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User experience in Digital Twin based applications

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Resumo

Digital Twins estão a tornar-se um elemento arquitetónico e funcional numa variedade de sistemas de gestão de sistemas físicos. Desde produtos complexos até à interligação de componentes em processos igualmente complexos, os Digital Twins estão a afirmar-se como o conceito cognitivo com o qual os operadores interagem para conceber, gerir, controlar e manter esses produtos e processos. As suas capacidades de monitorização em tempo real, simulação e análise preditiva trazem uma grande inovação para inúmeras áreas.

Apesar desta evolução, continua a haver um conhecimento limitado sobre como implementar a interação humana e a experiência do utilizador neste tipo de sistemas. Esta dissertação aborda essa lacuna na literatura propondo uma metodologia de design centrado no utilizador, com o objetivo de melhorar a usabilidade, acessibilidade e eficiência dos sistemas baseados em Digital Twins. Através de uma revisão exploratória da literatura e entrevistas a especialistas, este estudo identifica os principais desafios da experiência do utilizador e estabelece requisitos de design de alto nível para sistemas baseados em Digital Twins. A abordagem proposta enfatiza a importância da aplicação de técnicas de design centradas no utilizador, como a implementação de interfaces orientadas por funções e o desenvolvimento baseado em protótipos, para apoiar uma interação eficiente entre humanos e máquinas.

A metodologia foi validada através da sua aplicação no projeto RENÉE, que promove princípios da economia circular através da remanufatura assistida por inteligência artificial. O caso de estudo envolveu o desenvolvimento de protótipos de interface a nível estratégico, tático e operacional, apoiados por avaliações de usabilidade. Os resultados obtidos demonstram que a integração de princípios de experiência do utilizador no desenvolvimento de sistemas baseados em Digital Twins aumenta a satisfação dos utilizadores, diminui a taxa de erros e simplifica o processo de tomada de decisões. Este trabalho contribui ainda para a mudança de paradigma industrial, ao promover a importância do ser humano no design de sistemas digitais, da sustentabilidade e da resiliência, valores que se alinham aos princípios da Indústria 5.0.

Abstract

Digital Twins are becoming an architectural and functional element in a variety of systems managing physical assets. From complex products to the interconnection of assets in complex processes, digital twins are becoming the overarching cognitive concept that operators interact with to design, manage, control and maintain those products and processes. Their real-time monitoring, simulation, and predictive analytics capabilities bring great innovation to numerous fields.

Despite this evolution, there is still limited knowledge on how to design the human interaction and user experience in these kinds of systems. This dissertation addresses this gap by proposing a user-centered design methodology aimed at enhancing usability, accessibility, and system efficiency in Digital Twin-based systems. Through an exploratory literature review and expert interviews, this study identifies critical user experience challenges and establishes high-level design requirements for Digital Twin-based systems. The proposed approach emphasizes the importance of employing user-centered design techniques, such as role-based user interfaces, and prototype-driven development to support efficient user interaction.

The methodology was validated through its application in the RENÉE project, which promotes circular economy principles via AI-enabled remanufacturing. The case study involved the development and testing of interface prototypes accross strategic, tactical, and operational user levels, supported by usability evaluations. The results obtained demonstrate that integrating user experience principles in the development of Digital Twin-based systems results in user satisfaction, reduced error rates, and facilitates decision-making. This work also contributes to the industrial paradigm shift, as it promotes human-centricity, sustainability, and resilience, which align with Industry 5.0 principles.

United Nations Sustainable Development Goals

The United Nations Sustainable Development Goals (SDGs) consist of a seventeen item list containing global goals to address global challenges and promote sustainable development. The SDGs are a universal call to action to end poverty, protect the planet, and ensure peace and prosperity for all by 2030. This dissertation aligns with and contributes to several of the SDGs, particularly those related to sustainable industry, innovation, and responsible consumption, namely SDG 9 and SDG 12.

The current study aims to enhance the functionality and usability of Digital Twin-based systems by introducing a user-centered methodology tailored to the needs of diverse industrial role. The integration of these practices in advanced digital technologies allows users to fully leverage the system's capabilities, increasing productivity, therefore encouraging a wider adoption of innovation in industrial contexts. Thus, it supports SDG 9 – build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.

Furthermore, one of the RENÉE project's primary goals is to enhance remanufacturing processes as part of a broader Circular Economy strategy. The integration of Digital Twins allows for lifecycle tracking, predictive maintenance, and intelligent decision-making—key enablers of waste reduction and resource efficiency. This objective strongly aligns with SDG 12, which aims to ensure sustainable consumption and production patterns. Table 1 shows how this dissertation can contribute to some SDGs' targets.

Table 1: SDGs' targets covered by this dissertation.

SDG	Target	Contribution	Performance indicators and metrics
9. Industry, Innovation and Infrastructure	9.4	Upgrades factories to make them more sustainable, with increased resource-use efficiency and greater adoption of environmentally-friendly industrial processes.	Indicator 9.4.1: C02 emission per unit of value added. Metric: Amount of CO2 emissions in the supply chain.
	9.5	Promotes scientific research of new advanced digital solutions in the industrial context.	Indicator 9.5.2: Researchers (in full-time equivalent) per million inhabitants. Metric: Increase the amount of researchers working on the project's development.
12. Responsible Consumption and Production	12.2	Promotes the sustainable use of natural resources by integrating CE principles in industrial processes.	Indicator 12.2.1: In Material footprint, material footprint per capita, and material footprint per GDP. Metric: Reduction in the use of raw materials per manufactured product through optimization and remanufacturing enabled by Digital Twin systems.
	12.5	Fosters CE principles, such as reduction, recycling and reuse, substantially reducing waste generation.	Indicator 12.5.1: National recycling rate, tons of material recycled. Metric: Amount of recycled material.
	12.6	Encourages companies from diverse fields and of various sizes to adopt sustainable practices and report them.	Indicator 12.6.1: Number of companies publishing sustainability reports. Metric: Increase the amount of companies publishing sustainability reports.

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Ana Beatriz Cruz Fontão

"It's hard to see things when you are too close.
Take a step back and look."

Bob Ross

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Abbreviations

DT	Digital Twin
CDT	Cognitive Digital Twin
UX	User Experience
UI	User Interface
GUI	Graphical User Interface
UCD	User-Centered Design
IoT	Internet of Things
AR	Augmented Reality
VR	Virtual Reality
XR	Extended Reality
PLM	Product Lifecycle Management
KPI	Key Performance Indicator
UC	Use Case
US	User Story
ML	Machine Learning
AI	Artificial Intelligence
2D	Two Dimensional
3D	Three Dimensional
NLP	Natural Language Processing
LLM	Large Language Models
I4.0	Industry 4.0
I5.0	Industry 5.0
O4.0	Operator 4.0
O5.0	Operator 5.0
SUS	System Usability Scale

Chapter 1

Introduction

1.1 Context and Motivation

In recent decades, the industry environment has changed dramatically due to the massive growth of technology, leading to great breakthroughs across numerous sectors. Framed in the paradigm of Industry 4.0, the creation of Digital Twin technologies has become a remarkable development.

Throughout the years, the concept of a Digital Twin (DT) has evolved significantly. Initially, the DT was described as a virtual replica of a physical product containing its information, which was manually collected and mostly paper-based [25]. However, over time, with the advancements of technologies like Internet of Things (IoT), Artificial Intelligence (AI) and Machine Learning (ML), the DT capabilities have expanded.

Nowadays, DTs are considered intelligent and evolving agents that not only duplicate their physical counterpart, but also have the ability to simulate, do predictive analysis, and directly deploy changes to the physical system. DTs continuously receive data from sensors and can, for instance, predict equipment failure and optimize processes in real-time, greatly improving the efficiency of operations. This technology has proved itself to be a great innovation in the industry sector since it allows real-time monitoring of systems.

Because of these capabilities, DTs brought numerous advantages to the sectors where they are inserted, such as manufacturing, aviation and healthcare [7]. For instance, they can predict when a device needs maintenance, helping to prevent failures and aid users in important decision-making moments [8]. Among other functionalities, they are able to optimize processes, like production, and simulate future scenarios for the Physical Twin. The physical twin includes the objects that are virtually modeled, which can be "a single observable entity, a system, or a set of interdependent entities" [42].

Despite the great importance the DTs have gained on the industry, the research and development in this area has been mostly focused on the technical aspects, such as real-time data processing and simulations [31], while the user interaction and experience side of it are still vastly underexplored.

Even with all the modernization observed in the industry, human performance still remains in charge of the quality of products and the productivity [52]. As these innovations become more prevalent in work spaces and even daily operations, User Experience (UX) plays a crucial role in overcoming the gap between complex systems and users. A well-designed UX creates a user-friendly and intuitive system that can minimize errors and increase efficiency and productivity.

1.2 Problem

Digital Twin systems deal with vasts amounts of data and, since they have the ability to, for example, simulate real-world conditions and predict outcomes, predict the need for maintenance of equipments, optimize production processes, and improve operational efficiency, they have become an essential element in the industry.

Despite this positive impact, there is a critical gap between the technical evolution and the user experience on DT systems. The current research and development is majorly focused on the technical capabilities of these technologies and tend to overlook the importance of interface design and user interaction.

As mentioned in section 1.1, the use of good UX practices, in most cases, enhances the user capabilities and, by doing so, also improves the overall performance of the process in question. Understanding how to accommodate users needs by studying their behaviors and preferences is essential to allow users to take advantage of the full potential of technologies. By implementing well-designed user interfaces, the system becomes more manageable and intuitive, ensuring that both expert and non-expert users are able to successfully use it. For instance, a poorly organized front-end with complex data causes users to have a hard time navigating, interpreting and operating the systems.

In the case of DT-based applications, the lack of consideration for user interaction in the development phase may have consequences for the users that operate them and for the industry where they are inserted. Possibly, by addressing the issue in question, users would be able to take advantage of the full potential of the DT, resulting in greater accuracy at crucial tasks like monitoring, predicting and simulating events. Furthermore, providing an intuitive and positive user experience results in lower rates of human error, reduced training time and overall a greater productivity and user satisfaction.

This gap between the lack of user-centered design and the major technological development on DTs is what motivated this dissertation. This project aims to address it by focusing on the design and prototype of a user interface for DT based applications, as well as contribute to future practical application and to the research on this topic.

1.3 Research questions

In order to better understand the impact of UX in DT based applications, the following questions were designed:

RQ1 In Digital Twin systems, how crucial is the development of a user-friendly User Interface, and which design approaches improve usability the most?

RQ2 How does User Experience affect the functionality and efficiency of Digital-Twin based applications?

RQ3 Is it relevant to define guidelines for Digital Twin development that integrate UX principles, and how could these guidelines improve user satisfaction and system performance?

This project's goal is to obtain a better understanding on how the integration of UX principals affects the development and the use of DTs. This will be done by carrying out tests and validations on how addressing UX challenges can enhance the operational efficiency of DT systems and the overall user interaction. Each question was created to comprehend how DT technologies can be optimized through improved design and user-centric development.

1.4 Report Structure

This report is composed of five main chapters. The current chapter presents the background and motivation for the research, identifying the problem and relevant research questions that guide the study. It highlights the relevance of Digital Twins in modern manufacturing activities, and the importance of improving their usability.

Chapter 2 reviews the existing literature regarding Digital Twin technologies, their integration in manufacturing and in Circular Economy practices. Additionally, it addresses the recent industrial paradigms, as well as relevant Circular Economy aspects. This chapter also brings focus to the current practices of User-centered development in Digital Twin systems, and presents the importance of user interfaces and user experience in complex environments.

Then, in chapter 3, the methodology employed in the study is detailed. It includes the description of the steps taken to develop the proposed approach, and the protocol used during the expert interviews. Furthermore, the chapter 4 presents the results from the methodology. These include the high-level requirements for User Experience in Digital Twin-based systems, as well as an approach for the design, development, and testing of these systems.

In chapter 5 the proposed methodology is applied to a case study from the RENÉE project. This chapter tests the applicability of the proposed approach within a real manufacturing context. It presents the results of usability testing, offering insights into system performance from a user perspective. Finally, chapter 6 summarizes the key findings and contributions of the study.

1.5 Project development

This section outlines the institutional and project framework in which the dissertation was developed, as well as the timeline of its execution.

1.5.1 INESC TEC and the RENÉE Project

INESC TEC (Institute for Systems and Computer Engineering, Technology and Science) is a private, non-profit research institution with 40 years of experience in research and development. This dissertation was developed in the Enterprise Systems Engineering Center (CESE) of INESC TEC, which create innovative services for industrial organizations while promoting high impact management and expanding the scientific understanding of enterprise systems engineering.

The research work is part of the ongoing European Union-funded project titled RENÉE – Flexible Remanufacturing Using AI and Advanced Robotics for Circular Value Chains in EU Industry. This project, which will be in course until 2027, is dedicated to advancing human-centric and AI-enabled production systems. The main focus of the project is the integration of Circular Economy principles within industrial manufacturing processes, which includes promoting remanufacturing practices that minimize waste of resources.

1.5.2 Dissertation Work plan

Figure 1.1. presents the Gantt Chart of the development phases for this dissertation.

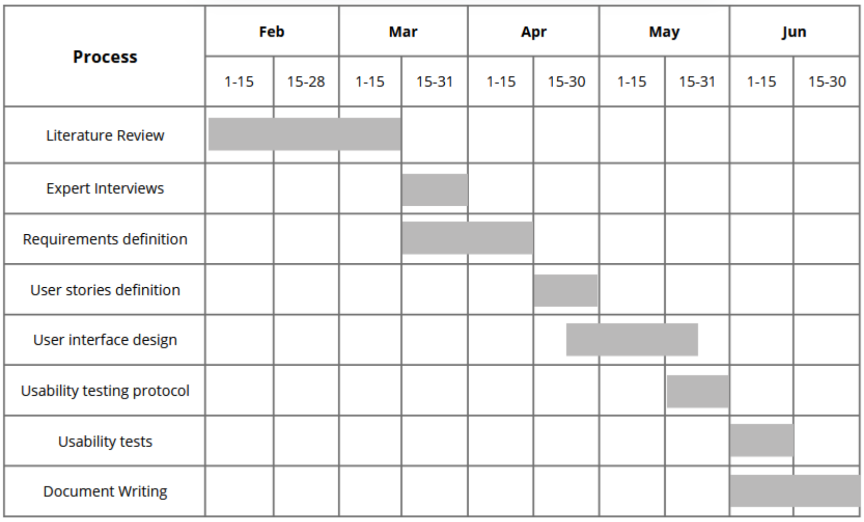

Figure 1.1: Gantt Chart

Chapter 2

Literature Review

Recently, Digital Twin technologies have been emerging rapidly and, with this evolution, the lack of attention given to UX and user interaction becomes more noticeable and critical. Understanding how the users interact with these complex systems is crucial in order to evaluate their usability and improve the efficiency of user interactions. Therefore, this literature review aims to obtain an overview of studies that have addressed this issue and similar topics.

2.1 Methodology

This literature review follows an exploratory technique. This approach was chosen due to its flexibility and the broadness of the theme at hand. It provides the opportunity to critically examine the most relevant literature for this project while not enforcing strict protocols.

The identification phase of this process had the goal of identifying a wide variety of research studies that addressed User Experience in Digital Twin based application and related topics. To ensure a broad and relevant research on the subject, the databases used were picked based on their relevance in the scientific community. The main data sources used were IEEE Xplore, SCOPUS, ScienceDirect, Clarivate Web of Science, and ACM Digital Library.

The following search terms used were chosen to find the most relevant studies and research on the topic: User experience, User interaction, Digital Twin, IoT, Human-Computer Interaction, Usability requirements, Circular Economy and Remanufacturing. To refine the search, boolean operator, such as "AND" and "OR", were used. By using search strings that include multiple relevant terms, the results become more specific and pertinent to the study. Additionally, an iterative process was employed to refine and improve the search results.

Then, the screening phase of the process aimed to filter and refine the results from the previous phase, including the removal of duplicates and exclusion of studies that do not comply with the defined inclusion criteria. In order to be included, a paper should be a result from the search query using the previously mentioned search strings, to guarantee that the information is recent and relevant to the theme. Moreover, it should be published in the English language, to allow better understanding and maintain consistency during the review, and also have full-text access. A publication should also be discarded if it is still a work in progress, as it may include incomplete analyses, lack robust conclusions and be subjected to significant changes during the peer-review phase before the final publication. This will prevent unreliable information to be included in the study.

Finally, in the selection phase, the contents of the selected publications are analyzed in multiple steps. Firstly, each publication is reviewed by its title, and, if it fits well with the topic, it passes to the following analysis step. After the title, the abstract is analyzed to confirm the relevance of the publication and its followed by the analysis of the conclusions. Finally, the full text of the document is examined.

During this analysis, the publication may be discarded at any step of the process when it is revealed to be outside the scope or irrelevant to the study. The main tool used for reference management was Zotero. This is an open-source software for managing bibliographic data and research-related materials. Zotero provided a more efficient process due to its features, such as customizable tagging, duplicate detection and automatic citation.

2.2 Digital Twin Technologies

This section aims to present an overview of concepts surrounding the Digital Twin technology, including basic definitions, a summary of the common architecture of these systems and some applications of Digital Twins.

2.2.1 Concepts and Architecture

The concept of the Digital Twin (DT) was first introduced in the early 2000s by Dr. Michael Grieves in the context of a Product Lifecycle Management (PLM) course [25]. At the time, the digital representation of physical systems was new and underdeveloped. Despite being a recent technology, the concept of mirrored systems has been explored for many decades. The initial definition of a Digital Twin referred to a virtual counterpart of a physical product that had the ability to simulate, analyze, and optimize its performance throughout its lifecycle [7]. During that time, information collection from the physical product was very rudimentary, since it was "limited, collected manually, and mostly based on paper" [25].

In the following decades, the concept of Digital Twin has evolved significantly, reflecting the technological advancements in various fields, such as the Internet of Things (IoT) and Machine Learning (ML). In recent years, the research surrounding these systems has increased immensely, but, despite this growing interest, there is a lack of consensus in the literature on the precise definition of the Digital Twin. Nevertheless, the Digital Twin is seen as a way to improve the performance of physical systems or entities through advanced computational methods executed by the digital counterpart [31]. It provides rich virtual representations of real-world products that are nearly indistinguishable from their physical twins. Through IoT sensors and other connected devices, the digital twin has the ability to receive and process information collected from the physical twin. This data is then used to make predictions or perform simulations of possible scenarios that the physical twin might encounter. These monitoring and managing abilities facilitate the analysis and understanding of the product's performance during its various life-cycle phases, leading to more informed decision-making regarding the design, operation, and maintenance of the physical counterpart.

The traditional DT architecture comprises three key components, the physical entity, the digital counterpart, and the data connections linking the two, as shown in Figure 2.1. The physical twin includes the objects that are virtually modeled, which can be "a single observable entity, a system, or a set of interdependent entities". It is equipped with sensors and other monitoring devices that collect real-time data, for instance of geometric shape, spatial position, behavioral state and the logical structure of multiple physical objects in the system (the last one is only applicable to the scenarios of a physical twin made up of multiple interdependent entities) [42].

The digital counterpart is a virtual representation of the physical twin, containing detailed design, behavior, and performance data [7]. It integrates multi-domain perspectives to form a high-fidelity model, with a software layer that employs Artificial Intelligence (AI) for diagnosis, prediction, and decision-making [42].

The communication layer enables real-time, bidirectional data exchange. The physical twin sends raw sensor data to the digital model, which processes it and returns useful outputs such as performance adjustments, diagnostics, or control commands [25]. Accurate, real-time data is essential for the digital twin to function reliably, forming a closed-loop system that continuously optimizes the physical twin.

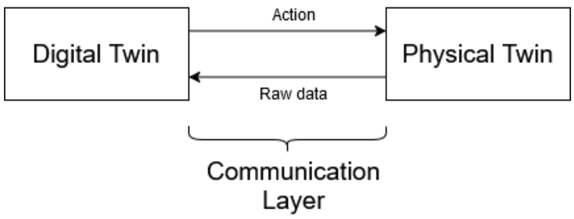

Figure 2.1: Traditional Architecture of a Digital Twin

The DT is a versatile system that can have different levels of complexity, and can be analised along different dimensions. For example, Shao et al. [59] show four dimensions of the desired capabilities of DTs as Connectivity, Granularity, Visibility and Analyzability.

While these aspects are commonly used to assess the system's performance, they also are closely related to user experience. The connectivity dimension refers to the level of communication exchanged between the physical and the digital twin, and impacts the reliability and how fast the users receive feedback from the system. Granularity represents the DT's level of detail, which can help the user to analyze future scenarios in different degrees. The analyzability aspect regards to the way the DT can be used to assist on decision-making. Finally, the visibility of the DT relates to their ease of perception for human beings. This topic is further explored in the coming sections of this study.

From a research point of view, the concept of Cognitive Digital Twin (CDT) introduces major conceptual innovations to DTs, including the additional layer of intelligence that provides cognitive abilities, such as autonomous adaptation, data-driven decisions, and learning capabilities [79, 3]. Although CDTs include the aforementioned capabilities, their implementation is highly complex and only guidance – e.g., the CDT reference architecture [79] – has been proposed to facilitate design. However, this guidance does not include any kind of UX orientation.

2.2.2 Applications of Digital Twins

Before the formal definition of Digital Twin, there were some remarkable accomplishments performed with mirrored systems, which share a similar concept. For instance, in 1970 during the Apollo 13 mission, NASA researchers developed a simulated environment that replicated the spacecraft to monitor it while being in distant physical spaces. During this mission, there was an oxygen tank explosion, which could have resulted in a tragic ending to the mission, as there were astronauts aboard, but, due to this mirrored systems, engineers on land were able to analyze the situation and come up with a solution. By doing so, they guided the astronauts on how to create an improvised air purifier using available materials on board and enabling their safe return to Earth [7].

Currently, DT technology has been adopted by many sectors to perform various activities. The first projects involving Digital Twins were mostly associated with aircraft, and the aviation industry [45]. The main functions of the Digital Twin in this sector were to mirror and predict the aircraft's condition, its expected lifespan, and the likelihood of mission success. This technology was used to simulate future missions, allowing engineers to study possible effects of various parameter changes, determine the impact of potential malfunctions and validate error mitigation strategies. Additionally, by receiving real-time data from sensors in the aircraft, the Digital Twin could obtain continuous updates from the environment of the physical system. Through the use of ML models, this data was employed to make continuous predictions of the physical twin's condition. By doing so, the team could create early diagnostics of failures or potential damage to the system and mitigate them rapidly [58].

Another application of the Digital Twin technology is in the development of smart cities, which present a holistic approach to urban development. The Digital Twins are useful for creating digital models of urban environments and real-time monitoring of the city's services, such as waste management and energy consumption. These functionalities improve the quality of life in these cities while also promoting sustainability through innovative solutions [45].

In conclusion, Digital Twins have numerous applications in various and diverse sectors. Apart from the ones presented above, it is also relevant to mention their importance in fields such as healthcare, energy, and the metaverse.

2.2.3 Digital Twins in Manufacturing

During the Industry 4.0 paradigm, Digital Twins gained traction in the field of smart manufacturing. In this case, their main purpose is to optimize the production processes in smart factories. They are operable through the entire lifecycle of the physical product, from the design and development stages to the end of its life cycle. The DT contributes to the improvement of the quality and operational efficiency of product manufacturing by analyzing historical and real-time data. [42] Additionally, the simulation abilities of Digital Twins are used in this environment as a way to predict the system's response to various events. This capacity allows manufacturers to optimize production processes, plan logistics, and improve decision-making over multiple aspects. Through the use of advanced technologies, including IoT, AI, and big data analytics, Digital Twins play a crucial role in the development of smarter factories, the improvement of general performance, and, eventually, the enhancement of digital management and low-cost manufacturing. [35].

As previously stated, Digital Twins are dynamic solutions that aim to improve physical entities at different dimensions and lifecycle stages. Therefore, distinct Digital Twins must have different characteristics and mechanics to achieve their intended goals [62]. Despite the fact that this dissertation does not specifically focus on CDT, there are clear parallels between the proposed architecture and the DTs used in the manufacturing context.

Firstly, to address the complexity of manufacturing processes, DTs are organized in a hierarchical, and modular structure, to obtain a more comprehensive representation of the environment and its dynamics [77]. The Product Digital Twin represents the physical product, combining a virtual model with relevant multidimensional information. Depending on their application, Product Digital Twins contain descriptions of the product's attributes, such as geometric information, and expected behavior [11]. This Digital Twin accompanies the product throughout its entire lifecycle, from design to manufacturing, and maintenance; and plays different roles, based on the product's lifecycle phase. For instance, during the design phase, it defines the product's information, and constraints. During the manufacturing phase, it tracks the different stages of the operation, and in maintenance processes, it provides data related to the product's history. such as its usage, failures, or optimizations. Due to its unified nature, which allows for information exchange between every phase, this model significantly benefits the manufacturing process.

Process Digital Twins are digital counterparts that focus on the manufacturing process. They are made up of product digital twins, manufacturing procedure models, and process attribute data, which connect the production and the product. They monitor, and control production activities, and use real-time data to simulate and make improvements on manufacturing steps. Their ability to detect errors, predict failures, and support decision-making activities promotes the optimization of workflows in production environments. Additional DT stratification, such as the layers seen in the CDT architecture, may be required depending on the system's complexity. Eventually, product and process DT can be linked, providing an integrated representation of the product life-cycle.

Secondly, the functional layers specify the functions provided by the CDT, both in the real and virtual space. It is important to note that these functions are not applicable to every DT. In this context, the monitoring of the physical twin's entire lifecycle becomes crucial to ensure reliable processes, waste reduction, and high quality remanufacturing processes [30].

In spite of their clear technological capabilitities, DTs are socia-technical systems, meaning that their value and performance derives from the effectiveness of human interaction. Thus, and as the industry 5.0 paradigm becomes more prominent, there is an increasing need to characterize these systems as tools that assists users. This shift requires DT systems to be designed with a heavy focus on usability, and that meet the needs of human users. The following sections explore this human-centered aspect by analyzing approaches used in DT-based systems and how they affect user interaction and experience.

2.2.4 Digital Twin-Based Systems

DTs are operacionalised as a component of a system that has as main purpose the management of a physical asset or process. A Digital Twin-based System is a system that integrates digital twins—virtual replicas of physical entities or processes—into its architecture to enable real-time monitoring, simulation, analysis, and optimization of the corresponding physical elements. These systems utilize continuous data flows between the physical and digital counterparts to support decision-making, predictive maintenance, lifecycle management, etc.. The digital twin is the base architectural component of the DT-based systems the whole inheriting the main characteristics of the DT: its bidirectional connectivity, allowing both the real-world asset to influence the digital model and the digital insights to inform changes or actions in the physical world.

A special type of DT-based system is a DT-based platform that combines DT technology with a digital platform and provide services for connecting other systems (usually involving different organizations) resulting in an evolving system-of-systems. An initial vision for this concept is proposed in [61]. The idea behind this concept comes from the need to manage multiple DTs in complex contexts, while, at the same time, providing users with a data-rich platform that supports the whole Product Lifecycle Management (PLM), and that may be used to support the creation of new business models that are focused on product-service systems. In this work, the authors state that the development of the DT-based platform concept includes not only the self-configuration and autonomy for increasingly complex environments enabled by increasingly advanced technologies, but also the adoption of socio-technical constructs that enable users to interact with the systems in order to fully integrate them in organizational processes ranging from decision-making to product development. [60]

Similarly, a DT-based system employs a singular DT as a technical infrastructure for the information systems of the organization, and as a service-provider. In this context, the singular functionalities of the DT, for instance, simulation, analysis, or optimization, collectively create more comprehensive and high-level business services, such as predictive maintenance, or condition monitoring.

2.3 Industry paradigms and Circular Economy

This section explores how industrial paradigms have evolved over time, brings emphasis to the associates changes in the workforce and technology connected to these developments, and explores the concept of Circular Economy.

2.3.1 The transition from Industry 4.0 to Industry 5.0

The concept of Industry 4.0 (I4.0), which represents the fourth industrial revolution, was proposed by the German government in 2011. It is an industrial plan to improve the efficiency of manufacturing processes through the adoption of advanced technologies, such as robotics, the Internet of Things (IoT), and Big Data Analytics. Through the collection and analysis of vasts amounts of data, these technologies enable smart automation in manufacturing and decision-making [13, 44].

These technological advancements have had a significant impact on human-machine interaction, and on the role of workers in manufacturing environments. The integration of Human-Cyber-Physical Systems (H-CPS) has contributed to the close collaboration between workers and machines, expanding the human capabilities [24]. However, many concerns are raised due to this technological paradigm, surrounds themes, such as environmental impacts, and job displacement. To address these socio-environmental challenges, Industry 5.0 (I5.0) was introduced by the European Commission in 2021 [19]. In contrast to I4.0, which focuses mainly technological advancements, I5.0 prioritizes human-centric practices, sustainable objectives, and social fairness [13, 24]. This new paradigm aims to improve productivity through automation (similarly to I4.0), while, simultaneously, creating a balance between humans and machines, to obtain successful collaboration that enhances creativity, and decision-making [13, 20].

Although the concept of I5.0 has been formally proposed in Europe, research suggest that its implementation is still in its early stages, with manufacturing operations focusing more on technical aspects, rather than societal ones.

2.3.2 Operator 4.0 and Operator 5.0

The Operator 4.0 (O4.0) concept emerges in the I4.0 paradigm, and represents a qualified worker that works with advanced I4.0 technologies, such as collaborative robots. Due to the complexity of modern manufacturing, the role of the operated was forced to adapt to new technological environments, requiring workers to develop high adaptability [13].

In addition to the imposed new skills of workers, there are other challenges associate to O4.0. For instance, the increased interface and data complexity brings a higher cognitive workload, or the stress caused by the uncertainty regarding the impact of digital transformation on the workforce [6]. In order to guarantee that these emerging technologies empower operators rather than burdening them, the importance of human-centered design is, once again, a crucial topic [4].

The Operator 5.0 (O5.0) is the evolution of O4.0, and aligns with the updates principles of I5.0. A key characteristic of O5.0 is the seamless collaboration between humans and machines.

In the I5.0 paradigm, the manufacturing equipments are specially design to make human-machine interactions more intuitive and adaptive to the workforce. Additionally, the shift to O5.0 also highlights how crucial it is to reduce the operator's cognitive workload of operators to improve efficiency, safety, and overall well-being [6, 20].

Similarly to the I5.0 concept, the O5.0 idea is relatively new, and, although it has a theoretical foundation, it lacks standardized guidelines for implementation. In order to achieve the full potential of O5.0, there is a need to involve multidisciplinary approaches, such as social sciences and engineering [13, 24].

2.3.3 Circular Economy

The Circular Economy (CE) is a model designed as an alternative to the linear economy. The latter follows a make-use-waste methodology, mainly relying on the use of readily available materials, and energy to produce cheap products, and sell them at the highest possible price [50, 39]. These practices result in an extremely high production of waste and excessive use of limited resources, leading to catastrophic outcomes such as climate change, resource scarcity, and environmental degradation [12].

The urgency to address these issues has emphasized the need for a more sustainable economy framework. The concept of CE proposes a regenerative and restorative structure for the global economy, with a focus on the conservation of resources [51, 68]. The two fundamental strategies outlined to achieve this goal are: slowing the resource loops, by extending the product's lifetime through a durable and maintainable design; and closing resource loops by making sure that materials can be recycled or reused after their use [68, 18].

Historically, the 3Rs (Reuse, Reduce, Recycle) framework has served has a pillar for sustainable practices and the concept of CE. However, over time, and due to the immense scalability of the previously stated issues, this model became too narrow and unsuitable. More recently, a new R-framework, or R-Strategies, consisting of ten layers, i.e., Refuse, Rethink, Reduce, Reuse, Repair, Refurbish, Remanufacture, Repurpose, Recycle, and Recover, has been proposed to broaden the fundamental principles of CE [12].

Figure 2.2 presents the 10 Rs, including a general framing, with the goal of the diverse components, and the correlation of the various layers with the circularity of the economy model [15].

In this context, the concept of sustainability and sustainable development are pertinent. These concepts were formally defined in 1987 by the United Nations Brundtland Commission, as a "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [29]. Since the manufacturing sector is one of the largest global energy consumers, manufacturers need to create ways to incorporate sustainable practices in their processes, while simultaneously maintaining their operational performance [14].

Sustainable manufacturing is a recent paradigm that ensures the sustainable production of new products while maintaining market competitiveness. In addition to creating more sustainable products, this process also entails employing more environmentally friendly techniques in the

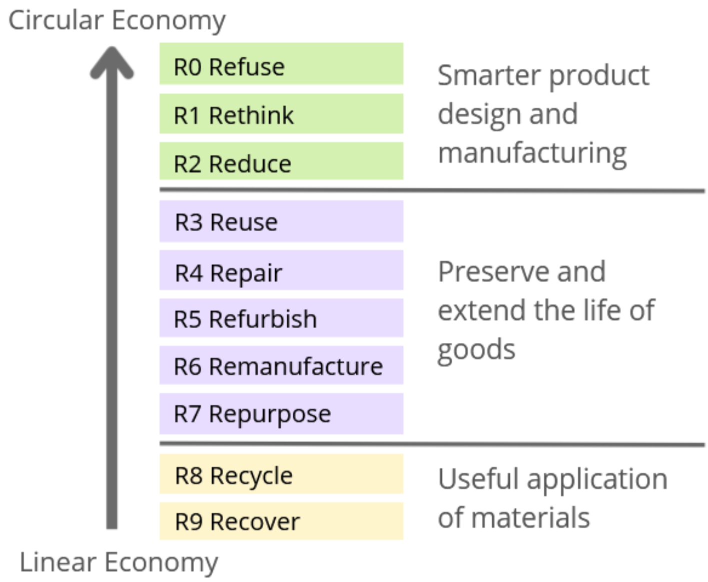

Figure 2.2: The 10Rs and their connection with the economic models.

entirety of the production system [28]. In order to meet the three level of sustainability [27]-environment, economy, and social-companies must evolve from traditional techniques to ones that take into account the environmental and societal implications of operations [28]. As suggested in [14], sustainability requires circularity mechanisms.

2.3.4 Remanufacturing and its challenges

Remanufacturing is one of the key components of the CE because of its ability to efficiently manage existing resources and contribution for sustainability. This strategy promotes the restoration and reuse of discarded products, typically referred to as cores, in order to reduce waste and unnecessary use of new resources [26, 55]. This process can have numerous stages, such as, inspection, disassembly, component reprocessing, reassembly, and testing to ensure it meets the desired product standard [21]. It has been proven that remanufacturing can bring remarkable advantages, including savings up to 50% in cost and 40% in energy consumption [74].

Unlike traditional manufacturing and open-loop supply chains, where raw materials are consistent and the production of new items is standardized, remanufacturing processes must consider different levels of wear and deterioration in returned objects. This is one of the major challenges that remanufacturing operations face; the unpredictability of quality and quantity of used items complicates the process, since it affects the production planning and cost management. Additionally, low automation levels and the fluctuation of processing and waiting times contribute to the uncertainty of the process [67, 34].

2.3.5 The role of Digital Twins in the Circular Economy

As mentioned in section 2.3.1, the Industry 5.0 concept, recently proposed by the European Commission, which primarily focuses on sustainability, resilience, and human centricity, presents new opportunities for remanufacturing. Advanced technologies, such as Digital Twins, can be enablers for smart remanufacturing operations, allowing for collaborative human-machine systems and adaptive precesses [74].

Digital Twins excel at predicative maintenance, and enhancing operational performance. In the remanufacturing context, these systems also play a crucial role in mitigating the challenges stated in section 2.3.4.

The perspective of lifecycle phases management presented on the proposed CDT architecture [79] is applicable to manufacturing DTs, more precisely, in the context of Circular Economy (CE) and sustainable practices, where DTs are enablers for smart remanufacturing operations, allowing for collaborative human-machine systems and adaptive processes [74]. By integrating robust algorithms and consistent data flow between the virtual and real environments, these systems enable better tracking, monitoring, and decision-making in the remanufacturing supply chain. Their technological abilities help to reduce the uncertainty of the process, while also optimizing inventory management and reducing delays [74, 26]. Additionally, simulation-based DTs can be employed to integrate sustainability and circularity metrics to assess the environmental impact and identify areas that can be improved [55]. For instance, Digital Twin-driven predictive maintenance can reduce unplanned failures and save up to 15% on operational costs [74].

Redesign is one of the main components of remanufacturing. It focuses on updating the function and structure of used products to improve them based on customer demand, and Digital Twin applications are increasingly being explored in this context. For example, based on real-time data provided by the physical twin, the digital model can return and iteratively optimize the design process, with the goal of obtaining the optimal design scheme and reducing the remanufacturing costs. By analyzing the used product's information and historical design data, the Digital Twin is employed to make design decisions and performance prediction, to perform a successful redesign process [33].

There are several case studies that highlight the practical implementation of Digital Twins in remanufacturing. For instance, Ke et al. [33] developed a Digital Twin to optimize the redesign of commercial vehicle clutches by integrating product data with virtual models, improving efficiency and reducing trial-and-error costs. This dynamic environment significantly contributed to the remanufacturing operations, and, consequently, to the sustainability of the company, by improving resource efficiency, reducing waste, and maximizing the reuse of materials. Huang et al. [30] implemented a DT for laser additive remanufacturing of composite materials. By detecting both visible and invisible defects via advanced image processing, their system improves reliability, reduces waste, and ensures quality—crucial in sectors like aerospace and energy. A third implementation of a Digital Twin solution in remanufacturing is proposed in a study by Wang et al. [66], which applied a Digital Twin to the Waste Electrical and Electronic Equipment (WEEE) recycling and remanufacturing process, enabling lifecycle tracking and data continuity. This Digital Twin maintains an updated record of the equipments through their whole lifecycle in order to facilitate tracking, and evaluation of such items. Moreover, by ensuring data continuity, and accessibility, this system contributes to decision-making during recycling and remanufacturing activities.

2.4 From user interaction to user experience in Digital Twin

The current research and development in the field of DTs is mainly focused on the technical capabilities of these technologies and tend to overlook the importance of interface design and user interaction. Despite their remarkable capabilities, the user interaction with these equipments tends to be challenging and often limited to complicated interfaces, due to their complex nature.

User Centered Development (UCD) is a process that involves identifying the specific user needs and designing solutions based on them, in order to ensure that their requirements are met. In the field of Digital Twins, this kind of development is rarely performed, however, when it is, the target users considered are mainly domain experts, and most times these processes are not well-documented [8]. This section presents some antecedent instances where UCD techniques and practices were conducted during the development process of Digital Twins.

2.4.1 Overview of User Interfaces in Digital Twins

As previously mentioned, Digital Twins are systems that have remarkable capabilities, however, due to their complexity, the user interaction with these equipments tends to be challenging and often limited to complicated interfaces. This section explores the current solutions for user interfaces in Digital Twin systems.

In a literature review performed by Barricelli and Fogli [8], multiple types of User Interfaces (UI) used in Digital Twins were identified. It is important to note that this study included twenty-three papers published between 2015 and 2021 that explicitly focus on the Digital Twin concept.

The most popular UI proposed in the studied articles includes Immersive Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). In VR environments, by using specialized equipment, such as a VR headset, the user can feel present and engage with the virtual world. AR connects the user to the virtual world through physical tools (mobile phones, tablets or special glasses) to overlap with virtual elements. MR results from integrating the two previously mentioned techniques to produce an interactive experience in which real and virtual components coexist and interact [2]. These are three-dimensional visualization techniques that merge the real and virtual environments and have to be paired with external input/output devices, such as Head Mounted Displays, which make the interaction immersive and more engaging when comparing to traditional graphical user interfaces (GUIs).

The second most common UI illustrated in the study is the traditional GUI. In this case, the user interacts with the Digital Twin by using keyboard and mouse or a touch screen. Contrary to VR, AR and MR technologies, which are three-dimensional visualization techniques, the traditional GUI offers the user a two-dimensional visualization of the system. Following the traditional

GUI, is the desktop VR technique. In opposition to the VR technique mentioned earlier, this one consists of using a desktop-based environment to visualize and interact with Digital Twin by using standard input devices (keyboard and mouse), alongside typical displays, to provide an interactive 3D virtual representation of the system.

Beyond the findings from the referenced research, the exploratory literature review conducted in this study provides a more detailed categorization of UI types in Digital Twin systems, which can be found in table 2.1. This analysis expands the previous assessments by highlighting each UI's characteristics, advantages, challenges, and identifies some of their implementations.

2.4.2 Large Language Models in Digital Twins

Recently, there have been emerging more instances of the integration of Large Language Models (LLMs) in the DT field. LLMs enable users to interact conversationally with DT systems, translating natural language inputs into structured queries through advanced Natural Language Processing (NLP) techniques. In order to ensure that the data being retrieved is reliable and correct according to the user input, it is crucial that the system is transparent and explains the reasoning behind the output. By giving a plausible explanation, it is ensured that the user is well-informed when performing decision-making activities, and acquires trust in the system. [80]. Given the complexity of DTs, for the user to receive trustworthy information for their queries, the operating LLM needs to be paired with structured data systems, such as databases or knowledge graphs [22]. Since Digital Twins perform real-time data analysis from the information acquired from the sensors installed in the physical system, it is crucial that this data is cleaned and stored in suitable data storage [72].

There are two main ways in which a user can communicate with a system using natural language: through text, using a chatbot, or by voice commands, which are translated to text using speech-to-text approaches. In the case of written queries, through a chatbot, the user can type questions or general inputs, and receive answers, replicating the interaction the user would experience speaking with a human expert [80]. These interfaces dynamically interpret user inputs and maps them to the functionalities of the present Digital Twin, retrieving relevant data and generating clear responses integrating the obtained information.

In [72], the authors present an approach that integrates LLMs into a Digital Twin system that manages complex Intelligent Computing Centers, combining expert knowledge and data-driven methods. The system consists of a multi-layered design, including a physical space, a digital space, and a multi-agent system powered by an LLM. The user interacts with the system through a natural language interface, a chatbot, and visualization tools. The interface includes an integrated feedback mechanism for users to correct errors or suggest different approaches. The Human-In-The-Loop (HITL) [63] workflow is used to integrate user feedback into AI and ML systems, improving system capabilities and mitigating common AI issues. The experiment demonstrated the system's ability to combine its own programmed analysis with expert feedback. However, it has not been extensively tested in real-world scenarios.

A second instance where the integration of LLMs with Digital Twin systems was tested is reported in a publication by Fortuna et al. [22] and uses a household electricity knowledge-based

Table 2.1: User Interfaces in Digital Twins

User Interface	Characteristics	Advantages	Challenges	Reference
Graphic-based traditional GUI	- Dashboard-based information display - Graphical visualizations (e.g. charts, tables) - User input through 2D interface (e.g. buttons, slides, menus)	- Familiarity and accessibility (2D interfaces are widely used, leading to an easier user adoption) - Structured data presentation provides clear insights into the system's performance - Cost-effectiveness (e.g. Lower R&D costs compared to XR interfaces) - Lower Computational Requirements	- Limited interactivity - Difficulty at showing large amounts of data - Scalability issues (as DTs get more complex, there is a growing struggle to represent their dynamics effectively)	[65, 54]
Traditional GUI with 3D models	- Similar Graphical display of information as the traditional GUI - 3D model integration of the physical twin	- User-friendly - Efficient monitoring through real-time data visualization, both graphically and visually	- Complexity of 3D visualizations (e.g.manipulation of 3D models) - Scalability issues - Learning curve, while still being a traditional GUI, the 3D models increase the complexity of the interface	[75, 38, 67, 76, 32]
Immersive Interfaces	Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR)	- Enhanced visualization through immersive 3D representations - Increased awareness and user engagement	- Data inaccuracy (e.g. due to sensor inconsistencies) - Latency issues - High implementation costs (investments in hardware, software, and data infrastructure) - User adoption (unfamiliar technologies to most users require proper training)	[33, 78, 16, 73]
Natural Language User Interface	- LLM enabled system - Chatbot-based interaction (text-based) - Speech-based interaction (automated speech recognition techniques)	- Intuitive natural language interaction - Suitable for non-expert users	- Speech recognition accuracy (e.g. diverse accents, ambient noise) - Computational complexity (running LLM systems demands high computational power and optimized models) - Hallucination risk (LLMs may generate plausible but incorrect answers) - User trust and transparency (users need clear explanations for AI-driven decisions)	[41, 72, 22, 80, 49]

DT. In this case, the user interface is designed to facilitate natural language interaction between the user and the system. The system uses a knowledge graph with models of electricity data and external information to enhance its context. Retrieval Augmented Generation (RAG) techniques are used to improve the accuracy of responses by providing real data and contextual information. The system's performance was evaluated using various complexities and architectures, and the model's ability to correctly utilize context was tested. The study found that ChatGPT combined with RAG was the most effective approach for precise and context-specific queries.

These documents outline innovative approaches using natural language interactions in complex systems while addressing common AI and Digital Twin challenges. LLMs can understand complex and even multiple queries at once, efficiently interpret them according to the context and generate appropriate and clear responses [23]. Furthermore, these models allow conversational interactions, which removes the need for high technical expertise when interacting with complex systems, such as Digital Twins.

2.4.3 Evaluation of user interfaces in Digital Twins

This section explores the two evaluation techniques reported to be used to evaluate user interfaces in Digital Twins: Situational Awareness and the Aesthetics model; and a maturity model for digital twins, which evaluates them from user experience point of view.

In the context of Digital Twins, Situational Awareness refers to the ability of a user to effectively comprehend the current state of the system based on the visual data it provides. It can be influenced by several factors, which may be related to the user's skills or logical rationality, or derived from the system's visual layout. In [57] the UI of a Digital Twin for machine tools was tested by the authors according to its efficiency to provide situational awareness to the users. This study uses the Analytic Hierarchy Process (AHP), which is a decision-making tool that incorporates subjective input from humans according to multiple criteria. It decomposes the problem in various levels, and, through pairwise comparisons, AHP uses mathematical calculations by associating relative weights, in order to establish priorities bases on the different elements [64]. In this particular evaluation scenario, the indicators selected to assess the interface were "logical reasoning, prominent focus, clear regional division, easy to remember structure, balanced layout, and user habits" and their weights were established through expert scoring and user surveys. The test cases of this study include eight Digital Twin interfaces with various layouts that were evaluated by the participants using the Likert scale. The most suitable design was determined by analyzing the final scores, that were calculated based on weighted averages and numerically ranked. This publication states that this method proved itself to be effective at evaluating situational awareness, and a useful tool for designers to develop better interface design solutions.

The Aesthetics model was firstly introduced in 1998 by Ngo et al. [48] as a quantitative framework to evaluate the quality of screen designs based on their visual appeal to users. This model operates through the use of mathematical measures to quantify the various characteristics that affect the quality of a visual interface. Initially, there were six quantifiable key aspects on this model, which were then expanded to fourteen in a later publication [47]. These measures address the arrangement and structure of elements on the screen, and bring an emphasis to the perceptual and experiential aspects of the interface design, adding more precision and objectiveness to the evaluation process. The updated aesthetic measures are the following: balance, equilibrium, symmetry, sequence, cohesion, unity, proportion, simplicity, density, regularity, economy, homogeneity, rhythm, order and complexity. Each one of these measures is associated with a mathematical formula that results on a score from zero, which is the worst classification, to one, the best classification. These objective scores can serve as feedback to possible adjustments to improve the visual appeal of the interface. Although this model was proposed as a tool for evaluation of already implemented screen designs, it can also work as a provider of design guidelines for the development of user interfaces, as high scores in this metrics translate in aesthetically pleasing representations, enhancing usability and operational efficiency [43].

The decision-making skills of users rely on their perception and processing of visual information present on interfaces. In complex information interfaces, the users tend to gather general information and then combine similar data for processing. Thus, it is crucial that the design of the interface and the information layout are thoroughly studied and carefully implemented [71].

There are multiple instances where this model is applied for the evaluation of Digital Twin UIs. Li et al. [37] applied it to assess and optimize an industrial machine tool Digital Twin interface, testing eight layouts with identical functional areas arranged in different displays. Six aesthetic measures were selected and complemented with AHP techniques, which integrates expert opinions for more accurate conclusions. Wu et al. [69] expanded this approach by integrating AHP with Grey Relational Analysis (GRA) to mitigate expert bias in Digital Twin decision-making. GRA is a mathematical method used in complex systems to address these issues, and it is effective in situations where subjective evaluations are performed, as it “quantitatively describes the correlations between factors and the similarity of their development trends, providing more scientific and reasonable support for group decision-making”.

In both cases, the interface parameters were obtained through the use of a graphic design software, namely Figma or Photoshop. These tools ensure accuracy and consistency when calculating the characteristics of the layout, such as element coordinates and dimensions, which are necessary parameters to calculate the aesthetic measures. Additionally, through a simple user performance test, it was proven that the layouts with the highest aesthetics scores led to faster response times and better task completion, validating the model’s relevance in practical cases.

In [1], a framework that evaluates DT maturity level from a UX perspective is proposed. This approach aims to address the gap in existing DT maturity models that largely overlook UX factors. It presents five dimensions - Understandability, Usability, Convenience, Dependability and Delight Factors - that are linked to common challenges in visualization and interaction, and can be assessed through more specific variables and metrics. This work can serve as a theoretical foundation for usability testing, requiring direct user interaction, for instance, through questionnaires.

2.4.4 User Centered Development implementation in Digital Twins

This section will focus on two practical cases where UCD was performed in the context of Digital Twin technologies: the first one is present in a publication by Lauer-Schmaltz et al. [36] where the authors document the process of designing and developing a Human Digital Twin for informal caregivers of stroke patients with interactive dashboards; and the second one by Riedelsheimer et al. [53] focusing on a Digital Twin concept with an emphasis on sustainability in the clothing industry. The techniques conducted in both of these studies follow similar methodologies, however, it is important to note that there are numerous approaches that can be employed during the distinct phases of the development. Each project has its own characteristics and context, which implies that not every approach will fit them, so there should be a meticulous study and process when choosing the most appropriate techniques.

The main strategies used during the Requirements Elicitation phase were Semi-Structured Interviews, in the case surrounding stroke rehabilitation, during which a diverse group of informal caregivers were interviewed to understand their needs and expectations for the platform; and Focus Group and Design Thinking, in the clothing industry case. These methods provided the developers with qualitative data that represented the users' desired specifications for the system, and, with this information, User Stories were developed to assist the creation of adequate system requirements. From the collected requirements, initial visual prototypes were designed and iteratively refined based on user feedback.

The user tests conducted during this iterative process provided the designers a better understanding of the current user experience and possible ways to improve features. Since the main end-users of both platforms are non-experts, there was a heavy focus on accessibility and simplicity. The results obtained from these projects, namely the successful user interaction, align with the concept that the practice of UCD is highly beneficial for crafting accessible and effective solutions while also enhancing the general user experience.

Chapter 3

Methodology

The present chapter presents the methodology followed to define an approach for the design of User Experience in Digital Twin-based systems.

3.1 Problem Description

DTs' ability to predict, optimize, and simulate real-world processes through real-time data exchange has led to their prevalence in industrial and manufacturing contexts. From a broader point of view, DT-based systems, which, alongside the DT functionalities, are embedded within broader platforms or infrastructures, and integrate organizational workflows, are socio-technical systems. These systems are particularly relevant in the manufacturing setting, where various user types have direct contact with the system, each interacting with different functionalities according to their roles and responsibilities.

DT-based systems are highly complex, involving high volumes of data, and supporting advanced functionalities. Nonetheless, their development mainly focuses on the technical aspects, and generally overlooks critical aspects of UX and interface design. Without careful consideration of these human factors, even highly advanced DT-based systems risk underperformance due to poor usability and limited user engagement.

The discrepancy between usability and technological advancement in DT-based systems is what motivated the current study. Therefore, the goal of this dissertation is to address this gap by proposing a UX design methodology that supports the development of DT-based systems. By emphasizing the relevance of user-centered development, this strategy aims to improve both usability and system efficiency in Digital Twin applications.

3.2 Development Process

In order to outline the key requirements for the design of UX in DT-based applications, a multi-step process was employed. Figure 3.1 illustrates the structured process followed to develop the proposed methodology.

Firstly, through an exploratory literature review, it was possible to synthesize a conceptual understanding of a DT-based system, and understand the current state of technological advancements. Additionally, it provided valuable insights into the existing UCD practices used in the field of DTs. From there, a research gap respective research questions were outlined (Phase A). After the consolidation of concepts, the next desired step would be to observe the direct interaction of end-users with the DT system. However, the fact that DT systems do not have a large user base, made it challenging to directly study their interactions. As a result, a speculative approach was adopted to outline the key high-level requirements for DT-based systems UX. The second step of this approach involved interviewing experts who are familiar with DTs in the manufacturing context and could make well-informed assumptions about how users interact with these systems. These interviews followed a semi-structured approach, meaning that, to guide these discussions, the participants were presented with the key aspects identified in the preliminary research along with some general questions, helping them to articulate potential interaction scenarios, and outline the key practices of UCD in DT-based systems. Based on the findings from the discussions, an approach for the design of UX in DT-based systems was defined (Phase B). Finally, to test the proposed approach, it was applied in a case study, and evaluated (Phase C).

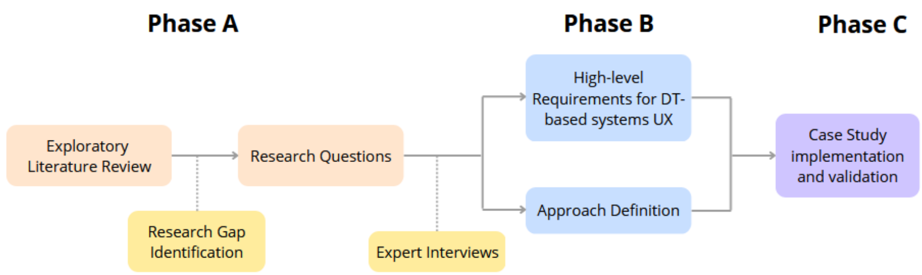

Figure 3.1: Process followed to develop the proposed UX design methodology for DT-based systems.

3.3 Interview Protocol

As previously mentioned, the interviews that contributed to the development of the proposed approach were conducted with individuals who specialize or are knowledgeable in DT-based systems. These interviews were conducted in a semi-structured manner, which gave the participants some freedom to discuss their experience and speculate on how the user interaction in DTs can be improved. During the interviews, the participants provided insights into the practices they find helpful in this context, and the challenges they have faced. Throughout the course of the interviews, and as new insights emerged, the interview script was refined to better suit the participants and their implementations. The collected information from these discussions played a crucial role in understanding the current state of user interaction in DT systems, and in defining the proposed approach.

3.3.1 Participants

Since this study mainly focuses on the manufacturing context, the participants interviewed specialize in either Process or Product Digital Twins. Furthermore, there was an effort made to meet with developers of multimodal UI implementations in DTs to broaden the amount of perspectives presented.

By incorporating insights from experts in diverse UI solutions, the study aimed to explore how different interface approaches contribute to user interaction, data visualization, and system usability in DT-based applications.

3.3.2 Interview questions

The questions defined for the interviews aimed to collect insights on the important aspects of user interactions, including the best design practices, key challenges, and considerations for usability improvement. As previously mentioned, the format of these interviews was semi-structured, which was done through open-ended questions and a flexible script that allowed participants to elaborate on their experiences, while ensuring consistent focus on the main topic.

Below are the base questions outlined for the discussions. It is important to emphasize that the questions evolved throughout the interviews, and the ones presented served as a guideline.

1. What are the types of users that interact with the Digital Twin?
2. What are the functionalities performed by the Digital Twin?
3. Describe the type of user interfaces from this system, and how the user interacts with it.
4. What kind of information do the users have access to when using the Digital Twin?
5. If there are multiple types of users, how do the user interfaces fit their different characteristics?
6. Is there a need for technical expertise or proper training to interact with the Digital Twin?
7. Does this Digital Twin accompany the product throughout its various lifecycle phases, and, if so, how does it affect the information presented to the user?
8. What do you think are good and bad practices regarding user experience in the Digital Twin?
9. Was the system tested for usability, and, if so, what were the techniques employed?

Chapter 4

User Experience Design in Digital Twin-based Systems

The approach presented in the following sections was developed from the insights obtained durring the interviews and literature review. This methodology proposes a structured plan to design the User Experience in DT-based systems.

4.1 High-level requirements for Digital Twin-based systems User Experience

The analysis above resulted in 18 high-level requirements (see table 4.1) used to create the vision for UX in DT-based systems bellow (seen in figure 4.1). Digital twin-based systems are bound to impact significantly how users interact with and manage complex cyber-physical systems. At the heart of this vision there's a commitment to real-time, and role and context-aware user experiences that place people at the center of decision-making and operational awareness.

With an effective UX, the DT-based system will act as a mirror of the physical world, offering users immediate visibility into the current state of assets [R1] through real-time synchronized updates that reflect any changes as they occur [R2]. Whether monitoring operations or running simulations, users are immersed in fluid, seamless visualizations that respond instantly to system dynamics [R3],[R4], helping them maintain situational awareness and confidence.

UX in DT-based systems is more than just interaction—it is a smart, context-aware partner. Each user experiences a tailored view that reflects their specific roles and responsibilities [R7], presenting only the essential information they need to act effectively [R8]. Users benefit from clear, simple graphical representations [R6] and can explore historical trends and past events to support decision-making and learning [R5].

Accessibility and inclusivity are to be built into the Ux foundation. The interface adheres to universal design and accessibility standards [R11], offering multimodal interaction formats such as touch, voice, and keyboard input, possibly under augmented reality technology [R10], and adjusting to different user interface profiles based on user characteristics [R9].

Table 4.1: High-level requirements for DT-based systems

ID	Requirement
R1	The DT-based system shall provide observable information about the current state of the physical system.
R2	The DT-based system shall automatically synchronize and update the displayed information in real-time to reflect changes in the physical system.
R3	The DT-based system should provide smooth visualization of data throughout a simulation.
R4	The DT-based system shall provide smooth visualization of data during the monitoring of the physical system.
R5	The system should provide users with access to visual representations of historical trends and events.
R6	The system shall display graphical data using clean and simple charts.
R7	The DT-based system shall provide differentiated information about the physical system based on the user's role.
R8	The DT-based system shall present only essential visual information to minimize the user's cognitive workload.
R9	The DT-based system should provide user interfaces with different formats depending on the user profile.
R10	The DT-based system should support multimodal implementation of user interfaces.
R11	The DT-based system's interface shall follow accessibility standards.
R12	The system shall notify users of critical errors through high-visibility notifications.
R13	The system shall notify users of non-critical alerts through dismissible notifications.
R14	The system shall provide a visual record, accessible to the user, of the resolved and unresolved alerts and errors.
R15	The system shall allow users to intervene at any point of the physical system's operation.
R16	The system shall provide clear explanations for AI-driven decisions.
R17	The system shall require user authentication before granting access to its functionalities.
R18	The system shall support role-based access control to restrict functionalities based on the user's role.

Event awareness is a critical aspect of the UX. High-visibility notifications ensure that users are immediately alerted to critical errors [R12], while non-critical alerts appear as dismissible messages that can be reviewed without interrupting tasks [R13]. Users can access a comprehensive visual log of both resolved and pending issues, enabling transparency and follow-through [R14].

Importantly, this is not a passive experience. Users retain the ability to intervene in system operations at any point [R15], with the support of clear, human-understandable explanations for all AI-generated decisions or actions [R16]. This ensures trust, accountability, and collaboration between human users and AI systems. Security is woven into the user experience as well. The system enforces secure user authentication mechanisms [R17] and applies role-based access control to ensure users only access functionalities relevant to their role [R18], protecting both the integrity and confidentiality of the system's operations.

In summary, the future of digital twin user experiences lies in creating fluid, responsive, inclusive, and intelligent interfaces that empower users to monitor, understand, and act effectively and efficiently—across the lifecycle of complex cyber-physical systems.

4.2 User Profiling

User profiling is a commonly used technique in the field of UCD. A user profile is made up of a collection of users' information data, that can express the needs, preferences, behaviors, and goals

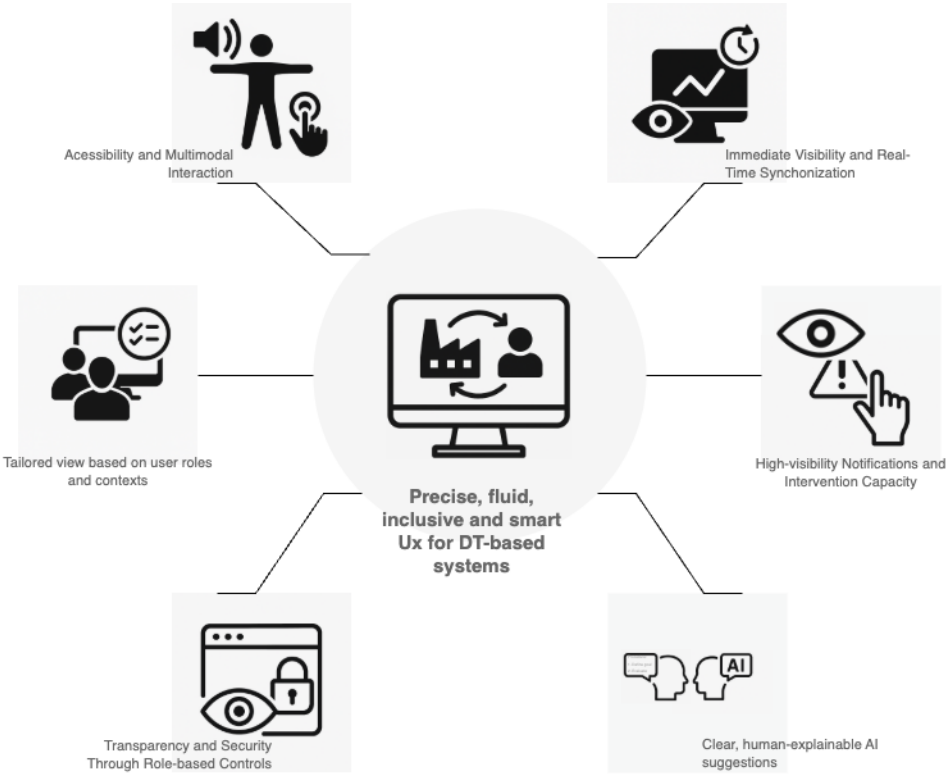

Figure 4.1: Vision for a precise, fluid, inclusive and smart Ux for DT-based systems

of a community of user [70]. In the context of DT-based systems, user profiling is essential to ensure that the system meets the needs of its intended audience. To achieve this, three key aspects should be considered when outlining user characteristics: technical abilities, level of decision-making and organizational roles, and background.

Firstly, the technical expertise of users plays a crucial role in their understanding and ability to operate systems [46]. The users of the DT-based system have varying levels of technical expertise, which directly impacts how they interact with the system. For example, in an industrial setting, there are several types of users. There are shop floor operators with limited experience in digital tools; engineers, who are highly skilled in advanced technologies; or managers that may not excel in digital technology, but are proficient in other fields. Understanding the familiarity of users with DT systems and related technologies is crucial for designing intuitive and effective interactions.

Secondly, the role of a user within an organization significantly influences how they interact with a DT-based system. Since DT-based systems are often used in industrial and manufacturing contexts, where users hold different levels of responsibility, their users have diverse informational needs. While high level actors, such as senior managers or department directors, have interest in historic data analysis to recognize pattern and support decision-making; operational users need real-time data visualizations for quick action.

Thirdly, a user's educational and professional background influences how they perceive and utilize a DT-based systems. Users have different expectations for the system since they come from a variety of fields. Furthermore, factors such as industry experience, familiarity with DTs, and previous exposure to simulation tools greatly affect the adaptability of users to the system. Considering these user characteristics ensures that the DT-based system is designed to accommodate a wide range of user perspectives and expertise levels.

4.3 Functionalities Mapping

A clear mapping of DT functionalities and services to user needs is essential for system effectiveness, and successful implementation. DT-based systems provide diverse functionalities and services with various levels of complexity, ranging, for example, from real-time data monitoring to complex simulations.

To ensure that the appropriate functionalities are provided to the users, a structured mapping of functionalities to user needs must be established. To do so, the developers should select appropriate techniques, for example user stories or use cases, to define practical workflows and real-world scenarios. This practice ensures that the services provided by the system align with the different user profiles, and allows them to perform their designated tasks efficiently.

4.4 User Interface prototype design

HCI is becoming increasingly more complicated as a result of the expansion of systems' capabilities and functionalities. Modern operators face the need to manage and interpret vast amounts of information in real-time and make strategic decisions quickly, which results in an increased cognitive effort [20]. Therefore, well-structured UIs are essential to ensure that DT-based systems provide an intuitive UX.

UI prototypes are an initial representation of the system, which can be of low-fidelity (on paper, for example), to high-fidelity (using interface design tools). They allow stakeholders to test the system's functionalities, and evaluate its usability and overall design, before its implementation. The first step to create UI prototypes is to outline its contents. One of the most important factors described by the interviewees is the visual context to support the users' decision-making. This context will vary from user to user, as it can be real-time data, for example about the state of a machine, or historical information, to detect trends and perform predictive analysis. Additionally, and independently of the data's nature, setting priorities is important to avoid cluttering the UI with unnecessary information.

A common misconception about DTs with 2D UIs is that they require a 3D model of the physical twin. While it may be a good practice in contexts where visual monitoring is necessary, it is unnecessary in other situations, even becoming distractive to the user. Furthermore, the specialists interviewed stand by the need of different UIs for different user profiles. This distinction may be performed through the use of UIs in the same category (e.g. 2D interface with different displays or information), or in different categories (e.g. AR interface for operators, and Graphics-based 2D UI for managers). Whatever the case may be, the main goal for this differentiation is to design a

UI appropriate to the users' needs and abilities. The advantages and challenges of each interface must be considered prior to their implementation.

Lower-fidelity prototypes are cheaper and quicker to make, but also lack in detail. Higher-fidelity prototypes are normally designed in interface design tools, such as Figma, and have interactive modules to simulate real-world interactions. Prototypes of immersive interfaces take greater effort because they require real-time rendering, AR/VR interactions, and 3D modeling, but they can also be implemented using design software like Unity or Vuforia.

4.5 Usability testing

Usability testing is a critical step in the development of DT-based systems to ensure that interfaces are intuitive, efficient, and aligned with user needs. Given the complexity of these systems, the usability evaluation must consider factors such as cognitive load and frustration levels. To obtain comprehensive evaluation, objective and subjective data should be collected. The first step of this usability testing approach is the definition of tasks that the participants will perform, as well as the participants who will be testing the system. These tasks should vary in difficulty and represent scenarios that the end users may perform.

This protocol uses the User Experience-Digital Twin Maturity Model framework defined in [1] as a guideline, and integrates it with standard questionnaires and practices of usability evaluation. In that work, the authors propose five evaluation variables to assess the UX in DTs and showcase problems from each, along with a possible solution. Despite this outlining of UX dimensions, the study does not present a method for their assessment and scoring, only suggests the elaboration of a questionnaire composed of Likert scale questions. To address this gap, the present study implements a small four-question survey for each of these dimensions, which are described below.

Firstly, the usability variable ensures that the DT-based system is easy to use, learn, and interact with, supporting meaningful, effective workflows. The questions oulined for this dimension are adapted from the System Usability Scale (SUS) questionnaire. Secondly, the understandability dimension assesses the user's awareness of the DT context, as well as the proposed tasks and their goal. Then, the convenience dimension of a DT reflects how effortless the user interactions with the system are. The questions for this dimension are adapted from the NASA-Task Load Index (NASA-TLX) survey. The dependability of a DT-based system reflect the accuracy, reliability and its ability to achieve the user's desired goals. Finally, the delight factors of a DT-based system solely rely on the users' enjoyment and appreciation of the UI.

Similarly to the standard SUS questionnaire, the questions for each dimension follow an alternative order, meaning that some are asked using afirmations and others using the negative. This technique provides more accurate results and helps to detect outliers in larger projects. As such, the score calculation of these kinds of questionnaires is given by equation 4.1, where P is the score of the positive questions, N the score of the questions in the negative, and n and m, are the number of negative and positive questions, respectively. This equation provides a final percentage for a defined group of questions by normalizing the test scores to a scale from 0 to 4, a technique also used in the calculation of the SUS score and other standardized instruments to promote consistency and comparability between results.

$$Score(\%) = \frac{\sum_{i=1}^{n}(P_i - 1) + \sum_{j=1}^{m}(5 - N_j)}{(n+m) \times 4} \times 100 \tag{4.1}$$

Along with these subjective inputs, some objective data can be collected. There several ways in which this information can be gathered. Supporting the convenience dimension, for instance, the effort of users can be quantified objectively through the use of monitoring devices – to register breath rate, heart rate, skin temperature, etc. [52]. Also, the analysis of the participants' task completion time can contribute to the evaluation of the usability variable of the system.

Furthermore, task success rate is a way to assess the understandability of a system. This metric is the relation between the amount of successful tasks and the total of tasks performed. It reflects the correctness of the participants' actions, which in turn correlates with their understanding of the system's context and the tasks' purpose. To obtain a more thorough evaluation, multiple success criteria can be considered. For instance, if the user is able to complete the task with a minor error, the task success rate should be 75%, rather than 0%. The overall task success rate of the system is calculated by averaging the task success rate for every participant and task.

The most adequate testing method and metrics differ from project to project and it is up to the developers to determine the best fit. Nevertheless, the dimensions and questions suggested by this approach for assessing UX in DT-based systems are designed to be broadly applicable across a wide range of systems.

Table 4.2: UX dimensions and evaluation measurements

UX dimension	Description	Questions
Understandability	Awareness of task and DT context	1. I understood what I was supposed to do in each task. 2. The objective of each task was not clear to me. 3. I always knew where I was in the system. 4. The terminology used was hard to understand.
Usability	Ease of use and learnability	1. I found the system unnecessarily complex. 2. I think I would need the support of a technical person to be able to use this system. 3. I thought the various functions of the system were well integrated. 4. I thought there were too many inconsistencies in the system.
Convenience	Reduced physical and cognitive barriers	1. The tasks required a lot of mental effort. 2. I was able to complete the tasks quickly. 3. I had to work hard to achieve a good performance. 4. I felt confident during the tasks.
Dependability	Availability, accuracy, and achievement of desired goals	1. I could repeat each task without difficulty. 2. I did not feel confident in the results presented by the system. 3. The information was available when I needed it. 4. I did not understand how the system arrived at its results.
Delight Factors	User enjoyment, the system is visually pleasant	1. I found the interface visually attractive. 2. I did not enjoy using the system. 3. The system's aesthetics made me feel more engaged. 4. The color, layout, and information flow of the interface did not benefit the interaction.

Chapter 5

Case Study: RENÉE project

This chapter presents the implementation of the proposed approach in case studies from the RENÉE project. The goal of this implementation is to test the pertinence of the outlined methodology and requirements in practical cases.

5.1 Case studies overview

Remanufacturing operations present increased challenges in comparison to linear economy new product design and manufacturing. Different kinds of difficulties affect the circular business model of a remanufacturing production system, from supply-chain uncertainties from end-of-use phase and end-of-life products volume and parts quality, to variation of disassembly challenges during operations, to training of operators to multiple product scenario and variability. Taking this in regard, the RENÉE project combines advanced remanufacturing methodologies and tools with simulation of supply-chain and remanufacturing production lines and cells, integrated with Digital Twins (SC and Remanufacturing environment) and AI based robotics solutions and advanced training operators in a human-machine approach.

This project is divided in four pilot industrial sectors, namely electric mobility, electronics, robotics, and bicycles. These case studies present varying levels of automation, need for upskilling, and product variability, to highlight the flexibility of the solutions proposed by the project. The methodology developed mainly considers the Decathlon work project, but can be adapted to the other case studies.

Figure 5.1 presents a diagram addressing the different dimensions of the proposed approach. The following sections explore and describe the remaining aspects of the implementiation in more detail.

5.2 Integration with ProductionDfX

The ProductionDfX methodology, proposed by Branco [10], extends the Lean Design-for-eXcellence (LDfX) framework [5] to enable multidimensional assessment of production systems. It is de-

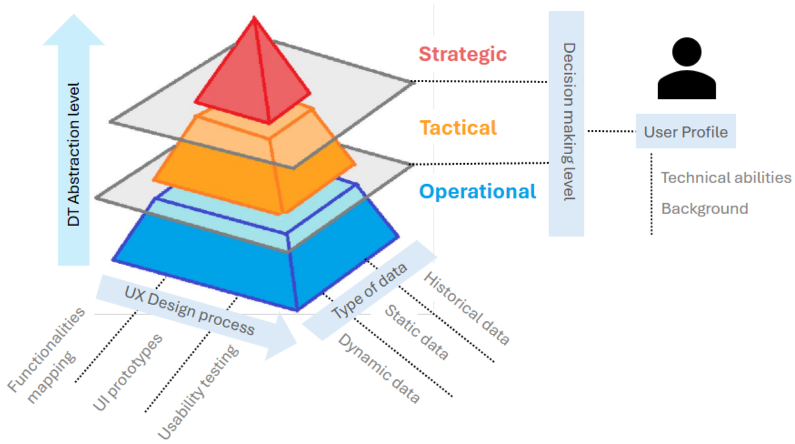

Figure 5.1: Dimension for the implementation of the proposed approach

signed to evaluate strategic, tactical, and operational dimensions through the integration of various X dimensions and Key Performance Indicators (KPIs), aligned with sustainability and circular economy principles [9, 56].

ProductionDfX builds upon foundational DfX approaches to assess both effectiveness – if the system does what it is supposed to do – and efficiency – quantifies resource usage, and identifies potential inefficiencies. This is achieved through a modular, color-coded dashboard system based on Multi-Layer Stream Mapping (MSM) [40], which supports quick identification of improvement areas.

Within the scope of the RENÉE project, two case studies were conducted: one on traditional bicycle manufacturing and another on remanufacturing. These studies confirmed the framework's capability to uncover performance trade-offs and supported its applicability in CE initiatives.

5.3 User Profiles

In the RENÉE project, the design of the Digital Twin-based systems considers the distinction of users mainly based on their decision-making level and organizational role. This is a typical distinction of users in the manufacturing context, which splits the organization into strategic, tactical, and operational levels [17]. However, to ensure effective system interaction and adoption, it is also crucial to consider users' technical abilities and background, which vary significantly across these roles.

The strategic perspective focuses on long-term decision-making and planning, and includes broad objectives, such as product quality, cost reduction, overall competitiveness, or sustainability indicators. The users that fit into this group include management personnel, administrators, and analysts. While they may not possess advanced technical expertise in digital systems, they often have a strong background in business strategy, and domain-specific knowledge. They have the goal of monitoring the general activity of the whole process, performing updates to the system, and improve the system's performance.

Tactical users, namely production managers and process engineers, deal with medium-term activities, for instance production line management, and aim to optimize workflows and resource utilization. These users possess intermediate to advanced technical skills, including familiarity with digital tools, manufacturing systems, and possibly some exposure to simulation environments. Their professional background is typically grounded in engineering or industrial management.

Finally, the operational perspective assesses the lower-levels of production lines, focusing on individual components. The decisions performed at this level have an immediate impact in operations, namely in a daily or weekly basis, and also have an influence directly the tactical level results. These users include shop floor operators and technicians, whose technical abilities may vary but are generally more limited in terms of advanced digital technologies. Their background tends to be rooted in hands-on experience rather than formal technical education.

5.4 Mapped Functionalities

To ensure that the user interface design aligned with the goals and expectations of its intended users, a set of core functionalities was identified and mapped based on user needs, and system capabilities. This mapping process was guided by the principles of UCD, and aimed to translate user profiles into actionable features that support real-world decision-making and interaction scenarios. To outline these features, a set of user stories was defined for each type of user, which are presented in the following sections.

5.4.1 Strategic User Stories

The user stories defined for the strategic user profile are prensented below.

- **US1**: As a Strategic User, I want to explore the Balanced Scorecard visually, so I can understand the company's strategic performance across different dimensions.
- **US2**: As a Strategic User, I want to view real-time sustainability metrics versus targets, so I can identify underperforming areas.
- **US3**: As a Strategic User, I want to track product flow (reception, processing and sales), so I can detect operational inefficiencies.
- **US4**: As a Strategic User, I want to compare current company expenses with the forecast, so I can plan corrective actions.
- **US5**: As a Strategic User, I want to ask the chatbot for simulation scenarios, so I can know the impact of possible actions in the company.

5.4.2 Tactical User Stories

The user stories defined for the tactical user profile are prensented below.

- **US6**: As a Tactical User, I want to monitor the capacity, and product flow of supply chain routes and points in real time, so I can act before bottlenecks occur.
- **US7**: As a Tactical User, I want to visualize detailed information of specific points of the supply chain, so I can know its performance and product flow.
- **US8**: As a Tactical User, I want to visualize general product inflow, so I can understand the state of the EOL products received.
- **US9**: As a Tactical User, I want to understand current production and sales performance against expectations, so I can identify deviations early.
- **US10**: As a Tactical User, I want to track operational and resource use performance, so I can ensure key efficiency metrics are within acceptable limits.
- **US11**: As a Tactical User, I want a quick summary of system alerts and key insights, so I can prioritize where to act.
- **US12**: As a Tactical User, I want to ask the chatbot for simulation scenarios, so I can know the impact of possible actions in the supply chain.
- **US13**: As a Tactical User, I want to visualize the forecasted product flow for different time frames, so I can plan inventory and logistics decisions accordingly.
- **US14**: As a Tactical User, I want to see the progression of product flow over a past time frame, so I can understand its evolution.
- **US15**: As a Tactical User, I want to view a list of predicted bottlenecks with severity levels, and reasoning, so I can take plan actions to avoid disruptions.
- **US16**: As a Tactical User, I want to track forecasted operational efficiency and resource use metrics, so I can evaluate expected performance against acceptable thresholds.
- **US17**: As a Tactical User, I want to receive automated simulation suggestions based on predicted issues, and create related optimization scenarios, so I can quickly apply corrective strategies.
- **US18**: As a Tactical User, I want to download the forecast report, so I can save it locally and support decision-making processes.
- **US19**: As a Tactical User, I want to run a custom simulation based on forecast data, so I can test the impact of different supply chain decisions.

- **US20**: As a Tactical User, I want to simulate changes on the supply chain's transport routes, so I can understand how they will affect the performance of the system.
- **US21**: As a Tactical User, I want to stress test the system, so I can view the possible effects and understand its maximum capacity.
- **US22**: As a Tactical User, I want to simulate custom increase product production of the supply chain, so I can evaluate the cost impact it has on the supply chain.
- **US23**: As a Tactical User, I want to view and compare previous scenarios, so that I can evaluate the effectiveness of past strategies.
- **US24**: As a Tactical User, I want to understand the impacto of a simulation scenario across multiple performance dimensions, so I can evaluate its benefits.
- **US25**: As a Tactical User, I want to view the cost impact of a scenario compared to the current state, so I can assess financial viability.
- **US26**: As a Tactical User, I want to compare the scenario's CO2 emissions, electricity, and fuel consumption to current values, so I can assess environmental impact.
- **US27**: As a Tactical User, I want to download the scenario analysis report, so I can document and share the results with stakeholders.
- **US28**: As a Tactical or Strategic User, I want to deploy the selected scenario directly from the results interface, so I can implement changes in the physical twin.
- **US29**: As a Tactical or Strategic User, I want to view a scenario's parameters, so I can keep track of the changes planned.
- **US30**: As a Tactical User, I want to compare multiple scenarios side-by-side, so I can choose the best-performing option before deploying.

5.4.3 Operational User Stories

The user stories defined for the operational user profile are prensented below.

- **US31**: As an Operational User, I want to have access to a visual representation the real-time state of a production line, so I can detect inefficiencies quickly.
- **US32**: As an Operational User, I want to monitor the effectiveness and efficiency of each process step, so that I can intervene when performance drops below thresholds.
- **US33**: As an Operational User, I want to monitor the current product flow, so that I can spot possible increases in product reception.
- **US34**: As an Operational User, I want to monitor the current performance and capacity of the production line, so I am aware when these are reaching unacceptable values.

- **US35**: As an Operational User, I want a quick summary of system alerts and key insights, so I can prioritize where to act.
- **US36**: As an Operational User, I want automated simulation suggestions when the production line is underperforming, so I can take quick action.
- **US37**: As an Operational User, I want to ask the chatbot for simulation scenarios, so I can know the impact of possible actions in the production line.
- **US38**: As an Operational User, I want to visualize the forecasted product flow for different time frames, so I can plan inventory and logistics decisions accordingly.
- **US39**: As an Operational User, I want to see the progression of product flow over a past time frame, so I can understand its evolution.
- **US40**: As an Operational User, I want to view a list of predicted bottlenecks with severity levels, and reasoning, so I can take plan actions to avoid disruptions.
- **US41**: As an Operational User, I want to track forecasted operational efficiency and resource use metrics, so I can evaluate expected performance against acceptable thresholds.
- **US42**: As an Operational User, I want to receive automated simulation suggestions based on predicted issues, and create related optimization scenarios, so I can quickly apply corrective strategies.
- **US43**: As an Operational User, I want to download the forecast report, so I can save it locally and support decision-making processes.
- **US44**: As an Operational User, I want to run a custom simulation based on forecast data, so I can test the impact of different production line decisions.
- **US45**: As an Operational User, I want to simulate the redistribution of stations manually or automatically within the simulation, so I can test whether reconfiguring resources improves performance.
- **US46**: As an Operational User, I want to customize product production and reception levels in the simulation, so I can assess the system's performance under different input/output scenarios.
- **US47**: As an Operational User, I want to stress test the system, so I can view the possible effects and understand its maximum capacity.
- **US48**: As an Operational User, I want to run simulation scenarios based on my custom configurations, so I evaluate the effects of planned changes before applying them in the real environment.

- **US49**: As an Operational User, I want to view and compare previous scenarios, so that I can evaluate the effectiveness of past strategies.
- **US50**: As an Operational User, I want to understand the impact of a simulation scenario across multiple performance dimensions, so I can evaluate its benefits.
- **US51**: As an Operational User, I want to view the cost impact of a scenario compared to the current state, so I can assess financial viability.
- **US52**: As an Operational User, I want to compare the scenario's CO2 emissions, electricity, and fuel consumption to current values, so I can assess environmental impact.
- **US53**: As an Operational User, I want to download the scenario analysis report, so I can document and share the results with stakeholders.
- **US54**: As an Operational or Strategic User, I want to deploy the selected scenario directly from the results interface, so I can implement changes in the physical twin.
- **US55**: As an Operational or Strategic User, I want to view a scenario's parameters, so I can keep track of the changes planned.
- **US56**: As an Operational User, I want to compare multiple scenarios side-by-side, so I can choose the best-performing option before deploying.

5.5 User Interface Prototypes

The UI prototypes developed for this study were guided by the high-level UX requirements outlined in the proposed approach, and the mapped functionalities. Three different UIs were implemented to accomodate the three decision-making levels defined earlier – requirements R7, and R9. Although there was an effort to fulfill every high-level requirement defined in the methodology phase, some of them were not implemented. Firstly, because the prototypes designed were static and only contained mock data, requirements R2, R3, R4, and R15 could not be accomplished. These requirements refer to the DT-based system's ability to receive real-time data and display smooth visualizations of the current state of the physical twin, and of simulations. Additionally, requirements related to errors and alerts (R12, R13 and R14) were not implemented due to time restrictions, but remain pertinent in the context of the system's implementation. Even though only 2D prototypes were designed, and requirement R10 was not able to be implemented, in the following sections, which explorse in more detail the design of the interfaces, some hypothesis for different implementations are presented.

There are some common features to every type of user, namely, authentication and a permanent chatbot feature on every page. The authentication, using a username and password, restricts the access to the system's functionalities, and fullfils the requirement R17. This process also aims to differentiate user profiles (according to the username), supporting role-based access crontol to functionalities – requirement R18. The chatbot allows users to communicate with the DT using natural language, which facilitates interactions and provides quicker access to functionalities. In a future implementation of this DT-based system, as requirement R16 entails, the system must provide clear explanations for AI driven-actions, more specifically, the answers given by the chatbot.

The design of every category of interface, contemplates a monitoring page, which provides updated and observable information about the current state of the physical system – requirement R1. This information is shown to the users mainly through bar charts, and follows accessibility standands, where these were possible – requirements R1, R6, and R11. Consistent page structure, color pallette, letter types and size, were some of the aspect considered to improve user experience and interaction with the system. Furthermore, the developed prototypes only provide the user with essential information, which enables more efficient interactions and quicker understanding of the system – requirement R8.

The prototypes designed aimed to address and implement the user stories defined earlier. The chosen technology to develop the prototypes was Figma due to its user-friendly interface and intuitive features.

5.5.1 Strategic User Interface

The level of DT abstraction required for the strategic level activities is very high, meaning that they are less detailed and focus on the broader objectives of the system. Therefore, the UI proposed for this kind of users is a traditional interactable dashboard, which presents company-level data, updated in real-time, and compared with target values. This kind of display provides the user with a general overview of the system's state and aids in the long-term decision-making process.

The strategic UI is composed of a monitoring page, with five main sections. Firstly, the interface includes a zoomable donut chart that allows users to analyze the four dimensions of the BSC, and their respective KPIs and X dimensions, by clicking on a section. The information present in this section is defined using ProductionDfX, and implements US1. Secondly, the sustainability section, addressing US2, visually displays key environmental KPIs, along with their target values. The percentage differences and clear, color-coded visual indicators help users identify underperforming areas immediately.

On the right top side of the page, the Product Flow section supports US3 by enabling users to analyze the current reception, production, and sales processes in comparison with predefined targets. The reception of products is segmented by lifecycle stages such as reuse, repair, and recycling, offering insight into product performance within the circular economy model. Furthermore, the Financial Analysis section presents a breakdown of current company expenses across various categories, alongside their target values, and presents visual cues to help users assess deviations, which fulfills US4. Finally, US5 is addressed through the integration of a chatbot feature that allows strategic users to interact with the system using natural language. This includes running simulation scenarios or querying the impact of different strategic decisions, making interactions dynamic and accessible.

Overall, the Strategic User Interface is structured to reduce cognitive load, enhance situational awareness, and empower strategic users to make informed, real-time decisions based on a comprehensive, user-centered design.

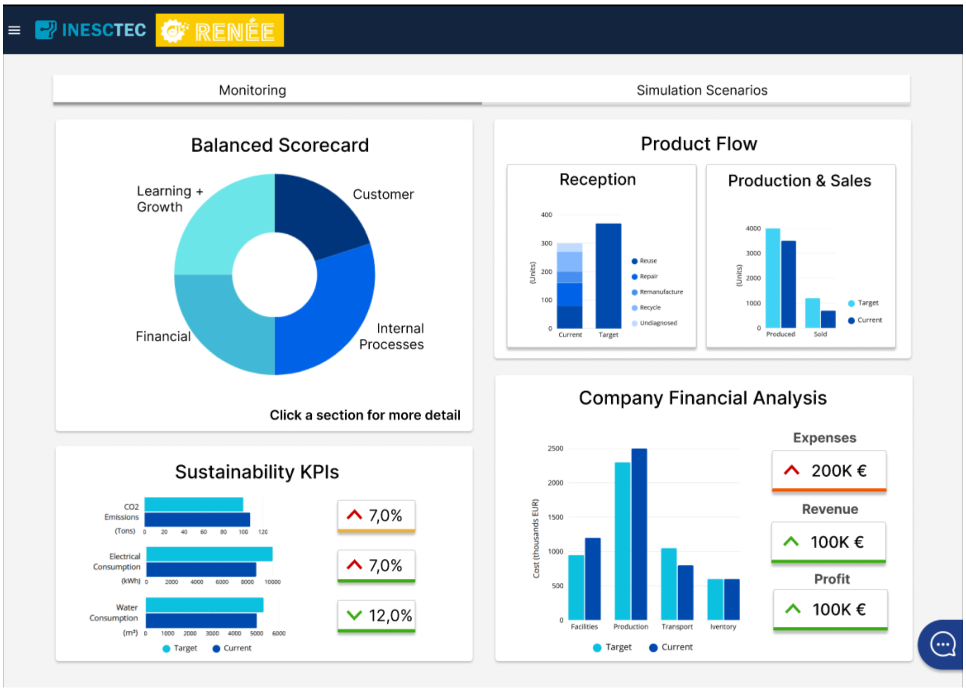

Figure 5.2: Strategic User Interface

5.5.2 Tactical User Interface

The DT-based system of this level is closely related to the supply chain, and was designed to support mid-level decision-making actors. The UI proposed for this kind of users is a traditional GUI, with a geographic component that is updated in real-time, and visual indicators. It is composed of three main pages – monitoring, forecasts and simulation –, which will be explored in this section.

Firstly, the monitoring page is presented in figure 5.3. To meet the needs described in US6, and US7, the interface includes a real-time, interactive map of the supply chain network. This map displays transportation routes and collection points, with dynamic indicators showing the operational status and capacity usage, when the user hovers a specific place of the supply chain. Warnings, such as “Close to max capacity”, are used to alert users of potential bottlenecks, allowing them to respond before disruptions occur. The user has the ability to click a node from the Supply chain and view details, as well as make simulations for that specific point. If it is a factory, the user has access to the production line’s 3D model, that updates in real-time. Then, the section presented in the right fulfills the functionalities proposed in US8 and US9. Here the user can visualize and quickly detect discrepancies between forecasted production, sales and reception of products against actual outputs, supporting early intervention in case of inefficiencies. To support US10 and US11, two performance indicators (current Operational and Resource Use Performance), and a summary pannel are displayed at the bottom of the interface. These sections provide contextual insights and help users prioritize their focus and actions. Just like in the strategic UI, the user has access to a chatbot component, accessible from the bottom-right corner (US12).

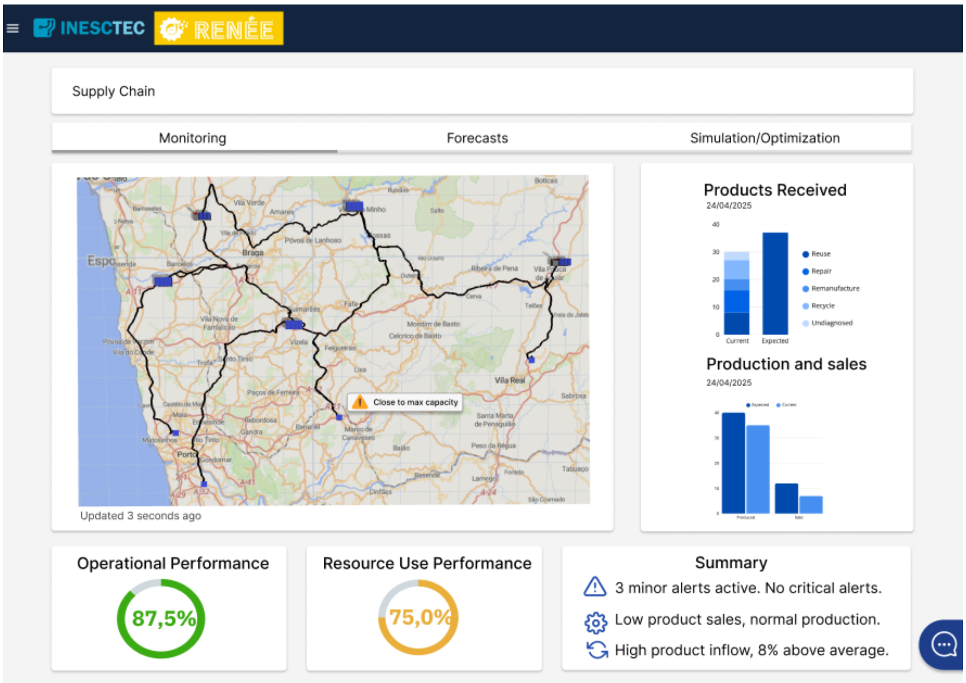

Figure 5.3: Tactical Monitoring Page

Secondly, the Forecasts User Interface, seen in figure 5.4, was designed to support tactical users in making proactive, data-driven decisions by providing a clear overview of projected supply chain performance. This page is changeable through the selection of a time frame on the topbar, allowing users to view based on the planning horizon relevant to their decisions – addresses US13. The “Expected Product Flow” line chart visualizes historical and forecasted data across sales, production, and reception. In addition to supporting US14, this section also adrresses requirement R5. A vertical marker labeled "Present" distinguishes past and future values, enabling users to observe trends over time and understand the evolution of product flow. Furthermore, forecasted performance indicators are displayed at the bottom left and show trend arrows, allowing users to assess whether these values are improving or declining relative to thresholds – fulfills US16. Supporting US15, the Bottleneck Overview panel on the right provides a scrollable list of predicted bottlenecks, where ach entry includes a severity indicator, capacity status, and the cause of the issue. It also includes a popup of the geographic model of the supply chain with visual indicators of the predicted state of its points. This gives users clear insight into which locations require intervention and its reasoning. Users can also download a forecast report, enabling local and offline access, which lines up with US18. When it comes to simulations and optimization scenarios, this pages provides a simulation suggestions pannel that offers recommendations based on the predicted bottlenecks and general innefficiencies – supports US17. Additionally, the user has the option to run customized simulations (US19), which takes them to the simulation page, presented in figure 5.5.

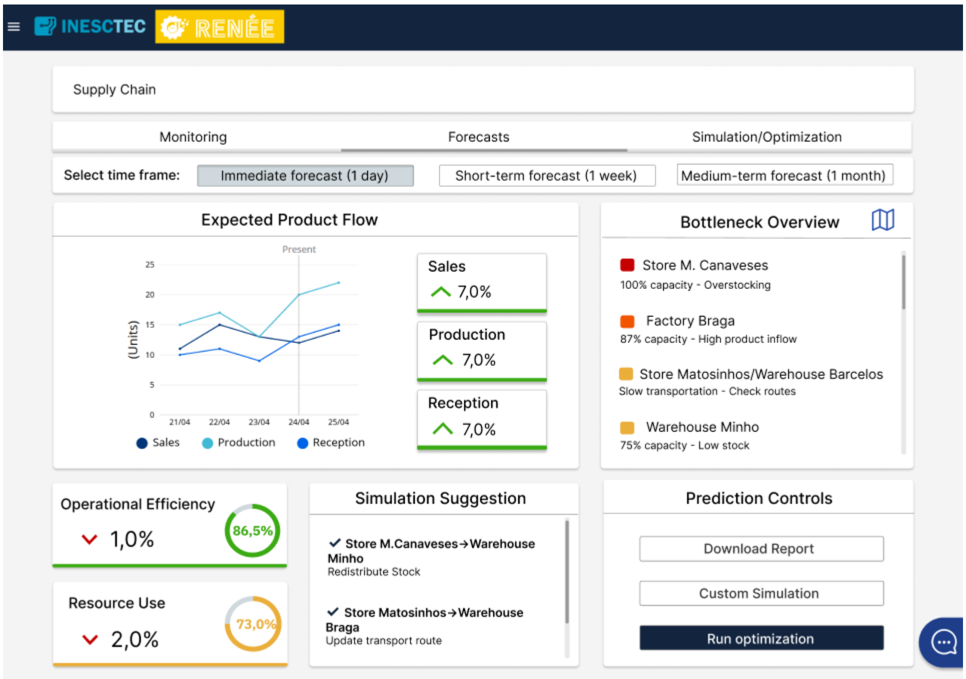

Figure 5.4: Tactical Forecasts Page

In this page, tactical users can explore potential scenarios and validate operational strategies for the supply chain. To enhance user understanding, this page showcases the current context and inneficiencies of the system, by displaying the geographic representation of the supply chain with visual performance indicators and a bottleneck overview section. The custom simulation controls, present at the bottom section of the page, namely the “Transport Routes” and "Product Production" components, allow users to assess how changes in transportation and product flows might impact system-wide performance, and the existing bottlenecks – addresses US20 and US22. Supporting US21, the “Test Maximum Product Production” button in the Simulation Controls panel enables users to conduct stress tests. This function simulates the effect of maximizing production across the supply chain, helping users understand system limitations, potential bottlenecks, and capacity thresholds under high-load conditions. Addressing US23, the “View Previous Scenarios” button in the Simulation Controls panel gives users access to earlier simulation runs. By revisiting and comparing historical scenarios, users can evaluate the effectiveness of previously implemented strategies and better inform future decision-making processes.

By clicking the "Run scenario" button on the bottom right corner, the user has access to the simulation scenario results, which can be seen in figure 5.6. The scenario results interface was designed to support decision-making in the context of simulation and optimization tasks.

Supporting US24, the "X Dimensions Impact" radar chart provides a multi-dimensional assessment of the scenario’s effects. Dimensions, previously defined for this level with ProductionDfX, such as sustainability, reliability, flexibility, ergonomics, and Six Sigma performance can be analyzed and compared against the current system. Additionally, the comparison of the

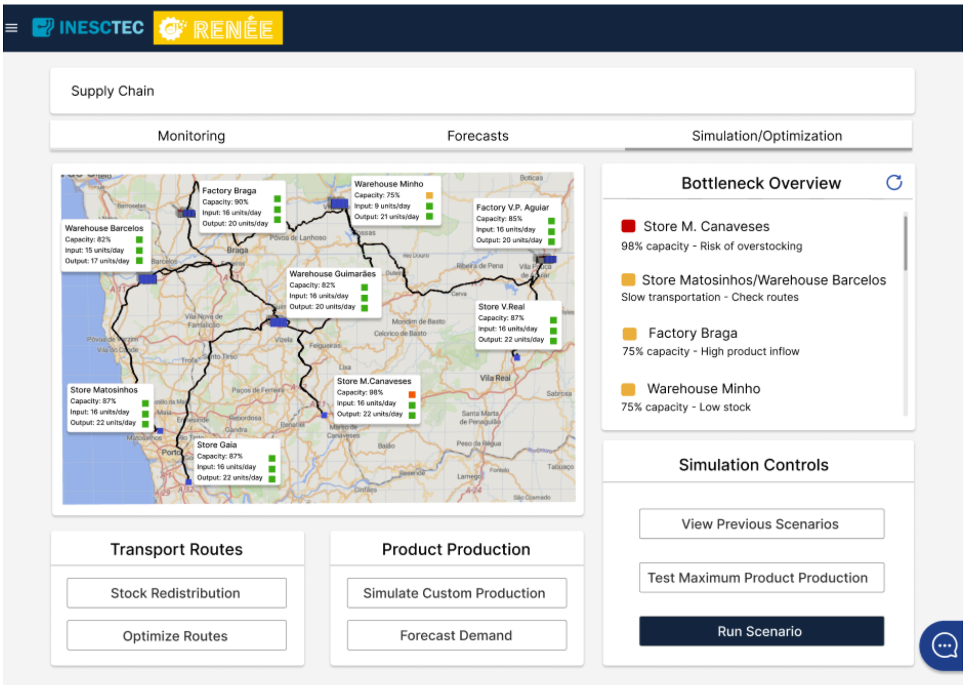

Figure 5.5: Tactical Simulation Page

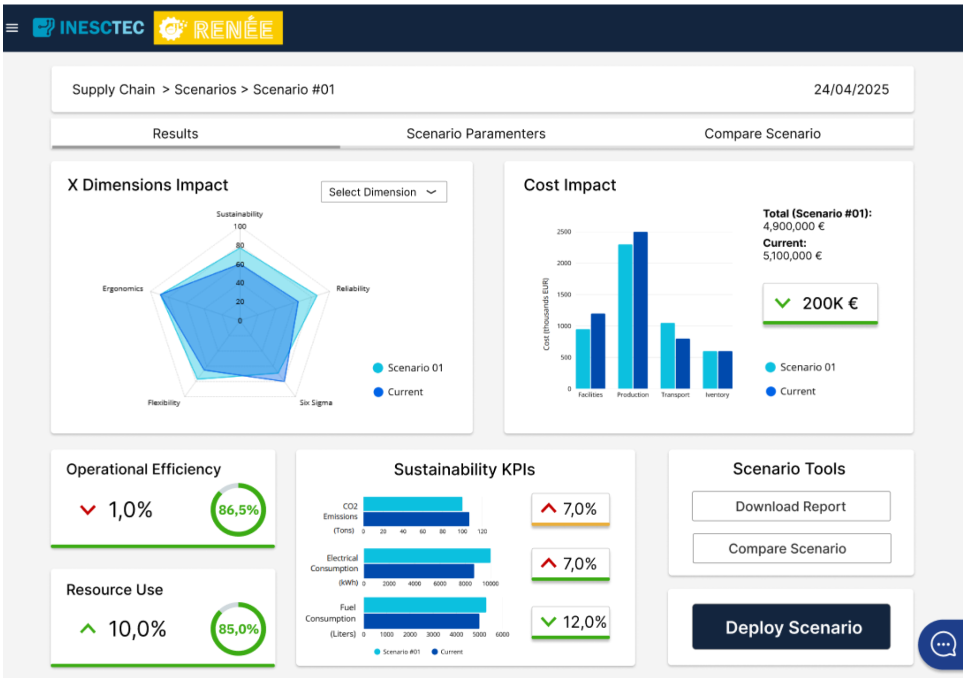

Figure 5.6: Tactical Scenario Results Page

operational and resource performance with the current state of the system are presented, allowing users to explore trade-offs and benefits in detail. The “Cost Impact” panel, designed to fulfill US25, displays a bar chart comparing cost categories (facilities, production, transport, inventory) between the selected scenario and the current state. It also shows the total financial difference, allowing users to evaluate the scenario's financial viability. Similarly, the Sustainability KPIs sections presents a side-by-side comparison of the metrics defined in US26, along with percentage indicators, in order to illustrate the environmental impact of the simulation. The section "Scenario Tools" allows users to export the report of the current scenarios, and to compare the scenario to other ones – addresses US27 and US30. Comparison between scenarios can also be performed by clicking the "Compare Scenario" tab, leading the user to the choice of scenario and then to the results page (see figure 5.7).

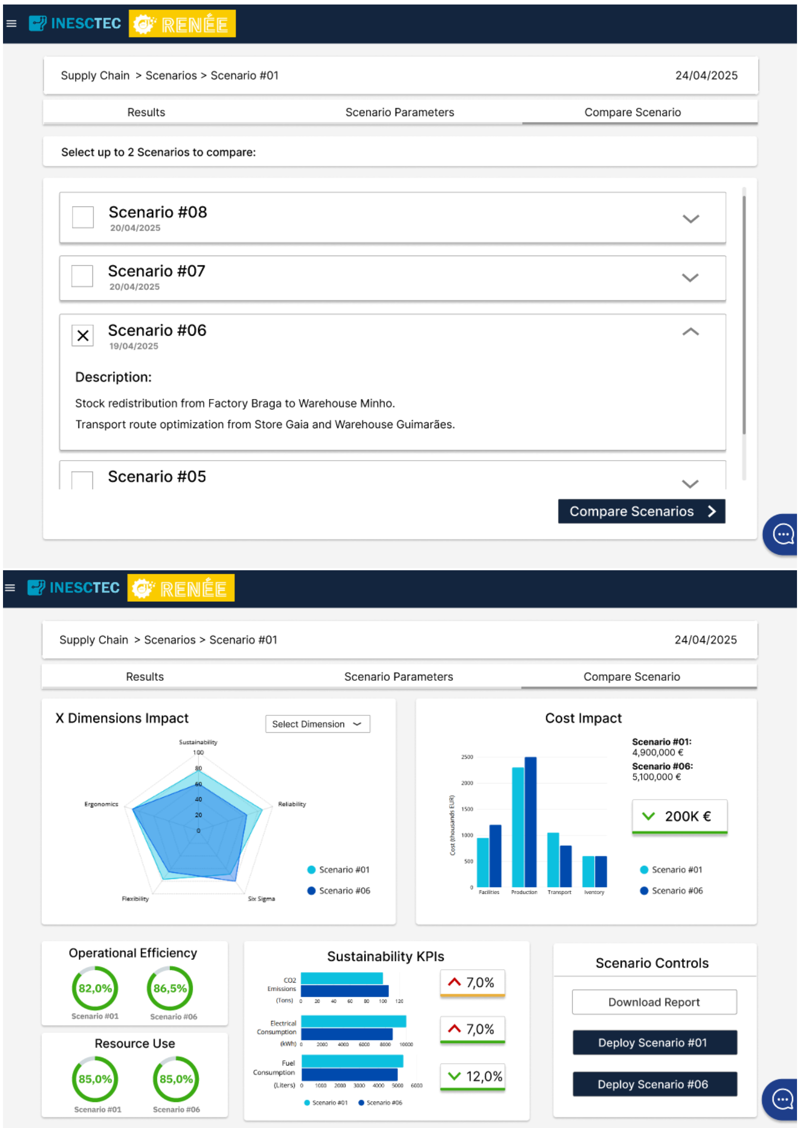

Figure 5.7: Tactical Compare Scenarios Pages

Addressing US28, the "Deploy Scenario" button enables direct implementation of the selected scenario into the system's physical counterpart. This bridges the digital and physical layers of the twin, allowing users to move seamlessly from planning a simulation to executing it based on validated simulation results. Finally, the parameter details are displayed in figure 5.8, and can be accessed through the tab "Scenario Parameters". This interface showcases a visual representation of the simulation impact on the supply chain, and the comparison of bottlenecks. Additionally, in the "Transport Routes" and "Product Production" sections, this UI displays the parameters of the scenrio, showing the potential changes in these dimensions.

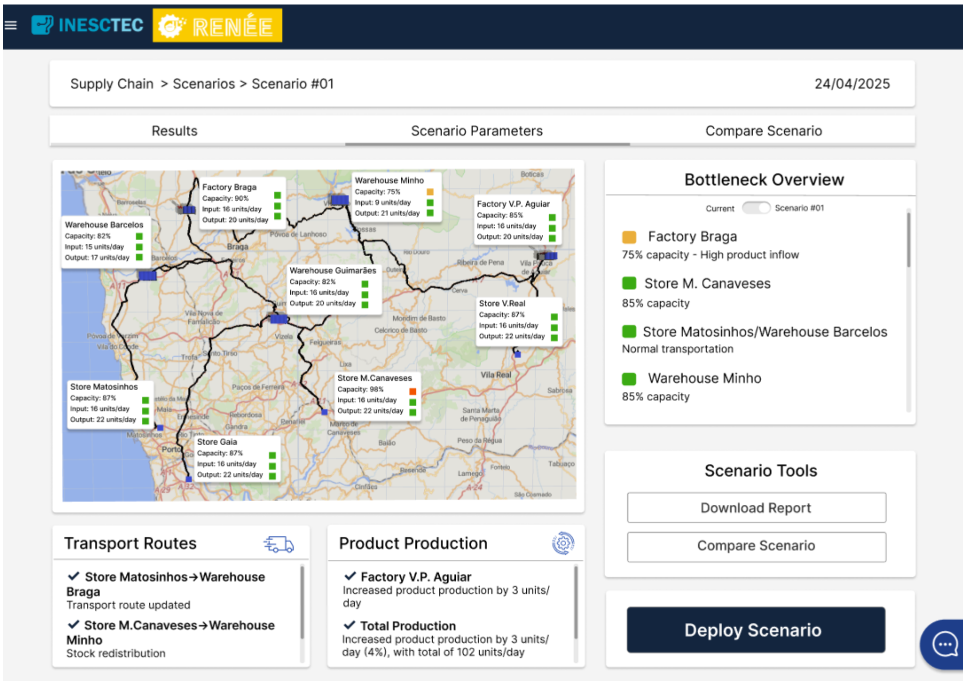

Figure 5.8: Tactical Scenario Parameters Page

5.5.3 Operational User Interface

The DT-based system of this level is closely related to the production line, and was designed for quick and immediate decision-making. The UI proposed for this kind of users is a traditional GUI, with a 3D visual representation of the factory floor at its core. Despite the chosen format of interface, other options were considered, but, due to the project's scope and lack of time, were not implemnted. The hypothesis of a immersive VR interface with speech recognition was considered. This approach would allow operators to navigate the 3D factory layout, inspect processes, and perform simulations using natural voice commands. The goal would be to improve situational awareness and reduce cognitive load during production monitoring tasks.

Similarly to the tactical users' UI, it is composed of three main pages – monitoring, forecasts and simulation –, which will be explored in this section. Firstly, the monitoring page (displayed in figure 5.9), composed of five main sections was designed to provided updated information about the production line state, allowing users to efficiently monitor the system. The 3D model of the production line, seen at the center of the page, fulfills US31, enabling operational users to visually track real-time activity across the factory floor. The panel presented in the right side of the page, simultaneously implements US32 and US33. Here, the user can use the toggle to change the display of the section, from the current state of process steps – color-coded to reflect their status, including efficiency, effectiveness and item flow rate – , to the monitoring of product flow, which shows the current production and reception of products. Regarding system performance (US34), the user has access to the current capacity and performance, displayed using colored circular gauges at the bottom of the page. This representation is able to alert users when values approach critical thresholds. To address US35, a summary panel synthesizes key alerts and insights. This includes warnings and comments, helping users rapidly identify and prioritize areas requiring attention. Furthermore in this page the user has access to suggested simulations when clicking the lighbulb icon, present in the troubled metric's section (interaction presented in figure 5.10).

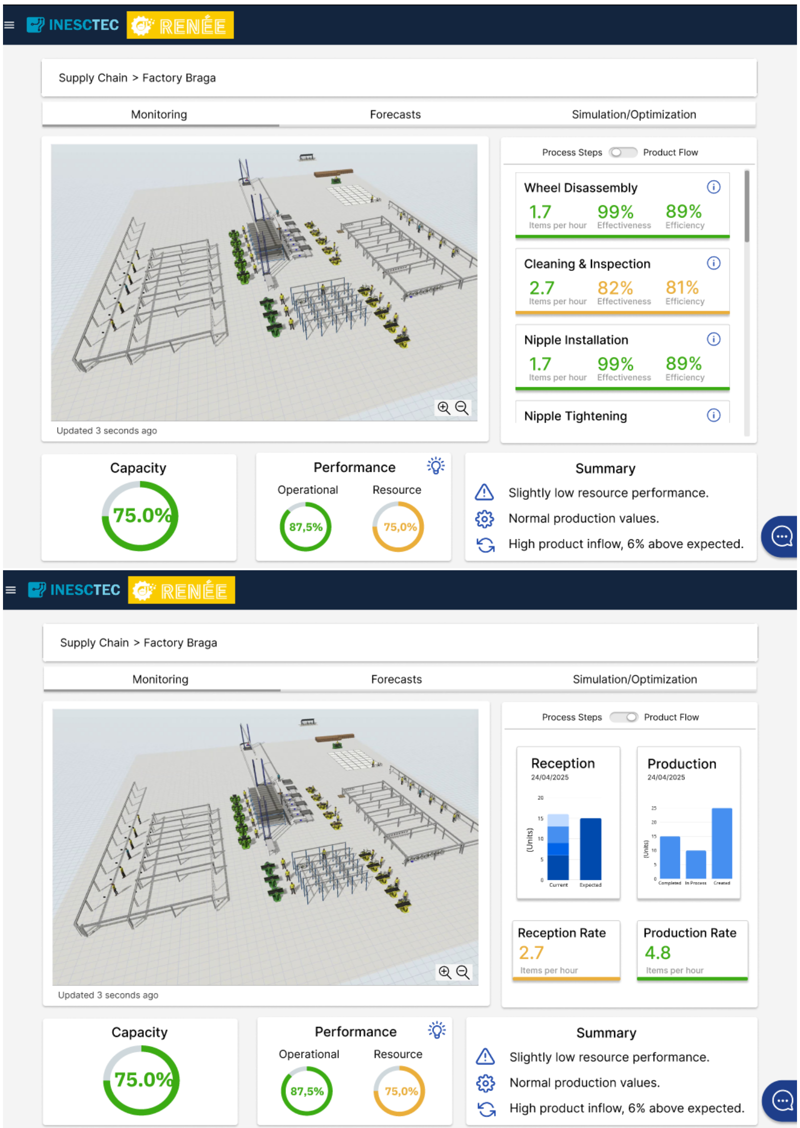

Figure 5.9: Operational Monitoring Page

The Forecasts page for operational users is very similar to the tactical foreacasts page, having the same high-level functionalities. The functionalities outlined in the operational user stories (US37 to US44) are implemented in the UI presented in figure 5.11. As these functionalities have

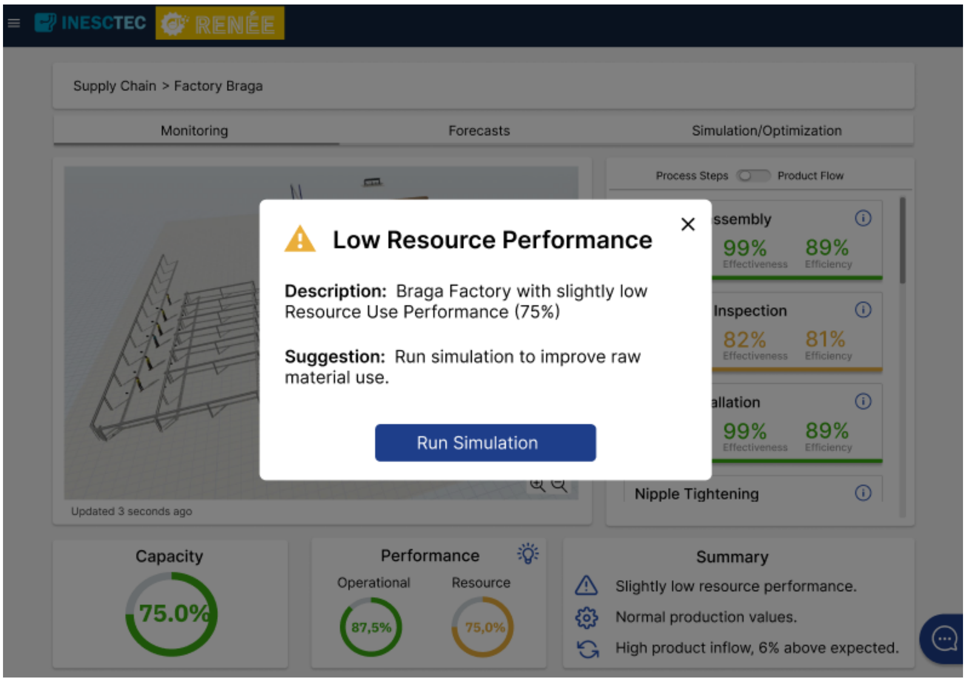

Figure 5.10: Operational Simulation Suggestion Page

already been described in the context of the tactical forecasts section, they will not be discussed again here.

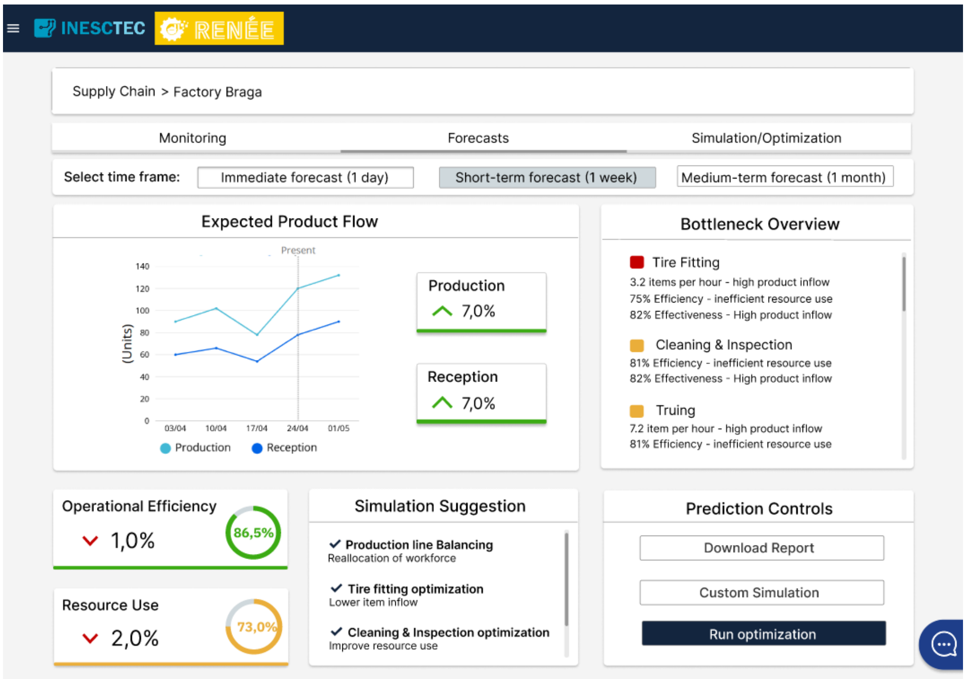

Figure 5.11: Operational Forecasts Page

The simulation page, displayed in figure 5.12, allows users to create custom simulation scenarios for the production line. The 3D model and bottleneck overview panel are kept from the monitoring page, allowing users to analyze the current state of the factory floor via visual indicators. To support US45, the section "Work stations" provides users with the options of manually redistributing work stations, or automatically optimize them by balancing the production line. In the "Custom Product Flow" panel, customized product production and reception can be tested, which helps users to assess the system's performance under different input/output scenarios (US46). The maximum amount of product flow can also be testes using the stress testing options present in the "Simulation Controls" section (US47).

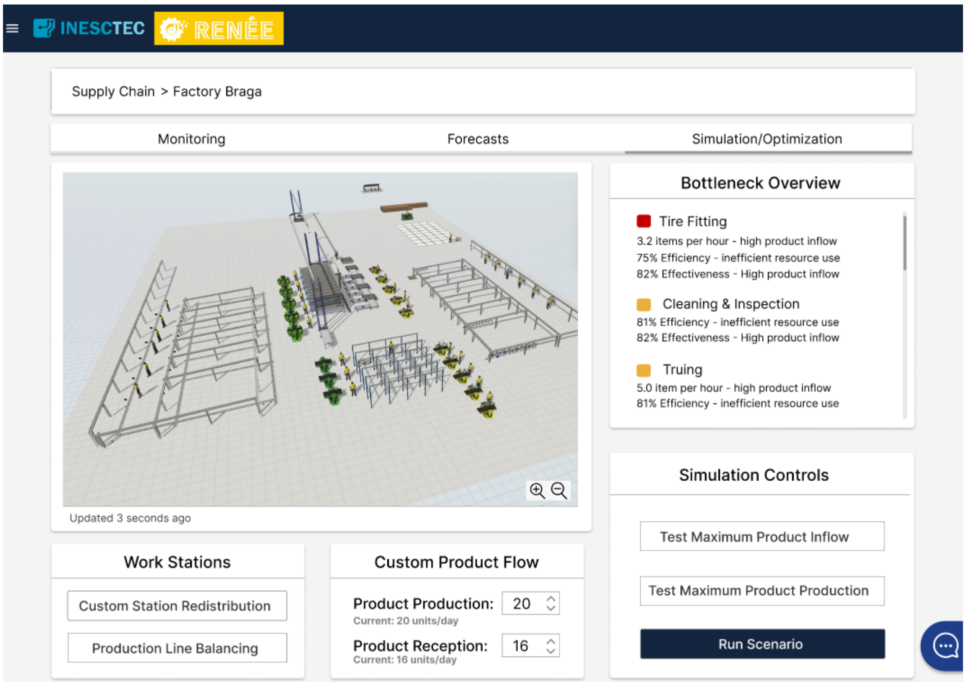

Figure 5.12: Operational Simulation Page

When clicking the "Run scenario" option – US48 –, the scenario is employed and users can evaluate the effects of planned changes before applying them in the real environment. The results and parameters of the simulation are presented on a page similar to the one presented in figure 5.13. These pages implement the user stories from US49 to US56, and, since they are so similar to the tactical functionalities, they will not be described again here.

5.6 Usability Testing

The usability testing phase was designed to evaluate how effectively users interact with the developed prototypes of the Digital Twin-based system and to simulate realistic interaction scenarios. This evaluation followed the usability testing protocol defined in section 4.5.

During the tests, participants were asked to perform a series of predefined tasks for each user profile without prior training, in order to assess the system's intuitiveness and first-time usability. The presented tasks were designed to represent the core functionalities of the platform, spanning operational monitoring, scenario simulation, and high-level decision support. Following each

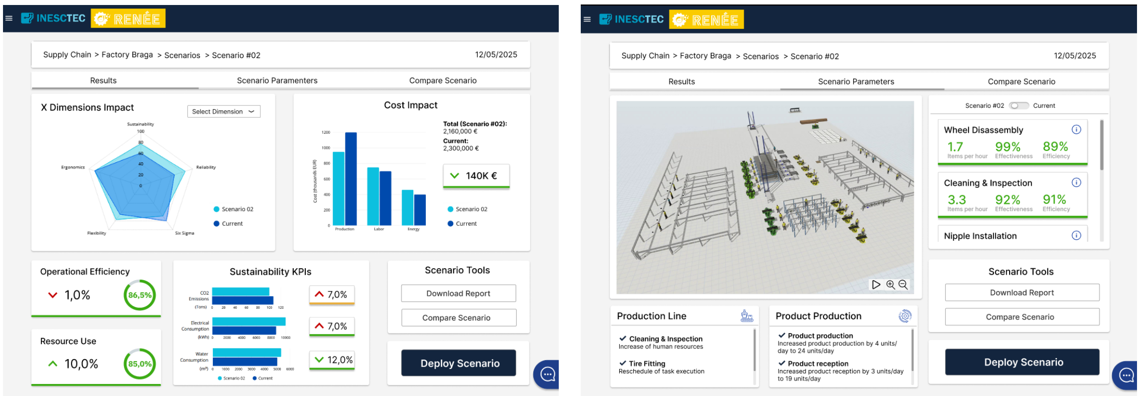

Figure 5.13: Operational Scenario Page

task, participants entered their answer to the task's question in a questionnaire and addressed its difficulty. At the end, they were asked to fill a brief survey that evaluates the five core UX dimensions. In addition to the technical questionnaire, demographic data was collected, and the testing sessions were audio recorded so that no feedback went unregistered.

5.6.1 Tasks Overview

Seven representative tasks that reflect realistic interactions within a Digital Twin-based manufacturing system were defined for the usability evaluation. Each task was designed with a specific goal and a set of steps that users were expected to follow. Tasks required interaction with various interface components and varied in difficulty. These tasks were categorized into tactical, operational, and strategic levels to assess the interface across a variety of contexts and decision-making scenarios. The strategic level tasks, which had to be completed in the corresponding UIs, were the first ones presented to the participants:

- **Task 1**: In the Balanced scorecards financial dimension, what is the best performing KPI?
- **Task 2**: Simulate the increase of capacity in factory Braga and product production by 20%, using natural language. How much would this change increase the company's expenses?

Secondly, the tasks defined for the tactical level are as follows:

- **Task 3**: What is the current operational performance of the supply chain?
- **Task 4**: Compare Scenario 1 and 6. Which has the higher transport costs?
- **Task 5**: How many products are expected to be produced next month?

Finally, the testers carry out the operational level tasks:

- **Task 6**: What is the current effectiveness of the tire fitting step?
- **Task 7**: What is the cost impact of increasing the production of products to 24 and the reception of products to 19, while also balancing the production line?

The expected flow for each task, alongside their pre and post conditions are presented in structured Use cases in table 5.1 (e.g. UC1 relates to Task 1).

5.6.2 Protocol

As proposed in section 4.5, the usability of the prototypes was evaluated using the proposed questions for the five UX dimensions. Additionally, to obtain a more comprehensive assessment of the interfaces, the participants evaluated the difficulty of each task, and objective data was collected, namely, task completion time and success rate.

The evaluation sessions were conducted using a computer, equipped with the user interfaces and a Google Form containing the questions, a chrnometer, to measure task completion times, and a phone to record the audio of the test. The time of a task starts when the user finished reading its description and starts to interact with the prototypes. It ends once they answer the respective question on the form. The success of a task can have four values:

- **0%,** if the user registers the wrong answer, and, through the observation of the test, it is clear that they did not understand the task's objective.
- **25%**, if the user completes the task with a major mistake, for instance, skips an important step of the task execution.
- **75%**, if the user understood the task's objective, but completes it with a minor erros, or registers the wrong answer on the form.
- **100%**, if the user successfuly registers the answer of the task and follows its main flow.

An evaluation session is considered complete when the participant has completed all assigned tasks, has answered all questions and submitted the form.

5.6.3 Participant Sample Characterisation

Ideally, the participants of the study would be end users of the final system. Since that was not possible, the participants of the tests consisted of ten individuals with the following characteristics:

- Aged between 23 and 45 years old, with a mean age value of 28, mode of 24 and standard deviation of 6.5.
- Mostly researchers (9 out of 10 – 90%), and a single participant being a software engineer.
- 70% male participants, and 30% female.
- Diverse levels of knowledge of Digital Twin-based systems, with a average value of 3.4 on a scale from 1 to 5, IQR of 1.0 and standard deviation of 1.26.

These demographic data suggests a relatively young participant group, academic-oriented with intermediate to advanced knowledge in DT-based systems.

Table 5.1: Tasks' use cases

ID	Precondition	Main Flow	Postcondition
UC1	User is on the main page.	1. Click the "Financial" section of the Balanced Scorecard chart. 2. Read the chart and fin the largest section.	User identifies Cost management as the top KPI.
UC2	User is on the main page.	1. Click chat icon. 2. Enter message (already defined) in the text box. 3. Submit query. 4. Read chatbot response.	User identifies 300.000€ as the expenses of the company.
UC3	User is on the monitoring page.	1. Check the operational performance section.	User identifies the performance as 87.5%.
UC4	User is on the monitoring page.	1. Click the "Simulation/Optimization" tab. 2. Click the "View Previous Scenarios" button. 3. Select scenarios 1 and 6 from the list. 4. Click the "Compare Scenarios" button. 5. Check cost impact section for transport costs.	User identifies that Scenario 1 has higher transport costs.
UC5	User is on the monitoring page.	1. Click the "Forecasts" tab. 2. Select the "Medium-term forecast (1 month)" option on the time frame section. 3. Check product flow chart for the forecasted production value.	User identifies 400 products will be produced.
UC6	User is on the monitoring page.	1. Scroll through the process steps list. 2. Check the "Tire Fitting" step for its effectiveness.	User identifies that the effectiveness is 87%.
UC7	User is on the monitoring page.	1. Click the "Simulation/Optimization" tab. 2. Set product production to 24. 3. Set product reception to 19. 4. Click the "Production line balancing" button. 5. Click the "Run simulation" button. 6. Check the cost impact section.	User identifies that the cost reduces by 140,000€.

5.6.4 Results

This section presents the results obtained from the usability tests performed. As previously mentioned, both objective – success rate and task completion time – and subjective – perceived task difficulty and UX dimensions questionnaire – data were collected.

In figure 5.14, a table with a color-coded representation of task success per participant is presented. In this context, the green sections represent 100% success, the yellow ones are 75% sucess, the orange ones are 25% of sucess, and the red squares represent 0% success.

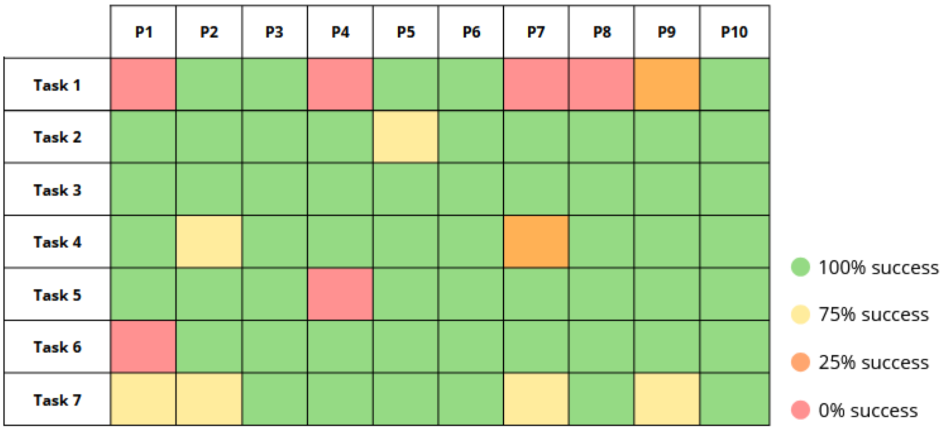

Figure 5.14: Task sucess rate

The analysis of task success rates revealed generally high levels of task completion, with most tasks achieving a 90% success rate or higher. Task 3 had a perfect success rate of 100%, followed closely by Task 2 at 97.5%. Tasks 4, 5, 6, and 7 all maintained a strong success rate of 90%, indicating consistent usability performance across these activities. However, Task 1 emerged as a significant outlier, with only 52.5% success rate. This suggests that Task 1 may present usability challenges that require closer examination and UI refinement. Overall, the average success rate across all tasks was 87.1%, reflecting generally effective task design with isolated issues.

The second objective measure studied is the task completion time. Since there is a general correlation between task completion time and perceived difficulty, it is relevant to present these measures side-by-side. Figure 5.15 presents the boxplots for task completion time, in seconds, and task perceived difficulty, asked using a 5-point Likert scale question at the end of each task.

Task 1 shows low completion times, with low spread, meaning that there was some consistency in participants regarding the time spent on this task. Its difficulty, according to the participants' answers, falls in the low/moderate range, with a mean difficulty of 2.2. An important point to note is that this task was the one that presented the lowest success rate, with only 52.5%. During the sessions, through direct observation of the participants' interaction with the system, it was clear that there was a design flaw in the donut chart presented, or in the question itself. Almost half of the users did not answer this question correctly, since they did not click the financial section of the chart, and instead just observed the first layer of the display, registering "Internal processes" as their choice.

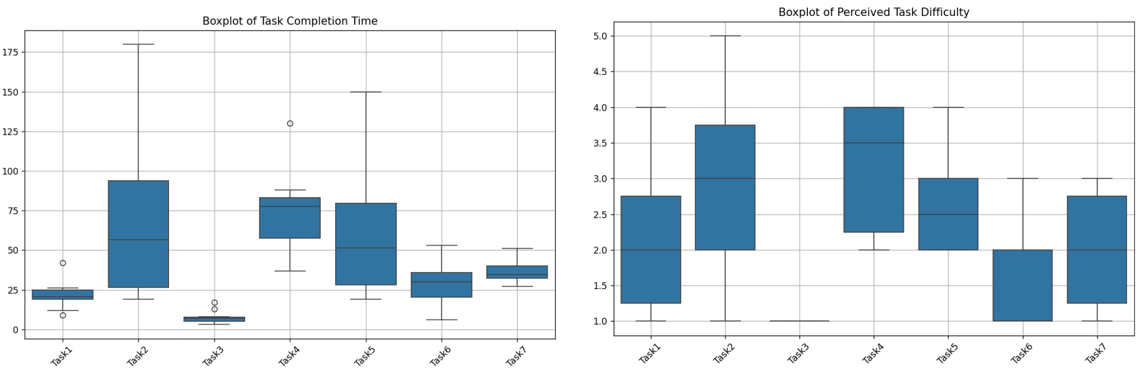

Figure 5.15: Boxplots for task completion time and perceived difficulty

The second task has the highest variability, concerning both difficulty and completion time. According to users, this was one of the most challenging tasks, having a mean difficulty of 2.8. Similarly to Task 1, the question formulated for this task created some confusion among users. This was because the question requested users to natural language to perform a simulation, which made the goal of using the chatbot component unclear to them.

Task 3, which had the lowest perceived difficulty, also had one of the shortest and most consistent completion times. This consistency of low values and success rate of 100% shows that the goal of the task was clear to the participants and that it was easy to complete. Then, similarly to Task 2, Task 4 has a high difficult tasks overall, with a median rating of 3. This suggests that users perceived this task as more challenging. The main struggle observed in this task was the low visibility of previous scenarios button in the simulation page. Although the majority of users navigated to this page, they had some difficulty to understand how to view and compare previous scenarios.

Task 5 presents moderate perceived difficulty, with a median of 2.5 and a fairly tight IQR, and relatively long completion times. These values suggest medium to high difficulty. Task 6 and Task 7 wer rated as relatively easy, with medians around 1–2, and short completion times, indicating they were easy and quick to complete. Since these tasks were the last ones to be performed, the users' prior use of the system may have had some impact on their low perceived difficulaty and completion times.

The final questionnaire about the system, composed of the questions previously outlined, aimed to assess the five UX dimensions. Figure 5.16 presents a spider chart with the values of each dimension. Overall, these varaibles present high values, above 80%, with the exception of the undersatndability, which obtained 79%. The variable with the best score is "Delight Factors", which shows that in general the users appreciated the aesthetics of the UIs. The convenience metric also presents a high score, of 84, which is relevant, because it implies that the system is user-friendly, does not frustrate users, and reduces cognitive and physical effort. Finally, the dependability and usability values suggest that the system provides reliable information, and replicable functionalities, while also being clear with its purpose.

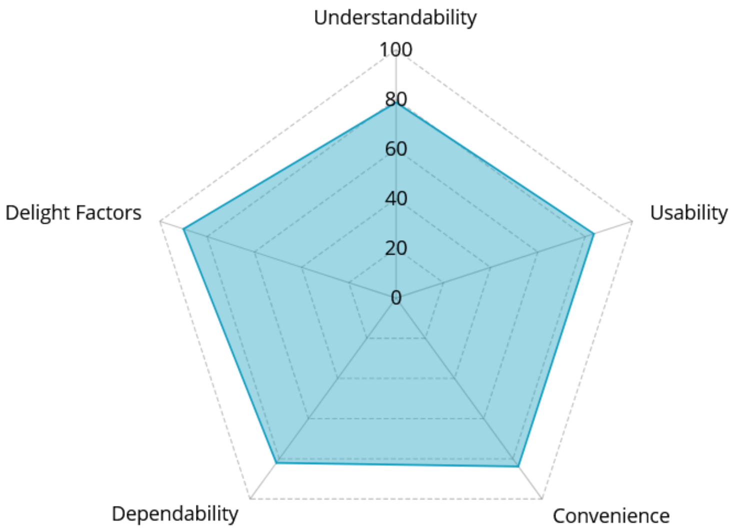

Figure 5.16: Spider chart for the 5 UX dimensions

These results indicate that the proposed UX design methodology successfully supports the design process in Digital Twin-based systems. Participants were able to interact effectively with the interface, and the feedback gathered confirms the alignment of the system's functionalities with the users' roles and expectations. The satisfactory outcomes validate the relevance of incorporating user-centered principles in the development process and demonstrate the potential for better performance and user satisfaction in industrial contexts.

Chapter 6

Conclusions

This study's main goal was to understand the importance of user interaction and experience in Digital Twin-based systems, and the pertinence of employing user-centered development techniques in this context. The exploratory literature review performed revealed that, while the technical capabilities of these systems have been evolving rapidly, their usability and the user experience (UX) dimension remains widely underexplored.

The core contribution of this dissertation lies in the comprehensive approach proposed for the development of UX in DT-based systems. It was constructed based on a thorough literature review, interviews with domain experts, and an applied case study in the RENÉE project, which enabled the validation of the methodology in a realistic manufacturing scenario. This methodology emphasizes the importance of understanding the users' roles, technical backgrounds, and information needs to develop appropriate user interfaces that enable smooth and efficient interactions with the system. It is composed of two main parts: a list of high-level requirements, that outline good UX practices and present a vision for UX in DT-based systems, and a four step structured methodology, that adopts standard practices of user-centered development – user profiling, functional mapping, prototype-driven development, and usability testing.

The implementation of this approach in the case study within the RENÉE project demonstrated the importance of aligning UI design with user needs to obtain higher satisfaction, and increased operational efficiency. These findings validated the importance of applying user-centered development techniques in the design of DT-based systems and suggest that doing so can lead to more inclusive, and effective industrial tools.

This work contributes to the growing interest and knowledge on socio-technical systems and highlights the need for greater integration of human factors in the development of emerging digital technologies. As DTs become more complex and embedded in manufacturing operations, efficient interaction between humans and machines becomes crucial. Furthermore, this dissertation supports the ongoing shift from Industry 4.0 to Industry 5.0, where human-centricity, sustainability, and resilience are growing priorities. In this context, designing DT-based applications with usability and accessibility in mind is a fundamental requirement for inclusive and effective digital transformation.

6.1 Future work

The future work of this study is envisioned on three parts. Further research could explore how AR, MR, and voice or chatbot-based interfaces affect user cognition and engagement, especially for non-expert users. Due to the scope of this project, the implementation of VR prototypes was not possible, but it was a pertinent option, mainly for the operational users. Testing the applicability of the proposed methodology in different contexts and implementations brings new opportunities to refine the approach to fit a wider range of user profiles, technical infrastructures and user interfaces.

Regarding the case study presented, future work relies on performing more iterations and progressing to the implementation of the system. Further iterations would allow for the refinement of the user interfaces based on direct user feedback obtained during the usability tests. This iterative approach is essential to ensure the system remains aligned with the needs of its diverse user base and adapts effectively to real-world usage scenarios. Additionally, implementing the system in the industrial environments present in the RENÉE would enable a more comprehensive evaluation of its performance, reliability, and long-term impact on user experience, operational efficiency, and decision-making processes. This real-world implementation in the different RENÉE pilots would also validate the methodology proposed in this study and identify areas for future enhancement.

6.2 Scientific Contribution

As part of the research workflow, a scientific article where we instantiate the UX requirements for a product-process digital twin-based system, with the focus on circularity and sustainability was developed and submitted during the dissertation process. The article, titled ***User Experience in Digital Twin-based Systems***, was peer-reviewed, accepted, and presented at the ***IEEE International Conference on Digital Twin (Digital Twin 2025))***.

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