with a greater focus on user-centric mobility services and better control of citizens' use of personal data (Urban Innovative Actions 2019)

It is a proven fact that public transport companies must focus on operations. It is, therefore, challenging to try out innovations also because the financial and workforce options in the public sector are usually limited. Innovations and genuinely disruptive changes are the adversaries of highly reliable and resilient systems like public transport. This is the case because dynamic activities resulting from such development usually shake the systems when they try to change them or try something new. This is a constant limiting factor for a public transport provider (I2.1).

Nevertheless, innovation is on the rise in the urban mobility sector, and there has been an increased focus on AI for public transport in both academia and business recently (Nikitas et al. 2020; Jha et al. 2021; Palomares et al. 2021b). The implication is that public transportation companies should not invest too much money in specific applications due to the high level of uncertainty and complexity. Instead, these organizations must address the issue of data availability as a first step. An external provider can develop the technology further. Still, to use these systems in a meaningful way in the future, the data must be available and usable in a suitable format (I2.1, I2.2).

This work has sufficiently demonstrated the dependence of AI on data as the critical aspect to success. To address this complex issue in conjunction with the importance of public transport, a global and unified strategy is needed, more valuable in the long term, and will have a more significant impact. Due to the importance of cities for the sustainable development of our world, the broad deployment of AI systems in this context is of great importance (Jha et al. 2021). Therefore, it should be pushed at the EU level and United Nations. This assumption serves as the basis for the three priorities outlined below. It was exemplarily raised to the overall level of responsible actors in the urban planning sector and can thus provide a broader picture.

4.2.4.3. Identified Priorities for Decision Makers for the Broad Implementation of AI Systems

Importance to focus on data. Being aware of the value of data, (UN Habitat 2020) supported their member states in setting up the necessary conditions for producing and using urban data for policymaking and to provide information on transformative actions. To enable countries to compare better and aggregate data consistently, the UN-Habitat supported their Member States in setting up the necessary infrastructure for the production and use of urban data for policymaking and to inform transformative action. Substantial progress in harmonizing urban data production for better comparability has been made (UN Habitat 2020). Above and beyond, UN-Habitat's City Prosperity Index (CPI), which promotes the strengthening of national institutions towards more integrated solutions, could provide significant assistance in this context. It is a flexible and practical framework built on six context-specific and globally comparable dimensions. The index is calculated using city-level data and measures how cities create and distribute socio-economic benefits and prosperity. With the data collected and the index calculated, cities can support data-driven and informed decision-making processes (UN Habitat 2020). These efforts need to be continually reenergized and their potential fully realized.

Importance to focus on collaboration. Highly complex urban infrastructure and urban mobility require intensive policy coordination when it comes to the implementation of AI systems. Investment decisions must be made in a multidisciplinary and highly informed manner (World Bank 2020). For an effective and trustworthy AI, the EU research programs need to address data exchange, communication networks, and policy on mobility and energy. That is supported, for instance, by the strategy for sustainable and smart mobility put in place by the European Commission in line with the ambition of the European Green Deal and the objectives of the EU's Digital Strategy (European Parliament 2020, 1). Integrating infrastructure (sensors, hardware, software) and data is vital for urban AI business cases in sustainable transport systems (I2.1, I2.2). European data spaces and ecosystems and cross-sectoral interoperability and harmonization will enable the implementation of urban AI. EU-wide support for infrastructure and governance in digitalization is therefore necessary. Therefore, it should be put a focus on the collaborative EU-wide data infrastructure, such as the Franco-German Gaia-X approach, to enable the broad deployment of AI systems (Gaia-X 2021). As with data, these efforts must always be encouraged and further incentivized.

Importance of fostering digital participation (by building trust in AI technology). The opportunity to collect, process, and use data is a sensitive issue and is a decisive factor that can increase or decrease social inequalities. That is why the UN is working vigorously on this issue.

Habitat has identified digital transformation and new technologies like AI as critical aspects of sustainable urban development. In 2020, a flagship program for "people-centered smart cities" was launched. It is in line with the smart cities' aspirations defined by Habitat, which indicates that the opportunities of digitalization and cutting-edge technologies should be harnessed (UN Habitat Flagship Programme 2020). The people-centered flagship program aims to address recent trends in civic technology, geographic information systems, the sharing economy, open data, and digital platforms. All these advances depend on data availability and have changed the way civil society interacts and participates in cities (UN Habitat Flagship Programme 2020). There is excellent potential for fair and ethical citizen participation through building trust in data security and privacy rights, and this potential must be harnessed to enable change.

4.2.5. Conclusion

As with the Covid-19 pandemic, the feeling of society regarding safety and health has changed dramatically. Behavioral trends such as increased road safety awareness, the tendency to work more from home, and the choice for a healthier mobility style are noteworthy. The new development is driven by the accelerated digitalization of offers, increasing market consolidation of private mobility providers, and the increased acceptance of new forms of mobility (Audenhove et al. 2021, 45–46). Considering these current developments and the potential of AI systems in public transport identified in this work, this represents a unique opportunity for the transition to a new mobility era towards greater social, economic, and environmental sustainability with the help of AI.

4.2.6. Limitations and Future Research

The underlying thesis is subject to a multitude of limitations, which will, however, be jointly discussed with the other authors due to remarkable congruence on this matter (see group thesis 6.3). Nevertheless, future research could explore AI in trustworthy, human-centered AI systems for urban transportation. This includes the research on support for needed infrastructure and governance in digitalization. These systems should focus on the transparency aspects of AI to increase citizen engagement. Further research should therefore be multidisciplinary, involving sociologists, technicians, and urban industry experts. In this sense, research on the role of AI in public transport is still in its early stages and should be further explored.

4.3. AI as a Strategic Tool to Contribute to Responsible Consumerism – SDG 12

4.3.1. Introduction

4.3.1.1. Relevance

Scientists call for change as "*overconsumption is driving the climate crisis"* (Frost 2020). As numerous research studies have revealed, unbridled consumption is by far the most propelling determinant of global impact (Mardani et al. 2019; Stern, Gerlagh, and Burke 2017) as it drives the overuse of finite resources and the resulting depletion and damage to nature (Holm et al. 2021). For more than half a century, the constant worldwide increase in prosperity has accelerated resource consumption and pollution far faster than they have been mitigated by technologies (Wiedmann et al. 2020). Increasing consumption worldwide and growing populations are raising concerns about society's sustainability efforts. Thus, in the face of environmental problems, *responsible consumerism* (RC) has become a new research focus (Ramakrishna et al. 2020). Additionally, technologies have had not only a significant societal impact affecting all aspects of individuals' lives and transforming the behavior of consumers but have driven overconsumption and concerning developments (Makridakis 2017). Organizations utilize emerging technologies such as *Artificial Intelligence* (AI) to better understand market trends, consumer preferences and to exactly meet consumer needs (Gene et al. 2019). By leveraging the internet and with the widespread use of AI technology, consumerism has no more limits (Makridakis 2017). Thus, the aim is to take a fresh perspective on AI in the context of RC to gain initial insights by investigating the contribution of AI as a strategic tool to enable and drive a transformation towards *sustainable consumer decisions* (SCD). First, the topic is brought into context by focusing and clarifying the terminology and assigning meaning to the role of AI-based on present literature. Due to the great dynamics of emerging technologies such as AI, the complexity of RC, and thus the lack of comprehensive theory within the research area (Di Vaio et al. 2020), qualitative research by means of expert interviews build the foundation of the present work (Saunders, Lewis, and Thornhill 2009b). Thereby, this study aims to gain first insights into the context or the application *potentials of AI to contribute to the Sustainable Development Goal 12 (SDG 12)*[22]. Because SDG 12 is multidimensional and contains many diverse driving factors, an attempt to narrow down the scope has been made by focusing on an individual's consumption decisions impacting the *material footprint*[23] and in turn, *reduce waste*[24] (United Nations 2021). The work is directed to practitioners and researchers in retail and consumer goods industry. To open this crucial field for individuals with lower levels of prior technical knowledge, an explorative research approach has been taken to investigate: *What are strengths, weaknesses, opportunities, and threats of AI as a strategic tool to contribute to responsible consumerism by supporting SCDs?*

4.3.1.2. Scope

Consumerism is "*the buying and using of goods and services*" (Oxford University Press 2021). The roots of consumerism can be viewed from different perspectives. Keynesian economics regards consumers as production drivers, whereas environmental sociology takes a supply-dominated stand (Lange 2018). While keeping in mind that multiple impactors play a role, the present work focuses on the impact resulting from consumer decisions. Consumer purchase decisions are the starting point to numerous transactions and activities along the supply chain

[22] The UN committed to 17 goals dedicated to stopping poverty, guaranteeing prosperity, and protecting the plant by 2018 - the Sustainable Development Goals (SDG). Amongst them is SDG 12, which addresses ensuring sustainable consumption and production to respect the biophysical limits and decouple human well-being and economic growth from resource use & environmental impacts.(United Nations 2021)
[23] Indicator 12.2 of SDG Target 12 (United Nations 2021)
[24]SDG target 12.5: Reduce waste generation through prevention, reduction, recycling, and reuse (United Nations 2021)

network. This perspective leads to the attribution of environmental impacts to individual's consumption behavior (Wiedmann et al. 2020). Therefore, fostering and managing RC is one of the driving forces to bring about development towards the achievement of SDG 12 (United Nations 2020). To date, emerging technologies such as AI have brought significant enhancements to each person's daily life and purchase and consumption processes. Consumers can decide and purchase anywhere at any time with maximum convenience and immediacy. (Krishnadas 2021; Sun et al. 2019; Yasav 2015) Thus, the progress brought by technologies to the way individuals make purchase decisions and consume is both a curse and a blessing. This is evident in the fact that the utilized resources to satisfy society's consumerism have tripled since 1970, and by 2050 an extra planet will be needed (McGinty 2021). This concerning development is also reflected in the alarming continuously increasing *material footprint* and *the amount of generated waste*[25]. Both are significant indicators of the pressure that lies on the environment to satisfy people's needs (United Nations 2021). Confirming these intuitions, the vast majority of researchers agree that technological change and individual consumerism are among the most important drivers of global impact (Haberl et al. 2020). Especially, high-income countries generate the most significant *material footprint* per capita (United Nations 2021), and 20% of all people consume 80% of the planet's resources (Acciona 2021.). Hence, excessive consumerism is mainly attributable to high-income countries (Agrawal and Gupta 2018). This emphasizes the central role of affluent consumers, who exert great pressure on the environment and points to the responsibility of individuals to pursue RC for sustainable change (Wiedmann et al. 2020). Therefore, this study focuses on consumer decisions by individuals' living in high-income countries. *RC* is, in this context, understood as consuming in a way that accounts for the foundations of sustainable development considering *economic*, *social*, and *environmental* impacts (Agrawal and Gupta 2018). Practicing RC can take various forms, such as purchasing

[25] The material footprint per capita describes the average "*amount of raw materials extracted to meet final consumption demands*"; SDG 12, Indicator 12.2.1 (United Nations 2021).

products with lower or positive environmental impacts (e.g., locally sourced), and also recognizing effects at different stages of the product life cycle (economiecirculaire.org 2021.; Webb, Mohr, and Harris 2008; Youmatter 2019). Increasing concerns about the impact of consumption on the environment require considering approaches that promote RC (United Nations 2021). First, consumers decisions can be transformed by fostering the consumption of, "*greener*" products (Gilg, Barr, and Ford 2005) "*which improves environmental impact or reduces environmental ,[…], damage throughout its entire life cycle*" (Durif et al. 2010)[26]. Second overall consumption can be reduced through prevention, reuse, and recycling (Papaoikonomou 2013). Moreover, building on the understanding of Palomares et al. 2021 throughout the work AI is understood as *AI systems* (AIS),[27] which can appear in three contexts, i.e., machine learning, computer vision, and autonomous vehicles. To gain value-adding insights on the potentials of AIS, positively impacting consumers purchasing decisions, it is necessary to investigate the problem by zooming in on the process of consumer decision: the *need recognition*, the *information search*, the *alternative*, and *purchase and consume of economic goods* (Darley, Blankson, and Luethge 2010). For an illustration of the investigated context, refer to Appendix 8a.

4.3.2. Theory and Related Work

The following section theoretically approaches AIS as a strategic tool to support SCDs. Without de-emphasizing the vital role of individuals focusing on transforming their consumption behavior, much of the potential to systematically address the problem seems to lie in innovative AI solutions that support individuals on their way towards RC. As mentioned, AIS are ubiquitous and hold enormous potential to revolutionize the way we live (Goralski and Tan 2020) by reshaping people's daily practices (Taddeo and Floridi 2018). AIS have the capacity

[26] In the context of this work referred to the *quality* of consumer decisions
[27] For the full definition of AI please consult section 2.1 in the group thesis

to improve the entire consumer experience (Gene et al. 2019). Nevertheless, the prerequisites for SCDs are raising awareness among consumers of daily consumption externalities (Collins et al. 2018), availability of information, and sufficient knowledge of the environmental impact (Amel, Manning, and Scott 2009). Collins et al., (2018) found evidence that awareness, improved knowledge, and thus the establishment of a direct reference of the impact of environmentally unfriendly resource consumption can positively influence the decision process. Research investigated the role of AIS in the context of environmental decision support systems claiming that "*an effective protection of our environment is largely dependent on the quality of the available information used to make an appropriate decision*" (Cortès et al. 2000, p.1). Due to the difficulty of gaining transparency through the vast amount of information (Cortès et al. 2000) consumers often face the challenge of identifying so-called green products with reduced environmental impact that prevents a behavioral change (Pickett-Baker and Ozaki 2008). Also, the lack of immediacy and the time it takes to see through consumption choices hinder SDCs (Tussyadiah and Miller 2019). The barriers consumers face offer the opportunity to support consumers in improving their purchase decision process towards greater responsibility (Tussyadiah and Miller 2019). Knowledge-based AIS entail enhancing basic monitoring and data analysis to provide more holistic environmental impact assessment for certain actions. The ever-increasing ease of use of AI-powered decision support systems can play a critical role in supporting less time and energy-consuming decisions. (Cortès et al. 2000) An example is the use of augmented reality technology as a complementary tool, where the impact of the consumed goods could be visualized and further raise awareness (Palomares et al. 2021c). Another string of research also recognizes the potential of *Green Information Systems* that could raise awareness on the impact by evaluating and rating sustainability levels. Multiple factors and consumption patterns could be considered to forecast sustainability data using predictive models. Sophisticated machine learning-based information systems could be integrated into various applications, for example, social media or streaming applications, to become part of daily use. Applications could utilize existing data to assess the sustainability level of their users' and their consumption behavior. Based on this information, green content could be promoted. (Moro and Holzer 2020) In the exemplary case of food retail, AIS supported by sensor-driven monitoring combined with big data analysis could provide the ability to aggregate and process data like supermarket consumption on a geographic and demographic basis or movement patterns and consumption variations over time (Euroconsumers 2020). Combined with augmented reality, the gained insights on the consumption impact can be visualized to create awareness about consumption patterns (Palomares et al. 2021c). The use of smart product labels for food retail is an example of AI-enabled problem resolution to increase transparency. Not only can ingredients and production data be presented (Euroconsumers 2020), but real-time environmental footprint details could also be utilized to provide consumers with key information on the product`s environmental impact (Pickett-Baker and Ozaki 2008). Combined with analytical capabilities of AI and technologies like blockchain, companies in sectors with long supply chains, such as fashion, could track all influencing factors, making environmental impacts visible to provide transparency to consumers (Euroconsumers 2020). Another potential use case for AIS is the automatization of design processes enabling consumers to actively participate in product design to exactly meet their needs (Gene et al. 2019). Such personalized experiences can increase the chances of reducing overconsumption by rising product satisfaction (The Independent 2020). Further, the emergence of new business models such as peer-to-peer websites for the rental or resale of clothing (Euroconsumers 2020) opens new avenues for AI as decision support systems (Gene et al. 2019). Options could be presented based on taste, location, and budget, making new consumption approaches more attractive (Euroconsumers 2020). By incorporating AI into automation machines, they can learn and make real-time personalized recommendations, independently evaluate options, and thus encourage behavior (Gene et al. 2019). The capabilities of AI, such as speech recognition and natural language processing through solution approaches like virtual assistants, can simplify consumer decisions (Z. Wang et al. 2019). However, research also recognizes barriers to harnessing the capabilities of AIS. Consumers' attitudes toward AI conditionally influence the effectiveness of AI to evoke positive behavior change (Tussyadiah and Miller 2019). The perception in society that AI manipulates one`s decisions (Euroconsumers 2020), leading to privacy concerns, and thus consumer distrust of the technology (Goralski and Tan 2020). AIS rely on the behavioral data that is provided to them. Hence, it is imperative that companies adhere to data privacy regulations and regain consumers` trust (Euroconsumers 2020). Further, the implementation of AIS entails high integration costs and are often accompanied by economic losses, which organizations may initially resist (Palomares et al. 2021c). AIS are very energy-intensive, leading to the positive aspects being overshadowed by the external environmental effects (Euroconsumers 2020). The unfolding of AIS capabilities to support SCD are impacted by the advancements in technology and the steadily increasing volume and variety of data (Vinuesa et al. 2020b) which further open the opportunity to quantify and visualize the economy and consumption (Z. Wang et al. 2019). Arising market trends such as conscious consumerism (The Independent 2020) and the next generation of consumers, generation z, who appreciate technology at any point where it can enhance their consumption experience (IBM Corporation 2018), are door openers to the utilization of AIS. However, the remaining question is how the power of AI can be further applied as a force of good (Taddeo and Floridi 2018). To assess this fundamental question in the context of SCD, qualitative research was conducted based on practical project examples and expert insights.

4.3.3. Results: Insights from Expert Interviews

The goal of the work is to provide initial insights into AIS as strategic tool to support SCD. Therefore an explorative approach, utilizing qualitative research based on semi-structured expert interviews (Saunders, Lewis, and Thornhill 2009b) was taken to investigate the topic. The interviews were recorded, transcribed, and analyzed by applying a three-step coding process (Strauss and Corbin 2008) (Appendix 8b). The coded insights build the basis for the subsequent presentation of the results, classified further as follows. As explained, this work regards AI as a strategic tool for organizations. Considering the intended research goal and addressed target audience, it seemed most appropriate to take a perspective from strategic management. A SWOT analysis further guided identifying and categorizing *strengths*, *weaknesses*, *opportunities*, and *threats* (Mintzberg 1994) of integrating AI as a strategic tool to support SCD[28]. For the complete analysis of the results and SWOT please refer to Appendix 8c.

4.3.3.1. Presenting Experts and Practical Implementation Examples

In order to remain within this work's scope, it was necessary to focus on a carefully chosen set of implementation examples and insights from a selection of subject matter experts and industry-relevant companies who shared experience and knowledge. The experts were purposively selected regarding their knowledge in the field of AI, consumer goods industry expertise, and their availability. For an overview of the interviewed experts and a description of their companies as practical implementation examples, consider Appendix 3.

4.3.3.2.Assessment of AI as a Strategic Tool to Support Sustainable Consumer Decisions

4.3.3.2.1. Strengths

The analysis revealed that AIS entail the capabilities to *minimize the barriers to SCDs*. The barriers can be summarized into the following categories: *information gap*, *knowledge gap*, and *attitude-behavior gap* that consumers face. Most experts pointed out one strength of AIS which can be summarized under the term *efficiency and effectiveness in the data analysis* and *collection* (I3.2, I3.3, I3.4, I3.5). It was expressed that AIS entail strong capabilities in image

[28] A comprehensive explanation of the research methodology can be accessed in section 3 Methodology in the group thesis

analysis (I3.2, I3.5), pattern identification (I3.4), and large-scale label reading (I3.2). AIS can easily interrelate and assign meaning to multiple internal and external factors (I3.2). It is also highlighted that historical internal product and external market data (I3.5) and all human interactions across time and location can be placed into a bigger picture (I3.4). On this basis, market trends can be predicted, and businesses can minimize surplus production (I3.4). In turn, by reducing data quantity to a simple and understandable level, meaning can be easily assigned to opaque product information. (I3.2, I3.3).

Experts indicated that the prerequisite for providing consumers with the needed support is *improving business understanding of the green consumer's needs* (I3.1, I3.3). This can be fostered by AIS (I3.3, I3.1), as they are highly efficient in analyzing consumer feedback, strong in text mining, natural language processing (I3.3), and with this data can predict consumer behavior (I3.1). Hence, businesses can be supported with identifying and predicting when and how consumers need information and where to interact with them to alternate their behavior (I3.1, I3.4, I3.5). All experts concurred that by raising awareness, AIS can minimize the *knowledge gap* of the existence of sustainable product alternatives and of the consumer's impact. AIS can track and forecast behavior, thus visualize consumers' environmental impact (I3.5) and future impact (I3.1, I3.4). *Information gap* is referred to as the lack of sufficient product information regarding materials, processes, and origin along the supply chain. This raises the insight that AIS can support in increasing the transparency of the environmental impact of products (I3.2). Further, it was described that this can be achieved by creating a digital supply chain network that provides real-time traceability and visibility of product environmental impacts at every step of the process and for all sustainability metrics (I3.5). Additionally, it was pointed out that supported by AIS material and chemical carbon footprint assessments can be used to predict future environmental impact (I3.2). This opens the possibility of providing environmental impact transparency needed to *decode the product information* for businesses and consumers (I3.3, I3.4, I3.5). The decoding of products' environmental impact is regarded as the key to reducing consumers' *information gap.* The convenience and simplicity of information presentation are increased (I3.4), information search processes optimized (I3.2, I3.4), and greenwashing attempts can be made visible (I3.3). Two solution examples that raise transparency are providing comprehensive product information directly on the product via a QR code (I3.4) and presenting sustainability ratings for products (I3.2). *Strong advisory capability* becomes apparent when considering AI in the form of decision support systems embedded into end-user applications (I3.1, I3.3). These can help increase product satisfaction and support consumers by, e.g., recommending the perfect clothing size and increasing purchase decision certainty. This can minimize consumed quantity, returns, and multi-size orders, thus reducing waste and Co2 emissions from return processing (I3.1). By minimizing the *information* and *knowledge gap,* consumers can be supported in following through with their intended behavior; thus, the *attitude-behavior gap* can be minimized. Therein lies the most crucial insight highlighted by all experts. The attitude-behavior gap describes that many people intend to follow SCD but do not put their intention into action due to the costs associated with the time and energy it would take them to change their behavior (I3.1, I3.2, I3.3, I3.4, I3.5). An approach to reducing the gap is by increasing the convenience of SCD through highly effective recommendation system. These can offer concrete alternatives to reduce impact (I3.1), support choosing the environmentally friendly product, and provide the right information at the point of need (I3.1, I3.2, I3.3).

4.3.3.2.2. Weaknesses

The subsequent section outlines the internal deficiencies of AIS in the context of SCD. Most notably, experts regarded the shortcomings summarized under the category of *resource intensity of AI integration* as particularly critical. *Resource intensity of AI integration* is regarded as all internal capacities that must be raised to develop and integrate AIS successfully. In this context, one factor experts agreed on, that the incredibly high costs that AIS integration entail work against the intended outcome (I3.2, I3.4, I3.5). For one thing, the initial monetary development and integration costs are extremely high. Then again, costs related to the great workforce capacity needed and the time-intensive training and continuous maintenance are recognized as major internal road blockers (I3.4). It was also pointed out that the heavy reliance on highly skilled labor, which is often not available, and the lack of technological understanding in the workforce are hindering factors (I3.1, I3.5). In addition, one expert raised concerns regarding the *high complexity of gaining all-encompassing organizational knowledge* and finding the right starting point internally for implementing AI (I3.4). It must be noted that the comprehensive knowledge required about consumers can be seen simultaneously as a strength and a weakness. As mentioned earlier, AIS can help companies understand their consumers. However, in order to identify the right interaction point, this understanding is a prerequisite. If that knowledge is not yet comprehensively available, it represents an adversary (I3.3, I3.1).

4.3.3.2.3. Opportunities

The factors expressed by the experts that pave the way and accelerate the implementation of AIS and unleash their full potential in terms of SCDs are grouped under the category *opportunities*. First, the societal opportunities resulting from *unmet consumer needs* are considered. These go hand in hand with the previously identified strengths, thus finding even better starting points to be fully developed. Experts recognized the pressure from consumers due to the lack of sufficient support in alternating their behavior as a business opportunity for change (I3.3, I3.4). Even though consumers may have the right attitude, inconvenience in the form of opacity and complexity of product information, lack of adequate alternatives, and laborious and time-consuming information search hinder the realization of their action (I3.3, I3.4). These represent promising business opportunities for implementing AIS to meet the consumers` needs by making the greener choice the easiest choice (I3.3). Moreover, the *shift in* *consumers mindset* towards sustainability (I3.2, I3.4) and a greener lifestyle (I3.3), particularly by generation Z (I3.2; I3.5) and the increasing understanding of the vital role of AI as a technology that encompasses the capabilities to evoke positive change and meet the needs are regarded as a major driver (I3.2, I3.4). In addition, experts expressed the relevance of opportunities resulting from economic factors such as *increasing environmental responsibility among businesses* due to consumers and institutional pressure (I3.2, I3.4) and triggers from industry leaders acting as role models to drive sustainability change (I3.5). Also, the potentials for positive change in high-income markets due to their immense material footprint, technological readiness (I3.1), and *market trends* such as circular economy are recognized as driver (I3.3). One expert particularly highlighted the opportunities resulting from *businesses` recognizing the economic advantages*. Businesses can increase product information efficiency (I3.5), improve demand prediction and reduce production surplus, refocus their labor resources to achieve cost reductions, and minimize environmental impact. By recognizing these advantages further paves the way for AIS (I3.5). Regarding the technological level, mainly opportunities resulting from *technology improvements* are referred to: Blockchain, which encourages collaboration and creation of a trusted, secure, and transparent ecosystem of people and businesses (I3.4). Machine learning can solve data scarcity (I3.1). However, the ever-increasing *data availability* (I3.1, I3.2, I3.3) driven by digitalization (I3.3) and the rising importance of digital commerce (I3.1) is recognized as the strongest lever. Lastly, the increasing importance of AI as an area of *great interest in research* and the consumer goods industry (I3.2) leverage the recognition of AIS as tool to support SCD.

4.3.3.2.4. Threats

The following section focuses on illustrating the concerns raised by experts regarding hindering external factors categorized as *threats.* Experts expressed concerns that one of the major risks to the intended implementation of AI is organizations' *instrumentalization of AI capabilities* to further drive environmentally harmful consumption. Especially, it was articulated that the risk is caused by the potential misusage of deep data-driven consumer understanding (I3.1). For example, by creating digital replicates of consumers, organizations are enabled to injection the digital channels to alternate consumers' decisions (I 3.5). These capabilities have the power to hyper-personalized advertising, perfect recommendations which minimize a major consumption blocker, induce convenience, and by thus driving unbridled consumption (I3.1, I3.3). This illustrates the challenge of the bilateral effect of AIS on consumerism and the environment (I3.3). Not only regarding the instrumentalization of the consumers but also in respect to the *negative environmental externalities* resulting from the high electrical energy consumption for training of AI models, which may surpass the positive effects (I3.3). Experts recognized the *lack of readiness of businesses and consumers* as a significant road blocker. The majority revealed that there is still a lack of understanding from businesses side about the potential of AI to drive sustainable change (I3.3, I3.4, I3.5). One expert highlighted the lack of understanding from the consumers' side for the need for change (I3.4). Most of the experts agreed that the lack of readiness may lead to *rejection from the business side*. Businesses' resistance appears due to: high dependency on shareholder approval, who might not recognize environmental ambitions as integral part of corporate performance (I3.5), uncertainty and risk of failure when training AI models (I3.3), fear of change management, business exposure, and giving up control (I3.4). Additionally, businesses are prevented by the perceived pressure from society to satisfy consumers, which hinders them in progressing on change, unfolding the full potential of AI (I3.4). Most experts remarked that a lack of readiness might also lead to *rejection from consumers.* This possible rejection was attributed to data privacy concerns (I3.1, I3.3, I3.4), associated mistrust from consumers (I3.1), and the perception of AI as a threat to society when used as a replacement to human labor (I3.4, I3.5). Besides this, lack of *data availability* (I3.2), the fragmentation of digital platforms, and the diversity of standards (I3.4, I3.5) were regarded as hindering. Lastly, a high dependency on regulatory requirements, uncertainty and fragmentation of the legal environment across countries, is regarded as major threat (I3.1, I3.3). In summary, experts agreed that to mitigate these threat prerequisites are building trust, ensuring data privacy protection, and altering the mindset among consumers and businesses by raising awareness of the urgent need for change and the potentials of AIS to support SCD.

4.3.4. Discussion

This chapter recaps the insights in light of previous research and addresses implications for the practical realization of the findings, the limitations, and provides arrays for future research.

4.3.4.1. Theoretical Contribution

The objective of this work is to gain insights into the strength, weaknesses, opportunities, and threats of AI to contribute to SDG 12. Hence, the dynamics and complexity of the research area open the possibility of providing an additional perspective and contributing to the current literature by presenting expert insights regarding AI as a strategic tool to support SCDs. Up to the present, the available research dealing with this specific area is scattered. Most research is centered around consumer behavior and the challenges regarding SCDs, added by whitepapers that theorize potential future scenarios and company reports capturing market trends. However, first-hand strategic and practical assessments are missing. Therefore, the insights from expert interviews create an initial subjective snapshot but also provide valuable insights into practical applicability. Research has shown that AI can enhance the consumer experience (Gene et al. 2019). However, experts highlighted that until today, the use of AI in the retail and consumer goods sector for the pursued goal of positively alternating consumer decisions is little to no common (I3.1, I3.3, I3.5). In line with research, expert interviews showed that the roots and barriers of the problem lie with the challenges consumers face and the complexity of SCD. To achieve the intended impact of SCD, AIS can function as a supportive tool to reduce the barriers (I3.1, I3.2, I3.3, I3.4., I3.5). First, raising awareness of the environmental impact could influence consumers' decisions (Collins et al. 2018). Secondly, the needed knowledge to identify alternatives is unavailable (Amel, Manning, and Scott 2009). Still, even though there is awareness consumers don't follow through with their intention due to complexity and inconvenience of SCD (Pickett-Baker and Ozaki 2008; Tussyadiah and Miller 2019). Experts' insights also illustrated three gaps: *information*, *knowledge*, and *attitude-behavior* as natural starting points for the implementation of AIS to elicit positive change (I3.1, I3.2, I3.3, I3.4, I3.5). However, it is noted that regarding awareness key is not only consumers' awareness of their impact but the awareness of product alternatives and lack of convenient and immediate information (I3.1; I3.4; I3.5). Research focuses on AI capabilities to perform holistic environmental impact assessment (Cortès et al. 2000) and consumption sustainability level analysis (Moro and Holzer 2020) of specific actions as problem solutions to facilitate SCDs. All necessary capabilities which lead to a holistic environmental impact assessment are also reflected in the experts' insights set out under *efficiency and effectiveness in the data analysis* and *collection* (I3.2, I3.4, I3.5). Besides tracking, forecasting, and visualizing consumers' environmental impact (I3.5), different approaches emerged to utilize the gained information. Experts ascribe great importance to utilizing identified AIS strengths to *decode products environmental impact* (I3.2). The recognized issue is that companies do not have the necessary transparency needed to assess the products' environmental impact. Hence, not only can companies be enabled to gain a comprehensive understanding of their products' impact throughout the entire supply chain, but the gained transparency can then be made visual to consumers (I3.2, I3.4, I3.5). Research reflects this intuition, pointing out that awareness of consumption sustainability levels can minimize the *information gap* (Moro and Holzer 2020). Besides this, expert insights revealed that the prerequisite for guiding consumers is improving companies' understanding of green consumers' needs (I3.3, I3.1, I3.3). Research leverages advisory systems (Euroconsumers 2020) to personalize recommendations, evaluate options autonomously, and drive behaviors (Gene et al. 2019; Z. Wang et al. 2019). This postulation can also be derived from expert insights highlighting the strong advisory capabilities of AI in the form of decision support systems: they can increase purchase certainty, enhance product satisfaction, and help consumers choose an alternative with lower environmental impact (I3.1, I3.3). Current research and the insights provided by the experts show that AI, as a strategic tool, can reduce complexity, increase transparency, and enhance persuasion, which minimizes the identified gaps and thus can alter consumer decisions. However, the experts' practical insights reveal an additional perspective, highlighting the importance of deciphering the environmental impact of products and the prerequisite for companies to understand consumers to provide the right level of support in the form of information at the time and place the consumer needs it. The focus in research lies in the assessment of the gaps and opportunities where consumers could be supported. However, what concerns experts more are the reasons why, until today, the strengths of AIS regarding the support of consumers in making sustainable decisions are only exploited to a small extent. The answer to these questions became clearer through the analysis of the *weaknesses*. In particular, the *resource intensity of AI integration* in terms of high monetary costs (I3.2, I3.4, I3.5), required workforce capacity (I3.4), lack of adequate technical expertise (I3.1, I3.5), extensiveness of business econometric analysis (I3.4), and opaqueness of the right starting point due to the complexity of consumer behavior (I3.3, I3.1) represent internal obstacles to businesses. The expert insights highlighted more the promising external developments that are paving the way for AIS than could be found in the research. However, it is essential to reflect that the experts come from the business world. Since most of them are founders or CEOs, they firmly believe in the future of AI as a force for good. Of great importance appears to be the shift in consciousness toward greener lifestyles (I3.2; I3.5) and openness to technology, particularly among Generation Z (IBM Corporation 2018), which can be retrieved in the unmet consumers' needs and the pressure on businesses to provide support to make the green choice the easiest one (I3.2, I3.3, I3.4). This development is also reinforced by the shift in mindset amongst business insiders (I3.2, I3.4), which recognizes the economic potential (I3.5) and the opportunity to leverage market trends. The opportunities that current market trends such as circular economy (I3.3), conscious consumerism (The Independent 2020), and the emergence of new business models (Gene et al. 2019; Euroconsumers 2020) offer are both recognized in research as well as through expert assessments. Besides improvements in peripheral technology, the ever-increasing amount of available data (Wang et al. 2019, I3.1, I3.2, I3.3) seems to be among the strongest driver. Data privacy concerns are to date a cucial topic and drive mistrust (Goralski and Tan 2020), fear of control loss, and resistance among consumers (I3.1, I3.3, I3.4). Besides the mentioned obvious two barriers, experts further point to the concerns among businesses and shareholders driven by success uncertainty, change management needs, exposure to the outside world, and risk of loss of control (I3.3, I3.4). Besides the apparent sustainable mindset shift of consumers, a limiting factor for businesses seem to be the perceived pressure from consumers and society to satisfy their consumption (I3.4). Probably the most interesting aspect that experts raised is the concern connected to the instrumentalization of AI. Besides the identified practical examples, it seems like the gained advantages through deep-data-driven consumer understanding and the potential to alternate decisions is instrumentalized by organizations to drive environmentally harmful consumption (I3.1, I3.3, I 3.5). Finally, training AI models does not come without environmental costs in terms of the high energy intensity (I3.3). The outcome of this work should less be regarded as a revise of the existing literature. Instead, it serves as a stimulus for researchers and practitioners new to the field to recognize the power of a strategic framework from management, like the SWOT framework, to provide a new perspective on AI as a strategic tool in the sustainability context and to further uncover where and why it would make sense to consider implementing AIS to support SCD.

4.3.4.2. Managerial Implications

The potential of AIS to transform people's lives and impact the way people consume has long been recognized (Gene et al. 2019). However, this work approached the potentials of AI as a strategic tool to contribute to RC, which entails value-adding insights for managers in the consumer goods and retail industry. This study aims to help raise awareness of AI as a strategic tool to change the way people consume for the better and shows organizations possibilities to elaborate, evaluate, and achieve this in their context.[29] Based on the expert insights, many practical implications have arisen. Within the scope of this study, two practical implications can be highlighted which relate to the interviewed companies. First, data privacy concerns are highlighted as the primary driver of consumers' mistrust and rejection of AIS as supportive tool. In the case of *prisize.ai* this should be recognized as an opportunity to bring the consumers on board to optimize their purchasing decision. *Prisize.ai* could visualize the consumers' data journey so that they are aware of and in control of their data to reduce the adoption barrier. Another exploratory idea would be integrating Finch, the product rating application, in smart-store solutions used by the food retail sector (e.g., *Amazon Go*), which allow consumers to scan products via QR codes and self-checkout. By providing relevant information in the application about the environmental footprint of products, awareness could be raised in an easily consumable way and minimize the gap between attitude and behavior.

4.3.4.3. Limitation & Future Research

The imposed limitations are primarily attributable to the underlying research method, which entails shortcomings that should be carefully considered. As the selected research method is consistent across all parts, a joint elaboration on the limitation is most appropriate.[30] The specific research area of this study opens additional arrays for further research in the field, which

[29] Further explanation to the general approach can be accessed in section 3 Methodology in the group thesis
[30] A comprehensive explanation of the imposed limitation can be accessed in section 6.3 in the group thesis

are briefly addressed here. Due to the novelty and great dynamic within this field, further research is needed to quantitively investigate SCD processes based on a large and diverse population to support businesses in uncovering the right starting point for AI-enabled support regarding cultural and demographic differences. Additional research perspectives are needed to understand the exact technological shortcomings of training and implementing AI as strategic tool to support consumers and to not only provide first insights to individuals who are new to the field but to provide fundamental knowledge to technological experts. On the one hand, research should be dedicated to investigating tools that can comprehensively calculate the environmental net benefit of AI-induced support tools in the specific case of retail and consumer goods industry. On the other hand, research is urgently needed that uncovers opportunities to further incentivize businesses to implement AI for the right cause of supporting SCDs.

4.3.5. Conclusion

This work aim is to gain initial insights into the potential of AI as a strategic tool to contribute to RC and thus come closer to achieving SDG 12. Expert interviews were used to identify and assess AIS's strengths, weaknesses, opportunities, and threats to supporting SCD to positively impact individuals' material footprint. The results revealed that AIS bear great potentials as a strategic tool for companies in the retail and consumer goods sector to sustainably change the way people make consumption decisions. The scope of this study, as well as the underlying methodology of this work, only allowed to touch the surface of the topic and does not allow for generalizable assumptions. However, the uncovered potentials of AI, the identified internal and external influencing factors, and the demonstrated added value of analyzing AI in this context using a framework from strategic management such as SWOT should be recognized as the main contribution of the work. This provides a new practical perspective on AI and relates to the question of why it may be of great value and assistance to use AI as a strategic tool to support consumers in their sustainability efforts. As laid out in this study, AI is a technology that is still evolving. The application of AI in the highly dynamic consumer goods industry is of great strategic and environmental importance but goes with a significant degree in complexity. Therefore, it is crucial to recognize and further explore the potential of AIS to support SCD and contribute to the achievement of sustainable development.

4.4. AI as a Strategic Tool to Reduce Marine Pollution – SDG 14

4.4.1. Introduction – Context of Using Artificial Intelligence to Reduce Marine Litter

4.4.1.1. Motivation and Relevance

Our oceans are a vital, yet highly vulnerable ecosystem. Polluting such an essential system may cause it to imbalance and eventually collapse. Ocean pollution in form of waste is called *Marine Debris* or also *Marine Litter (ML)*, which is defined as any form of "persistent, manufactured or processed solid material discarded, disposed of or abandoned in the marine and coastal environment." (UNEP 2005, 3). It can originate from a plethora of sources including land-based and sea-based human activities, such as litter washed away from landfills or abandoned or lost fishing gear (UNEP 2005). It is reported that 60 to 80% of marine debris is made of plastic (Barnes et al. 2009; Martínez-Vicente et al. 2019) and, somewhat between 4.8 million and 12.7 million metric tons of plastic have entered the ocean in 2010 alone (Jambeck et al. 2015). Plastic debris can be categorized by its size, with categories varying from scholar to scholar (Cole et al. 2011). This work is consistent with heavily cited research and differentiates macroplastic (>5mm) and micro-plastics (<5mm) (Barnes et al. 2009; P. J. Kershaw and Rochman 2015). Litter can be found in different parts of the water column: While free-floating litter is found on the water surface, submerged plastic litter is found below the surface or even covering the seafloor. The massive amount of ML has vast implications for our oceans: It destroys coral reefs and mangroves and poses marine wildlife to the danger of entanglement and indigestion – consequently threatening the survival of various plant and animal species (Murray and Cowie 2011; P. Kershaw 2016; van Franeker et al. 2011). With macroplastic decomposing into microplastics, synthetic materials are ingested by animals more easily and toxic chemicals and pathogens end up in the food chain of animals and humans – a problem for which the consequences are yet to be explored (OSPAR Commission 2017; Teuten et al. 2009; P. Kershaw 2016; Werner et al. 2016). Moreover, ML threatens the complex system of different organisms such as algae and seagrass, therefore affecting the earth's role as the largest carbon-dioxide absorber and source of oxygen (Shen et al. 2020; Sjollema et al. 2016). To account for the importance of preserving our oceans, the UN set up SDG 14 (Life Below Water), including its Target 14.1 that aims to reduce ML of all kinds (UN General Assembly 2015). The purpose of this work is to investigate how Artificial Intelligence can contribute to this specific SDG target.

4.4.1.2. Scope of this work

Briefly touching upon the detrimental effects of ML, especially plastics, signals how evitable it is to ensure a reduction of ML to preserve the habitability of the planet. As macro-litter being regarded as one of the major sources of microplastics (OSPAR Commission 2017), this work focuses on the reduction of marine macro-litter[31]. The importance of ML prevention and recycling is widely recognized, however, due to the present accumulation of existing ML, this work will center around the in-situ management of ML and investigate opportunities to reverse the damage that already exists. The extensive work done by Bellou et al. (2021) presents several innovative solutions that can help to tackle the ML problem. Their framework of the PMC functions[32] is used here to clearly define the scope of this work (see Figure 1): Focusing on the in-situ management of ML, the prevention function and modeling as a sub-activity of monitoring proposed by the original authors are excluded, as both aspects are not considered to be happening at site (in-situ). Thus, the potential of AI will be analyzed in 1) the monitoring of

[31] Therefore, the term *macro-litter* is hereafter equated with *marine litter (ML)*, *debris,* or *pollution*
[32] The three PMC functions presented in their work are: 1) Prevention, 2) Monitoring and 3) Collection

ML, including its sub-forms detection (recognizing and locating ML) and identification (differentiating types of ML) and 2) the collection of ML.

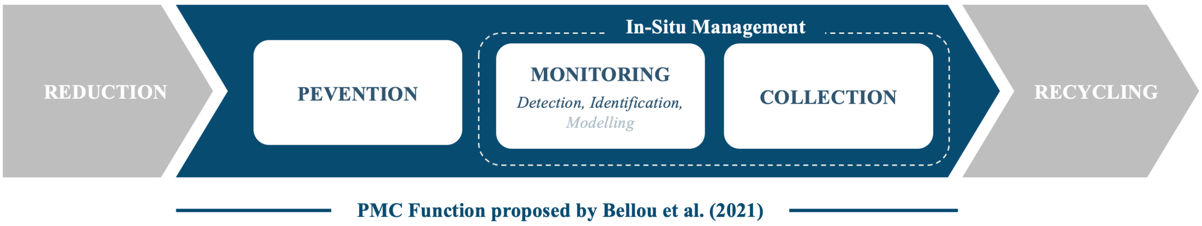


Figure 1 Delineation of the scope based on a modified version of the PMC functions proposed by Bellou et al (2021)

4.4.1.3.Related Work: AI Systems in the In-Situ Management Marine Litter

4.4.1.3.1. Applications of AI in the context of Marine Litter Management

A plethora of buzzwords is used in connection to AI, with robotics, machine learning, natural language processing, and computer vision to just name a few. The following aims to reduce the complexity so that the reader understands how AI can be used in the context of ML. Following Palomares et al. (2021a) AI is understood as a software system (henceforth this system is referred to as *AI system* of *AIS*), that can *percept* its environment by acquiring data about it, processes this information, and *derives a suitable course of action* to achieve the desired end goal[33]. Thus, in this work's context, an AIS collects data about its environment (e.g., flora, fauna, litter), uses algorithms to process this data, and derives a course of action to properly monitor or collect the ML. This paper therefore examines three subtypes of AI that are predominant in ML management: 1) Machine Learning and its subform Deep Learning, 2) Computer Vision (CV), and 3) Robotics[34] (for a definition of each see Appendix 9a). Depending on the specific solution, the subforms are present to varying degrees. The following will outline research that investigated AI within the monitoring and collection of ML.

[33] For a full definition of AI, the reader is referred to Section 2.1 (Definition of AI) of the Group Thesis
[34] It is important to note that these 3 sub forms are not mutually exclusive, but rather can be part of another. For example, deep learning algorithms can be a crucial aspect of computer vision.

4.4.1.3.2. Research on AI systems in Marine Litter Monitoring

Even though researchers such as Thomas Mace (2012) already provided a comprehensive overview of technologies that can be used to monitor ML, the body of research around AI in ML monitoring is relatively new. Yet, the studies are rich in variety, as different technologies and perspectives can be used for the in-situ monitoring [35] of litter. UAVs (unmanned aerial vehicles), ASVs (autonomous surface vessels) and AUVs (autonomous underwater vehicles) have been used in combination with onboard cameras, sonars, and other sensors to monitor litter from the air, on sea-level or below water. Computer vision and deep learning algorithms were shown to be effective forms of AI to detect floating macro litter from onboard cameras (e.g. Kylili et al. 2019), UAVs (e.g. Garcia-Garin et al. 2020; Jakovljevic, Govedarica, and Alvarez-Taboada 2020) or to detect submerged litter with AUVs (e.g. Fulton et al. 2019; Valdenegro-Toro 2016). Both sub-forms of monitoring, litter detection, and identification, are essentially using machine learning or deep learning algorithms to derive information about an object using a classification logic (classification in detection: no litter vs. litter, classification identification no litter vs. multiple litter classes). Due to the similarity in terms of functionality, it is not surprising that many scholars that tested algorithms for detection also tested and proved the capability of these algorithms to identify different types of debris (Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Kylili et al. 2019; Valdenegro-Toro 2016). The work done by these scholars shows that deep learning algorithms and CV are two very well-performing forms of AI that (jointly) are well suited to be used in the context of ML monitoring. Additionally, as many monitoring solutions operate based on self-directed drones to cover a large area autonomously, AI is integrated in the form of robotics, especially in the subform of autonomous vehicles. Even if the autonomous navigation of aquatic vessels is not as popularly discussed as their land- or air-based counterparts, research and practice already developed and employed a variety of

[35] Similarly to Maximenko et al. (2019) we exclude satellite imagery from in-situ monitoring of litter

concepts for ASVs and AUVs in marine science that are working autonomously thanks to AI (Manley 2008; Wynn et al. 2014).

4.4.1.3.3. Research on AI Systems in Marine Litter Collection

Many AI solutions for ML collection that were explored in the past are integrated into autonomous vehicles. What differentiates the collection solutions from monitoring solutions is that these machines often use AI in the form of advanced robotics to practice movements such as grabbing, pulling, or towing to extract the debris from the water column. Kasparavičiūtė et al. (2019) have constructed a theoretical simulation on how an AUV could roam the water column in the mission to efficiently extract plastic debris. Martins et al. (2020) recently developed and tested a robotic solution, the IRIS AUV, that is built to locate and retrieve lost fishing gear by using a gripper hook. Even though the results of both research teams are promising, it can be said that research in this field is limited and rather in its infancy.

4.4.1.3.4. Illustrative Organizations using AI in the In-situ Management of Marine Litter

AIS in the domain of ML is not only a theoretical matter. A variety of organizations are testing or already using deep learning, CV, and autonomous vehicles to monitor or collect ML. The German NGO *Everwave* uses an aerial drone that feeds images into an algorithm developed by the German Research Centre for Artificial Intelligence for a preliminary scan of the operation area to inform their manual collection boat about the location of litter accumulations (Everwave 2021). *Clearbot* from Hongkong and *Ranmarine Technology* from the Netherlands are just two exemplary companies that deploy small ASVs to roam different water bodies, detect floating debris, and collect it subsequently. For this, imaging sensors are creating input for algorithms that are trained to detect objects (Clearbot 2021; RanMarine 2021). *The SeaClear Project* initiated from TU Delft is a great example for solutions that focus on the collection of submerged litter: The project is using a fleet of boats, UAVs, and AUVs equipped with an extensive arsenal of sensors (e.g., RGB cameras, 2D forward-looking sonar), to feed the AI algorithm and allow detection and retrieval of litter underwater (SeaClear 2021).

4.4.2. Analysis: AI as a Strategic Tool in the In-Situ Management of Marine Litter

Knowing the different forms in which AI can be applied, this section aims to assess the technology's potential as a strategic tool in the context of ocean litter monitoring and collection. To do so, the SWOT framework is used to analyze the strengths, weaknesses, opportunities, and threats that can be connected to disruptive technology in the context of ML. For this, AI-based ML monitoring and collection is implicitly contrasted to conventional approaches that are not implementing the technology (e.g., staffed expedition boats that are manually monitoring and collecting litter). As outlined earlier, qualitative research[36] was conducted to derive the insights of this analysis: The authors conducted interviews with an expert that were representatives of organizations that engage in the marine litter problem using AIS (e.g., *Everwave, Clearbot, Ranmarine, The SeaClear Project*) and of organizations that have not yet implemented AI-based systems (e.g., *Ocean Conservancy, Peniche Ocean Watch*). An overview of interview partners and their assigned aliases can be found in Appendix 4. The interviews were recorded, transcribed, and coded using a three-step coding mechanism (see Appendix 9b). The coded insights were then assigned to the four dimensions of the SWOT framework. To work with this framework, a differentiation had to be made between internal factors (Strengths and Weaknesses) and external factors (Opportunities and Threats). A total of 6 of strengths, 4 of weaknesses, 7 of opportunities, and 7 of threats were identified. The following is summarizing the main findings, while a more detailed dissection can be found in Appendix 9c.

[36] For a more comprehensive description of the methodology of the qualitative research approach the reader is referred to the Section 3 (Methodology) in the group thesis.

4.4.2.1. Insights from Expert-Interviews

4.4.2.1.1. Strengths

Large scale of litter monitoring. One of the main strengths that were named by the interviewed experts in this specific context is the ability of AIS to increase the scale of litter monitoring, which allows for a broader, and simultaneously deeper understanding of the problem. Applying the algorithms to the data could help with the identification of leakage points where large amounts of waste enter the water and allow for the mapping of high impact areas in so-called trash heat maps which can be used for more targeted cleanup campaigns (I4.1, I4.2, I4.4, I4.6) and gives information about the most predominant types of litter (I4.4).

High efficiency of litter monitoring. Besides increasing the scale of monitoring, implementing AI can make monitoring more efficient. We define efficiency as „the ability to do something or produce something without wasting materials, time, or energy“ (Merriam-Webster 2021). This is achieved as sensors are stated to be more accurate than human eyes (I4.3) and AI's capability to time-efficiently compute and compare the presence of litter across larger areas with high accuracy, in order to prioritize areas for cleanups (I4.6, I4.7). This is stated to allow the monitoring of large water areas in a shorter period (by using AUVs or satellite imagery) (I4.7).

Validity of data from monitoring supports decision-makers upstream and downstream. Another benefit that stems from using AI in the process of monitoring litter is that the large amounts of data that are collected can be used as valid inputs to support decision-makers in their decision-making processes (I4.1). This benefit can be used upstream and downstream of the in-situ management of ML: Upstream, the vast amount of high-quality information can be used for accurate decisions about material bans and supports policymakers in setting up the right incentivization programs to avoid pollution in the first place (I4.1, I4.2). Downstream, the information can also be used to improve the recycling processes, due to a pre-assessment of recyclability of the monitored debris (I4.1, I4.5).

Large-scale litter collection. AI also has the capability of improving litter collection. Based on the insights of the expert interviews, one benefit of implementing AI into ML retrieval comes from the technology's ability to collect litter at large scale, as AI is providing an additional workforce to the human capital that is cleaning the ocean (I4.1, I4.3) and the ability of these solutions to "work[s] 24/7", so long periods, without the occurrence of fatigue or loss in attention (I4.3, 48,49). At this point, the relationship between improved monitoring and improved collection shall be highlighted: The more efficient and the larger the scale of monitoring activities, the more efficient and (thus larger in scale using the same resources) will the collection process be. Simultaneously, a more efficient and larger-scale collection process allows to feed the algorithms with high quantity data of collected or nearby objects, and consequently improving the deep learning algorithms for monitoring.

Highly efficient litter collection. Another strength mentioned in the expert interviews was the high efficiency in litter collection that comes from the ability to process large amounts of data in real-time and translate these into actions (I4.1, I4.2, I4.3, I4.5, I4.6). This data can originate from connected solutions used for monitoring such as drones (e.g., Everwave) or AUVs (e.g. SeaClear Project), and help to direct the collection entity to the relevant spot (I4.1, I4.7). Also, external data about environmental factors, for example, weather forecasts, can be integrated in real-time and optimize the clean-up process – or as Sidhant Gupta, CEO of Clearbot phrases, integrating such data at real-time allows his company to know "what direction of the tides pushing the waste in, and therefore, how can they optimize the collection activity" (I4.1, 40,41).

Efficacious supporting tool for human cleanup activity. Three interview partners stated that AIS can directly optimize cleanup efforts by humans by providing extensive information about the site in which litter is necessary (I4.4, I4.6, I4.7). Furthermore, AI was mentioned to have the power to make ocean cleaning activities safer, by running complex simulations and hence identify the potential negative and dangerous effects of human activity, such as picking up a piece of debris from the seafloor (I4.2). Using AI-based collection solutions was noted to be "safer by just not having that many people on the water near constricting debris" (I4.3, 55).

4.4.2.1.2. Weaknesses

Integration of AI is highly resource-intensive. According to the experts, a major weakness of AIS is the high resource intensity (I4.6, I4.7). A source of this was stated to be the need for multidisciplinary teams, and the demand for team members with high technical expertise (I4.6). Further, AI solutions require high computing power, which of course comes at a cost (I4.7). Also, many experts named high costs for advanced sensors that are however crucial components to the systems as a weakness (I4.3, I4.5, I4.6, I4.7). Moreover, the resources intensity is also elevated due to the need for great amounts of high-quality data and the necessary efforts to prepare the data so that it can be used properly (especially data preprocessing.) (I4.2, I4.7). AI applications are thus reported to show significant (upfront) cost while there is often no clarity about the value that it brings to the organization's efforts – or as Nick Mallos from the Ocean Conservancy phrases it: "As an NGO, always happy to invest in promising technologies and research, but doing so without a clear understanding of how we'll be able to use that information to advance our work… It's sometimes hard to justify that investment." (I4.6, 256-258).

Inflexibility of algorithms to react to special types of litter. Another weakness of AI-based solutions was stated to be the inflexibility of algorithms to react to special types of litter. Mainly large pieces of trash were named as a risk to the autonomous collection vessels (I4.1, I4.5, I4.7).

Lack of instinct to recognize and protect life forms and organic material. Another weakness of AI that was addressed is the lack of intrinsic motivation to recognize and protect life forms and organic material. Three interview partners mentioned the problem that AI solutions are limited in terms of deciding whether to retrieve litter or not once a piece of litter has become a new habitat for organisms (I4.2, I4.3, I4.5). Some lifeforms were reported to be sometimes mistaken with ML: “the only marine creature we've had some challenges with is jellyfish because they look quite similar to a plastic bag floating under the surface.” (I4.1 193-195)

Inability to imitate complex human actions sufficiently. Another noteworthy weakness mentioned was the insufficiency of AIS to imitate the complex actions that humans pursue to extract litter from the water. Ben Wolf highlighted the complexity of imitating hand movements for the manual extraction of debris, especially underwater: “The one thing that hasn't been matched with or hasn't been matched by AI is the disparity of our hands and fingers. […] So just normal grabbing in just air environments, that's already challenging. Bringing it on the water brings up additional challenges” (I4.3 82-91).

4.4.2.1.3. Opportunities

AI as a growing field in research and practice. In total, five experts stated that opportunities arise from AI being a growing field for researchers and practitioners. Especially the awareness of AI as a powerful technology and the increased willingness of multidisciplinary teams (including non-experts) to join forces was mentioned throughout many interviews (I4.2, I4.3, I4.4, I4.7). The following statement by Ben Wolf can be taken as an example of this: “This is not something that we just as AI specialists work in silos, we have experts. For instance, in our supervisory board […] there are ecologists that at least watch along with our progress and inform us on what to do with these kinds of situations.” (I4.3 36-39). Beyond that, the collaboration of different players in academia, industry, and the governmental landscape was named to be an important factor paving way for the implementation of AIS in the problem context (I4.1, I4.3). Moreover, Professor Teigland mentions that opportunities arise for AIS in this context from the increased number of platforms and online communities (e.g., Kaggle.com) that bring together data scientists and experts from different fields, but also the opportunity of the increased availability of educational programs in the field of AI and data science (I4.2).

Increasing importance of sustainable development in the socio-political context. Five experts mentioned that the implementation of AI has a great opportunity ahead due to the increasing perception of sustainable development being an important topic and the increasing awareness among politicians and governmental intuitions for related issues (I4.1, I4.2, I4.5, I4.6, I4.7). As Richard Hardiman noted: "There's certainly a bigger push from a political side to remove waste from water" (I4.5, 269-270). This is reported to embody itself in the increased financial support of innovative solutions, helping organizations to develop and deploy more solutions using AIS (I4.2, I4.7). Political support was also mentioned to raise the awareness of individuals and companies within our society for sustainable development (I4.1, I4.2, I4.5).

Continuously expanding data inventory. As reported by four experts, further great opportunities for the implementation of AI solutions come from the continuous expansion of data inventory that these solutions rely on. The accumulation of large amounts of data was referred to as a critical factor increasing the utility of AIS (I4.2, I4.5). Especially the increase in open-source data and the emergence of the field of citizen science[37], which allows different stakeholders to use their personal devices to contribute data easily, was said to be opening opportunities for AIS to be integrated (I4.2, I4.3, I4.6).

Advancements in component technologies[38]. Some of the greatest opportunities for AI-based ML solutions mentioned arise from the improvements of technologies that are components of the AI system but are not directly considered to be the AI software itself. In total, four experts mentioned the Improvements in the field of computing hardware, such as the emergence of quantum computing devices and edge computing devices, to be crucial for the utility of AIS. Such advancements are said to allow for highly accurate, real-time processing of data that is

[37] Citizen science is understood as the integration of volunteers into scientific process, often in the form of data collection (European Commission 2020, 2)
[38] Following Zhang et al. (2017) we define a component technology as a technology (e.g. sensor, hardware, etc.) that is supporting the core technology (in this case the AI software system)

collected and the integration of such data into the decisions and actions taken by machines (I4.1, I4.2, I4.7). Also, practitioners have mentioned a decrease in cost for these highly powerful computing devices, allowing them to distribute their solutions at a larger scale (I4.1, I4.5). Sidhant Gupta additionally noted that due to the increase of computing power relative to its hardware size, high-performance computers can now be integrated into smaller, wireless devices such as UAVs, AUVs, ASVs making them more suitable for complex tasks in ML management. Also, improvements in information and communication technology (ICT) are stated to ease the integration of AIS, driving transmission speed of data and interconnectivity of devices (I4.1, I4.7). Further, it was stated that the emergence of new, highly accurate sensors allows AI systems to generate more detailed and reliable information about the environment and objects (I4.3, I4.7). The decreasing size and the decreasing cost for highly accurate sensors were stated to also open opportunities for the integration of AIS into ML management (I4.1, I4.5). As Richard Hardiman stated, the decrease in cost and the increase in efficiency of batteries has further been crucial for autonomous solutions such as the Wasteshark (I4.5).

4.4.2.1.4. Threats

Challenges due to unpredictability and complexity of the environment in which solutions operate. A common theme found in five of the expert interviews was the challenges that arise from the high complexity of the environment: External forces in rivers and oceans such as currents, swells, and weather conditions are stated to threaten autonomous collection vessels (I4.2, I4.2, I4.5) and heavy winds challenge the operation of aerial drones for monitoring (I4.7). The movement of ML, which is often induced by just these external factors, additionally makes monitoring difficult and may cause ML pieces to be detected several times (I4.7). Experts named optical properties specific to water, such as a higher refractive index as air, color distortion, and the presence of less light in higher waters with larger depths, as further factors that complicate the monitoring of submerged litter (I4.3, I4.5, I4.7). In addition to these optical properties of inherent to water in general, unclear water and the fact that much of the plastic debris is see-through is amplifying the challenges for monitoring submerged litter (I4.3).

Insufficient quality and quantity of raw data. Four of the experts mentioned threats that arise from AI's high dependency on the quality and quantity of input data. To cite Dr. Floehr: "The biggest limitation is, the algorithm always depends on the data that it gets" (I4.7, 99-100). Especially the low quantity of existing data has been reported as a challenge, which is often related to the high complexity of data collection in oceanic environments (I4.1, I4.2, I4.3). Also, challenges arise from the sheer magnitude of factors that AI must account for to cover the complexity of oceanic systems (I4.2). The Co-Founder and CTO of Everwave voices: "I mean water is probably, I'd say, the trickiest element of all, because it never just does what you want. It's hard to predict because there are so many factors." (I4.7 152-159).

Challenges due to limitations of component technologies. The interviewees indicated that the performance of AIS in the considered context is threatened by the high dependency of AIS on component technologies. The rather limited efficiency in terms of energy technology, especially in form of bulky and heavy batteries and solar panels, has been reported to limit the use of autonomous, often small vehicles equipped with AI (I4.5). These smaller, autonomous vessels as a medium to move AIS around in the physical world come with further limitations that impact the contribution that AI solutions can make: The vessels are reported to have a somewhat small capacity for litter collection, and therefore call for a frequent offloading of the collected trash, making them less autonomous then ideal (I4.5). Moreover, the navigation of underwater vessels through the three-dimensional water column (especially when coordinating multiple vessels simultaneously) is a highly complex and challenging task and calls for highly advanced communication protocols between devices (I4.3)[39]. In terms of ICT, the lack of reliable network connectivity in open oceans has been reported to be a big limiting factor for AIS that operate in these areas, as many of them rely on a fast and stable communication infrastructure (I4.5).

Lack of supporting legal framework and slow adaptation of regulations. Disruptive technologies often face the problem that the legislative body lags in adapting quickly enough to foster their benefits. This is also stated by several experts in the conducted interviews: The existence of legal regulations for the operation of aerial drones are reported to be a big challenge for AIS that use UAVs for litter monitoring (I4.5, I4.7). In contrast to that, the operation of autonomous aquatic vessels was reported to be regulated quite loosely, which in turn causes a lot of insecurity by operators of how this domain will be regulated in the future (I4.5). Further, it was stated that the lack of regulations that support and even promote the sharing of data is posing a problem to the integration of data-hungry AIS (I4.2).

High Dependency on Governmental Incentivization and Support. Experts reported the lack of governmental incentivization and support in form of funding as another great limitation of implementation of AIS (I4.1, I4.2, I4.4, I4.7). Dr. Tilman Floehr highlighted the lack of funding for smaller organizations impeding the integration and development of AI in the field (I4.7).

Challenge of economic viability of cleanup efforts. Professor Teigland mentioned that one threat of AIS stems from the lack of a proper business model for ocean litter (I4.2). Further, finding a customer for cleanup solutions is difficult as the ocean "technically belongs to nobody" (I4.1).

Risk of rejection of AI solutions by society. The last threat arises from the relationship of humans with AI. It was noted that AI-based devices are quite expensive and deploying them in low-income areas, organizations might meet the resentment from the population in form of

[39] The smooth navigation and coordination of multiple vessels is also depended on the performance of algorithms so that labelling this aspect as a *weakness* is not incorrect. It is argued however, that the need for reliable communication protocols is at the very forefront of this challenge, thus this aspect is denoted as an external factor.

vandalism or theft (I4.7). It was implicitly stated that it must be ensured that AI is supporting not replacing human activity to avoid the aversion of society due to the fear of job loss (I4.7)

4.4.3. Discussion

The discussion section aims to fulfill multiple purposes. Bringing together the findings from our interviews with findings of previous research on AIS in ML management (or in related fields) will help us interpret our results and validate whether the statements were relevant and representative. For the sake of clarity and conciseness, we will guide this part of the discussion along the four dimensions of the SWOT framework and discuss only the most relevant findings of the four dimensions. Secondly, to not leave the reader with in-actionable results, we will derive managerial implications from the work done and give recommendations for future research. Lastly, this section will be used to make one of the major implicit contributions of this explorative research paper by identifying the gaps that future research should address.

4.4.3.1. Setting this study in the context of existing literature

Discussion of Strengths. Much of the strengths that were mentioned in the expert interviews were reflected in the still very young field of research around AI applications for the in-situ management of ML. Much of the research accessible to the authors validated the opinion of the experts that AIS is highly efficient in litter monitoring: Scholars have proved the high accuracy in detection and estimation of quantity and size of litter (Kako, Morita, and Taneda 2020, 9; Kylili et al. 2019, 17095). Garcia-Garin et al. (2020) even contrasted the superior accuracy of AIS compared to manual methods. While the results of our interviews reported that one strength of AIS might be the additional scale of litter monitoring, this is not explicitly stated in research. However, one explanation of this might be that the increase of efficiency in litter monitoring will implicitly lead to a larger scale of such operations using the same number of resources. This image repeats itself looking at litter collection: There is not much literature on the increased scale of ML collection that is induced by the implementation of AIS, however, the increase in efficiency has been addressed by research groups such as Fulton et al. (2019).

Discussion of Weaknesses. Also, many of the weaknesses of AIS that we present here in consolidated form have been explored in the dispersed body in the past. The variety of objects and forms in which debris exists has been acknowledged as a limitation to AIS (Fulton et al. 2019, 5752; Valdenegro-Toro 2016), while the expensive sub-components of AIS (e.g. sensors, high-powered computing hardware or AUVs) are recognized as drivers of the resource intensity of AI across a magnitude of contexts (Kako, Morita, and Taneda 2020; Zereik et al. 2018).

Discussion of Opportunities. The close relationship between the performance of component technologies and the performance of AIS has been discussed widely by previous research. Scholars implicitly note the performance improvements of AIS in the context of ML management provoked by improved component technologies such as drones, sensors or ICT (e.g. Kako, Morita, and Taneda 2020; Garcia-Garin et al. 2020; Deidun et al. 2018; Wynn et al. 2014; Zereik et al. 2018). It is highly important to note here that the development of these component technologies is found to be both, an opportunity, and a threat: While fast developments are raising opportunities, slow advancements are considered a threat usually. As examining the current speed at which computing devices, sensors, and information and communication technologies advance would go beyond the scope of this work, it is not possible to fully evaluate whether this development should be seen more as an opportunity or a threat. Knowing of the high dependency of AIS on the developments in component technologies is nevertheless crucial. Further, it is noteworthy to discuss the opportunities that arise from the ever-increasing data inventory that the interview partners mentioned. This is an argument that is backed by research and practice: The amount of ocean data that is accessible is growing each day, as there is an "unprecedented ability to collect and analyze information about our environment and human uses of marine natural resources and to create significant opportunities for improvement in science and decision-making" (Trice et al. 2021, 1). This positive development has been acknowledged by highly respected organizations such as the World Economic Forum (Markussen and Teleki 2021). Also, the availability of open-source data for ocean purposes is increasing, with many platforms emerging lately, such as the *Ocean Data Platform* that will launch in summer 2022 (Centre for the Fourth Industrial Revolution 2021). Moreover, research has shown that citizen scientists, can be a relevant source of data and thus a huge asset in the management of ML (Hidalgo-Ruz and Thiel 2015).

Discussion of Threats. The opportunity from the accumulation of data is interestingly on the other end of one of the major threats identified: the insufficient quality and quantity of raw data. This contradiction can be explained: Even though, the data inventory is growing continuously, the high dependency on the currently limited amount of data perimeters the present performance. Data as a limiting factor is an observation that was already made by scholars in the past (e.g. Valdenegro-Toro 2016; Fulton et al. 2019). So, while the threat in terms of data is more concerned with the present, the opportunity emphasizes the benefits that developments of the future hold. The same picture emerges for the threat from the component technologies: While the previously discussed developments were found to be a relevant opportunity, the high dependency of AI on such is posing a threat to the potential of AIS. in the context of ML. Scholars have also acknowledged the challenges that arise for AI due to the inherent limitations that some crucial component technologies have. The literature mentions especially challenges due to the limitations of the sensor resolution (Jakovljevic, Govedarica, and Alvarez-Taboada 2020). Earlier scholars have acknowledged that choosing the altitude at which UAVs are used for monitoring litter creates a tradeoff between high resolution and the area covered (Deidun et al. 2018) – a finding that was not reflected in the interviews conducted. This might be explained by the small number of companies interviewed that use drones for monitoring. Previous research also highlighted the need for a constant environment in which AIS operate, with weather as a critical factor affecting both monitoring and cleanup activities with or without AIS (Garcia-Garin et al. 2020; Deidun et al. 2018; T. H. Mace 2012; Jakovljevic, Govedarica, and Alvarez-Taboada 2020). Similarly, the dispersed body of research outlined the challenges that are specific to monitoring litter in water, such as the movement of litter, refraction of light, or the degradation of sight with increasing depths (e.g. Fulton et al. 2019; Marin et al. 2021). Similar to this work, past research also found the lack of supportive regulations to limit the use of autonomous drones and vessels (Barfield 2018; Garcia-Garin et al. 2020).

4.4.3.2. Managerial Implications

One of the main aspects that arise from this work is that AI has the potential to contribute to a cleaner ocean. However, AI does not prove to be an invincible tool. It has its internal and external limitations that need to be carefully considered for efficient integration of the technology. Simultaneously, organizations should always include the organization-specific context into their contemplation. This includes, among others, the following factors: Internal resources available (financial, technological, human resources, data, partnerships), the external environment in which the organization operates (region, waterbody, vertical domain), and the task that the organization is focused on (monitoring or collection, type of litter). Matching these contextual factors with the internal and external factors of AI in ML should help organizations to find strategies to integrate AI in a way that leverages the strengths, diminishes weaknesses, exploits opportunities, and minders threats of AI. Since the author had the chance to visit POW's facilities for multiple days in November and engage there closely with Professor Teigland's and other representatives of the organization, POW and their internal resources should serve as an example in the following (for a profile of the organization see Appendix 9d).

Using organizational resources to leverage the strength of AI. It is recommended that the organization uses their advanced UAV developed for scanning pelagic fish stock in their Peladrone Project and endow it with algorithms for litter detection. This helps to leverage the strength of *AI as a supporting tool for human activity* in their litter-related project (Ghost Ocean Project): the new algorithm can be used to monitor lost or abandoned fishing nets, inform fishermen about the location, and help with the efficient and safe collection. The use of the existing resource in this case also minimizes a weakness, namely the high costs often associated with the integration of AIS induced by the need for high-performance sensors.

4.4.3.3. Limitations and Future research

It must be acknowledged that this work has some limitations, mainly due to its scope and how it is designed[40]. Although these limitations affect all the sub-themes of sustainable development studied, they provide avenues for future research specifically in the context of ML management: First, extending the scope beyond the in-situ management of ML would create a more holistic picture. This includes the application of AI in further aspects connected to ML, such as reduction in plastic consumption and recycling. Second, it is suggested that the scope of this work is extended by including microplastics as well. Third, from discussing the interview results and setting them in the context to the present state of research, a magnitude of topics that were not specifically addressed in past research was discovered:

i. Quantification of the additional scale in ML monitoring and collection through AIS
ii. Extensive study on crucial component technologies technological and their maturity
iii. Exploration of AIS which integrate citizen scientists into the ML management
iv. Excavation of business models for ML to ensure economic viability of ML management

This shall not be seen as an exhaustive list of all relevant topics, but rather it should indicate how broad the potential for future research is and inspire scholars to investigate in the future.

[40] Due to the similarities of the limitations that arise in the sections concerned with SDG 3, SDG 11, and SDG 12, a more detailed presentation of the limitations can be found in Section 6.3 (Limitations) of the group thesis

4.4.4. *Individual Conclusion and Outlook*

The aim of this paper is to evaluate the potential of AI as a valuable strategic tool for the in-situ management of ML and consequently contribute to achieving SDG target 14.1, the minimization of ML. Carefully analyzing the interviews with experts, reveals that AI has the potential to significantly support the reduction of ML, especially by increasing the efficiency and scale of cleanups. Obviously, such systems show weaknesses: AI algorithms are resource-intense and show a low maturity in terms of handling complex situations. This work argues however that many of the weaknesses, will be diminished in the future, especially due to the many opportunities that were identified: The accumulation of data, the improvement of component technologies, and the increased collaboration and improved technological education for individuals and organizations within our society are just a few of such opportunities. Even though threats were identified, the strengths and opportunities are also expected to be limiting these challenges if the AI is implemented with care. Therefore, with respect to the focus of this research paper, it is suggested to look with benevolence on the integration of AI as a strategic tool in ML management.

5. Results Synthesis

The findings of the individual studies of AIS in the four selected SDGs were brought together into a consolidated SWOT (see Appendix 10). This consolidation of the investigated findings uncovers, that the internal factors are rather homogenous and low in number (3 Strengths and 3 Weaknesses) compared to the external factors (6 Opportunities and 8 Threats). The consolidated SWOT framework serves as the basis for the following discussion.

6. Discussion

6.1. Discussion of Results

The overarching goal of this work is to examine the potential of AI as a strategic tool in the efforts to achieve SD. To do so, strengths, weaknesses, opportunities, and threats of AI were investigated in its' application within all three pillars of SD. The subsequent discussion aims to identify common themes that emerged across the pillars. For this purpose, the findings are outlined along the four dimensions of the SWOT-matrix in the following.

Clusters of Strengths. One of the most noted strengths across the different domains was the *ability of AI systems (AIS) to increase the efficiency* in the activities that influence SD. This strength can take various forms, such as the highly efficient collection and processing of large amounts of data, the efficient identification of patterns and the streamlining of a magnitude of processes. A closely related strength that was identified across all three pillars of sustainability was their *ability to support individuals within the highly delicate task of decision making*. The information that AI can provide is manifold and spans across many fields: In the field of economic sustainability, AI is said to improve both the decisions taken by consumers and companies. In the field of environmental sustainability, AI can support governments and organizations to implement the right measurements to effectively counter the detrimental effects on our ecosystems. In terms of social sustainability, the technology can provide support in the decisions taken by medical personnel but also help with the predictive planning of urban traffic. Besides making them more efficient, AIS were reported to have the power to *increase the scale* of activities that contribute to SD. For the domain of social sustainability, this includes better accessibility of (high-quality) diagnostic services in the health sector and the potential wide-scale shift towards more sustainable and accessible transportation systems. In terms of economic sustainability, AI can be used to leverage the multiplicativity of sustainable solutions to consumer problems. Environmental sustainability benefits from amplification in scale of environmental activities such as the management of marine litter.

Clusters of Weaknesses. One common denominator that could be identified through the consolidation of the individual findings was the *high resource intensity of AIS*. Experts reported that the high input data requirements could make the implementation of AIS rather costly. Data preparation and integration is often a costly and time-consuming factor that is unavoidable. Further, a highly experienced team of AI experts is needed to implement AIS, which is evidently affecting costs for personnel. Further, a cluster could be drawn around the *Complex Artificial Intelligence Architecture*. This was mainly noted to be an issue in social sustainability, especially in the SDG related to sustainable cities and communities, where the dependence on multiple data sources creates problems of data availability and data integration and calls for complex computational processes. Also, the *lack of technological maturity* of AIS was reported to be a weakness through the three pillars. In the realm of the environment, AI is not yet well advanced enough to imitate the highly complex behavior of humans, which makes it difficult to deploy AIS in complex and sensitive environments such as in the marine ecosystem. In terms of social responsibility, AI is not yet mature enough to take on tasks that require a high level of trust – particularly reflected in the efforts to develop innovative autonomous transport systems.

Cluster of opportunities. Opportunities are regarded as external factors, fostering the utilization and unfolding of the full potential for AIS as strategic tools. The main insight that can be drawn from the elaboration is that a *shift in mindset* of various stakeholders in all three areas seems to be of great importance. For one thing, the increasing *environmental awareness* and importance of sustainable change among socio-political stakeholders, individuals, and businesses, which seems to be of particular importance in the economic pillar. This includes the increasing importance of SD in the socio-political context and raising awareness among consumers. A further opportunity arising is the *openness towards technology and innovation:* This entails not only the growing pro-innovation mindset but also specifically the increasing openness towards using the technology in the context of SD among industry insiders. Both shifts foster the increasing recognition among society, industry, and regulators of AIS as a possibility to contribute to a sustainable transformation. The second strongest enabler which emerged across all three pillars is the improvement of *component technologies.* Particularly in the area of environmental sustainability, the improvements of battery, computing, sensor, and information and telecommunication technologies plays a major role as a door opener for AIS. In contrast, aspects such as continuous digitalization and improvements in production technologies play a greater role in the retail and consumer goods industry. The last factor addressing all three pillars is the *increasing value of data* which, in this realm, concerns the increasing availability of data, open-source data, and the constant accumulation of data. The growth of personal data such as all-embracing medical data and the interlinkage of this data from multiple stages and departments is specifically important in the context of AIS contributing to social sustainability. *Supportive market developments* further drive AIS in multiple forms. For one thing, industry-specific developments such as the comprehensive formation of a well-defined and proactive regulatory framework and increased financial support for medical AI solutions or the growing incentives for businesses to support responsible consumerism give impetus to AIS in general. Furthermore, the rise of new business models and big corporates as sustainable leaders are two factors mainly impacting the economic side, especially in the realm of the consumer good industry. Legal developments such as the GDPR provide increased clarity and uniformity across Europe and represents a first legal framework for data protection and thus also pave the way for the implementation of AIS in the world of SD. Additionally, experts' insights, foremost in the social and economic area, revealed the power implied in the *advancements in research in the area of AI*. Specifically, continuous research at the intersection of AI and the consumer good industry and the scientific prove of AI as a practical tool in the medical field can drive AIS implementation in the future. One last factor specific to the economic pillar is the pressure from *unmet consumer needs* for supporting tools and AIS to further drive sustainable consumer decisions. Overall, the expert insights provided a highly promising but diverse set of opportunities which can be traced back to the multidimensional nature of factors that are specific to the underlying industry.

Cluster of threats. For the threats, a similar picture arises as for the opportunities in terms of diversity and multidimensionality. This set of external factors negatively affect AIS or hinder them from contributing to SD. The greatest risk seems to result from potential *societal rejection.* This risk, mostly in form of data privacy concerns, appears to be determinantal barrier to AIS: Concerns about sensitive personal data, mistrust due to unreliability, bias and lack of integration, and negative perceptions of AI as a threat to society as a means of eliminating jobs are just a few of the many associated problems. Special concerns arise in the health industry due to historic aversion towards new technology and the sensitive nature of data involved in processes. Furthermore, barriers can arise due to the *high dependency on data.* For one thing, the insufficient data quality may be hindering, which might, in specific cases, lead to the amplification of (systemic) biases. Then again, the lack of data quantity due to data fragmentation within the HC industry can represent a major hurdle. Also, the necessary development of component technologies and the high dependency on the dragging progress in unifying platforms and establishing standards seem to pose challenges for AIS. Another factor that arose in all fields is *obstructive regulations.* The high dependency on externally determined regulations and political decision making may slow the progress of AIS. Especially the lack of supportive frameworks or even the implementation of inadequate legal frameworks, with overly strong data-protection laws may limit AIS. It is challenging that the adaptation of regulations and the development of appropriate frameworks for mobility service sharing and secure data use cannot keep pace with the rapid AI developments. Hindering legal factors are closely related to *institutional barriers* that are specific to the health area. These may appear due to a lack of interoperability within HC institutions and insufficient exchange between regulators and outside providers. Paired with the high dependency on governmental incentivization and support, these factors can be particularly hampering AIS' adoption and performance in the health area. Moving away from inhibiting legal and institutional factors, insights from the research done in all three areas of SD revealed the *lack of an economic model* as potentially negatively affecting the utilization of AI. Regarding medical AI solutions, high costs of input data for imaging solutions are noted as well as the lack of adequate business models for such solutions. Furthermore, there are challenges such as economic viability in the specific area of cleanup efforts, relinquishment of control, and high uncertainty of success, which increase the risk of companies rejecting the implementation of AI solutions. The field of social sustainability is subject to inhibiting influences from *operational complexity*. In terms of urban transport, these influences revolve around the challenges posed by the diversity and complexity of urban traffic and the number of vehicles on the road. Furthermore, the protracted, diverse and gradual transition in the sector prevents the full potential of AI applications from being realized. The permanent balancing act between satisfying basic, everyday and reliable transport needs for all while at the same time introducing innovative technologies that usually shake up the systems hampers implementation. Overall, different threats regarding the *negative externalities of AIS* were indicated. For example, in the context of the consumer industry, the net benefit of using AI models must be carefully assessed in terms of their environmental impact, as this is a usually highly energy-intensive process. Moreover, concerns around the potential misusage of data in the medial area arose. Lastly, experts emphasized the uncertainties related to the ever-increasing power of organizations and the potential instrumentalization of AI capabilities to further drive environmentally harmful activities, such as fueling unbridled consumption.

Overall, the discussion shows that the path and circumstances impacting the potential deployment of AIS as a tool to contribute to SD is marked by a diverse and multidimensional set of internal and external factors. It emerged that number and variety of internal and external influencing factors for the different topics varies: The internal factors (strengths and weaknesses) are quite homogeneous across the three pillars of sustainability (here the 4 SDGs), whereas the external factors (opportunities and threats) are highly diverse and numerous.

6.2. Managerial Implications

To avoid leaving the findings in the vacuum of theory, this section aims to derive implications for organizations working in the field of SD that are faced with the question of whether they should implement AI solutions or not. As a basis to translate the findings into practice, it is suggested that organizations working in the problem context should develop clear strategies for using the full potential of AIS as a strategic tool. In contrast to this work, where the focus was to evaluate whether AI can contribute to SD in general, organizations must now find ways to do so in particular. This requires a two-step approach: First, a clear picture must be generated about the influential factors on the utility of AI as a strategic tool. This is a step in which this work has made a contribution by using the SWOT framework. However, it is of utmost importance to know that factors related to the specific context in which an organization is working in could not have been addressed here, as this work approaches the subject in a more general way. Therefore, organizations should conduct a similar analysis but with a greater emphasis on their situation. Second, from the extensive knowledge that the first step generated, organizations should be able to leverage the internal and external factors in such a way that allows them to integrate AIS as a useful strategic tool to contribute to SD – an approach that is related to the TOWS framework often used in practice and discussed by other scholars.

6.3. Limitations

It is important to note that this work comes with its limitations. Both literature and interview research encounter boundaries, so that their findings cannot be considered as consensus. Thus, the present limitations may serve as a starting point for future research. To begin with, the choice of the utilized core literature underlies the subjective assessment of the authors and certainly does not include all relevant, existing publications within this research field. Secondly, findings of scholarly and professional research may also be subject to the authors' method and the hypotheses they have formulated beforehand. Moreover, the conducted qualitative research is also subject to an array of limitations, mainly arising from deficiencies in data quality, which can further be divided into issues regarding i) *reliability*, ii) *forms of bias* and iii) *generalizability* (Saunders, Lewis, and Thornhill 2009). The issue of data reliability has already been addressed in section 3.1.1.4, concluding that, while the chosen approach yielded rich and novel insight, it is assumed that other researchers might not generate comparable outcomes. This is strengthened by the fact that the data analysis was guided by the team's formulated research question so that a different overall perspective may have revealed disparate insights. The issue of data reliability is further exacerbated by various biases. The conducted interviews are subject to *interviewer bias:* All interviewers exhibit a background in strategic management and not in the area of AI, which induces a management-heavy perspective. The interpretation of answers is further based on the subjective perception of the interviewers. Apart from that, results are also prone to *interviewee bias*, with interviewees only reflecting subjective perspectives on AI. Regarding the last point, it is obvious that no generalizable assumptions can be drawn from the collected evidence, as the data only reflect a specific point in time in a dynamic situation. Further, the sample size of interview partners is too small to draw a consensus from the analysis. Moreover, one must note that the limited scope of this thesis did not allow for a comprehensive examination of all possible aspects relevant to each field. Thus, the developed SWOT frameworks do not intend to provide an extensive view on the matter but rather a glimpse into major relevant factors. Therefore, the managerial implications are not validated propositions but should be regarded as thought-provoking impulses. Besides, this work inherently lacks a quantitative measurement of AI's impact on SD. Also, this work only addresses subfields of a selection of SDGs, impeding a holistic view of AI's potential as a strategic tool to contribute to SD.

6.4. Future Research

Based on the previously identified limitations, the authors jointly formulated directions for future research in this field. The potential of AI as a strategic tool to contribute to SD could further be explored in a larger research effort to yield more significant results. Thus, future research shall employ a better experimental design by including a larger number of interviewees (n>23) and shall further account for potential biases during information collection by, for instance, carrying out control-condition interviews. Moreover, the performed research and analysis should be explored with an extended team of experts more experienced in the field of AI as well as in the respective subfields. It may be considered to perform a similar analysis in the context of a more comprehensive set of SDGs to obtain a more holistic view of the contributions that AI makes to SD. At last, future research should seek to find a better, more quantitative measurement to evaluate the impact of AIS on selected SDGs. Subsequently, the identified measures should be used to quantify the impact of AI's integration.

7. Conclusion

AI and SD are both topics that are disrupting almost all aspects of people's lives – yet research on the potential of AI as a groundbreaking technology to contribute to the indispensable shift towards sustainable management of our earth is rather scarce. This paper shows that AIS bare the potential to be used as a strategic tool to contribute towards SD. A comprehensive assessment of AI in the respective context is a more complex picture than merely focusing on the inherent strengths and weaknesses of the technology. Beyond these internal factors, this paper explores the variety of external factors that affect the contribution that AI can bring to the table of SD. Due to its explorative nature, the aim of this study was not to derive a conclusive result about this but rather act as an impetus of thought and help to understand the complexity of the problem at hand. For this, the research team explored both internal and external factors affecting AI's potential as a strategic tool in the context of four different SDGs. Even though the derived insights help to explore interesting new fields of research, these discoveries were limited to the four SDGs in focus and to the insights that the small set of interview partners shared. However, superimposing the findings in the realm of the four different SDGs revealed that the internal factors were rather homogeneous across the different subtopics of SD, while the external factors were somewhat heterogeneous and higher in number. With this important insight, this paper shows that the ability of AI to function as a strategic tool depends on a variety of factors that go far beyond the strengths and weaknesses inherent to the technology. Based on this, the authors recognize AI is a valuable strategic tool for SD, yet it should not be seen as a universal solution to all problems related to this context or a panacea in the world of SD. Hence, it is suggested that researchers, policymakers, and practitioners that are exploring or using AI in the context of SD are very aware of both its potential, but also its dependency on external factors. This paper shows that the SWOT framework, when adapted to the context, can be a valuable tool to identify opportunities for integrating AI into SD efforts.

8. Appendices

Appendix 1. Profiles of Interviewed Experts – SDG 3

EXPERTS	ROLE	COMPANY	DESCRIPTION	Abbreviation	Date	Audio, Transcript, Coded
Ségolène Martin	*Co-Founder, CEO*	Kantify	Ségolène Martin has a background in business administration and science. Her company develops machine learning solutions for pathology, detecting specific forms of cancers in Whole Slide Images from blood smears and tissue samples. She is further a member of the EU Science Hub.	I1.1	21.10.21 22.10.21	Yes
Jasper zu Putzlitz	*Healthcare Operating Partner at Triton Partners* *Former Research Fellow in Medicine at HMS*	Triton Partners Harvard Medical School	Jasper zu Putzlitz is a trained medical doctor, but shifted his career path to business-related fields. He has been as, among other things, a healthcare partner at McKinsey & Company and private equity fund Triton Partners.	I1.2	01.11.21	Yes
Giles Tully	*CEO*	PinPoint Data Science	Giles Tully is an entrepreneur and angel investor. His company developed the PinPoint test, a machine learning solution analyzing standardized blood tests of patients referred to cancer testing to give physicians a calibrated probability that a patient has cancer.	I1.3	03.11.21	Yes
Orit Wimpfheimer	*CMO (Chief Medical Officer)*	Zebra Medical Vision (now Nanox)	Orit Wimpfheimer is a trained medical doctor and has worked in radiology before joining Zebra. Zebra is an AI-based image analytics engine that helps radiologists detect various medical issues including diseases of the bone, liver, lung and cardiovascular system based on CT scan slides.	I1.4	08.11.21	Yes
Joseph Mossel	*Co-Founder, CEO*	Ibex Medical Analytics	Joseph Mossel has an academic background in software engineering and Computer Science from Tel Aviv University. His company Ibex Medical analytics provides AI-based imaging solutions for diagnostics for cancer: Their FIRST READ product "pre-cooks" the case for the pathologist, marking which slides are benign, which are cancerous, degrading them in advance, and preparing a draft of the pathology report. The SECOND READ product is a quality control application that analyzes slides in parallel with the pathologist and alerts in case of discrepancies with high clinical significance (e.g. a missed cancer).	I1.5	10.11.21	Yes

Appendix 2. Profiles of Interviewed Experts – SDG 11

EXPERTS	ROLE	COMPANY	DESCRIPTION	Abbreviation	Date	Audio	Transcribe	Coded
Tiago Farias	*CEO*	Carris	CEO of Carris, the public transport provider for the city of Lisbon. Helped and supported by many comments and interesting insights as well as connecting me to the Innovation & Strategy Manager of Carris, Mr. Vieira.	-	12.10.21	No	No	No
João Vieira	*Innovation & Strategy Manager*	Carris	Mr. Vieira´s insights have been the most useful and interesting, as we had a long call and he really addressed the most important factors and challenges regarding the implementation of new technologies such as AI for a public company.	I2.1	02.11.21	Yes	Yes	Yes
Pedro Machado	*Former Advisor to the Deputy Mayor of Mobility, Safety, Economy and Innovation of the Cjty of Lisbon, from 2017 to 2021*	City of Lisbon	For the elected period between 2017 and 2021, Pedro Machado was the advisor to the Deputy Mayor of Mobility, Safety, Economy and Innovation. His focus was on transport and his insights brought much value to this work.	I2.2	05.11.21	Yes	Yes	Yes
				I2.3	02.11.21	Yes	Yes	Yes
				I2.4	11.11.21	Yes	Yes	Yes
				2.5	11.11.21	Yes	Yes	Yes
				2.6	17.11.21	Yes	Yes	Yes

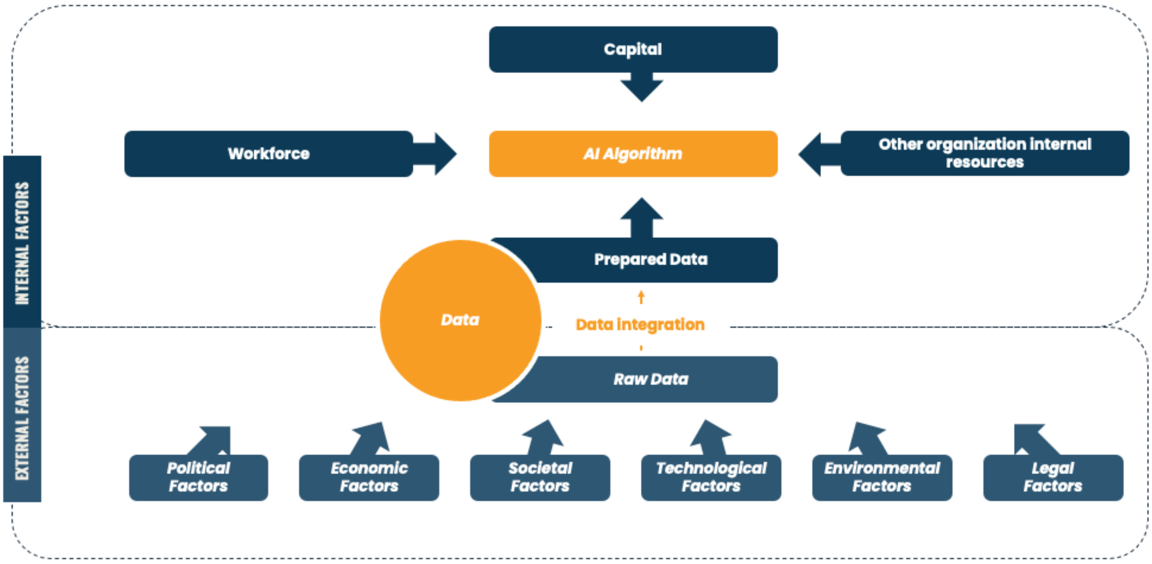
Appendix 3. Profiles of Interviewed Experts – SDG 12

EXPERTS	ROLE	COMPANY	DESCRIPTION	Abbreviation	Date	Audio	Transcript	Coded
Leon Szeli	*Co-Founder, CEO*	presize.ai	Leon Szeli Co-Founder and CEO of presize.ai, which is an application that supports consumers in optimizing their purchase decisions by providing them with the perfect clothing size (presize.ai 2021).	I3.1	29.10.21	Yes	Yes	Yes
Lizzie Horvitz	*Co-Founder*	Finch	Lizzie Horvitz, Founder of Finch dedicates her start-up to decode sustainability for consumers. Through a browser extension, Finch provides simple and reliable product ratings, giving back control to individuals, simplifying sustainable decisions and providing them with the necessary transparency and know-how to choose responsibly (Finch 2021).	I3.2	01.11.21	No	No	Yes
Professor	*AI & Sustainability, Ecosia*	Green Consumption Assistant	A professor teaching at a renowned German university involved in the Green Consumption Assistant (GCA) project which is an AI-supported assistance system and implemented as Ecosia browser extension. The GCA supports consumers at the point of purchase by providing sustainability information of a product, product alternatives in an easy consumable way to foster and ease green consumption (Green Consumption Assistant 2021).	I3.3	02.11.21	Yes	Yes	Yes
Mary Wallace	*Retail & Consumer Behaviour SME Senior Managing Consultant Global Centre of Competence IBM iX*	IBM	Expert in the consumer business and accompanied many AI implementation projects in the industry.	I3.4	04.11.21	Yes	Yes	Yes
Michele Camuri	*Director, Global Business Applications Sales | Retail & Consumer Goods | EMEA & Asia Lead · Microsoft*	Microsoft	Expert in the consumer business and accompanied many AI implementation projects in the industry.	I3.5	12.11.21	Yes	Yes	Yes

Appendix 4. Profiles of Interviewed Experts – SDG 14

Interviewee	Organization	Role	Profile	Abbreviation	Date of Interview	Audio, Transcript, Coded
Sidhant Gupta	Clearbot	CEO and Co-Founder	Sidhant Gupta has an academic Background in Engineering at University of Hong Kong, and is CO-Founder of multiple companies including Clearbot, an organization that was created from a University Project. Clearbot is currently deploying autonomous vessels to collect floating litter.	I4.1	22.10.21	Yes
Professor Robin Teigland	Peniche Ocean Watch	Co-Founder	Professor Teigland is a Professor of Strategy, Management of Digitalization at Chalmers University of Technology (Sweden) and founded Peniche Ocean Watch and the Ocean Tech Hub, which aims to bring projects in the realm of sustainability to the coastal community of Peniche.	I4.2	02.11.21	Yes
Ben Wolf	SeaClear Project (TU Delft)	Postdoctoral Researcher	Ben Wolf is an expert in the fields of Artificial Intelligence and Robotics. He was a post-doctoral research at University of Groningen (Netherlands) and currently works for the Se Clear Project (TU Delft).	I4.3	04.11.21	Yes
Kacky Andrews	Ocean Conservancy	Chief of Strategy	Kacky Andrews has a background in law and is the Director of Strategy at Ocean Conservancy. Prior to this role, she was Executive Vice President, Global Strategies, at one of the largest conservation organizations in the world (The Nature Conservancy)	I4.4	11.11.21	Yes
Richard Hardiman	Ranmarine Technology	CEO and Co-Founder	Richard Hardiman has a background in business and is the Founder and CEO of RanMarine Technologies, a company that developed the Wasteshark, an autonomous vessel that is roaming on the water surface to collect floating litter	I4.5	12.11.21	Yes
Nicholas Mallos	Ocean Conservancy	Senior Director, Trash Free Seas	Nicholas Mallos is a marine biologist, with a master degree in Environmental Management. He has been working for the Ocean Conservancy for more than 11 years already and is currently the Senior Director of the Trash Free Seas Program,	I4.6	17.11.21	Yes
Dr. Tilman Floehr	Everwave	CTO and Co-Founder	*Dr. Tilman Floehr is a doctor in marine biology and expert in the field of water pollution. He has been working for the Helmholtz Center for Enviromental research and currently the CTO of the german NGO Everwave that uses its collection vessel to clean rivers*	I4.7	18.11.21	Yes

Appendix 5. Overview of the Distinction Between Internal and External factors



- ***Pre-processed data***: Raw data (primary data) is data that has not been processed for use. It is collected and gathered from data sources such as IT resources.

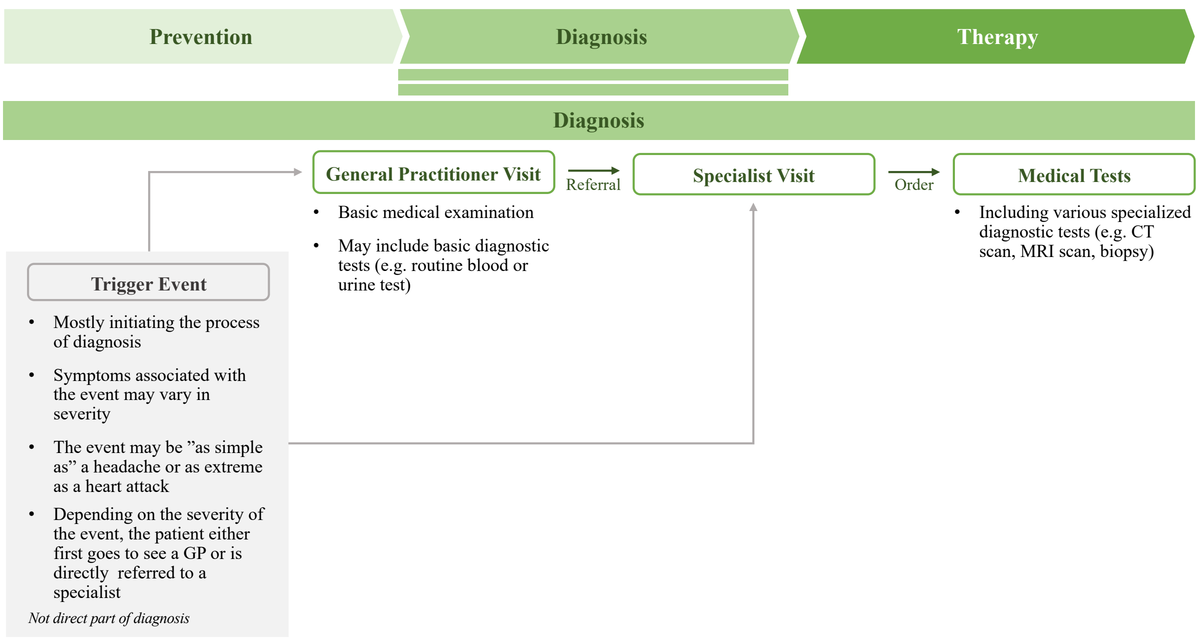
- ***Post-processed data***: Prepared data (input data) is raw data transformed so that it can be processed by machine learning algorithms. This requires the step of data integration therefore involving internal resources.

Appendix 6. Supplements to Individual Part on SDG 3

a. List of Abbreviations

AI	Artificial intelligence
NCD	Non-communicable disease
CVD	Cardiovascular disease
HC	Healthcare
HIC	High-income countries
LMIC	Low-to-middle-income countries
MI	Medical imaging
CT	Computed tomography
MRI	Magnetic resonance imaging
PET	Positron emission tomography
WSI	Whole slide images
CAD	Computer-aided diagnosis

b. Simplified & Generalized Patient Journey for Diagnosis for NCDs



c. World Bank Classification into HIC and LMIC

HIGH-INCOME ECONOMIES ($12,696 OR MORE)

[80]

Andorra	Greece	Poland
Antigua and Barbuda	Greenland	Portugal
Aruba	Guam	Puerto Rico
Australia	Hong Kong SAR, China	Qatar
Austria	Hungary	San Marino
Bahamas, The	Iceland	Saudi Arabia
Bahrain	Ireland	Seychelles
Barbados	Isle of Man	Singapore
Belgium	Israel	Sint Maarten (Dutch part)
Bermuda	Italy	Slovak Republic
British Virgin Islands	Japan	Slovenia
Brunei Darussalam	Korea, Rep.	Spain
Canada	Kuwait	St. Kitts and Nevis
Cayman Islands	Latvia	St. Martin (French part)
Channel Islands	Liechtenstein	Sweden
Chile	Lithuania	Switzerland
Croatia	Luxembourg	Taiwan, China
Curaçao	Macao SAR, China	Trinidad and Tobago
Cyprus	Malta	Turks and Caicos Islands
Czech Republic	Monaco	United Arab Emirates
Denmark	Nauru	United Kingdom
Estonia	Netherlands	United States
Faroe Islands	New Caledonia	Uruguay
Finland	New Zealand	Virgin Islands (U.S.)
France	Northern Mariana Islands	
French Polynesia	Norway	
Germany	Oman	
Gibraltar	Palau	

UPPER-MIDDLE-INCOME ECONOMIES ($4,096 TO $12,695)

[55]

Albania	Gabon	Namibia
American Samoa	Georgia	North Macedonia
Argentina	Grenada	**Panama**
Armenia	Guatemala	Paraguay
Azerbaijan	Guyana	Peru
Belarus	Iraq	**Romania**
Bosnia and Herzegovina	Jamaica	Russian Federation
Botswana	Jordan	Serbia
Brazil	Kazakhstan	South Africa
Bulgaria	Kosovo	St. Lucia
China	Lebanon	St. Vincent and the Grenadines
Colombia	Libya	Suriname
Costa Rica	Malaysia	Thailand
Cuba	Maldives	Tonga
Dominica	Marshall Islands	Turkey
Dominican Republic	**Mauritius**	Turkmenistan
Equatorial Guinea	Mexico	Tuvalu
Ecuador	**Moldova**	
Fiji	Montenegro	

LOWER-MIDDLE INCOME ECONOMIES ($1,046 TO $4,095)

[55]

Angola	Honduras	Philippines
Algeria	India	**Samoa**
Bangladesh	**Indonesia**	São Tomé and Principe
Belize	**Iran, Islamic Rep**	Senegal
Benin	Kenya	Solomon Islands
Bhutan	Kiribati	Sri Lanka
Bolivia	Kyrgyz Republic	Tanzania
Cabo Verde	Lao PDR	**Tajikistan**
Cambodia	Lesotho	Timor-Leste
Cameroon	Mauritania	Tunisia
Comoros	Micronesia, Fed. Sts.	Ukraine
Congo, Rep.	Mongolia	Uzbekistan
Côte d'Ivoire	Morocco	Vanuatu
Djibouti	Myanmar	Vietnam
Egypt, Arab Rep.	Nepal	West Bank and Gaza
El Salvador	Nicaragua	Zambia
Eswatini	Nigeria	Zimbabwe
Ghana	Pakistan	
Haiti	Papua New Guinea	

LOW-INCOME ECONOMIES ($1,045 OR LESS)

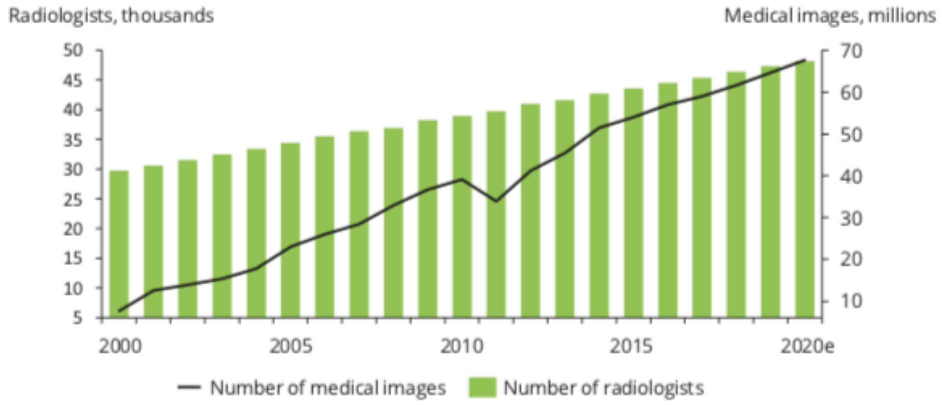
[27]

Afghanistan	Guinea-Bissau	Somalia
Burkina Faso	Korea, Dem. People's Rep	South Sudan
Burundi	Liberia	Sudan
Central African Republic	Madagascar	Syrian Arab Republic
Chad	Malawi	Togo
Congo, Dem. Rep	Mali	Uganda
Eritrea	Mozambique	Yemen, Rep.
Ethiopia	Niger	
Gambia, The	Rwanda	
Guinea	Sierra Leone	

From: (World Bank 2021)

d. Comparison of Evolution of Radiologists and Medical Images

Figure 3: 62% more radiologists vs. 792% more medical images: PET, MRI, CT (EU 2000-2020)



Source: Eurostat, Deloitte analysis

e. 3-Step Coding Process for Data Analysis

See the following link to the Excel file:

https://novasbe365-my.sharepoint.com/:f:/g/personal/43931_novasbe_pt/Elt2yaGCRlBNkXpfT8OO9D8BQZTeWGxed05OoEaeb8YMHw?e=q1DQrv

f. Detailed View of the Results in the SWOT Framework

STRENGTHS
Row Labels
⊟ (Partially) exceeds human capabilites in medical diagnostics
AI extends human medical possibilities
AI has the ability to (can be trained to) look at blood results from patients as "blank sheet" and reduce human ascertainment bias
AI in blood analysis exceeding human capabilities
Machine learning-algorithms are able to perform blood analysis better and cheaper at scale (than humans)
Machine learning-algorithms are able to see smaller, less obvious patterns in blood tests (than humans)
Machine learning-algorithms have ability to do repetitive, complex, numerical-related tasks much faster than humans
⊟ Enables earlier detection of chronic conditions
AI clinical decision support tools help diagnose and treat chronic conditions earlier
AI enables early detection of at-risk patients
AI in CT scans has ability to recognize chronic conditions earlier
⊟ Enhanced triaging and stratification of patients
AI enables more effective stratification of patients
Machine-learning algorithms help triage and prioritize patients more effectively
⊟ Improved collaboration across processes / steps of patient journey
AI has the ability to combine processes across primary and secondary care (or even broader, across the overall HC system)
Machine-learning algorithms have the ability to combine processes across multiple care stages of the healthare system
⊟ Increased accessibility of (high-quality) diagnostic services
AI able to increase reach of medical practicians
AI as a replacement in LMIC
AI closing quality gap in diagnostics in HIC
AI improves diagnostics (in pathology) at a reasonable price
AI increasing medical imaging acessibility by offering affordable option
AI providing better, faster and cheaper diagnosis for rare diseases
⊟ Increased accuracy of diagnosis
AI can screen a CT scan more broadly and not only for the initial purpose the CT scan was arranged for
AI in CT scans enables a more holistic & thorough view on patients' health conditions
AI reduces errors in diagnosis of cancer
⊟ Increased efficiency of diagnostic processes
AI decreases the running costs in diagnosis
AI drives automation of medical labs
AI enables more efficient use of physician's time
AI enables treatment of more patients and decreases costs associated with it
AI increases speed of cancer diagnosis
AI making diagnosis better, easier and faster
AI will make diagnosis cheaper
Grand Total

WEAKNESSES
Row Labels
⊟ **Lack of maturity of algorithms**
Lack of maturity of medical AI solutions as obastacle to emergence of medical AI companies
⊟ **Resource-intensive implementation of AI**
Solutions time savings & productivity gains still do not compensate for costs
Grand Total

OPPORTUNITIES
Row Labels
⊟ Comprehensive formation of well-defined and proactive regulatory framework for medical AI solutions
Clear regulation on AI for medical devices and virtual diagnosis in Europe
Vision of protective but also supportive regulatory framework for AI in Europe
Well-defined regulation for medical AI systems is enabling factor medical AI technology
⊟ Further increasing accessibility of (high-quality) diagnostic services
AI as a replacement in LMIC
AI has potential to increase medical coverage in LMICs
⊟ Growing access to large volumes of all-embracing medical data
Access to big data significantly supports training of AI
Sufficient access to data needed to create improving system
⊟ Growing number of scientific proof for practicability of medical AI
Clinical validation studies promote medical AI-algortihms
Enabler: extensive amount of validation studies
Increase in clincal validation studies as enhancer for implementation
⊟ Growing pro-innovation mindset across cultures
AI now more seen as tool than threat by physicians
British law more pro-innovation
Enabler: promotion by renowned (health) institution
Overarching HC organization supporting implementation of medical AI solutions needed
Positive reference from world (health) bodies reinforces adoption of medical AI technologies
Pro-innovation attitude across cultures enables adoption of medical AI solutions
⊟ High potential of increased application of AI in non-visual, POC testing
Machine learning-algorithms in blood testing have huge industrial scaling potential
Machine learning-algorithms in non-visual area have great potential but are currently not focused on
Machine learning-algorithms well-suited for POC tests, easy to scale up and to maximize efficiencies
⊟ Improvements in Computing Technology
Computing power as enabler for imaging solutions
⊟ Increased financial support for medical AI solutions
Elevated funding as enabling factor for medical AI companies
Enabler (for growth): Sufficient VC funding
⊟ Patient data integration from multiple sources in the HC system
Complete and extensive data on patient's medical history is huge advantage
Enabler (for medical AI technology): Access to consolidated medical data
Future potential: AI's ability to synthesize data and create holistic picture of patient
⊟ Stronger focus on application of AI for earlier detection of chronic conditions
Patients with chronic health conditions usually get their diagnose and treatment too late
Problem: chronic conditions get diagnosed too late
⊟ Vision for AI in medical diagnostics
Future potential: AI can help to reduce availability bias
Future potential: AI can significantly increase quality and reduce time of diagnosis
Future potential: AI could replace doctors in the future where there is a shortage
Future potential: AI helping to develop a more thorough understanding of the human system
Future potential: AI improving continuous health monitoring of patients
Future potential: AI outperforming the human eye
Future potential: AI technologies that diagnose patients on-the-spot
Future potential: Being able to create holistic medical diagnostic tool with AI
Future potential: Creation of whole medical AI ecosystem that enables communication across all levels
Future potential: full automation of mundane tasks
Future potential: Transforming pathology through combination of automation & outperformance of human capabilities
Grand Total

THREATS
Row Labels
⊟ High cost of input data for medical AI imaging solutions
Image-analysis is currently field of focus for medical machine learning-algorithms but images are expensive to get
⊟ Imparting (systemic) biases through insufficient data quality & quantity
Biases in medical AI are known to exist but the root cause is unclear
Insufficient data quality and access reinforce the threat of biases
⊟ Insufficient institutional conditions for optimal adoption of medical AI
AI solution cannot unfold its potential in a system that works in silos.
Difficult and time-consuming to navigate through big, "political" bureaucracies as a small player
Potential barrier to implementation: non-existence of that overarching organization
⊟ Lack of business model of medical AI solutions
Missing business model for medical AI solutions as obastacle to emergence of medical AI companies
⊟ Misuse of provided, sensitive medical data
All-embracing patient data is needed to reduce biases, but is silmultaneously at risk of being misused if made available
⊟ Persistence of poor data quality
Data quality is current and future pain point
⊟ Persistent fragmentation of medical data
Availability of medical data dependent on country's medical system
Dispersion of medical data impeding factor
Medical information is currently fractioned = inefficient
⊟ Resource-intensive implementation of AI
Companies may currently be worse off with medical AI solutions than without
⊟ Restrictive course of regulations limiting possibilities of AI applications in diagnostics
Future compliance of medical AI products with regulation obscure for many companies
Hurdle: regulatory approval
Lack of holisitic regulation framework for AI introducing unceràinty
Regulation hampering combination of processes and systems through AI
Strict regulation Europe that is expected to intensify
⊟ Tedious change management in HC industry
Big risk: inability to attain approval from medical community
Change is tedious in medical community
Change-aversion and simple disinterest of people for new medical AI solutions is barrier for adoption
Conservatism and skepticism of physicians as barrier to implementation
Failure of competitors may fully destroy confidence in medical AI from physicians
Fear of replacement by AI among physicians as barrier to implementation
Hampered change management as obastacle to emergence of medical AI companies
Hurdle: clinican buy-in
Inertia in the current healthcare systems as barrier
Lack of technological literacy among physicians as barrier to implementation
Risk: change happening too slowly
Risk: Failure of competitors
The implementation / adoption of AI depends on willingness of humans to use it
Grand Total

Appendix 7. Supplements to Individual Part on SDG 11

a. List of Abbreviations

AI	Artificial intelligence
SDG	Sustainable Development Goal
UN	United Nations
ANN	Artificial Neural Network
GDPR	General Data Protection Rights
ML	Machine Learning
DL	Deep Learning

b. Criticism on SDG and NUA framework

The complex nature of creating sustainable cities and communities presents a methodological challenge that required a further monitoring framework. Complementing the SDG framework, the "New Urban Agenda (NUA)" was the conclusion paper of the United Nations Conference on Housing and Sustainable Urban Development in 2016. The aim of this framework is to assist in identifying the specific actions that can be taken to achieve sustainable urban development. This includes legal, political, administrative, and financial planning. While being a globally agreed deal such as the SDG`s, they are both of decisive importance for the achievement of sustainable urbanization (UN Habitat SDG, n.d.). However, these frameworks have several serious drawbacks. One of the most noticeable findings of the study by (Giles-Corti et al., 2020, pp. 588–590) on the SDG and NUA framework indicators is the differences in urban and health indicators, which can lead to confusion and inconsistency among cities when monitoring their performance and attempting to benchmark them. Therefore, the design and implementation of adequate sustainable policies becomes even more difficult. With their highly complex infrastructure, intensive policy coordination always be carried out and investment decisions must be made in a multidisciplinary and very well-informed manner (World Bank 2020). In the interest of coherence with the other selected SDGs, the focus of this work is on SDG target 11.

c. 3-Step Coding Process for Data Analysis

See the following link to the Excel file:

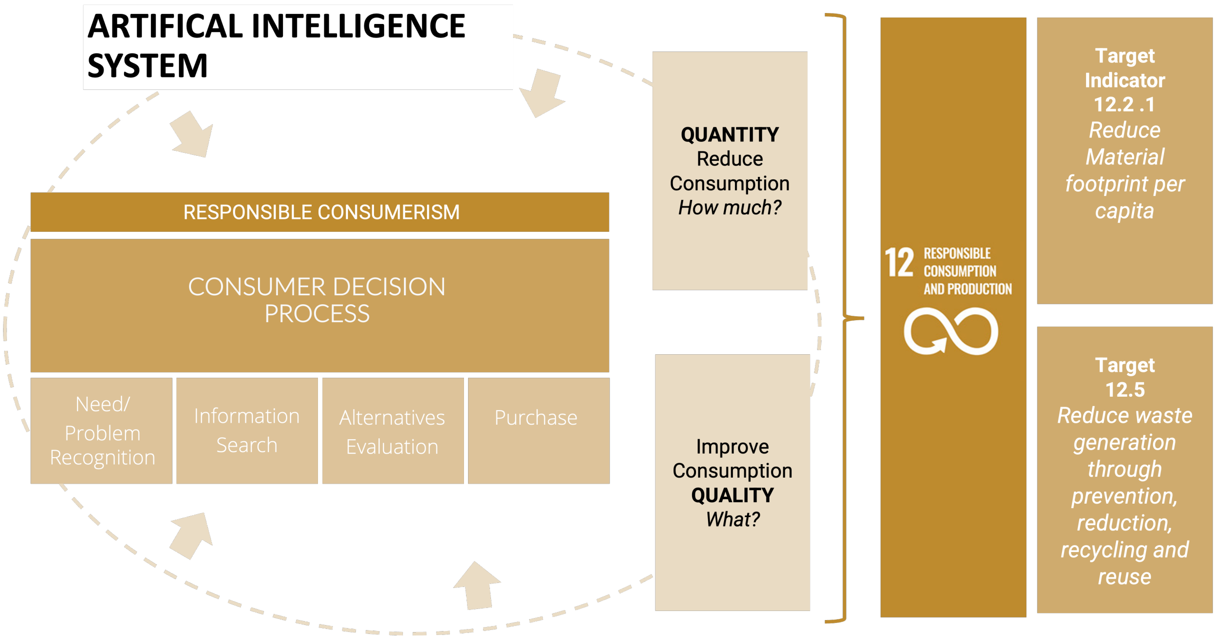
https://novasbe365.sharepoint.com/:x:/s/Mastermastern/Ef51MAFbgaBFirtVB_eQNoMBb5rvlLJSY8BOQFMuVMRV8g?e=tjcAvF

d. Detailed View of the Results in the SWOT Framework

Row Labels
Opportunity (external)
Collaboration and commitment
Good communication and exchange between regulators and providers within the transportation sector
Wide range of stakeholders are working on solutions
Exponential growth of available data
Availability of Open Source data
Constantly growing databases
Supportive Legal frameworks
GDPR brought legal clarity and uniformity across Europe
Supportive tool for human interactivity
Digitalized participation of people in cities
Strength (internal)
Improve operational excellence
Predictive event planning, changes or corresponding offers
Predictive maintenance in public transport
Quality and efficiency enhancing tool for employees
Improve safety & service quality for customers
Avoid disruptions and accidents
Improving service quality in public transport
Reduce congestion & pollution
Improve air quality and reduce noise pollution
Reduce traffic congestion
Threat (external)
Data volume and data protection issues
Even more power to organizations that have a lot of data
Overly strong data-protection regulations or inadequate framework on data ownership and usage may slow down the progress of AI technologies.
Operational focus
Bad communication and exchange between regulators and providers outside the transportation sector
Insufficient innovation can result in irrelevance of public transport companies
Satisfying daily reliable transport needs while at the same time innovating and introducing new technologies
Potential increase in traffic
More autonomous vehicles on the street
Regulations and warranty
Guarantees or maintenance contracts that undermine ability to integrate innovations fast
Lack of supporting legal framework due to fast-paced developments and slow adaptation of regulations (including problems with accountability)
Shift in power towards organizations and companies
Changes could eradicate jobs
Protracted, diverse and gradual transition
Skepticism about the technology
Public transport needs human interaction to be trustworthy
Trust has to be built and the opportunities have to be used sensibly
Weaknesses (internal)
Data dependence and resource intensity
Maintenance of a variety of data sources (reduce fragmentation and incompatibility)
Time-consuming and costly data preparation and integration (prepared data availability)
High demand for human resources
Hard to attract talent for a public transport company
High requirements for the expertise of human resources
Implementation difficulties
Complex calculation process with multidimensionality and large amount of differently formatted data
Task-specific use of AI - human resources manage the big picture
Grand Total

Appendix 8. Supplements to Individual Part on SDG 12

a. Illustration of the Investigated Context



b. Three-Step Coding Process for the Data Analysis

See the following link: https://novasbe365-my.sharepoint.com/:f:/g/personal/43931_novasbe_pt/EszgKhWVzE1Iv-Qdymacf-8BagAJh1f5t2Swh7GuAHGGaw?e=KIfBnC

c. Detailed View of the Results in the SWOT Framework

STRENGTHS
Row Labels
Efficiency and effectiveness in data analysis
Ability to assign meaning to opaque product information
Ability to reduce data quantity to the essential level
AI can help looking at a large scale at when a product will reach the end of its life the next stage of its life, when it goes to recycling or being repurposed or
Capability of AI to simply data to a easy understandable level for consumers and businesses
Finding and aggregating data into a green data base
Integration of all human interactions across time and location and place it into a bigger picture
Integration of multiple external and external factors such as parent company, country of manufacturing, and material to define products environmental impact
Optimized data scraping and integration of historical internal and external market data improves understanding of market trends minimizes surplus development and production
Efficiency and effectiveness in data collection
Capability of AI in large-scale label reading
Efficiency in pattern identification
Strong ability in image analysis
Strong ability in image analysis improves forecasting
Improves businesses understanding of the green consumer
Identification of exactly when and how to consumers need information
Increased accuracy and richness of predicting consumer behaviour
Increases efficiency in analysing consumer feedback
Strengths in text mining, language processing, and behaviour forecasting to close the consumer knowledge gap for businesses
Incentives for businesses to support responsible consumerism
Reducing return rate unlock efficiencies and represents incentives for business
Increases transparency of products environmental impact
Autodection of diverse elements across the web to define products sustainability
Capability of AI to define chemicals carbon footprint and predict future impact
Capability of AI to visualize scale making and identify starting points for change
Capability of AI: Material and energy selection & utilization assessment to define environmental impact of products
Capability of AI: Material assessment to define environmental impact of products
Creation of digital supply chain network replicate to provide Realtime traceability and visibility across the value chain
Increased accuracy in estimating products environmental impact
Increases environmental transparency for consumers by uncovering greenwashing attempts
Integration of multiple internal factors to define products environmental impact
Prediction of future environmental impact of a product
Uncovering starting points for proactive intervention to reduce environmental impact
Visibility across the value chain opens the possibility to make proactive interventions and to reduce environmental impact
Minimizing the barriers to sustainable consumer decisions
Highly effective recommendation system to reduce the environmental impact
Providing transparency to businesses and consumers
Use of AI to interact with individuals at the time and place the are trying to make responsible consumption decision making
Use of AI to support individuals at responsible consumption decision making
Minimizing the barriers to sustainable consumer decisions: attitude-behaviour gap
Convenience of place of AI solution integration at point of need
Highly effective recommendation system reducing environmental impact
Highly effective recommendation system reducing return rates
Improving brand engagement to raise awareness and tricker responsible consume
Increasing the Convience of making responsible consumption decision making by saving time
Increasing the Convience of responsible consumption decision making
Offering concrete alternatives to reduce impact
Providing incentivize to consumer to make better purchasing decisions
Use of AI to support individuals at responsible consumption decision making
Minimizing the barriers to sustainable consumer decisions: information gap
Capability of AI to decode products environmental impacts
Increase Convience of information presentation to the consumer by presenting easy understandable product information
Increasing the Convience of information presentation by embedding information on the product life-cycle directly to the product
Real time tracking and tracing of all sustainability metrics to increase visibility and transparency to the market, to their shareholders, and to the end market
Use AI to close consumers information gap on the environmental impact of products
Use of AI to accelerate and optimize the information search process for consumers
Minimizing the barriers to sustainable consumer decisions: knowledge gap
Application of machine learning models to provide product rating
Ease the identification of sustainable alternatives
Effectiveness in raising awareness visualizing future consumption impact
Engagement across all digital touchpoints in real time to raise awareness
Improving brand engagement to raise awareness
Uncovering and visualizing consumers environmental impact to raise awareness by tracking and forecasting behaviour
Use of AI to increase efficiencies for individuals in making responsible consumption decisions
Multiplicativity of sustainable solutions to consumer problems
Capability of AI to leverage problem solution at large scale and replicating them
Scalability of AI solutions: Potential multiplier of responsible consumption patterns around the globe
Strong advisory capability
Forecasting market developments to improve business decison making and optimize product and market fit
Improves decision certainty for consumers minimizes consumed quantity and reduces waste
Improves decision certainty for consumers minimizes returns and multi-size orders
Improves decision certainty for consumers minimizes returns and multi-size orders to reduce return processing
Improves decision certainty for consumers minimizes returns and multi-size orders to reduce transportation
Improves decision certainty for consumers minimizes risk of wastage
Improves individuals consumption decison making to reduce quantity
Support in choosing the environmentally friendly alternative
Grand Total

WEAKNESSES

Row Labels
⊟ High technological complexity
Requires highly skilled workforce which are lacking
⊟ Integration of AI is resource intensive
Demands for continuous maintenance and great workforce capacity
High complexity of finding the right starting point for an AI integration
High costs for AI integration
Iterative and time intensive training
Requires highly skilled workforce which are lacking
Grand Total

OPPORTUNITIES

Row Labels
⊟ Economical: Growing incentives for businesses to support responsible consumption
Better meeting the green consumers needs
By gaining better understanding of the new way of consuming optimizing product market fit
Optimizing demand prediction and reduction of surplus
Potential of AI to increase product information efficiency
Recognizing the Opportunity for cost reductions
Recognizing the Opportunity for increasing efficiencies and thereby minimizing environmental impact
Recognizing the Opportunity for refocusing resources
⊟ Economical: Increasing environmental awareness and understanding of the importance of AI to gain understanding of consumers and awareness of the potential starting point to evoke positive change among consumers
Awareness of the possibility to improve decison making on all level: Consumer, Business, Stakeholder
Pressure on business from institutions, consumers and next generation for change
Recognizing the Opportunity for complementarity of human and machine intelligence
UN climate change conference publishes alarming signs
Unmet business need: gaining better understanding of their products environmental impact along the value chain
⊟ Economical: Industry leaders as trigger for change
Big corporation as role models for driving responsible consumption
⊟ Economical: Market trends
Circular economy
Countries with high technological readiness
High-income markets bare great potentials
⊟ Economical: Openness among industry insiders for technology and innovation
Decreasing traditional concerns
Need for transparency along the value chain
⊟ Economical: Recognition of increasing economical advantages for businesses
Increasing awareness of opportunities
Increasing leverage of AI on the industry
Optimizing demand prediction and reduction of surplus
Unmet business need: gaining better understanding of the new way of consuming optimizing product market fit
Urgent need for consumer data and behaviour forecasting
⊞ Societal: Shift in consumers mindset
⊟ Technological: Continuous digitalization and rising importance of online shopping
Rising importance of online shopping
⊟ Technological: Data availability
Continuously increasing availability of data as lever for improvement
Continuously increasing availability of data as lever for improvement in market and consumer behaviour predictions
Digitalization drives consumer understanding helps uncover starting points
⊟ Technological: Research
Continuous research and development in the area of AI
⊟ Technological: Shift towards experience shopping
Emergence of new forms of marketing
⊟ Technology improvements
Autodection of diverse elements across the web to create a green data base
Avatar as sustainability advisor
Block chain encourages a collaborative way of working and supports to create an ecosystem of people.
Improvements in machine learning solving for data scarcity
Improvements in production technologies: Potential of AI to foster demand based production
⊟ Unmet green consumer needs
Unmet consumer need for support in closing the attitude behaviour gap
Unmet consumer need: Convenience of responsible consumption
Unmet consumer need: Reducing the barriers to consume more responsibly
Unmet consumer need: Reducing the information gap
⊟ Unmet need from institutes
EPA & FDA are backlogged
Grand Total

THREATS
Row Labels
⊟ Environmental impact of training AI models
Training AI models is highly energy intensive
⊟ Instrumentalization of AI capabilities to drive unbridled and environmentally harmful consumption
AI through recommendation minimizing the main consumption blocker of purchase uncertainty which drives consume
Bilateral effect of AI application on consume
Bilateral effect of AI application on consume - improvement of one consumption aspect can shift the problem and drive consumption elsewhere
Creation of digital replicates of consumer Injection of all a set of automation capabilities, understanding capabilities into the digital channels that the users would actually use.
Employment of AI capabilities to simulate and foster environmentally harmful consumption
Questionable effect of AI on responsible consumption and the environment
Risk of misusage of deep data driven consumer understanding
Risk that capabilities of AI are implemented to further simplify consume
The greater the improvement the higher the risk for misusage to drive consumption
Use of AI to personalize advertising and recommendation drives consume
Use of AI to simplify and drive consumption
⊟ Legal: High dependency on regulations and political decisions
Barriers due to fragmented regulations across countries
Major challenges due to existing obstructive regulations and changing regulatory environment
Risk from introduction of obstructive regulations
Risk of misjudgement and pressure on individual empowered to impose regulations on the usage of AI
⊟ Prerequisite Understanding Consumers Needs: Closing the knowledge gap for businesses
Challenge gaining and remaining customer focus to find the right starting point to guide them
Challenge of identifying the right place and form to provide support
Challenge understanding consumer needs
Challenge understanding consumer needs: Identify the right place and timing for decision guidance
Challenge understanding consumers
High dependency on comprehensive consumers understanding to uncover starting points for change
⊟ Readiness among businesses and consumers
Barrier is the mindset of Businesses and consumers to embrace the potential of AI
Consumer mindset change needed
Lack of understanding of the possibilities of combining human and AI capabilities and the potentials that can arise from it
Missing understanding from business side of the capability of AI to advice people and support them by consuming responsibly
Potential of AI to drive sustainable change in the retail and consumer good industry not yet recognized
Prerequisite: Integration of environmental impact into businesses - Lack of urge to change among business
Resistance among society due to lack of understanding for the need of change, the roots of the problem and missing awareness of potential of AI to support this
⊟ Risk of business rejection of implementation of AI solutions
High dependency on shareholder approval to include the environmental ambitious into the corporate performance ambition
High uncertainty of success of the model
Integration of AI entails change management, business exposure, giving up control
Obstruction by pressure from society to satisfy consume: Hindering businesses progress of change in unfolding AI potential
⊟ Societal: Risk of consumer rejection of the AI solution
Changing consumer attitudes
Data privacy concerns
Mistrust from consumers due to perceived loss of control over personal data
Perception of AI solution as threat to society when used as a replacement to human labour
Prerequisite democratizing AI bringing it closer to individuals
Prerequisite: Unite people to exploit the potential of the AI - in particular for technology distant industries
Risk of data leaks by subsequent companies and loosing consumers trust
⊟ Technological: Data availability
Missing data reduces forecasting accuracy
Operability of AI depends on data availability
⊟ Technological: High Dependency on the progress in the unification of platforms, data and the establishment of standards
Barriers are fragmented digital platforms different standard
Grand Total

Appendix 9. Supplements to Individual Part on SDG 14

a. Definitions of AI Subforms

Machine Learning	"Machine Learning is a subset of Artificial Intelligence that uses statistical learning algorithms to build systems that have the ability to automatically learn and improve from experiences without being explicitly programmed."	Roy (2020)
Deep Learning	Deep Learning is a further subtype of Machine Learning that is using so-called Neural Network Architecture to simulate the functionality of the human brain and can learn from the examples it is given	Roy (2020)

Computer Vision	"[C]omputer vision [is a] field of artificial intelligence in which programs attempt to identify objects represented in digitized images provided by cameras, thus enabling computers to "see".	(Britannica 2021a)
Robotics	Robotics is the "design, construction, and use of machines (robots) to perform tasks done traditionally by human beings. Robots are widely used in such industries as automobile manufacture to perform simple repetitive tasks, and in industries where work must be performed in environments hazardous to humans. Many aspects of robotics involve artificial intelligence; robots may be equipped with the equivalent of human senses"	(Britannica 2021b)

b. 3-Step Coding Process for Data Analysis

See the following link to the Excel file:

https://novasbe365-my.sharepoint.com/:f:/g/personal/43931_novasbe_pt/EklnIF7vtOxPubng9k3xFjMBIEw42INMdXpGah0SxrLw2g?e=p6sncn

c. Detailed View of Results in the SWOT Framework

STRENGHTS
Row Labels
⊟ **Efficacious supporting tool for human cleanup activity**
Increased safety for human activity through simulation of effects of Actions / Acitvities within Marine Ecosystem
Increased safety for human activity through targeted replacment of manual collection of hazardous waste through autonomous vehicles
AI as a tool to enable to optimize different kinds of cleanup efforts
⊟ **High Efficiency of Litter Monitoring**
Sensors are more accurate than the human eye
Aerial Drones reduced time for scanning an area
AI can make prioritizing where cleanups are needed more efficient
⊟ **Highly Efficient Litter Collection**
Autonomous Subsurface litter collection is cost efficient
Targeted, autonomous collection through (real time) processing of information from different sources (e.g. from monitoring function, prediction models, weather forecasts)
⊟ **Large Scale Litter Collection**
AI allows for scaling in Collection and Detection
Autnonomous solutions do not get tired
Autnonomous solutions do not lose attention
Autnonomous solutions do not need human intervention
Allows coordination of bigger systems with mutiple autonomous vessels
⊟ **Large Scale of Litter Monitoring helps to create holisitic understanding of the problem**
Large-scale mapping of geographical areas that are highly affected (trash heat maps, mapping of leakage points and high impact areas)
Builds models on large datasets to predict how natural forces (e.g. of tides, currents, etc.) affect the movement of waste
Identification of prominent litter types
⊟ **Validity of data from monitoring enables support decision makers upstream and downstream**
Potential for integrating AI in further steps of solving the problem: AI in prevention
Support companies & Policy makers in decision making about material bans / use
Use AI to create understanding about incentivization programs
Enables better recycling process through pre-screening of trash (recyclabililty, value, etc.)
Grand Total

WEAKNESSES

Row Labels
⊟ Inabililty to imitate human skills sufficiently
Imitation of human skills is hard (e.g. finger movement, decision making)
Challenges of robotic-movements under water
⊟ Inflexibility of algorithm to react to special types of litter
Large trash pieces and other objects can be threat to the autnomous vessel
(Variety of objects as debris)
⊟ Integration of AI is highly resource intensive
AI calls for multidisciplinary teams
High computing power needed for AI applications
High complexity of AI intergration
High costs of advanced sensors (lowers cost effiency)
High cost for satellite Imagery
High upfront cost for testing
High expertise required for AI Integration
Need for high quality data sets and ressource intense data processing
⊟ Lack of instinct to recognize and protect life forms and organic material
Conflicts with jellyfish due to similarity with plastic bags
Litter as new habitat for organisms
Potential enounters with marine life
Unintentional collection of Biomass
Grand Total

OPPORTUNITIES

Row Labels
⊟ AI as a growing field in research and practice
Emergence of educational programs
Increasing collaboration of Acadademia, Industry and Governments
Emergence of platforms to intergrate non-experts
Awareness of AI as a powerful technology and increased willingness of multidisciplinary teams (including non-experts) to contribute
⊟ Continiously expanding data inventory
Availabililty of Large Data Sets
Availabililty of Open Source Data
Data generation through Citizen Science
⊟ Improvements in battery technology
Battery technologies are getting cheaper
Battery technologies become more efficient
⊟ Improvements in Computing Technology
Computing technologies are getting cheaper
Quantum computing could increase efficency of AI
Edge Computing & Real time data collection can increase efficency and join functions
Emergence of small, highly powerfull computing devices (supercomputers) allow the integration of high computing power into drones, AUVs, etc.
⊟ Improvements in Information and Communications Technology
Improved Connectivity & communication in the future
⊟ Improvements in Sensor Technologies
Sensor technologies are getting decreasing in costs
Sensor technologies are becoming more compact
Emergence of highly accurate sensors (Infrared Sensors, Hyperspectral imaging, 3D images, LiDar etc.)
⊟ Increasing importance of sustainable development in the socio-political context
Shift in consumer mindset
Importance of Governmental Support for funding
Incresing Governmental Support to create awareness
Grand Total

THREATS

Row Labels
⊟ Challenge of economic viability of cleanup efforts
Lack of clear business model for retrieved plastic
Lack of clear customer base for ocean cleanup
⊟ Challenges due to limitations of component technologies
Limitations of Autonomous Vessels: low detection radius
Limitations of Autonomous Vessels: Capacity problem due to small size of vessels
Limitations of Information and Communication Technology: Risk of persistently low network connectivity in open seas
Limitations of Energy Technology: Solar Panels are not space efficient
Limitations of Energy Technology: Batteries are not space efficient (heavy and bulky)
Limitations of Autonomous Vessels: Navigation of complex systems of autonomous vessels through 3D water column need very advanced communication protocols
⊟ Challenges of unpredictability and complexity of operational environment
Constant environment best suitable for AI solutions
Objects (Bridges etc.) affecting detection with drones
Unclear water reduces vision (from air and from underwater) and makes detection and identification hard
High amount of see-through debris
Movement of litter and refraction of water makes detection and identification hard
External forces in rivers and oceans (e.g. currents, weather, etc.) can be a threat to the autonomous collection vessel
Wind and weather conditions can affect detection with aerial drones
Limited perspective of aerial drones allows no reliable information volume, only about area of waste carpet
Optical properties of water (Low light situation, refraction of light, color distortion, low contrast and loss of detail) makes monitoring of submerged litter hard
⊟ High Dependency on Governmental Incentivization and Support
Governments must incentivize and fund the development and implementation innovative AI projects of all sizes
⊟ Insufficient Quality and Quantity of Raw Data
Low quantity of existing data for marine ecosystems
High complexity of data collection in marine environment
Highly complex ecosystem with many variables that need to be integreated as data
⊟ Lack of supporting legal framework and slow adaptation of regulations
New regulations can be build on the knowledge of other domains with autonomous vehicles
Existing legal regulations limiting the use of aerial drones
Lack of framework that facilitates and promotes the data collection and sharing
Lack of clear regulations on navigation of aquatic vessels
⊟ Risk of rejection of AI solutions by society
Potential Vandalism and destuction of vessels
Preception of AI solution as threat to society when used as a replacement to human labour
Grand Total

d. Profile of Peniche Ocean Watch

Peniche Ocean Watch (POW) is a Portugal-based organization founded by Professor Robin Teigland. The organization is engaged in a magnitude of projects aiming to create solutions for social and environmental challenges in the coastal community of Peniche, Portugal. For a better understanding of the Managerial Implications in this work, two of their main projects, the Peladrone Project and the Ghost Ocean Project are further described below.

The knowledge about the projects and the company was generated through the interview with Professor Robin Teigland (I4.2), multiple informal conversations with representatives of the organizations that were conducted during the author's visit to the POW facilities in Peniche (see Pictures). The chance to engage closely with the organizations is also the reason why the two projects were chosen as examples for the managerial implications in Section and the information found on the company webpage that were listed here:

The Peladrone Project – Website Description

> *„Using the latest artificial intelligence and patented drone technology - developed by Norwegian firm, Birdview AS, and adapted to Portuguese conditions - the PELADRONE project aims to implement a drone-based reconnaissance solution for Portuguese SME fisheries to more sustainably and efficiently locate, track, and catch pelagic fish.*
>
> *The PELADRONE Project is part of the Peniche Ocean Watch Initiative led by Ocean Tech Hub LDA (OCT) in Peniche, Portugal. PELADRONE is a collaboration among Ocean Tech Hub LDA, the local fishing community in Peniche, the Norwegian high-tech companies Birdview AS and Borgen Eckey AS, and its International Advisory and Research Board with expert practitioners and researchers from Portugal, Norway, and Sweden."(Peniche Ocean Watch 2021b)*

NOVA SCHOOL OF BUSINESS & ECONOMICS

The Ghost Ocean Project – Website Description

> *"The aim of the Goast Ocean project is to address the challenges of scalable collection of sub-surface waste by fishermen. Today, fishing boats are not specifically equipped to conduct the retrieval of marine litter from the sea. To bring up the litter from the seafloor is risky as nets can get entangled in coral reefs while disturbances to seafloor sediments release nutrients and heavy metals as well as other articles.*
>
> *Combining marine litter retrieval with fishing at the same time is not easy for the fishermen. There are currently few incentives since marine litter retrieval has limited economic value. The scope of the Ghost Ocean project contains collaboration with the GhostNetWork as well as local fishermen in Peniche in the "Fishermen Collection of Marine Waste from the Ocean". In order to reach our goal, safe and sustainable solutions for the recovery of marine waste will be developed – following international guidelines and standards. By preparing an incentive program for the fishermen participating in waste collection work, the trapped values in the fishing community could be unlocked." (Peniche Ocean Watch 2021a)*

Impression of Author's visit of the POW facilities Peniche Ocean Watch

(4^{th} – 7^{th} of November 2021)

Appendix 10. Consolidated and Clustered SWOT-Findings for All Four Selected SDGs

STRENGHTS	Column Labels			
	Economy	Environment	Society	Grand Total
Driver for Efficiency	**2**	**2**	**9**	**13**
(Partially) exceeds human capabilites in medical diagnostics			1	1
Efficiency and effectiveness in data analysis	1			1
Efficiency and effectiveness in data collection	1			1
Enables earlier detection of chronic conditions			1	1
High Efficiency of Litter Monitoring		1		1
Highly Efficient Litter Collection		1		1
Improve air and noise pollution			1	1
Improved collaboration across processes / steps of patient journey			1	1
Increased efficiency of diagnostic processes			1	1
Improving service quality in public transport			1	1
Avoid disruptions and accidents			1	1
Ressource efficiency in public transport			1	1
Employee supporting tool in public transport			1	1
Support for Decision making	**4**	**2**	**3**	**9**
AI solutions as a supporting tool for human cleanup activity		1		1
Enhanced triaging and stratification of patients			1	1
Improves businesses understanding of the green consumer	1			1
Increased accuracy of diagnosis			1	1
Increases transparency of products environmental impact	1			1
Strong advisory capability	1			1
Validity of data from monitoring enables support decision makers upstream and downstream		1		1
Minimizing the barriers to sustainable consumer decisions	1			1
Reduce traffic congestion			1	1
Driver for Scale	**1**	**2**	**1**	**4**
Increased accessibility of (high-quality) diagnostic services			1	1
Large Scale Litter Collection		1		1
Large Scale of Litter Monitoring helps to create holisitic understanding of the problem		1		1
Multiplicativity of sustainable solutions to consumer problems	1			1
Grand Total	**7**	**6**	**13**	**26**

WEAKNESSES	Column Labels			
	Economy	Environment	Society	Grand Total
High Resource Intensity	**1**	**1**	**5**	**7**
Different data sources (reduce fragmentation and incompatibility)			1	1
Integration of AI is resource intensive	1	1	1	3
Meet the requirement of data volume (i.e. sufficient data-sets)			1	1
High requirements for the expertise of human resources			2	2
Lack of Technology maturity		**3**	**2**	**5**
AI can not imitate human skills sufficiently		1		1
Inflexibility of algorithm to react to special types of litter		1		1
Lack of instinct to recognize and protect life forms and organic material		1		1
The expectations in terms of possibilities and speed of implementation are very high and should be justified			1	1
Public transport needs human interaction to be trustworthy			1	1
Complex Artificial Intelligence Architecture			**3**	**3**
Data from multiple sources complexes computation process			1	1
Difficult data integration & availability			1	1
Challenge of Operation within a responsible, sustainable and user-centred architectural AI framework			1	1
Grand Total	**1**	**4**	**10**	**15**

OPPORTUNITIES	Column Labels			
	Economy	Environment	Society	Grand Total
Unmet Needs	**2**			**2**
Unmet green consumer needs	1			1
Unmet need from institutes	1			1
Supportive market developments	**4**		**4**	**8**
Comprehensive formation of well-defined and proactive regulatory framework for medical AI solutions			1	1
Further increasing accessibility of (high-quality) diagnostic services			1	1
Increased financial support for medical AI solutions			1	1
Shift towards experience shopping	1			1
Industry leaders as trigger for change	1			1
GDPR brought legal clarity and uniformity across Europe			1	1
Growing incentives for businesses to support responsible consumerism	1			1
New business models and readiness among high income countries	1			1
Mindset shift	**4**	**2**	**4**	**10**
AI as a growing field in research and practice		1		1
Growing pro-innovation mindset across cultures			1	1
Increasing importance of sustainable development in the socio-political context		1		1
Shift in consumers mindset	1			1
Increasing environmental awareness and understanding of the importance of AI to gain understanding of co	1			1
Openness among industry insiders for technology and innovation	1			1
Recognition of increasing economical advantages for businesses	1			1
Wide range of stakeholders are working on solutions			1	1
Good communication and exchange between regulators and providers within the same sector			1	1
Participation of people in cities changed dramatically			1	1
Advancements in research in the area of AI	**1**		**3**	**4**
Growing number of scientific proof for practicability of medical AI			1	1
High potential of increased application of AI in non-visual, POC testing			1	1
Stronger focus on application of AI for earlier detection of chronic conditions			1	1
Consumer good industry research in the field of AI	1			1
Increasing data value	**1**	**1**	**4**	**6**
Availability of Open Source data			1	1
Continiously expanding data inventory		1		1
Data availability	1			1
Growing access to large volumes of all-embracing medical data			1	1
Merger of patient data from multiple stages / departmetns in the HC system			1	1
Constantly growing databases			1	1
Improvements in component technology	**2**	**4**	**1**	**7**
Improvements in battery technology		1		1
Improvements in Computing Technology		1	1	2
Improvements in Infromation and Telecomunication Technology		1		1
Improvements in Sensor Technologies		1		1
Improvements in production technologies and machine learning to solve for data scarcity	1			1
Continious digitalization and rising importance of online shopping	1			1
Grand Total	**14**	**7**	**16**	**37**

NOVA SCHOOL OF BUSINESS & ECONOMICS

THREATS	Column Labels			
	Economy	Environment	Society	Grand Total
Obstructive regulations	**1**	**1**	**4**	**6**
Course of regulations limiting possibilities of AI applications in diagnostics			1	1
Overly strong data-protection regulations or inadequate framework on data ownership and usage may slow down the progress of AI technologie			1	1
Lack of supporting legal framework and slow adaptation of regulations due to fast-paced AI developments		1	1	2
Accountability & Contract Constraints			1	1
High dependency on regulations and political decisions	1			1
Operational Complexity		**1**	**3**	**4**
Challenges of unpredictability and complexity of operational environment		1		1
More vehicles on the street			1	1
Protracted, diverse and gradual transition			1	1
Satisfying basic daily needs of transport while at the same time innovating and introducing new technologies			1	1
Lack of economic model	**1**	**1**	**2**	**4**
Challenge of economic viability of cleanup efforts		1		1
High cost of input data for medical AI imaging solutions			1	1
Lack of business model of medical AI solutions			1	1
Risk of business rejection due to exposure, relinquishing control and great success uncertainty	1			1
Institutional barriers		**1**	**2**	**3**
HC institutions' set-up & operation hampering AI's adoption and thrive			1	1
High Dependency on Governmental Incentivization and Support		1		1
Bad communication and exchange between regulators and providers outside the own sector			1	1
Negative externalities of AI systems	**2**		**2**	**4**
Environmental impact of training AI models	1			1
Instrumentalization of AI capabilities to drive unbridled and environmentally harmful consumption	1			1
Misuse of provided, sensitive medical data			1	1
Even more power to organizations that have a lot of data			1	1
High data dependency		**1**	**3**	**4**
Amplification of (systemic) biases through insufficient data quality & quantity			1	1
Insufficient Quality and Quantity of Raw Data		1		1
Persistence of poor data quality			1	1
Persistent fragmentation of medical data			1	1
Risk of societal rejection	**2**	**1**	**5**	**8**
Readiness among consumers	1			1
Risk of rejection of AI solutions by society		1		1
Tedious Change management in HC industry			1	1
Trust has to be built and the opportunities have to be used sensibly			1	1
Citizens must become active and engaged participants - to make a city smart			1	1
Changes could eradicate job			1	1
Personal data - AI solutions to be inclusive and secure, counting on reliable, non-biased, fairly shared data, still preserving EU citizens' privacy			1	1
Perception of AI solution as threat to society, mistrust, and data privacy concerns	1			1
High dependency on component technologies	**1**	**1**		**2**
Challenges due to limitations of peripheral technologies		1		1
High Dependency on the progress in the unification of platforms, data and the establishment of standards	1			1
Grand Total	**7**	**7**	**21**	**35**

9. References

Abduljabbar, Rusul, Hussein Dia, Sohani Liyanage, and Saeed Asadi Bagloee. 2019. "Applications of Artificial Intelligence in Transport: An Overview." *Sustainability* 11 (1): 189. https://doi.org/10.3390/su11010189.

Acciona. n.d. "Natural Resources Deficit." ActiveSustainability. Accessed September 16, 2021. https://www.activesustainability.com/environment/natural-resources-deficit/.

Agrawal, Richa, and Sudhanshu Gupta. 2018. "Consuming Responsibly: Exploring Environmentally Responsible Consumption Behaviors." *Journal of Global Marketing* 31 (4): 231–45. https://doi.org/10.1080/08911762.2017.1415402.

AI for Good. 2021. "Goal 12: Responsible Consumption & Production - AI for Good Foundation." 2021. https://ai4good.org/ai-for-sdgs/goal-12-responsible-consumption-production/.

Allam, Zaheer, and Zaynah A. Dhunny. 2019. "On Big Data, Artificial Intelligence and Smart Cities." *Cities* 89 (June): 80–91. https://doi.org/10.1016/j.cities.2019.01.032.

Amel, Elise L., Christie M. Manning, and Britain A. Scott. 2009. "Mindfulness and Sustainable Behavior: Pondering Attention and Awareness as Means for Increasing Green Behavior." *Ecopsychology* 1 (1): 14–25. https://doi.org/10.1089/eco.2008.0005.

Audenhove, Francois-Joseph Van, Jérôme Pourbaix, Guillaume Rominger, Rick Eagar, and Jerome Carlier. 2021. "The Future of Mobility Post- COVID-19 – Turning a Crisis into an Opportunity." *Ad Little*, 18.

Barfield, Woodrow. 2018. "Liability for Autonomous and Artificially Intelligent Robots." *Paladyn, Journal of Behavioral Robotics* 9 (1): 193–203. https://doi.org/10.1515/pjbr-2018-0018.

Barnes, David K. A., Francois Galgani, Richard C. Thompson, and Morton Barlaz. 2009. "Accumulation and Fragmentation of Plastic Debris in Global Environments." *Philosophical Transactions of the Royal Society B: Biological Sciences* 364 (1526): 1985–98. https://doi.org/10.1098/rstb.2008.0205.

Beck, Jan-Philipp, Jorge Fernández García, Dr. Angela Spatharou, Solveigh Hieronimus, and Jonathan Jenkins. 2020. "Transforming Healthcare with AI: The Impact on the Workforce and Organizations." McKinsey & Company.

Bellou, Nikoleta, Chiara Gambardella, Konstantinos Karantzalos, João Gama Monteiro, João Canning-Clode, Stephanie Kemna, Camilo A. Arrieta-Giron, and Carsten Lemmen. 2021. "Global Assessment of Innovative Solutions to Tackle Marine Litter." *Nature Sustainability* 4 (6): 516–24. https://doi.org/10.1038/s41893-021-00726-2.

Biundo, Eliana, Pease Andrew, Koen Segers, Michael De Groote, Thibault D'Argent, and Edouard De Schaetzen. 2020. "The Socio-Economic Impact of AI in Healthcare."

Britannica, The Editors of Encyclopaedia. 2021a. "Computer Vision." In . Encyclopedia Britannica. https://www.britannica.com/technology/computer-vision.

———. 2021b. "Robotics." In . https://www.britannica.com/technology/robotics.

Cambridge Dictionary. 2021. "Expert." 2021. https://dictionary.cambridge.org/dictionary/english/expert.

Centre for the Fourth Industrial Revolution. 2021. "Ocean Data Platform." Centre for the Fourth Industrial Revolution. 2021. https://oceandata.earth.

Choy, Garry, Omid Khalilzadeh, Mark Michalski, Synho Do, Anthony E Samir, Oleg S Pianykh, J Raymond Geis, Pari V Pandharipande, James A Brink, and Keith J Dreyer. 2018. "Current Applications and Future Impact of Machine Learning in Radiology." *Radiology* 288 (2): 318–28.

Clearbot. 2021. "Clearbot - How Does It Work." Clearbot. 2021. https://www.clearbot.org.

Cole, Matthew, Pennie Lindeque, Claudia Halsband, and Tamara S. Galloway. 2011. "Microplastics as Contaminants in the Marine Environment: A Review." *Marine Pollution Bulletin* 62 (12): 2588–97. https://doi.org/10.1016/j.marpolbul.2011.09.025.

Collins, Andrea, Alessandro Galli, Nicoletta Patrizi, and Federico Maria Pulselli. 2018. "Learning and Teaching Sustainability: The Contribution of Ecological Footprint Calculators." *Journal of Cleaner Production* 174: 1000–1010. https://doi.org/10.1016/j.jclepro.2017.11.024.

NOVA SCHOOL OF BUSINESS & ECONOMICS

Cortès, Ulises, Miquel Sànchez-Marrè, Luigi Ceccaroni, Ignasi R-Roda, and Manel Poch. 2000. “Artificial Intelligence and Environmental Decision Support Systems.” *Applied Intelligence* 13 (1): 77–91. https://doi.org/10.1023/A:1008331413864.

Cui, Miao, and David Y Zhang. 2021. “Artificial Intelligence and Computational Pathology.” *Laboratory Investigation* 101 (4): 412–22.

Darley, William K., Charles Blankson, and Denise J. Luethge. 2010. “Toward an Integrated Framework for Online Consumer Behavior and Decision Making Process: A Review.” *Psychology & Marketing* 27 (2): 94–116. https://doi.org/10.1002/mar.20322.

Dash, Penelope, Grail Dorling, Katherine Linzer, Aditi Ramdorai, Jaana Remes, Kristin-Anne Rutter, and Shubham Singhal. 2020. “How Prioritizing Health Could Help Rebuild Economies.” *New York: Global Institute), July*.

Deidun, A., A. Gauci, S. Lagorio, and F. Galgani. 2018. “Optimising Beached Litter Monitoring Protocols through Aerial Imagery.” *Marine Pollution Bulletin* 131 (June): 212–17. https://doi.org/10.1016/j.marpolbul.2018.04.033.

Di Vaio, Assunta, Rosa Palladino, Rohail Hassan, and Octavio Escobar. 2020. “Artificial Intelligence and Business Models in the Sustainable Development Goals Perspective: A Systematic Literature Review.” *Journal of Business Research* 121: 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019.

Durif, Fabien, Caroline Boivin, and Charles Julien. 2010. “In Search of a Green Product Definition.” *Innovative Marketing* 6 (1): 25–33.

Easterby-Smith, M., R. Thorpe, P. Jackson, and A. Lowe. 2008. *Management Research*. 3rd ed. Sage London.

economiecirculaire.org. n.d. “Responsible Consumption.” Economiecirculaire.Org. Accessed November 12, 2021. https://www.economiecirculaire.org/static/h/responsible-consumption.html.

Euroconsumers. 2020. “How Consumer Centered AI Can Power the Green Transition.” euroconsumers. https://downloads.ctfassets.net/iapmw8ie3ije/5SHcIwwjZNdkbdOmaSrkNO/83b93b5c29d758ca6a1798ce4a74c66c/Euroconsumers_AI_White_Paper.pdf.

European Commission. 2020. “Citizen Science for Environmental Monitoring.”

European Parliament. 2020. “A European Green Deal | Strategy for Sustainable and Smart Mobility.” October 2021. December 2020. https://www.europarl.europa.eu/legislative-train/theme-a-european-green-deal/file-sustainable-and-smart-mobility#:~:text=On%209%20December%202020%2C%20the,of%20the%20EU's%20Digital%20Strategy.

Eurostat. 2020. “Urban and Rural Living in the EU.” February 2020. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/edn-20200207-1.

Everwave. 2021. “The Garbage Boat CollectiX.” *CollectiX* (blog). 2021. https://garbage-boat.com/en/product/.

FDA. 2018. “Medical Imaging.” FDA. FDA. March 11, 2018. https://www.fda.gov/radiation-emitting-products/radiation-emitting-products-and-procedures/medical-imaging.

Fernández García, Jorge, Dr. Angela Spatharou, Solveigh Hieronimus, Jan-Philipp Beck, and Jonathan Jenkins. 2020. “Transforming Healthcare with AI: The Impact on the Workforce and Organizations.” McKinsey & Company.

Franeker, Jan A. van, Christine Blaize, Johannis Danielsen, Keith Fairclough, Jane Gollan, Nils Guse, Poul-Lindhard Hansen, et al. 2011. “Monitoring Plastic Ingestion by the Northern Fulmar Fulmarus Glacialis in the North Sea.” *Environmental Pollution* 159 (10): 2609–15. https://doi.org/10.1016/j.envpol.2011.06.008.

Frost, Rosie. 2020. “Overconsumption Is Driving the Climate Crisis, Warn Scientists.” Euronews. July 13, 2020. https://www.euronews.com/green/2020/07/13/overconsumption-is-driving-the-climate-crisis-warn-scientists.

Fulton, Michael, Jungseok Hong, Md Jahidul Islam, and Junaed Sattar. 2019. “Robotic Detection of Marine Litter Using Deep Visual Detection Models.” In *2019 International Conference on Robotics and Automation (ICRA)*, 5752–58. Montreal, QC, Canada: IEEE. https://doi.org/10.1109/ICRA.2019.8793975.

Gaia-X. 2021. “Gaia-X and European Smart Cities and Communities - Whitepaper.” https://gaia-x.eu/sites/default/files/2021-10/Gaia-X%20SCC%20white%20paper.pdf.

Garcia-Garin, Odei, Asunción Borrell, Alex Aguilar, Luis Cardona, and Morgana Vighi. 2020. "Floating Marine Macro-Litter in the North Western Mediterranean Sea: Results from a Combined Monitoring Approach." *Marine Pollution Bulletin* 159 (October): 111467. https://doi.org/10.1016/j.marpolbul.2020.111467.
Gene, Chao, Jane Cheug, Karl Haller, and Jim Lee. 2019. "The Coming AI Revolution in Retail and Consumer Products: Intelligent Automation Is Transforming Both Industries in Unexpected Ways." United States of America: IBM Corporation.
Giles-Corti, Billie, Melanie Lowe, and Jonathan Arundel. 2020. "Achieving the SDGs: Evaluating Indicators to Be Used to Benchmark and Monitor Progress towards Creating Healthy and Sustainable Cities." *Health Policy* 124 (6): 581–90. https://doi.org/10.1016/j.healthpol.2019.03.001.
Giles-Corti, Billie, Anne Vernez-Moudon, Rodrigo Reis, Gavin Turrell, Andrew L Dannenberg, Hannah Badland, Sarah Foster, et al. 2016. "City Planning and Population Health: A Global Challenge." *The Lancet* 388 (10062): 2912–24. https://doi.org/10.1016/S0140-6736(16)30066-6.
Gilg, Andrew, Stewart Barr, and Nicholas Ford. 2005. "Green Consumption or Sustainable Lifestyles? Identifying the Sustainable Consumer." *Futures* 37 (6): 481–504. https://doi.org/10.1016/j.futures.2004.10.016.
Goralski, Margaret A., and Tay Keong Tan. 2020. "Artificial Intelligence and Sustainable Development." *The International Journal of Management Education* 18 (1): 100330. https://doi.org/10.1016/j.ijme.2019.100330.
Greenpeace. 2021. "Oceans Issues & Threats." *Greenpeace USA* (blog). 2021. https://www.greenpeace.org/usa/oceans/issues/.
Grober, Von Ulrich. 1999. "Der Erfinder der Nachhaltigkeit." ZEIT ONLINE. 1999. https://www.zeit.de/1999/48/Der_Erfinder_der_Nachhaltigkeit.
Gunčar, Gregor, Matjaž Kukar, Mateja Notar, Miran Brvar, Peter Černelč, Manca Notar, and Marko Notar. 2018. "An Application of Machine Learning to Haematological Diagnosis. Sci Rep. 2018; 8: 411."
Haberl, Helmut, Dominik Wiedenhofer, Doris Virág, Gerald Kalt, Barbara Plank, Paul Brockway, Tomer Fishman, Daniel Hausknost, Fridolin Krausmann, and Bartholomäus Leon-Gruchalski. 2020. "A Systematic Review of the Evidence on Decoupling of GDP, Resource Use and GHG Emissions, Part II: Synthesizing the Insights." *Environmental Research Letters* 15 (6): 065003. https://iopscience.iop.org/article/10.1088/1748-9326/ab842a.
Haller, Karl, Jim Lee, and Jane Cheug. 2020. "Meet the 2020 Consumers Driving Change - Why Brands Must Deliver on Omnipresence, Agility, and Sustainability." IBM Institute for Business Value.
Herweijer, Celine, and Dominic Kailash Nath Waughray. 2019. "Why Tech Will Be Key in Our Quest to Hit the SDGs." World Economic Forum. 2019. https://www.weforum.org/agenda/2019/09/technology-global-goals-sustainable-development-sdgs/.
Hidalgo-Ruz, Valeria, and Martin Thiel. 2015. "The Contribution of Citizen Scientists to the Monitoring of Marine Litter." *Marine Anthropogenic Litter*, June, 429–47. https://doi.org/10.1007/978-3-319-16510-3_16.
Holm, Courtney, Katja Van Beaumont, Marc Rietra, Markus Winkler, Jean-Marie Lapeyer, Tim Bridges, Mazza Lindsey, et al. 2021. "Circular Economy for a Sustainable Future." Capgemini. a. https://www.capgemini.com/wp-content/uploads/2021/11/Circular-Economy_11112021_v10_web.pdf.
IBM Corporation. 2018. "What Do Gen Z Shoppers Really Want?" https://www.ibm.com/downloads/cas/W07A8QGE.
ICSU and ISSC. 2015. "Review of the Sustainable Development Goals: The Science Perspective. Paris: International Council for Science (ICSU)." *2015*. https://council.science/publications/review-of-targets-for-the-sustainable-development-goals-the-science-perspective-2015/.
Jakovljevic, Gordana, Miro Govedarica, and Flor Alvarez-Taboada. 2020. "A Deep Learning Model for Automatic Plastic Mapping Using Unmanned Aerial Vehicle (UAV) Data." *Remote Sensing* 12 (9): 1515. https://doi.org/10.3390/rs12091515.

Jambeck, Jenna R., Roland Geyer, Chris Wilcox, Theodore R. Siegler, Miriam Perryman, Anthony Andrady, Ramani Narayan, and Kara Lavender Law. 2015. "Plastic Waste Inputs from Land into the Ocean." *Science* 347 (6223): 768–71. https://doi.org/10.1126/science.1260352.

Jha, Avinash Kumar, Awishkar Ghimire, Surendrabikram Thapa, Aryan Mani Jha, and Ritu Raj. 2021. "A Review of AI for Urban Planning: Towards Building Sustainable Smart Cities." In *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, 937–44. Coimbatore, India: IEEE. https://doi.org/10.1109/ICICT50816.2021.9358548.

Kako, Shin'ichiro, Shohei Morita, and Tetsuya Taneda. 2020. "Estimation of Plastic Marine Debris Volumes on Beaches Using Unmanned Aerial Vehicles and Image Processing Based on Deep Learning." *Marine Pollution Bulletin* 155 (June): 111127. https://doi.org/10.1016/j.marpolbul.2020.111127.

Kantify. 2021. "AI for Breast Cancer Detection Using Whole-Slide Images." 2021. https://www.kantify.com/insights/ai-for-breast-cancer-detection-using-whole-slide-images.

Kantrow, Alan. 1980. "The Strategy-Technology Connection." *Harvard Business Review*, July 1, 1980. https://hbr.org/1980/07/the-strategy-technology-connection.

Kaplan, Andreas, and Michael Haenlein. 2018. "Siri, Siri, in My Hand: Who's the Fairest in the Land? On the Interpretations, Illustrations, and Implications of Artificial Intelligence." 2018. https://doi.org/10.1016/j.bushor.2018.08.004.

Kelly, Christopher J, Alan Karthikesalingam, Mustafa Suleyman, Greg Corrado, and Dominic King. 2019. "Key Challenges for Delivering Clinical Impact with Artificial Intelligence." *BMC Medicine* 17 (1): 1–9.

Kershaw, P. J., and C. M. Rochman. 2015. "Sources, Fate and Effects of Microplastics in the Marine Environment: Part 2 of a Global Assessment." *Reports and Studies-IMO/FAO/Unesco-IOC/WMO/IAEA/UN/UNEP Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection (GESAMP) Eng No. 93*.

Kershaw, Peter. 2016. *Marine Plastic Debris and Microplastics: Global Lessons and Research to Inspire Action and Guide Policy Change*. United Nations Environment Programme.

Ketzler, Bernd, Vasilis Naserentin, Fabio Latino, Christopher Zangelidis, Liane Thuvander, and Anders Logg. 2020. "Digital Twins for Cities: A State of the Art Review." *Built Environment* 46 (December): 547–73. https://doi.org/10.2148/benv.46.4.547.

Konux. 2021. "The KONUX Predictive Maintenance System for Rail Switches." Konux. 2021. https://www.konux.com/solutions/.

Krishnadas, R. 2021. "Understanding Customer Engagement and Purchase Behavior in Automobiles: The Role of Digital Technology." In *Handbook of Research on Technology Applications for Effective Customer Engagement*, 1–13. IGI Global. http://doi:10.4018/978-1-7998-4772-4.ch001.

Kylili, Kyriaki, Ioannis Kyriakides, Alessandro Artusi, and Constantinos Hadjistassou. 2019. "Identifying Floating Plastic Marine Debris Using a Deep Learning Approach." *Environmental Science and Pollution Research* 26 (17): 17091–99. https://doi.org/10.1007/s11356-019-05148-4.

Lange, S. 2018. *Macroeconomics without Growth: Sustainable Economies in Neoclassical, Keynesian and Marxian Theories. Wirtschaftswissenschaftliche Nachhaltigkeitsforschung*. Vol. 19. Metropolis-Verlag.

Liu, Xiaoxuan, Livia Faes, Aditya U Kale, Siegfried K Wagner, Dun Jack Fu, Alice Bruynseels, Thushika Mahendiran, Gabriella Moraes, Mohith Shamdas, and Christoph Kern. 2019. "A Comparison of Deep Learning Performance against Health-Care Professionals in Detecting Diseases from Medical Imaging: A Systematic Review and Meta-Analysis." *The Lancet Digital Health* 1 (6): e271–97.

Lovell, N, and J Bibby. 2018. "What Makes Us Healthy? An Introduction to the Social Determinants of Health." *The Health Foundation, London*.

Mace, Thomas H. 2012. "At-Sea Detection of Marine Debris: Overview of Technologies, Processes, Issues, and Options." *Marine Pollution Bulletin* 65 (1–3): 23–27. https://doi.org/10.1016/j.marpolbul.2011.08.042.

Makridakis, Spyros. 2017. “The Forthcoming Artificial Intelligence (AI) Revolution: Its Impact on Society and Firms.” *Futures* 90: 46–60. https://doi.org/10.1016/j.futures.2017.03.006.

Manley, Justin E. 2008. “Unmanned Surface Vehicles, 15 Years of Development.” In *OCEANS 2008*, 1–4. Ieee.

Mardani, Abbas, Dalia Streimikiene, Fausto Cavallaro, Nanthakumar Loganathan, and Masoumeh Khoshnoudi. 2019. “Carbon Dioxide (CO2) Emissions and Economic Growth: A Systematic Review of Two Decades of Research from 1995 to 2017.” *Science of the Total Environment* 649: 31–49. https://doi.org/10.1016/j.scitotenv.2018.08.229.

Marin, Ivana, Saša Mladenović, Sven Gotovac, and Goran Zaharija. 2021. “Deep-Feature-Based Approach to Marine Debris Classification.” *Applied Sciences* 11 (12): 5644. https://doi.org/10.3390/app11125644.

Markussen, Bjorn Tore, and Kristian Teleki. 2021. “How Data Is Transforming How We Care for the World’s Ocean.” World Economic Forum. May 4, 2021. https://www.weforum.org/agenda/2021/04/how-a-digitized-version-of-the-ocean-can-help-the-planet-gtgs/.

Marshall, C., and G. R. Rossman. 1999. *Designing Qualitative Research*. 3rd ed. Sage.

Martínez-Vicente, Víctor, James R. Clark, Paolo Corradi, Stefano Aliani, Manuel Arias, Mathias Bochow, Guillaume Bonnery, et al. 2019. “Measuring Marine Plastic Debris from Space: Initial Assessment of Observation Requirements.” *Remote Sensing* 11 (20): 2443. https://doi.org/10.3390/rs11202443.

Maximenko, Nikolai, Paolo Corradi, Kara Lavender Law, Erik Van Sebille, Shungudzemwoyo P. Garaba, Richard Stephen Lampitt, Francois Galgani, et al. 2019. “Toward the Integrated Marine Debris Observing System.” *Frontiers in Marine Science* 6 (August): 447. https://doi.org/10.3389/fmars.2019.00447.

McGinty, David. 2021. “5 Opportunities of a Circular Economy.” February 3, 2021. https://www.wri.org/insights/5-opportunities-circular-economy.

McKinney, Scott Mayer, Marcin Sieniek, Varun Godbole, Jonathan Godwin, Natasha Antropova, Hutan Ashrafian, Trevor Back, Mary Chesus, Greg S Corrado, and Ara Darzi. 2020. “International Evaluation of an AI System for Breast Cancer Screening.” *Nature* 577 (7788): 89–94.

Merriam-Webster. 2021. “Efficiency.” In *Merriam-Webster Dictionary*. https://www.merriam-webster.com/dictionary/efficiency.

Michael L. Littman, Ifeoma Ajunwa, Guy Berger, Craig Boutilier, Morgan Currie, Finale Doshi-Velez, Gillian Hadfield, et al. 2021. “Gathering Strength, Gathering Storms: The One Hundred Year Study on Artificial Intelligence (AI100) 2021 Study Panel Report.” *Stanford University*, September.

Mora, Camilo, Derek P. Tittensor, Sina Adl, Alastair G. B. Simpson, and Boris Worm. 2011. “How Many Species Are There on Earth and in the Ocean?” Edited by Georgina M. Mace. *PLoS Biology* 9 (8): e1001127. https://doi.org/10.1371/journal.pbio.1001127.

Moro, Arielle, and Adrian Holzer. 2020. “A Framework to Predict Consumption Sustainability Levels of Individuals.” *Sustainability* 12 (4): 1423. https://doi.org/1423; https://doi.org/10.3390/su12041423.

Murray, Fiona, and Phillip Rhys Cowie. 2011. “Plastic Contamination in the Decapod Crustacean Nephrops Norvegicus (Linnaeus, 1758).” *Marine Pollution Bulletin* 62 (6): 1207–17. https://doi.org/10.1016/j.marpolbul.2011.03.032.

National Academies of Sciences, Engineering, and Medicine. 2015. *Improving Diagnosis in Health Care*. National Academies Press.

National Geographic. 2017. “Threats Facing The Oceans and Their Species.” Environment. May 1, 2017. https://www.nationalgeographic.com/environment/article/ocean-threats.

NCI. 2011a. “Definition of Diagnosis - NCI Dictionary of Cancer Terms - National Cancer Institute.” NciAppModulePage. Nciglobal,ncienterprise. February 2, 2011. https://www.cancer.gov/publications/dictionaries/cancer-terms/def/diagnosis.

———. 2011b. “Definition of Laboratory Test - NCI Dictionary of Cancer Terms - National Cancer Institute.” NciAppModulePage. Nciglobal,ncienterprise. February 2, 2011. https://www.cancer.gov/publications/dictionaries/cancer-terms/def/laboratory-test.

Nikitas, Alexandros, Kalliopi Michalakopoulou, Eric Tchouamou Njoya, and Dimitris Karampatzakis. 2020. "Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era." *Sustainability* 12 (7): 2789. https://doi.org/10.3390/su12072789.

Noguerol, Teodoro Martín, Félix Paulano-Godino, María Teresa Martín-Valdivia, Christine O Menias, and Antonio Luna. 2019. "Strengths, Weaknesses, Opportunities, and Threats Analysis of Artificial Intelligence and Machine Learning Applications in Radiology." *Journal of the American College of Radiology* 16 (9): 1239–47.

Nosratabadi, Saeed, Amir Mosavi, Ramin Keivani, Sina Ardabili, and Farshid Aram. 2019. "State of the Art Survey of Deep Learning and Machine Learning Models for Smart Cities and Urban Sustainability." Madrid.

OSPAR Commission. 2017. "Assessment Document of Land-Based Inputs of Microplastics in the Marine Environment." In *The Convention for the Protection of the Marine Environment of the North-East Atlantic. Environmental Impact of Human Activities Series*.

Oxford University Press. 2021. "Consumerism Noun - Definition, Pictures, Pronunciation and Usage Notes | Oxford Advanced Learner's Dictionary at OxfordLearnersDictionaries.Com." 2021. https://www.oxfordlearnersdictionaries.com/definition/english/consumerism.

Palomares, Iván, Eugenio Martínez-Cámara, Rosana Montes, Pablo García-Moral, Manuel Chiachio, Juan Chiachio, Sergio Alonso, et al. 2021a. "A Panoramic View and Swot Analysis of Artificial Intelligence for Achieving the Sustainable Development Goals by 2030: Progress and Prospects." *Applied Intelligence* 51 (9): 6497–6527. https://doi.org/10.1007/s10489-021-02264-y.

———. 2021b. "A Panoramic View and Swot Analysis of Artificial Intelligence for Achieving the Sustainable Development Goals by 2030: Progress and Prospects." *Applied Intelligence* 51 (9): 6497–6527. https://doi.org/10.1007/s10489-021-02264-y.

———. 2021c. "A Panoramic View and Swot Analysis of Artificial Intelligence for Achieving the Sustainable Development Goals by 2030: Progress and Prospects." *Applied Intelligence* 51 (9): 6497–6527. https://doi.org/10.1007/s10489-021-02264-y.

Papaoikonomou, Eleni. 2013. "Sustainable Lifestyles in an Urban Context: Towards a Holistic Understanding of Ethical Consumer Behaviours. Empirical Evidence from Catalonia, Spain." *International Journal of Consumer Studies* 37 (2): 181–88. https://doi.org/10.1111/j.1470-6431.2012.01111.x.

Paranjape, Ketan, Michiel Schinkel, Richard D Hammer, Bo Schouten, RS Nannan Panday, Paul WG Elbers, Mark HH Kramer, and Prabath Nanayakkara. 2021. "The Value of Artificial Intelligence in Laboratory Medicine: Current Opinions and Barriers to Implementation." *American Journal of Clinical Pathology* 155 (6): 823–31.

Peniche Ocean Watch. 2021a. "Ghost Ocean." Peniche Ocean Watch. 2021. https://www.penicheoceanwatch.com/ghost-ocean.

———. 2021b. "Peladrone." Peniche Ocean Watch. 2021. https://www.penicheoceanwatch.com/peladrone.

Pickett-Baker, Josephine, and Ritsuko Ozaki. 2008. "Pro-environmental Products: Marketing Influence on Consumer Purchase Decision." *Journal of Consumer Marketing* 25 (5): 281–93. https://doi.org/10.1108/07363760810890516.

Policy Department for Economic, Scientific and Quality of Life Policies. 2021. "Artificial Intelligence in Smart Cities and Urban Mobility." European Parliament. https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/662937/IPOL_BRI(2021)662937_EN.pdf.

Purvis, Ben, Yong Mao, and Darren Robinson. 2019. "Three Pillars of Sustainability: In Search of Conceptual Origins." *Sustainability Science* 14 (3): 681–95. https://doi.org/10.1007/s11625-018-0627-5.

Quiñonero-Candela, Joaquin, Masashi Sugiyama, Neil D Lawrence, and Anton Schwaighofer. 2009. *Dataset Shift in Machine Learning*. Mit Press.

Ramakrishna, Seeram, Alfred Ngowi, Henk De Jager, and Bankole O. Awuzie. 2020. "Emerging Industrial Revolution: Symbiosis of Industry 4.0 and Circular Economy: The Role of Universities." *Science, Technology and Society* 25 (3): 505–25. https://doi.org/10.1177/0971721820912918.

RanMarine. 2021. “Wasteshark.” *RanMarine Technology* (blog). 2021. https://www.ranmarine.io/products/wasteshark/.
Rathore, M. Mazhar, Awais Ahmad, Anand Paul, and Seungmin Rho. 2016. “Urban Planning and Building Smart Cities Based on the Internet of Things Using Big Data Analytics.” *Computer Networks* 101 (June): 63–80. https://doi.org/10.1016/j.comnet.2015.12.023.
Reid, Philip C., Astrid C. Fischer, Emily Lewis-Brown, Michael P. Meredith, Mike Sparrow, Andreas J. Andersson, Avan Antia, et al. 2009. “Chapter 1 Impacts of the Oceans on Climate Change.” In *Advances in Marine Biology*, 56:1–150. Elsevier. https://doi.org/10.1016/S0065-2881(09)56001-4.
Robboy, Stanley J, Sally Weintraub, Andrew E Horvath, Bradden W Jensen, C Bruce Alexander, Edward P Fody, James M Crawford, Jimmy R Clark, Julie Cantor-Weinberg, and Megha G Joshi. 2013. “Pathologist Workforce in the United States: I. Development of a Predictive Model to Examine Factors Influencing Supply.” *Archives of Pathology and Laboratory Medicine* 137 (12): 1723–32.
Robson, C. 2002. *Real World Research*. 2nd ed. Oxford: Blackwell.
Roy, Rupali. 2020. “Understanding the Difference between AI, ML and DL!!” Medium. May 1, 2020. https://towardsdatascience.com/understanding-the-difference-between-ai-ml-and-dl-cceb63252a6c.
Saunders, M., P. Lewis, and A. Thornhill. 2009a. *Research Methods for Business Students*. Pearson Education Limited.
———. 2009b. *Research Methods for Business Students*. 5th ed. Pearson Education Limited.
Schönherr, Norma, and André Martinuzzi, eds. 2019. *Business and the Sustainable Development Goals: Measuring and Managing Corporate Impacts*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-16810-0.
Schuett, Jonas. 2019. “A Legal Definition of AI.” *SSRN Electronic Journal*, January. https://doi.org/10.2139/ssrn.3453632.
SeaClear. 2021. “About SeaClear.” 2021. https://seaclear-project.eu/about-main/about-seaclear.
Shen, Maocai, Shujing Ye, Guangming Zeng, Yaxin Zhang, Lang Xing, Wangwang Tang, Xiaofeng Wen, and Shaoheng Liu. 2020. “Can Microplastics Pose a Threat to Ocean Carbon Sequestration?” *Marine Pollution Bulletin* 150 (January): 110712. https://doi.org/10.1016/j.marpolbul.2019.110712.
Shrivastva, krishna mohan. 2014. *Cloud Computing: Need, Enabling Technology, Architecture, Advantages and Challenges*. https://doi.org/10.1109/CONFLUENCE.2014.6949224.
Silverman, D. 2007. *A Very Short, Fairly Interesting and Reasonably Cheap Book about Qualitative Research*. Sage London.
Sjollema, Sascha B., Paula Redondo-Hasselerharm, Heather A. Leslie, Michiel H.S. Kraak, and A. Dick Vethaak. 2016. “Do Plastic Particles Affect Microalgal Photosynthesis and Growth?” *Aquatic Toxicology* 170 (January): 259–61. https://doi.org/10.1016/j.aquatox.2015.12.002.
Spatharou, Angela, Jorge Fernández García, Solveigh Hieronimus, Jan-Philipp Beck, and Jonathan Jenkins. 2020. “Transforming Healthcare with AI: The Impact on the Workforce and Organizations.”
Stern, David I., Reyer Gerlagh, and Paul J. Burke. 2017. “Modeling the Emissions–Income Relationship Using Long-Run Growth Rates.” *Environment and Development Economics* 22 (6): 699–724. https://doi.org/10.1017/S1355770X17000109.
Strauss, A., and J. Corbin. 2008. *Basics of Qualitative Research*. 3rd ed. Sage.
Sun, Chenshuo, Zijun June Shi, Xiao Liu, Anindya Ghose, Xueying Li, and Feiyu Xiong. 2019. “The Effect of Voice Ai on Consumer Purchase and Search Behavior.” *NYU Stern School of Business*, 1–43. http://dx.doi.org/10.2139/ssrn.3480877.
Taddeo, Mariarosaria, and Luciano Floridi. 2018. “How AI Can Be a Force for Good.” *Science* 361 (6404): 751–52. https://doi.org/10.1126/science.aat5991.
Teuten, Emma L., Jovita M. Saquing, Detlef R. U. Knappe, Morton A. Barlaz, Susanne Jonsson, Annika Björn, Steven J. Rowland, et al. 2009. “Transport and Release of Chemicals from Plastics to the Environment and to Wildlife.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 364 (1526): 2027–45. https://doi.org/10.1098/rstb.2008.0284.

The Independent. 2020. "Could Technology Help Me Shop More Sustainably Online?" The Independent. November 10, 2020. https://www.independent.co.uk/20-pledges/technology-sustainable-beauty-industry-b1641344.html.
Trice, Amy, Chris Robbins, Nidhisha Philip, and Matt Rumsey. 2021. "Challenges and Opportunities for Ocean Data to Advance Conservation and Management." *Ocean Conservancy, Washington DC*.
Tussyadiah, Iis, and Graham Miller. 2019. "Perceived Impacts of Artificial Intelligence and Responses to Positive Behaviour Change Intervention." In *Information and Communication Technologies in Tourism 2019*, 359–70.
UITP. 2018. "Artifical Intelligence in Public Mass Transport." International Association for public transport. https://cms.uitp.org/wp/wp-content/uploads/2020/08/UITP-AP-CTE-AI-in-PT-Executive-Summary-Dec-2018_0.pdf.
UN DESA. 2021. *Sustainable Development Goals Report 2021*. S.l.: United Nations.
UN ECOSOC. 2021. "Progress towards the Sustainable Development Goals Report of the Secretary-General."
UN General Assembly. 2015. *Transforming Our World: The 2030 Agenda for Sustainable Development*. UN.
———. 2017. "Resolution Adopted by the General Assembly on 6 July 2017." A/RES/71/313.
UN Habitat. 2020. "Department of Economic and Social Affairs | United Nations Human Settlements Programme (UN-HABITAT)." 2020. https://sdgs.un.org/un-system-sdg-implementation/united-nations-human-settlements-programme-un-habitat-24511.
UN Habitat Flagship Programme. 2020. "People-Centered Smart Cities | UN-Habitat." 2020. https://unhabitat.org/programme/people-centered-smart-cities.
UN Habitat SDG. n.d. "Sustainable Development Goals Cities | UN-Habitat." Accessed November 18, 2021. https://unhabitat.org/programme/sustainable-development-goals-cities.
UN, Statistic Division. 2021. "SDG Indicators - Goal 12, Ensure Sustainable Consumption and Production Patterns." United Nations, Department of Economic and Social Affairs. https://unstats.un.org/sdgs/report/2019/goal-12/.
UNEP. 2005. "Marine Litter, an Analytical Overview."
———. 2017. "One Planet Network." UNEP - UN Environment Programme. October 4, 2017. http://www.unep.org/explore-topics/resource-efficiency/what-we-do/one-planet-network.
United Nations. 1948. "Universal Declaration of Human Rights | United Nations." 1948. https://www.un.org/en/about-us/universal-declaration-of-human-rights.
———. 2020. "Responsible Consumption & Production: Why It Matters." https://www.un.org/sustainabledevelopment/wp-content/uploads/2019/07/12_Why-It-Matters-2020.pdf.
———. 2021. "Goal 12 | Department of Economic and Social Affairs." 2021. https://sdgs.un.org/goals/goal12.
United Nations - Department of Economic and Social Affairs. 2018. *World Urbanization Prospects: The 2018 Revision*.
United Nations - DESA. 2016. "Goal 11." 2016. https://sdgs.un.org/goals/goal11.
———. 2021. "The Sustainable Development Goals Report 2021." 2021. https://unstats.un.org/sdgs/report/2021/goal-11/.
United Nations Conference on Trade and Development. 2021. *Digital Economy Report 2021: Cross-Border Data Flows and Development*. S.l. https://unctad.org/system/files/official-document/der2021_en.pdf.
UNOOSA. 2021. "Sustainable Development Goal 3: Good Health and Well-Being." 2021. https://www.unoosa.org/oosa/en/ourwork/space4sdgs/sdg3.html.
Urban Innovative Actions. 2019. "VoxPop - People, Processes & Technology towards the digital transformation of the urban mobility system of Lisbon." VoxPop - People, Processes & Technology towards the digital transformation of the urban mobility system of Lisbon. 2019. https://www.uia-initiative.eu/fr/uia-cities/lisbon.
Valdenegro-Toro, Matias. 2016. "Submerged Marine Debris Detection with Autonomous Underwater Vehicles." In *2016 International Conference on Robotics and Automation for Humanitarian Applications (RAHA)*, 1–7. Amritapuri, Kollam, Kerala, India: IEEE. https://doi.org/10.1109/RAHA.2016.7931907.

Van Vugt, Martin, and Moniek Van der Liende. 2021. "ReShare Makes Fashion Retail More Sustainable with AI." *Capgemini* (blog). July 27, 2021. https://www.capgemini.com/pt-en/client-story/reshare-part-of-the-salvation-army-makes-fashion-retail-more-sustainable-with-ai/.

Varghese, Cherian. 2017. "Reducing Premature Mortality from Non-communicable Diseases, Including for People with Severe Mental Disorders." *World Psychiatry* 16 (1): 45.

Vinuesa, Ricardo, Hossein Azizpour, Iolanda Leite, Madeline Balaam, Virginia Dignum, Sami Domisch, Anna Felländer, Simone Daniela Langhans, Max Tegmark, and Francesco Fuso Nerini. 2020a. "The Role of Artificial Intelligence in Achieving the Sustainable Development Goals." *Nature Communications* 11 (1): 233. https://doi.org/10.1038/s41467-019-14108-y.

———. 2020b. "The Role of Artificial Intelligence in Achieving the Sustainable Development Goals." *Nature Communications* 11 (1): 233. https://doi.org/10.1038/s41467-019-14108-y.

Wang, Dayong, Aditya Khosla, Rishab Gargeya, Humayun Irshad, and Andrew H Beck. 2016. "Deep Learning for Identifying Metastatic Breast Cancer." *ArXiv Preprint ArXiv:1606.05718*.

Wang, Zhaohua, Mengtian Xue, Yutao Wang, Malin Song, Shanjun Li, Ricardo A. Daziano, Bo Wang, Guanhua Ma, Ke Chen, and Xiangtao Li. 2019. "Big Data: New Tend to Sustainable Consumption Research." *Journal of Cleaner Production* 236: 117499. https://doi.org/10.1016/j.jclepro.2019.06.330.

Webb, Deborah J., Lois A. Mohr, and Katherine E. Harris. 2008. "A Re-Examination of Socially Responsible Consumption and Its Measurement." *Journal of Business Research* 61 (2): 91–98. https://doi.org/10.1016/j.jbusres.2007.05.007.

Werner, Stefanie, Ania Budziak, Jan van Franeker, François Galgani, Georg Hanke, Thomas Maes, Marco Matiddi, et al. 2016. *Harm Caused by Marine Litter: MSFD GES TG Marine Litter - Thematic Report*. http://edepot.wur.nl/411865.

WHO. 1995. "Constitution of the World Health Organization."

———. 2013. *Global Action Plan for the Prevention and Control of Noncommunicable Diseases 2013-2020*. World Health Organization.

———. 2017. "Tracking Universal Health Coverage: 2017 Global Monitoring Report."

———. 2021a. "Noncommunicable Diseases." April 13, 2021. https://www.who.int/westernpacific/health-topics/noncommunicable-diseases.

———. 2021b. "Ethics and Governance of Artificial Intelligence for Health: WHO Guidance." World Health Organization. June 28, 2021.

Wiedmann, Thomas, Manfred Lenzen, Lorenz T. Keyßer, and Julia K. Steinberger. 2020. "Scientists' Warning on Affluence." *Nature Communications* 11 (1): 3107. https://doi.org/10.1038/s41467-020-16941-y.

Wiedmann, Thomas O., Heinz Schandl, Manfred Lenzen, Daniel Moran, Sangwon Suh, James West, and Keiichiro Kanemoto. 2015. "The Material Footprint of Nations." *Proceedings of the National Academy of Sciences* 112 (20): 6271–76. https://doi.org/10.1073/pnas.1220362110.

Witman, Sarah. 2017. "World's Biggest Oxygen Producers Living in Swirling Ocean Waters." *Eos*, September. https://doi.org/10.1029/2017EO081067.

World Bank. 2020. "Urban Development by the World Bank." World Bank. April 2020. https://www.worldbank.org/en/topic/urbandevelopment/overview.

———. 2021. "World Bank Country and Lending Groups – World Bank Data Help Desk." 2021. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

World Commission on Environment and Development. 1987. *Our Common Future*. Oxford; New York: Oxford University Press.

Wynn, Russell B., Veerle A.I. Huvenne, Timothy P. Le Bas, Bramley J. Murton, Douglas P. Connelly, Brian J. Bett, Henry A. Ruhl, et al. 2014. "Autonomous Underwater Vehicles (AUVs): Their Past, Present and Future Contributions to the Advancement of Marine Geoscience." *Marine Geology* 352 (June): 451–68. https://doi.org/10.1016/j.margeo.2014.03.012.

Yasav, Sue. 2015. "The Impact of Digital Technology on Consumer Purchase Behavior." *The Journal of Financial Perspectives: EY Global Financial Services Institute* 3 (3).

Yin, R. K. 2003. *Case Study Research: Design and Methods*. Sage.
Youmatter. 2019. “Responsible Consumption: Definition and Examples.” Youmatter. 2019. https://youmatter.world/en/definition/definitions-responsible-consumption-examples/.
Zereik, Enrica, Marco Bibuli, Nikola Mišković, Pere Ridao, and António Pascoal. 2018. “Challenges and Future Trends in Marine Robotics.” *Annual Reviews in Control* 46: 350–68. https://doi.org/10.1016/j.arcontrol.2018.10.002.
Zhang, Guanglu, Daniel A. McAdams, Venkatesh Shankar, and Milad Mohammadi Darani. 2017. “Modeling the Evolution of System Technology Performance When Component and System Technology Performances Interact: Commensalism and Amensalism.” *Technological Forecasting and Social Change* 125 (December): 116–24. https://doi.org/10.1016/j.techfore.2017.08.004.