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A human-centric framework for enhancing usability in a vineyard digital twin system

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ABSTRACT

This paper develops and applies a human-centric framework to design a Digital Twin (DT) by applying a people-led approach to a vineyard automation scenario. Current DT systems in agriculture often focus on technical performance, which creates usability challenges such as data overload, lack of role-specific interfaces, and reduced trust among non-technical users. The study applies Personas to represent user groups and introduces a human-centric framework for mapping tasks and decision processes. The framework makes an original contribution by demonstrating how established human-centric methods can be systematically integrated into a coherent DT development process, addressing a recognised methodological gap in the literature. The objective of this research is to evaluate how a structured, human-centric approach can improve usability, cognitive alignment, and stakeholder engagement in vineyard automation. These processes are modeled using Personas, Decision Ladders and Control Task Analysis to align system functionality with user roles and cognitive needs. The research methodology integrates Personas, ConTA, and Decision Ladders within a real-world vineyard case study. This study showcases the impact of applying a structured human-centric DT design framework on improving decision-making support, user engagement, and system efficiency in agricultural contexts. Moreover, it provides expert-informed evidence in what way human-centric methods can be operationalised in a consistent and transparent way for DT redesign. Overall, the work demonstrates how a structured, people-led approach can enhance the usability and adoption of both new and existing DT systems, offering a transferable framework with relevance beyond agriculture.

1. Introduction

Modern agriculture (for example vineyards) face challenges such as unpredictable weather, labor shortages, and the need for sustainable practices, driving demand for innovative tools that enhance operational performance and address diverse user requirements. Digital Twin (DT) technology has emerged as a transformative solution, bridging the physical and virtual realms to enable real-time monitoring, predictive maintenance, and data-driven decision-making (Grieves, 2014; Stjepandić et al., 2022; Ariesen-Verschuur et al., 2022; Zhang et al., 2023; Medina and Hernandez, 2025). By creating a synchronized digital representation of physical systems, DTs allow users to analyze, optimize, and simulate processes with high accuracy. In agriculture, DTs have demonstrated potential for improving resource efficiency, automation, sustainability, and user experience personalization, offering significant benefits to farmers, technicians, and consumers (Pylianidis et al., 2021; White et al., 2021; Semeraro et al., 2021; Verdouw et al., 2021; Warren and Neubauer, 2023; Cesco et al., 2023). Vineyards, for example, benefit from DTs that integrate robotic automation, sensor-based monitoring, and environmental data analytics, optimizing resource utilization while improving customer experience (Semeraro et al., 2021). However, despite their growing adoption, agricultural DTs face unique challenges due to environmental variability, and diverse user roles, requiring DTs to be highly adaptable and user-friendly (Krupas et al., 2024).

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Although DTs offer powerful capabilities, many implementations remain highly technical, failing to accommodate diverse stakeholders' usability needs (they are system-centric, focusing on efficiency and productivity, rather than on humans). Studies have shown that existing DT designs often prioritize data integration, productivity and automation over user experience, resulting in interfaces that are difficult to navigate, excessive data overload, and cognitive misalignment (Fett et al., 2024; Agrawal et al., 2023; Krupas et al., 2024). Whilst some studies highlight the importance of the human in the DT system, procedures and use (Osama, 2024; Coll et al., 2025), the role played by human-digital twin interactions remain unclear and uncertain. This disconnect can lead to inefficiencies, inappropriate decisions, and reduced trust in the system, ultimately hindering the adoption of DT technologies (Tao et al., 2019; Peruzzini et al., 2023).

While several studies have acknowledged the importance of incorporating human-centric principles into Digital Twin design (for example Agrawal et al., 2023; Peruzzini et al., 2023; Osama, 2024), these contributions often remain conceptual or focus on localised enhancements such as interface adjustments or role-based filtering. Existing approaches rarely operationalise human-centricity through structured cognitive modelling methods, nor do they demonstrate how such methods can be coordinated into a practical and repeatable design workflow for real DT systems. Moreover, reviews of human-centric DTs (Krupas et al., 2024; Semeraro et al., 2021) highlight that, while human–machine collaboration is increasingly discussed, there remains a lack of methodological clarity on how to embed user workflows and cognitive requirements systematically within DT development. This gap motivates the present work, which integrates and novelly combines existing human-centric methods, i.e. Personas, Control Task Analysis (ConTA), and Decision Ladders, into a unified framework and evaluates their coordinated use within an operational agricultural DT.

The limitations indicate a practical rather than theoretical gap: many existing DTs underperform not because of technical constraints, but because their design overlooks the cognitive characteristics of the diverse users who must interact with the Digital Twin. The absence of explicit alignment between system functions and stakeholder decision processes often results in inefficient use, reduced trust and avoidable operational errors.

The key usability challenges in DT adoption include lack of role-specific interfaces where many DTs present the same interface and data visualization to all users, regardless of their expertise level, leading to inefficiencies for non-technical stakeholders such as farm managers and customers. Moreover, DTs often provide raw and unstructured data, making it difficult for decision-makers to extract actionable insights (Tao et al., 2019). In addition, non-technical users frequently struggle to navigate complex DT dashboards, reducing their ability to leverage DT capabilities effectively (Agrawal et al., 2023). Addressing challenges such as data overload, lack of role-specific interfaces, and poor usability requires a fundamental shift in DT design philosophy, from a technology-centric framework to a human-centric one, prioritizing cognitive alignment and intuitive user interaction. Interface redesign only is not sufficient if the usability of the DT is not designed with a human-centric framework in mind (Palmer et al., 2023).

Human Factors (HF), a field grounded in the optimization of human well-being and overall system performance, has historically focused on ergonomics, human–machine interaction, and cognitive engineering (Shorrock and Williams, 2016). While extensively applied in sectors like aviation and manufacturing, its integration into the rapidly evolving domain of DTs remains underdeveloped.

The lack of human-centric considerations in DT frameworks is evident in ISO 23247, the leading international standard for DT architecture in manufacturing. While ISO 23247 provides the foundational structure for including human elements, the depth of human-centricity, such as detailed cognitive load, ergonomic analysis, or complex human-robot interaction dynamics, is not the primary focus of the core standard. Semeraro et al. (2021) highlights that ISO 23247 lacks specific guidance on human factors, usability, and cognitive alignment.

This gap is not only a design challenge but also raises ethical concerns. When DT systems are deployed without accounting for user cognitive diversity, decision-making styles, or accessibility, they risk excluding non-technical users, reinforcing power imbalances, and introducing unintended operational risks. Ethical DT development must ensure fairness, transparency, and inclusivity, particularly in sectors like agriculture where users range from technicians to customers with varying levels of digital literacy. The absence of such principles in ISO 23247 highlights the urgency of embedding human-centric and ethical design practices into future DT frameworks.

To address the disconnect between technical functionality and human centred interaction in DT, Control Task Analysis (ConTA) and Decision Ladders offer a structured framework for enhancing DT usability. ConTA is a method for identifying user tasks facilitating the identification of key operational tasks and mental processes, while Decision Ladders visualize how users make decisions step-by-step, helping ensure that the system supports those thought processes effectively (Vicente, 1999; Palmer et al., 2023). These tools enable a design framework where DTs are not only technologically robust but also cognitively intuitive, ensuring that users can efficiently perform their tasks (Peruzzini et al., 2023; Krupas et al., 2024). Despite their theoretical potential, these methods have yet to be systematically evaluated in DT design, particularly in the agricultural domain, where environmental variability and diverse user needs present unique challenges (Naikar et al., 2006).

This paper presents a comparative evaluation of an existing DT for vineyard automation and a newly developed human-centric DT prototype, designed using ConTA and Decision Ladders. While prior DT research has concentrated primarily on technical functionality (Tooth et al., 2024), this study shifts focus toward integrating structured usability methods into DT design. The research evaluates usability and decision-making challenges in an existing DT through user feedback and workflow analysis. It analyzes an existing vineyard DT, identifies role-based cognitive and decision-making challenges, and applies a human-centric redesign framework using Personas, ConTA, and Decision Ladders. Moreover, it shows the development and implementation of a human-centric DT model for a real vineyard, incorporating ConTA insights to align system functionality with the cognitive and operational needs of different stakeholders. A conceptual comparison between the original and a retrofitted DT illustrates how structured human factors methods can address cognitive misalignment, improve decision support, and enhance user experience. Additionally, it compares the conventional and redesigned DTs, demonstrating how ConTA and Decision Ladders address usability limitations while having the potential to improve overall user satisfaction and system performance. In doing so, this study contributes a methodological foundation for future human-centric DT development, particularly in agricultural contexts.

This work showcases how well-established human factors tools can be coordinated into a practical and transferable framework for enhancing DT usability. As such the contribution of this work lies in demonstrating how established human-factors tools including Personas, ConTA, and Decision Ladders, can be systematically integrated into a coherent and transferable framework for Digital Twin usability enhancement.

The remainder of this paper is structured as follows: Section 2 presents the proposed human-centric DT framework, including the use of Personas, ConTA, and Decision Ladders. Section 3 applies this framework to a vineyard case study and demonstrates the usability improvements. Section 4 discusses the comparative evaluation between the retrofitted and conventional DTs. Finally, Section 5 concludes with key findings and suggestions for future research.

2. Methodology: Human-Centric DT framework

2.1. Overview of the methodology

This section outlines the approach used to develop a Human-Centric DT framework by integrating the Persona method with DT design principles. This framework enhances user interaction, cognitive alignment, and usability by adapting well-established persona-driven design techniques to DT applications (Palmer et al., 2025). While the framework draws on established human-centric methods, its contribution lies in combining these techniques into a coherent structure specifically tailored to Digital Twin design. To our knowledge, this integrated use of Personas, ConTA and Decision Ladders has not previously been operationalised as a unified approach for DT development, within agricultural settings.

In contrast to this human-centric method, conventional DT design frameworks tend to focus on technological features such as data collection, process automation, and technical performance without explicitly considering the cognitive needs, workflows, or usability challenges of different stakeholder groups. These methods often emphasize data integration and predictive modeling, assuming that users can navigate and interpret complex datasets equally well. This results in gaps between DT functionality and user expectations, particularly for non-technical users (Kober et al., 2024).

The framework consists of two key components: (1) the Persona method and its components, and (2) its adaptation to DT design through the integration of ConTA and Decision Ladders. Following this, the framework is applied in two ways: to retrofit existing DTs or to design them correctly from the outset.

2.2. Persona method and its components

2.2.1. Identifying and constructing Personas

The Persona method, originally developed for Human-Centric Design (HCD) (Miaskiewicz and Kozar, 2011), is a structured framework that models different user archetypes to guide system design. In this context, users are fictional representations of real users, i.e. people in the physical world. They are developed based on user research, expert insights, and practical observations to reflect the distinct roles, goals, and challenges encountered in the automation scenario. The framework identifies distinct user groups, their goals, workflows, and interaction need, ensuring that technical systems align with cognitive and practical user expectations. Personas allow consideration of key stakeholder groups throughout development, recording assumptions and through careful engagement with stakeholder can reduce stereotype bias.

2.2.2. Applying personas in digital twin contexts

In the context of DTs, the Persona Method involves: A) user role identification by defining key stakeholders (for example customers, farm managers, technicians) who interact with the DT,

B) behavioral and cognitive modeling to map user needs, decision-making processes, and expected system interactions, and C) scenario-based analysis for designing representative usage scenarios to evaluate how well the DT supports various user workflows, that is, the typical sequences of tasks, decisions, and interactions users perform to achieve their goals within the system. This method ensures that the DT is not just a data-driven automation tool but also an intuitive, human-compatible system.

2.2.3. Expert interviews and data collection for persona development

To ensure the methodological steps could be replicated, a structured data collection process was followed. Expert participants were identified based on (a) their experience with agricultural automation or human-technology interaction, and (b) familiarity with DT-supported vineyard operations. Two experts contributed to each persona, resulting in six experts in total. Semi-structured interviews were conducted using role-specific prompts derived from Naikar et al. (2006). These interviews provided the primary source material for constructing the ConTA tables and subsequent Decision Ladders.

2.2.4. Integrated human-centric framework contribution

The novelty of the proposed framework lies not in the individual techniques themselves which are well established within Human Factors, but in their structured integration for Digital Twin development. To our knowledge the only research that links persona driven user characterisation with ConTA based task modelling and Decision ladder based cognitive flow analysis is that of Palmer et al. (2003). This paper represents a first application real world industrial application of this approach. Existing human-centric DT approaches typically emphasise system usability or interface design but do not provide a methodological pathway for embedding cognitive work models into DT development. The framework presented here explicitly operationalises these tools as a cohesive process, offering a transferable and practice-oriented approach for both retrofitting existing DTs and guiding first-time-right DT design.

2.3. Adapting the persona method to DT design

DTs traditionally focus on data integration, modeling, simulation, data analysis and process optimization but often lack human-centric considerations. The adaptation of the Persona Method to DT design ensures that DTs cater to the needs of diverse stakeholders, enhancing usability and cognitive alignment. This study integrates Personas with ConTA and Decision Ladders to systematically align the DT with user workflows.

ConTA: This approach identifies the specific tasks performed by different users and maps their cognitive processes. ConTA ensures that DT functionalities are structured around actual user requirements, reducing cognitive overload and improving decision support (Naikar et al., 2006).

Decision Ladder: These models capture the sequential steps users take to process information and make decisions within the DT environment. Decision ladders help identify gaps in DT design, ensuring that users receive timely and relevant information tailored to their decision-making needs (Naikar et al., 2006).

Adaptive user interfaces: By leveraging persona-driven insights, the DT is designed with user-specific interfaces that filter and prioritize information based on role-specific workflows. This customization improves further usability by presenting only the most relevant data for each user type. These adaptive interfaces are generated based on the integrated output of the Persona Method, ConTA, and Decision Ladders ensuring that the interface design is directly informed by user roles, task flows, and cognitive processes.

As illustrated in Fig. 1, the adaptation of the Persona method in this study introduces a structured framework as follows:

1. **Define Personas:** Identify key user groups and characterize their goals, challenges, and interaction patterns.
2. **Conduct ConTA:** Map user workflows and decision-making processes.
3. **Develop Decision Ladders:** Visualize cognitive workflows and identify potential bottlenecks in system usability.
4. **Design role-specific interfaces:** Customize DT interactions based on persona-driven insights to enhance user experience.

By embedding persona-driven principles into DT design, this framework ensures that DTs are not only technologically sophisticated but also intuitive and accessible for diverse users. This framework enhances DT adoption, reduces cognitive barriers, and improves decision-making efficiency across different stakeholder groups (Friess, 2012; Miaskiewicz and Luxmoore, 2017).

Emerging AI-based analytical tools can offer new opportunities to support cognitive modeling processes such as ConTA and Decision

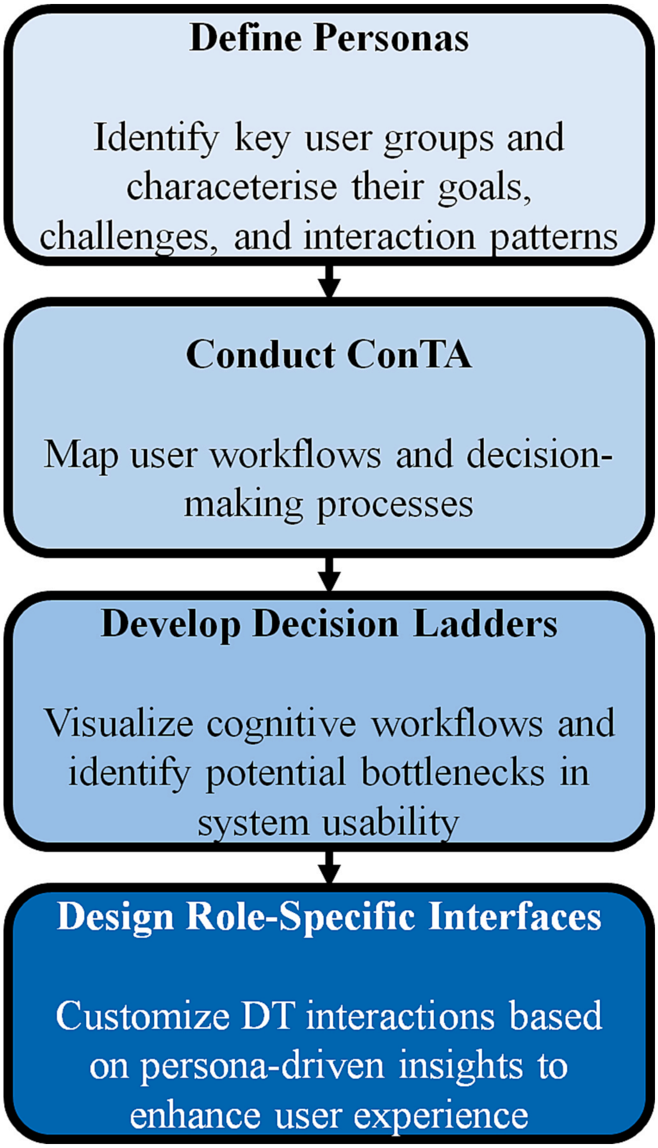

Fig. 1. Adaptation of the persona method, ConTA and decision ladder to DT design.

Ladders. Recent advances in natural language processing and pattern recognition enable automated extraction of task structures, decision cues, and workflow patterns from interview transcripts or operational logs. While expert interpretation remains essential for validating the cognitive models, these AI tools can reduce the time required for manual mapping by generating initial task hierarchies and decision sequences that analysts can refine. Incorporating such semi-automated approaches could make the framework more scalable and repeatable, particularly in contexts where extensive expert involvement is challenging. From a human-centric artificial intelligence perspective, the framework aligns with emerging Industry 5.0 principles by prioritising human agency, transparency, and cognitive compatibility. Future implementations could leverage adaptive AI techniques to dynamically refine personas or decision pathways based on observed user behaviour, enabling Digital Twin interfaces to evolve in response to stakeholder needs while maintaining human oversight.

Beyond usability improvements, the integrated framework also addresses key ethical considerations related to accessibility, fairness, and transparency in Digital Twin design. By grounding system functions in explicit representations of user cognitive processes and workflows, the framework reduces the risk of excluding non-technical or less digitally literate stakeholders and helps avoid reinforcing existing power asymmetries. Personas and ConTA ensure that diverse user needs including those with varying experience levels are systematically identified, while Decision Ladders make information flows more transparent by clarifying how decisions are supported within the system. This structured alignment contributes to fairer access to decision-relevant information and enhances transparency by making system logic traceable and interpretable to all user groups.

Our procedure for constructing the Personas and ConTA tables follows the structured workflow demonstrated in recent Digital Twin research (Palmer et al., 2025). To support reproducibility without adding unnecessary length to the manuscript, we include a concise Persona template and a corresponding ConTA template in Supplementary Material S1. These provide the minimum information needed to replicate our data collection, coding, and mapping to the Decision Ladder while keeping ConTAthe presentation brief and focused.

The following section explores how this framework is applied to both retrofitting existing DTs and designing new DTs from the ground up to ensure first-time-right usability and human-centric functionality.

2.4. *Retrofitting existing DTs and designing from scratch for first-time-right implementation*

The Human-Centric DT Framework serves two primary functions:

1. **Retrofitting existing DTs:** This framework enhances usability and human alignment in legacy DT by restructuring interfaces, improving data presentation, and integrating persona-based workflows. This function is the primary focus of this paper and is demonstrated through a case study of vineyard automation.
2. **Designing DTs correctly from the start:** This framework ensures that DTs are built with human-centric principles from the beginning, eliminating the need for later modifications. While this function is conceptually outlined in the framework, it is not explored through a dedicated case study in this paper and is suggested as a direction for future work.

2.4.1. *Retrofitting existing DTs*

Many current DT implementations were developed with a primary focus on process control and automation, often neglecting user experience. By applying the Persona Method, ConTA, and Decision Ladder modeling, existing DTs can be systematically upgraded to improve decision-making efficiency, accessibility, and usability for all stakeholders. Key enhancements in retrofitting are as follows:

Customized dashboards: User-specific interfaces tailored to different roles.

Cognitive workflow optimization: Decision ladders guide users in complex decision-making tasks.

Improved data representation: Simplified analysis and visualization techniques ensure that critical insights are easily accessible to non-technical users.

A further motivation for emphasizing retrofitting is that many organizations already operate DT infrastructures that are difficult to replace due to cost, integration dependencies, and organizational inertia. In such settings, the barriers to deploying new DTs from scratch are considerably higher than the barriers to enhancing an existing system's human-centricity. The proposed framework addresses this practical constraint by functioning as an overlay that targets cognitive alignment rather than altering the underlying data architecture or automation logic. This allows improvements in interpretability, task support, and stakeholder engagement to be achieved without interrupting ongoing operations or requiring major redevelopment cycles. Consequently, retrofitting becomes not only an efficient strategy but also a feasible route for improving DT acceptance in real industrial environments.

2.4.2. Designing DTs correctly from the start

A proactive framework to DT development involves embedding human-centric design principles at the initial stages rather than applying modifications post-implementation. This reduces usability gaps and ensures that DTs serve their diverse user base efficiently from the outset.

Advantages of first-time-right DT design include minimized usability issues that avoid the need for potentially costly modifications and usability enhancements later. Moreover, integrating human-centric features ensures DT interfaces align with the decision-making and cognitive processes of different user groups. In addition, seamless stakeholder adoption increases user trust, engagement, and operational effectiveness (Müller et al., 2023; Hwabamungu and Shepherd, 2024).

By combining persona-driven design principles with DT development, this methodology establishes a framework for ensuring that DTs are both technologically advanced and intuitively usable by their intended audiences.

3. Application: Minimal invasive retrofitting an existing DT (vineyard case study)

The case study focuses on a real-world vineyard that employs a DT system to optimize its operations by integrating automation, real-time monitoring, and predictive analytics. A real vineyard in the south of the UK was chosen as a template because it utilizes robotic systems for harvesting, irrigation management, and grape quality assessment, while environmental sensors provide continuous data on soil moisture, weather conditions, and grape ripeness. Customers visiting the vineyard engage in guided tours and sustainable grape selection experiences, making the interaction between automation and human decision-making crucial.

The existing DT (Fig. 2) serves as a central hub, synchronizing robotic activities, monitoring vineyard conditions, and assisting in scheduling harvesting operations based on real-time and historical data. However, despite its advanced capabilities, DT faces significant usability challenges, particularly in accommodating the different cognitive needs of farm managers, technicians, and customers. This vineyard scenario is used as a representative case to illustrate the broader applicability of the combined human-centric framework, integrating the Persona Method, Control Task Analysis (ConTA), and Decision Ladders. The following sections demonstrate how this framework can be applied not only to this specific context but also to other industrial DT systems where stakeholder diversity and user alignment are critical to performance and adoption.

3.1. Usability challenges evaluation in the existing DT

The existing DT contributes several important properties that help the vineyard operation. It continuously gathers and integrates data from robots such as navigation accuracy, task completeness rates, and battery levels. Moreover, it collects environmental data such as weather condition, soil moisture, grape ripeness factors. In addition, it controls robots in presence of navigation errors, low level batteries or mechanical downtime and warns the technician. It also shows the environmental changes that can affect the operation such as heavy rain or wind. Using historical data and the operation procedure, the DT predicts the potential malfunctions in the robotic system where the technician can solve the problems effectively. This feature reduces unexpected downtime and ensures continuity of harvesting tasks. The DT can contribute a live map of the vineyard where it shows the robot positions, grape clusters conditions and the places that the customers visit. This helps to ensure safety and resource allocation efficiency. It supports customer reservation by connecting timing data to operation scheduling. For instance, it highlights parts of the vineyard that are ready for harvesting according to customer visit schedules and grape ripeness.

While the existing DT offers various specific technical features, there are several limitations in its capability for overcoming the different vineyard users' needs. Initially, it was designed as a general-purpose monitoring tool and lacks role specific features. Users such as farm managers or technicians suffer challenges for filtering their relevant task data, while the customers do not interact with the system. Inconvenient interfaces and system technical features make it inaccessible for non-technical users. Although, the DT integrates sustainability data such as using pesticide and water consumption, this information is not presented in a form that is easily understandable for customers or farm managers. Users like farm managers or technicians are faced with an excessive amount of data and limited filter options. For example, the DT presents all robotic and environmental metrics in a single interface and asks the users to manually identify critical information relevant to immediate tasks. In the existing DT, predictive maintenance and repair capabilities are focused on robotic systems and gaps remain in other aspects such as operational programming. For example, it does not suggest optimal harvesting based on grape ripeness and customer reservation, capabilities that would help align operations with business goals and visitor satisfaction. Similarly, it does not highlight the areas that need to be harvested manually during the system downtime which can lead to delays, resource misallocation, and loss of product quality. These limitations reduce the DT's effectiveness in supporting real-time decision-making and adaptive operational strategies during critical harvest periods.

Fig. 2. Existing vineyard DT system coordinating robotics and monitoring.

The limitations of the existing DT appear in several operational challenges in the vineyard. Lack of integrity between customer preferences, sustainability metrics and operational programming leads to inefficiency especially during peak time. Moreover, non-technical users such as customers and farm managers suffer extracting the data from the DT because of the technical complexity and lack of an appropriate interface. Additionally, while the DT gathers the relevant information, it cannot use the data for increasing effective user interaction.

The existing DT analysis is typical for technology-only focused designs and highlights the need for human-focused design which considers different needs of all users. The new DT should be designed to improve the existing limitation by developing role specific features tailored to the cognitive workflows and technical expertise of each user, simplifying information presentation, especially for non-technical users to ensure accessibility and engagement and incorporating dynamic filtering mechanisms to reduce information overload and improve efficiency.

3.2. Applying the persona method, ConTA, and decision ladders

In this study, the human-centric approach is employed to systematically evaluate and address the capability gaps and cognitive misalignment challenges in the existing DT. This framework ensures that the DT is designed not just for operational efficiency but also for seamless user interaction and decision-making support. It involves multiple stages, including the development of user personas to representing distinct stakeholder needs, the application of ConTA through expert input to map user workflows and decision-making processes, and the construction of Decision Ladders to identify cognitive demands and system alignment gaps. These steps collectively provide a structured framework for refining DT usability and enhancing its role as an intuitive decision-support tool. Each step is detailed below.

3.2.1. Persona method implementation

The personas used in this study were selected through a structured framework to ensure they accurately represent the key user groups interacting with the vineyard DT. First, an initial user analysis was conducted, identifying primary stakeholders based on their roles and responsibilities in vineyard operations. This was followed by expert consultations with two domain specialists in agricultural technology and human–computer interaction, who validated the relevance of each persona. The final selection was based on three core user groups (customers, farm managers, and technicians), each with distinct cognitive and operational requirements. This allowed, in addition, to recognize human specific properties to increase inclusiveness of the DT.

The vineyard DT was retrofitted to accommodate three distinct personas, Emma (Eco-Friendly Customer), Mark (Farm Manager), and Alex (Technician), ensuring that system functionalities align with their specific workflows.

Emma, eco-friendly customer (Fig. 3)**:** Emma is a 32-year-old marketing professional with seven years of experience who values sustainability and meaningful engagement with nature. As part of a digitally fluent generation, she is accustomed to intuitive technology and expects transparency from the systems she uses. She seeks digital tools that support informed and conscious decision-making. During her vineyard visit, Emma prefers systems that provide clear and accessible sustainability insights, allowing her to explore eco-conscious grape selections without unnecessary complexity. Her interaction with the DT is purpose-driven, aiming to align her purchasing choices with her environmental values.

Mark, the farm manager (Fig. 4)**:** Mark is a 47-year-old farm manager who has supervised the vineyard for over two decades. As part of Generation X, he has experienced the evolution from conventional agricultural methods to increasing levels of automation and digitalization. He bridges traditional farming values with emerging technologies like DT, making him a key figure in operational management, customer satisfaction, system efficiency, and sustainability promotion.

Fig. 3. Emma, an eco-conscious customer, seeks intuitive DT support to make informed and sustainable grape selections aligned with her environmental values.

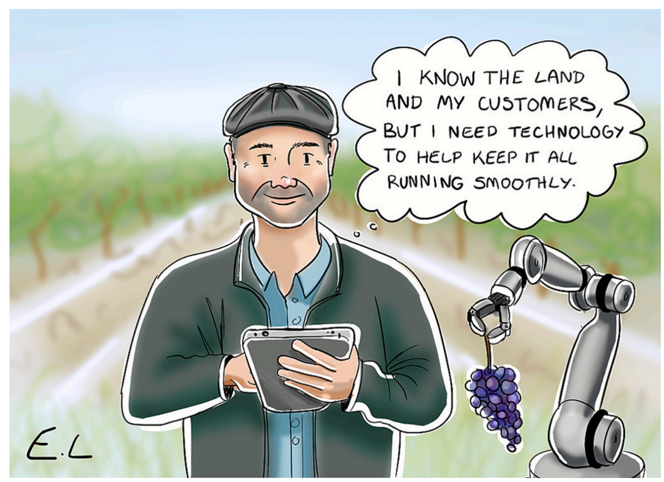

Fig. 4. Mark, the experienced farm manager, combines traditional agricultural practices with modern DT tools to oversee operations, enhance efficiency, and promote sustainability.

Alex, the technician (Fig. 5)**:** Alex is a 29-year-old technician with

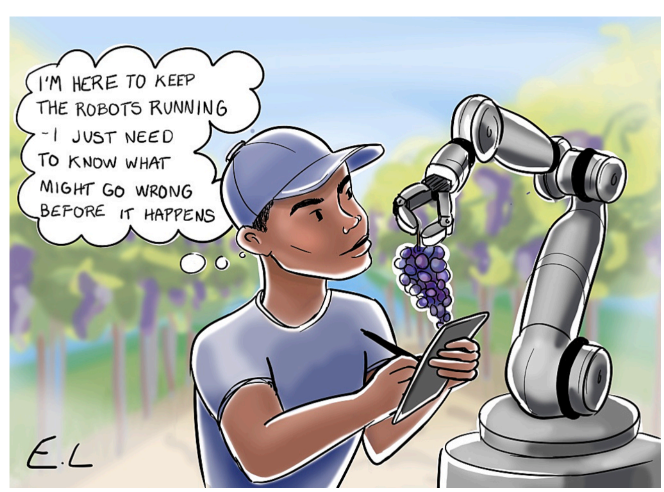

Fig. 5. Alex, a technician ensuring vineyard robots operate efficiently through maintenance, diagnostics, and data interpretation.

around five years of experience who is responsible for robot repair and maintenance. He ensures that the robots work well in the vineyard. He focuses on maintenance and repair, prediction, technical diagnostics and interpreting the data from the system.

These personas are defined based on the vineyard scenario and two experts comment on each persona. Personas are considered essential tools to guarantee that the next analysis and designs align with the real-world needs and workflow of the users.

3.2.2. ConTA implementation

ConTA is part of cognitive work that focuses on identifying the physical and cognitive processes required for achieving the system goal. It ensures that all combinations of work situations, performances and control tasks are captured and is vital for DT design that aligns with human roles and needs (Naikar et al., 2006; Krupas et al., 2024).

Naikar et al. developed a technique to perform ConTA comprising sets of prompts and generic keywords (Krupas et al., 2024). The prompts are grouped in the categories to reflect various aspects of interactions including:

Work function: Performed tasks and their relationship with persona goals, acknowledging that these goals are derived from the integration of the persona-driven, people-led approach proposed by Palmer et al. (23).

Alerts: Signal or conditions that start the actions or show potential issues.

Information: Data that is needed for decision making or completing the tasks.

System state: How users understand the current operation situations and processes.

Options: The options that the users can address to solve the problems or achieve the goals.

Goals: The goals that guide the users' actions and decisions.

Target state: The optimal condition users aim to achieve through their actions and decisions.

Tasks and procedures: Actions that the users perform to achieve their goals such as adjustments for unexpected conditions.

The prompts were revised into questions based on the needs of each persona. These ConTA questions were designed to extract precise information for the tasks that each person performs, cognitive requirements for those tasks, and the ways that DT supports task execution.

Table 1 for Emma, Table 2 for Mark, and Table 3 for Alex present detailed answers to these questions based on relevant experts' point of view. The analysis followed a consistent procedure across all personas. Interview transcripts were coded manually according to the ConTA categories (work functions, alerts, information, system state, options, goals, target states, tasks, and procedures), and each coded segment was synthesised into the structured ConTA tables. This provided a traceable mapping from raw expert input to the cognitive structures used in the redesign process and an overview of user tasks and the DT's role in supporting them. Two experts were interviewed for each persona, selected based on their professional relevance. The interviews were designed to elicit unexpected insights within predefined areas, and the experts' practical experience ensured that the findings reflect real-world practice.

3.2.3. Decision Ladder implementation

A Decision Ladder is a conceptual framework that is used for modeling cognitive steps and decision-making processes required for achieving specific goals or completing the tasks in complex systems. It shows a flow from recognizing a need for action, through understanding of the situations to planning and execution including potential shortcuts and feedback loops. Its importance is for helping the designers and analyzers to understand and support the human decisions in technical systems such as DT (Naikar et al., 2006; Krupas et al., 2024).

The Decision Ladders in this case study were created by translating

Table 1
ConTA summary for Emma an eco-conscious customer, outlining her tasks, cognitive needs, and DT support based on expert insights.

Control Task	Question	Answer
Work Function	What does Emma's visit involve?	She wants to have a peaceful outdoor experience, learn from sustainable farming and find delicious grapes that are grown responsibly. She wants to bring some home for her family to enjoy
Alert	How would Emma start to visit vineyard?	She is alerted by an application, or she may come to vineyard based on her needs or her motivation to experience.
Alert	What does Emma find most confusing?	When information about grape quality or eco certifications are too technical. She needs simple information that shows environmental impacts without unnecessary details.
Information	What information does Emma need to make her decisions?	She needs to know which grapes are ripe, which ones are pesticides free or whether there is sustainable packaging. She is interested to know which steps have been passed to minimize environmental impacts like water conservation soil care natural pest control. She loves to know about unique grape varieties or stories about the farm's history.
Information	Is there any information available which tells Emma how she can reduce her carbon footprint when choosing her grapes?	Yes, Mark shares details about sustainable grape clusters, where pesticides were avoided and where water saving has occurred. She is interested in some guidance on ways she can make a more eco friendly choice like which grape types are local, and which need fewer resources to grow. Knowing the way that the grapes travel to reach the customers is interesting
Information	What specific information would help Emma make eco-friendly grape selections more easily, without feeling overwhelmed by technical details?	A quick guide that shows ripeness and sustainability is helpful. Visual markers like notes on eco-friendly grapes help her to select the clusters without a lot of explanations.
System State	What is the state of the vineyard for Emma?	The vineyard has clearly organized with marked paths for ripe grapes along with signs informing the regions that robots work, so she feels safe and can select the grapes comfortably.
System State	How does Emma find out about the best part of the vineyard to visit?	Mark describes Emma to the best section with ripe grapes and low robot activity. It may be a map that highlights the eco-friendly areas, so she knows exactly where to go.
Options	How does Emma choose her grapes?	She goes by how ripe the grapes are, if there are sustainability markers and Mark recommendations. She wants to be sure that her selection is based on the items that are important for her such as quality and eco friendship. She looks for grapes that have been grown naturally without too many chemicals.
Options	How does Emma's focus on eco-friendly practices guide her choices in grape selection and packaging?	She selects the clusters that have marked pesticide free and pick biodegradable packaging or without packaging to reduce waste. She prefers selection based on supporting sustainable farming.

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Table 1 (*continued*)

Control Task	Question	Answer
Goals	What is Emma's goal for her visit?	She wants to select grape clusters with high quality and sustainable growth to have a relaxing and enjoyable experience on farm.
Target State	How does Emma know she made the right choice?	She is satisfied if she knows the grape has grown sustainably and the packaging is eco friendly. It makes her feel she is helping to reduce her carbon footprint. It is important for her to support businesses that value the earth.
Task	What tasks does Emma perform during her visit?	She evaluates the grape clusters and tags the ones which fit her eco-friendly criteria and goes through checkout using minimal packaging to avoid waste.
Task	Would Emma need to adjust her grape selection process if only a few clusters meet her eco-friendly and ripeness standards, or if grape availability is limited?	If there are not many options that align with her standards, she selects fewer grapes or adjusts a bit on ripeness. However, she is committed to the sustainability part. Quality is more important than quantity for her.
Task	Are there any additional tasks Emma might need to complete to ensure her grape selection aligns with her eco-friendly values?	It is excellent if the tags are degradable.
Procedure	How does Emma navigate the grape selection process?	She follows Mark guidance to find ripe grapes and watch the grapes herself to tag the clusters which align eco friendly criteria.
Persona Based	What are Emma's chief concerns?	Her main concerns are sustainable grape growing, minimizing waste and having a smooth and enjoyable experience without technical details.

the ConTA outputs into sequential perceptual cognitive action steps. The authors extracted key cues, decision points, and task transitions directly from the coded ConTA data and arranged them according to the canonical Decision Ladder structure (starting from "activation or alert" and to further stages such as "observation", "interpretation", "evaluation", "option selection", "planning", and "execution"). Draft ladders were verified with the same experts who contributed to the ConTA tables, ensuring the accuracy of the cognitive steps and the plausibility of the shortcuts represented in the models. Each Decision Ladder is designed to shape the cognitive process that each persona interacting with a DT faces and provide a sequential visualization of the users' decision-making process. The decision ladders for the three personas in this paper are presented as follows:

Emma's decision ladder (Fig. 6): The diagram follows the standard Decision Ladder structure, showing how Emma progresses from an initial trigger to selecting and executing an action. Only the key cognitive steps relevant to her sustainability-oriented interaction. Her interaction begins when she receives a notification from the DT system about grape clusters that have reached optimal ripeness. Using the mobile interface, Emma views the location and sustainability data associated with the clusters. She then selects her preferred clusters based on eco-friendly criteria such as pesticide-free status or sustainability-led usage. After selection, she tags the chosen grape clusters digitally through the interface. These digital tags are recognized by the vineyard's robotic harvesting system, which then autonomously identifies and picks the tagged clusters. This process allows Emma to make conscious, sustainability-aligned choices without engaging in the technical complexities of the system, reinforcing her desire for an intuitive and value-driven user experience.

Mark's decision ladder (Fig. 7): The diagram highlights only the stages that are essential to Mark's operational decision-making. The

Table 2
ConTA summary for Mark the farm manager, highlighting key tasks, cognitive needs, and DT support based on expert insights.

Control Task	Question	Answers
Work Function	What does Mark's role involve?	Mark monitors the vineyard daily operations, ensures customer satisfaction, guides the customers in the grape selection process and manages robotic and conventional agriculture. Moreover, he manages the vineyard eco system including soil monitoring, ensuring the grapes health.
Alert	What would suggest to Mark that a visit is taking place?	Customer reservation, DT notifications, or signals from reception that inform the visitors arrived.
Alert	What would signal to Mark that a problem is occurring?	If the DT shows irregularities such as robot malfunction, customer complaints, or missed harvests or if he sees unsafe performance from robots. If the customers complain that they cannot find ripe grapes or the weather changes.
Information	What information does Mark need to manage operations?	He needs real time data about grape ripeness, customers' schedules, robot performance and environmental conditions in Vineyard. He needs to know the water consumption amount and soil nutrient levels.
Information	What data does Mark need to ensure customer satisfaction?	Customers' feedback, their preferences details and data about grape ripeness for effective guidance.
Information	What operational data is essential for Mark's decisions?	Robot status, grape inventory, weather forecast, historical harvest performance and energy consumption are vital for farm performance optimization.
Information	How does Mark know where the customers and robots both are, to ensure safety?	DT presents a live map that represents the customers and robot locations for avoiding overlapping and ensuring safety
Information	What additional information would help Mark guide customers on grape selection and highlight the vineyard's eco-friendly practices?	Data on which rows have sustainably grown grapes, visual eco certification markers and ripeness indicators. It will be helpful if the customers know which grape clusters have been grown with the least number of resources such as lower water consumption or organic soil.
System State	How does Mark know the state of the farm operations?	By monitoring DT real time updates that represent the robot performance, grape ripeness and environmental conditions. Moreover, he inspects the vineyard visually to make sure that the system matches reality.
System state	How does Mark know if customer needs are met during visits?	He emphasizes the customers' feedback through the surveys, their satisfaction and observing whether they easily completed their selection processes.
Options	How does Mark decide how to interact with the robot?	Based on the customers' feedback, He decides if he needs to adjust robots manually or let them to continue independently.
Options	What options does Mark have if a robot malfunctions?	He can reboot the system, alert Alex for repair and maintenance or perform the tasks manually until the problem is solved.
Options	How does Mark decide which farming operations to improve?	He analyzes the performance criteria, customer feedback and

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Table 2 (*continued*)

Control Task	Question	Answers
		cost benefit ratio to identify areas for efficiency and sustainability enhancement.
Options	How does Mark choose which traditional farming practices to keep?	He prioritizes the methods that are important for customers and align with sustainability such as organic growth.
Goals	What are Mark's operational goals?	To maintain vineyard smooth performance, provides an enjoyable experience for customers, minimizing the environmental footprints and balance sustainability with efficiency.
Target State	How does Mark know the farm operations are optimal?	If the customers are satisfied, robots work without errors and the grapes are harvested effectively without compromising the environment. Moreover, when there are no delays and the sustainability criteria such as water saving and reducing pesticide usage are met.
Task	What specific tasks does Mark perform daily?	He monitors the vineyard situations, guides the customers, manages the robot assignments and handles issues.
Task	When would Mark need to make decisions?	When there is a problem for a robot, customer feedback suggests an issue, or the environmental conditions threaten the performance.
Procedure	How does Mark monitor robot performance and vineyard health?	He uses the DT for real time updates and evaluates it with observations during daily rounds.
Persona Based	What are Mark's chief concerns?	Maintaining safety, ensuring customer satisfaction and safety, and achieving a balance between modern efficiency and traditional farming value.

ladder illustrates how he gathers cues from the DT, evaluates conditions, and selects appropriate actions. Mark's decision-making process begins with an alert from the DT system, either a scheduled customer visit, an operational irregularity, or environmental concern. He may also receive direct signals from the reception or observe unsafe behavior in the field. Upon activation, he uses the DT to assess grape ripeness levels, robot activity, customer locations and preferences, and environmental factors such as water usage and soil conditions. Customer feedback and sustainability indicators help him plan a tailored experience. He identifies the current state of the vineyard by comparing real-time data with on-ground observations, checking for consistency and readiness. Using this information, Mark evaluates possible responses: adjusting robot routes, assigning manual tasks, suspending robots, or alerting Alex for maintenance. He also considers improvements aligned with sustainability targets, such as optimizing water usage or upgrading fertilization strategies. His goals include maintaining smooth vineyard operations, ensuring safety, providing meaningful customer experiences, and promoting sustainable practices. From these options, Mark selects actions that harmonize tradition and technology, defining tasks such as preparing packaging, optimizing robot schedules, and engaging with visitors. He organizes and executes these tasks through coordinated planning, briefing customers, guiding tours tailored for inclusiveness and sustainability, and monitoring robotic operations, adapting in real-time as needed to maintain efficiency and customer satisfaction.

Alex's decision ladder (Fig. 8): The diagram emphasises the diagnostic stages most relevant to Alex's work, including cue identification, system state evaluation, and option selection. The layout retains the canonical form of the Decision Ladder while clarifying how the steps

Table 3
ConTA summary for Alex the technician and his cognitive and physical tasks and the system's role in supporting his decision-making.

Control Task	Question	Answer
Work Function	What does Alex's job involve?	His tasks include monitoring the robotic system, regular maintenance and troubleshooting any issues that arise. Moreover, He is responsible for analyzing DT data and ensuring effective robots' performance in outdoor conditions. He ensures the robots are fully operational by monitoring their navigation, battery systems, and sensors. He also handles mapping the vineyard layout and adapting the robots programming to change the environment, like inclines or ground type.
Alert	What would signal to Alex that there's a problem?	If the DT shows a performance drop such as slower harvesting or navigation error, he knows there is a problem. Alerts or unexpected stops are also key factors.
Alert	How would Alex find out that he might expect weather-related problems?	He checks the real time weather data integrated with DT. Sudden alerts about rain, high winds and temperatures help him to predict the potential malfunctions. Wet ground or debris after storms affects traction, navigation or sensors accuracy.
Information	What information does Alex need to fix the robots?	He needs access to error logs, the diagnostics data, activity history, battery health, payload weight and gripper calibration. Environmental data such as ground condition or temperature are important for identifying the problem.
Information	How does Alex prioritize maintenance tasks?	He looks at the severity of the issue, whether it's impacting the operations and how vital it is for day goals. For instance, the robot which is harvesting in a high demand area gets immediate attention.
Information	What information does Alex access to come up with creative solutions?	He looks at the system's diagnostic data, past performance trends or weather conditions. Sometimes, he refers the DT predictive analytics for ideas. He considers ground maps, load evaluation and sensor feedback.
Information	What additional diagnostic data could enhance Alex's ability to troubleshoot and optimize robot performance?	Data related to battery health, joint wear and terrain adaptation help him to adjust the performance. Live thermal imaging of the robots' motors can also prevent overheating issues. Moreover, robot learning algorithms derails for maneuvers, gripper force thresholds and emergency stop activations help him.
System State	How does Alex know the robot's condition?	DT gives him real time updates about motor situation, battery level and navigation accuracy. He also inspects robots manually during routine checks.

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Table 3 (*continued*)

Control Task	Question	Answer
Options	What options does Alex have for troubleshooting?	He can reset the system remotely or override robot tasks manually.
Options	What does Alex do if the issue is too complex for on-site repair?	He organizes a more detailed maintenance session, ordering the components or referring the problem to an outside specialist if needed.
Goals	What is Alex's goal for the robot's performance?	Ensuring the optimal robot performance and safety and minimizing the downtime.
Target State	How does Alex know the robot is functioning properly?	When it performs harvesting goals without errors and does all tasks in an expected time.
Task	When would Alex need to intervene?	When the robot stops unexpectedly, it shows a performance drop or face with an obstacle.
Procedure	How does Alex ensure minimal robot downtime?	He uses predictive maintenance and repair tools from DT and prepares the spare components for replacement. He maintains a checklist for regular inspections such as gripper calibration, sensor cleaning and battery replacement.
Persona Based	What are Alex's chief concerns?	Preventing downtime, ensuring the customers and staff safety and keeping the robots adaptable to the vineyard changing environment.

relate to his maintenance workflow. Alex's workflow begins when the DT system generates an alert event, such as a drop in robot performance, navigation errors, or unexpected downtime. These alerts may also stem from environmental conditions like wet ground or debris following rain, which can affect traction and sensor accuracy. Alex monitors these through the DT's real-time dashboard, which integrates robot diagnostics with environmental data. He observes key performance indicators such as battery health, motor status, navigation accuracy, gripper alignment, and payload status to understand the severity and impact of the issue. Upon identifying a specific problem such as a stuck robot, miscalibrated gripper, or degraded battery, Alex cross-references alerts with diagnostic data to pinpoint the root cause. He evaluates the system state to assess the robot's operational readiness and determines whether the issue requires immediate attention or scheduled maintenance. Alex then considers available options such as recalibrating the robot, swapping parts, running controlled diagnostics, or temporarily reassigning its tasks to another unit. If necessary, he escalates the issue by consulting technical manuals or contacting suppliers. His goal is to restore the robot to full functionality, ensuring smooth harvesting, navigation accuracy, and minimal downtime. To do this, Alex defines clear tasks such as replacing or recalibrating the faulty component, updating navigation maps, or adjusting robot parameters to current terrain conditions. He develops a procedure involving the repair or maintenance of the robots, monitoring post-repair performance through the DT, and scheduling follow-up maintenance if needed. Using predictive maintenance features, spare part inventories, and real-time feedback, Alex ensures the robot returns to optimal performance, contributing to the vineyard's operational reliability and safety.

3.2.3.1. Cognitive bottlenecks and implicit coordination via the DT. The decision ladder was designed to identify specific bottlenecks and cognitive dissonances within the existing DT systems. By analyzing the decision-making processes of Emma, Mark, and Alex, we found several areas for improvement. For Emma, the challenge was simplifying information flow and reducing unnecessary technical details. Mark's bottleneck involved balancing an overload of environmental and operational data, which required better prioritization of critical information. For Alex, the cognitive burden (Zhao et al., 2024) centered around diagnosing robotic malfunctions quickly with clear diagnostic pathways. These insights were integrated into the decision ladders by streamlining each user's decision-making steps and highlighting key areas where cognitive load could be reduced, improving the overall user experience.

Although each persona operates independently within their own task domain, the DT system functions as a shared platform and indirect communication channel. For example, when Emma tags grape clusters, Mark can see these choices reflected in the harvesting schedule, and Alex may adjust robot paths accordingly. While the personas do not communicate with each other directly, the DT acts as a central feedback loop by coordinating and updating task-relevant information in real time. This decentralized but interconnected interaction model supports individualized workflows while maintaining operational coherence. In future developments, more explicit collaborative features such as shared alerts or inter-user messaging could be introduced to enhance teamwork across roles.

3.2.4. Integration of the persona method, ConTA, and decision ladder into the DT

The methodologies presented about the Persona Method, ConTA, and Decision Ladders were systematically applied to the existing DT to create a redesigned, human-centric version that improves usability, decision-making, and efficiency. This integration ensures that the DT aligns with stakeholder needs, supports intuitive interactions, and optimizes cognitive workflows for different user roles. The application process followed the following key steps:

3.2.4.1. Embedding Personas into the DT structure. The DT is modified to include user-specific interfaces, ensuring that each persona (Emma, Mark, and Alex) interacts with the system in a way that matches their cognitive and operational needs. Emma now has access to a simplified sustainability dashboard, which visually presents eco-certifications, pesticide usage, and water consumption in an easy-to-understand format. Mark operates with an adaptive management interface, meaning the dashboard dynamically updates based on operational priorities such as weather alerts, robot performance, and customer schedules. Alex benefits from real-time diagnostics and predictive maintenance alerts.

To ensure a transparent link between analysis and design, each design decision was explicitly derived from a corresponding insight in the ConTA tables or Decision Ladders. For example, Emma's ladder showed that sustainability cues must be identifiable early in the decision sequence. This informed the placement of simplified eco-indicators on her dashboard. Mark's ConTA revealed that cross-referencing environmental and operational data was a repeated bottleneck, which motivated the integration of an adaptive, priority-based manager interface. For Alex, diagnostic shortcuts identified in his ladder guided the development of focused maintenance alerts and structured troubleshooting pathways. This traceability ensures that the redesign decisions can be replicated or adapted in other DT contexts.

3.2.4.2. Applying ConTA to optimize workflows. User workflows are mapped, and task-relevant information is prioritized to reduce cognitive overload. Alerts and notifications are refined to provide clear, actionable insights, enabling faster and more effective responses for each user role.

3.2.4.3. Implementing decision ladders for improved decision-making. The DT is adjusted to support a step-by-step decision-making process, ensuring that users receive information in a structured manner. For instance, Mark's dashboard now highlights critical vineyard conditions first, allowing him to assess the situation, interpret insights, and take actions efficiently. Alex benefits from guided troubleshooting workflows, reducing the complexity of robotic maintenance decisions.

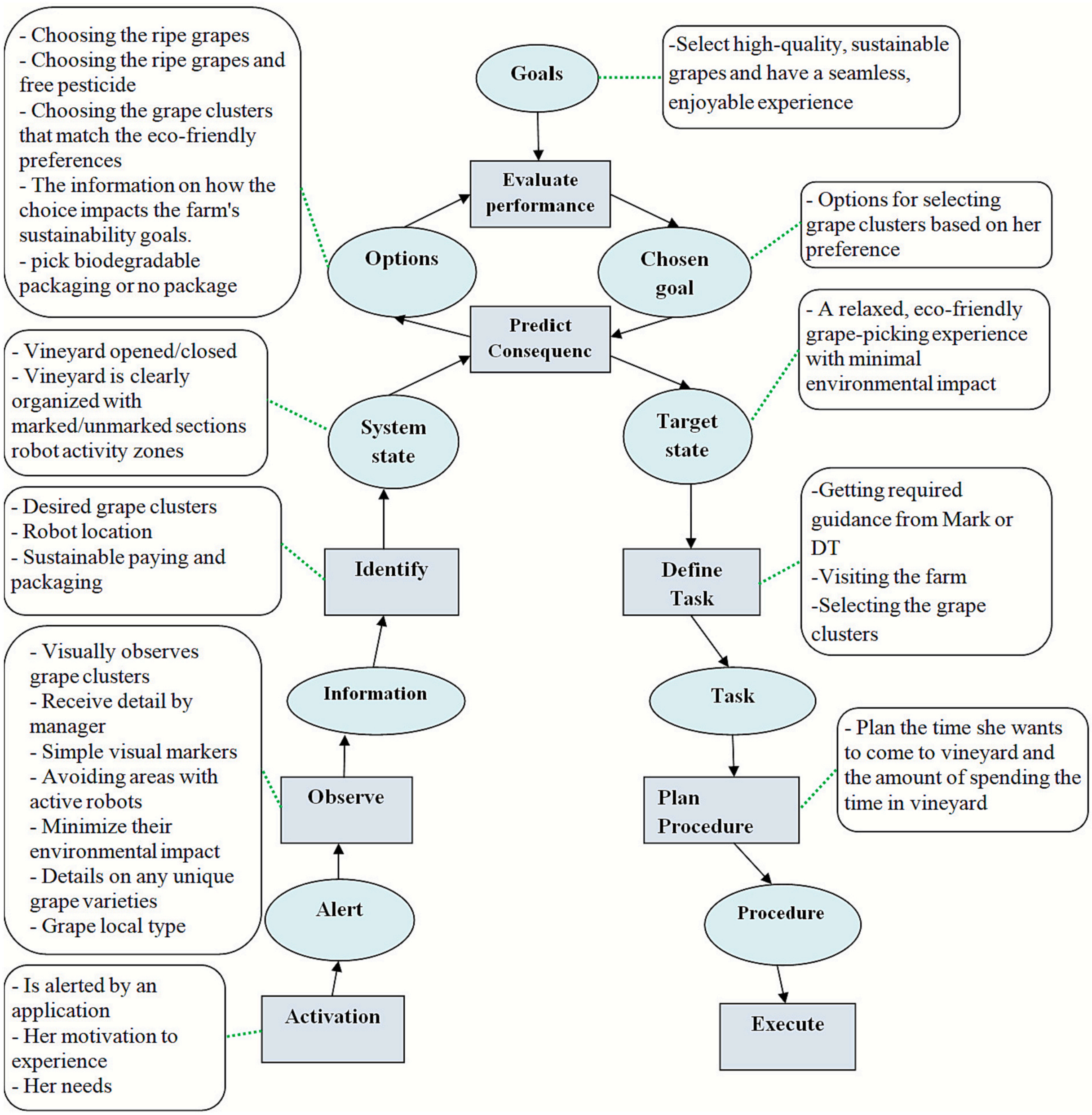

Fig. 6. Emma's decision ladder illustrates her intuitive interaction with the DT system to select and tag sustainable grape clusters for robotic harvesting.

Through the integration of these methodologies, the existing DT is successfully retrofitted into a more human-centric system. The redesigned DT now provides customized user experiences, improved decision-making pathways, and a more intuitive interface for all stakeholders. This transformation ensures that the DT is not just a data-driven automation tool but a practical, user-friendly system that enhances productivity and engagement.

3.3. Improvements in decision-making, user interaction, and efficiency

The retrofitting of the vineyard DT through the integration of the Persona Method, ConTA, and Decision Ladders has led to significant enhancements in decision-making, user interaction, and overall system efficiency. These improvements addressed key usability challenges in the existing DT, making it more human-centric, accessible, and aligned with the needs of various stakeholders.

Given the social-technical nature of human-centred DT interactions, quantitative measurements are not generalisable across contexts. Instead, consistent with human-factors evaluation practice, qualitative indicators are reported derived from expert walkthroughs, ConTA outputs, and Decision Ladder analysis. These indicators highlight reductions in information filtering effort, removal of decision bottlenecks, and clearer system-supported pathways for task execution.

3.3.1. Enhanced decision-making

One of the most critical limitations of the existing DT was its overwhelming amount of data presented without prioritization, making it difficult for users to make quick and informed decisions. By applying decision ladders and persona-driven design, the DT now tailors information delivery to each user's cognitive workflow, ensuring that only the most relevant data is presented at the right time. To illustrate how these improvements impact different users, the following sections examine the decision-making enhancements experienced by the farm manager, technician, and customer:

3.3.1.1. Improved customer's decision-making (Emma).

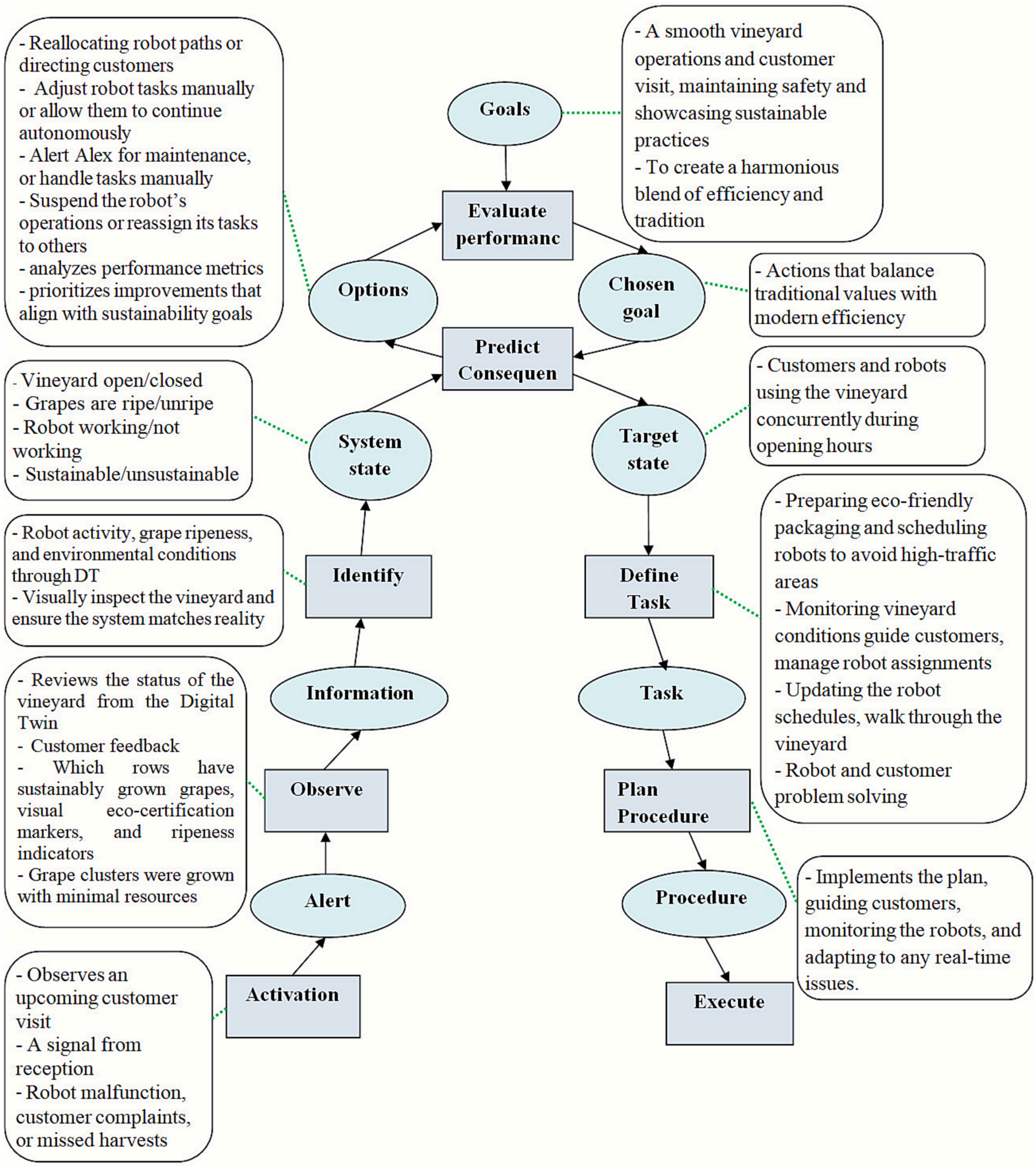

Fig. 7. Mark's decision ladder shows how he uses DT insights and field data to manage operations, enhance sustainability, and coordinate robots.

- Previously, customers had no direct interaction with the DT and relied on farm managers for information, limiting their engagement in the vineyard experience.

- As shown in Fig. 9, Emma can now use the interactive DT interface to explore sustainability metrics, receive recommendations on organic grape clusters, and tag grape selections based on eco-friendly criteria.

- The system simplifies the decision-making process by visually displaying sustainability ratings and guiding Emma through a streamlined purchasing experience.

3.3.1.2. Improved farm manager's decision-making (Mark).

- Previously, Mark had to manually sift through an extensive array of system parameters, including irrigation schedules, robot status, and weather conditions, which resulted in delayed responses and potential operational inefficiencies.

- With the redesigned DT shown in Fig. 10, automated alerts and role-specific dashboards now highlight critical factors such as approaching storms and water usage, allowing Mark to make proactive decisions without being overwhelmed by unnecessary technical details.

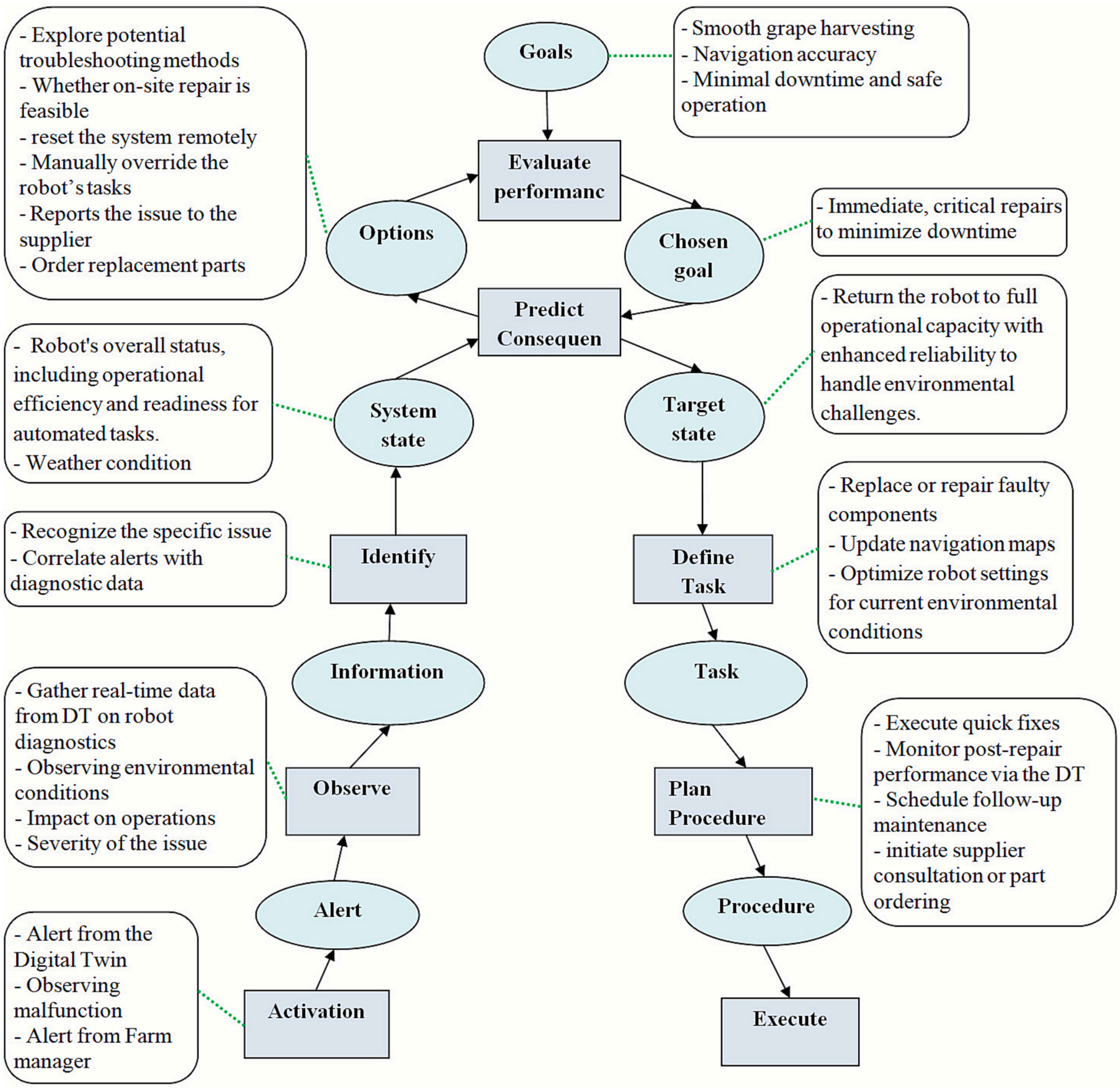

Fig. 8. Alex's decision ladder shows how he uses DT data to diagnose and resolve robot issues for reliable vineyard operations.

- Additionally, the system has the potential to suggest optimal harvesting schedules by analyzing weather forecasts and customer reservation data, improving grape yield and customer satisfaction.

3.3.1.3. Improved technician's decision-making (Alex).

- The original DT provided raw sensor data for robotic operations, requiring Alex to manually diagnose system failures and predict maintenance needs.

- The retrofitted DT in Fig. 11 now includes robot navigation and status, reducing the cognitive burden on Alex. If a robot's navigation accuracy drops, the DT automatically flags potential calibration issues, allowing Alex to address the problem before a failure occurs.

- Real-time visual diagnostics and historical performance data enable Alex to assess system health more effectively, reducing downtime and improving vineyard automation reliability.

3.3.2. Improved user interaction

A major drawback of the original DT was its one-size-fits-all interface, which failed to accommodate different user needs. By implementing persona-driven dashboards and adaptive interfaces, the DT now provides customized interactions that improve usability across different roles. Customized interfaces for each user are as follows:

- **Emma (Customer):** Uses a mobile-friendly interface that simplifies vineyard navigation, highlights sustainable practices, and offers an intuitive grape selection process (Fig. 9).
- **Mark (Farm manager):** Receives a structured dashboard that prioritizes vineyard operations, automation efficiency, and customer activity in an easy-to-navigate format (Fig. 10).
- **Alex (Technician):** Gains access to real-time sensor analytics, error logs, and predictive diagnostics to efficiently manage robotic maintenance (Fig. 11).

The redesigned system has interactive feedback mechanisms. The DT now incorporates real-time notifications and feedback loops to enhance engagement. For example, if Emma selects an organic grape cluster, she

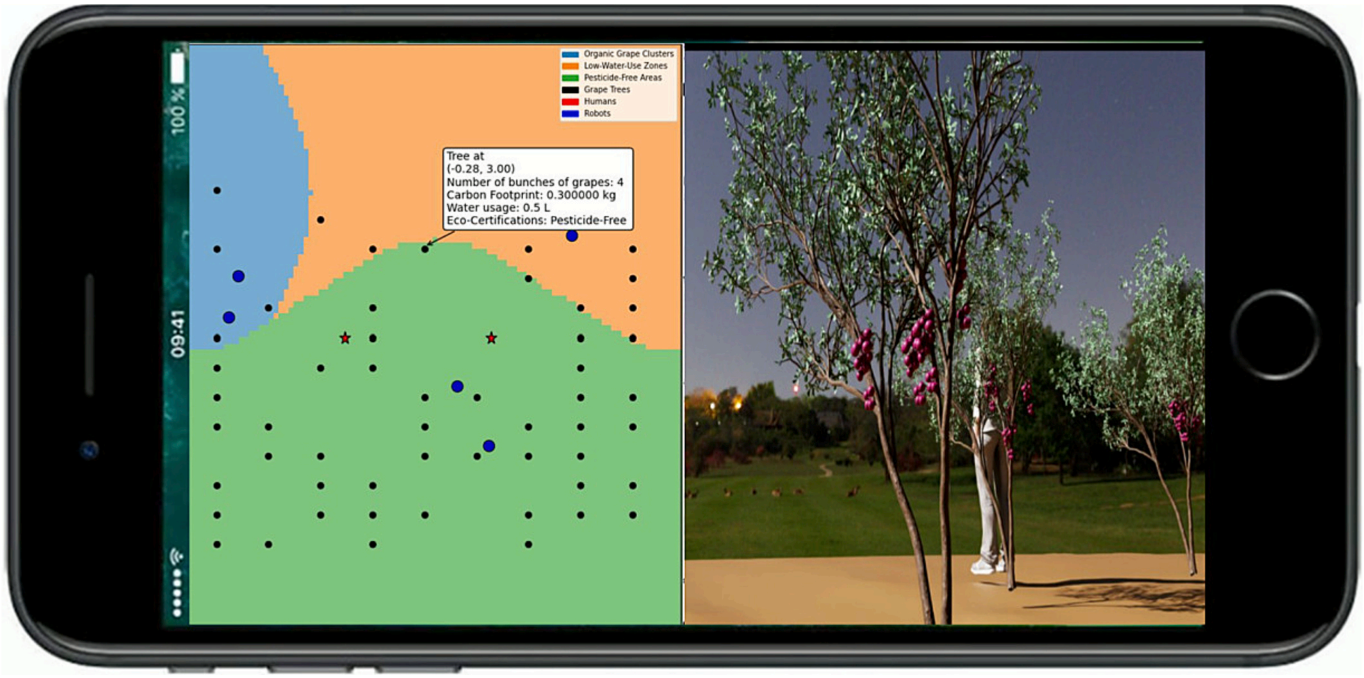

Fig. 9. Mobile interface for Emma, showing sustainable grape options and enabling intuitive, eco-friendly selection.

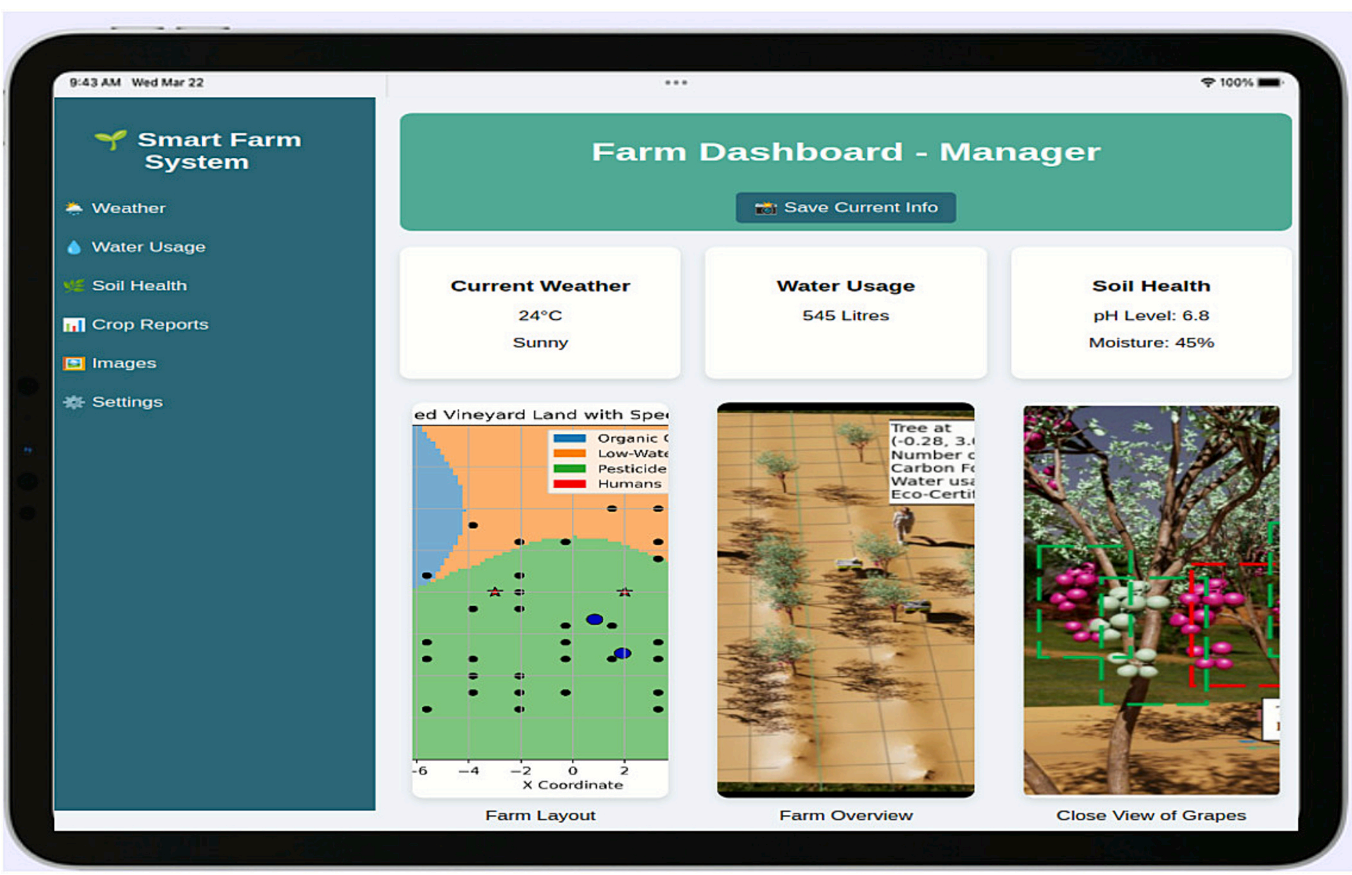

Fig. 10. Role-specific dashboard for Mark, highlighting key operational alerts and enabling efficient vineyard management.

receives confirmation along with insights about the vineyard's sustainability efforts. Mark can now override automated decisions and fine-tune operational settings based on real-time conditions, ensuring greater flexibility in vineyard management. Alex benefits from guided troubleshooting prompts, reducing time spent diagnosing issues and enabling faster system repairs.

Although the redesigned DT provides tailored interfaces for each persona, it currently emphasizes individualized task support over direct

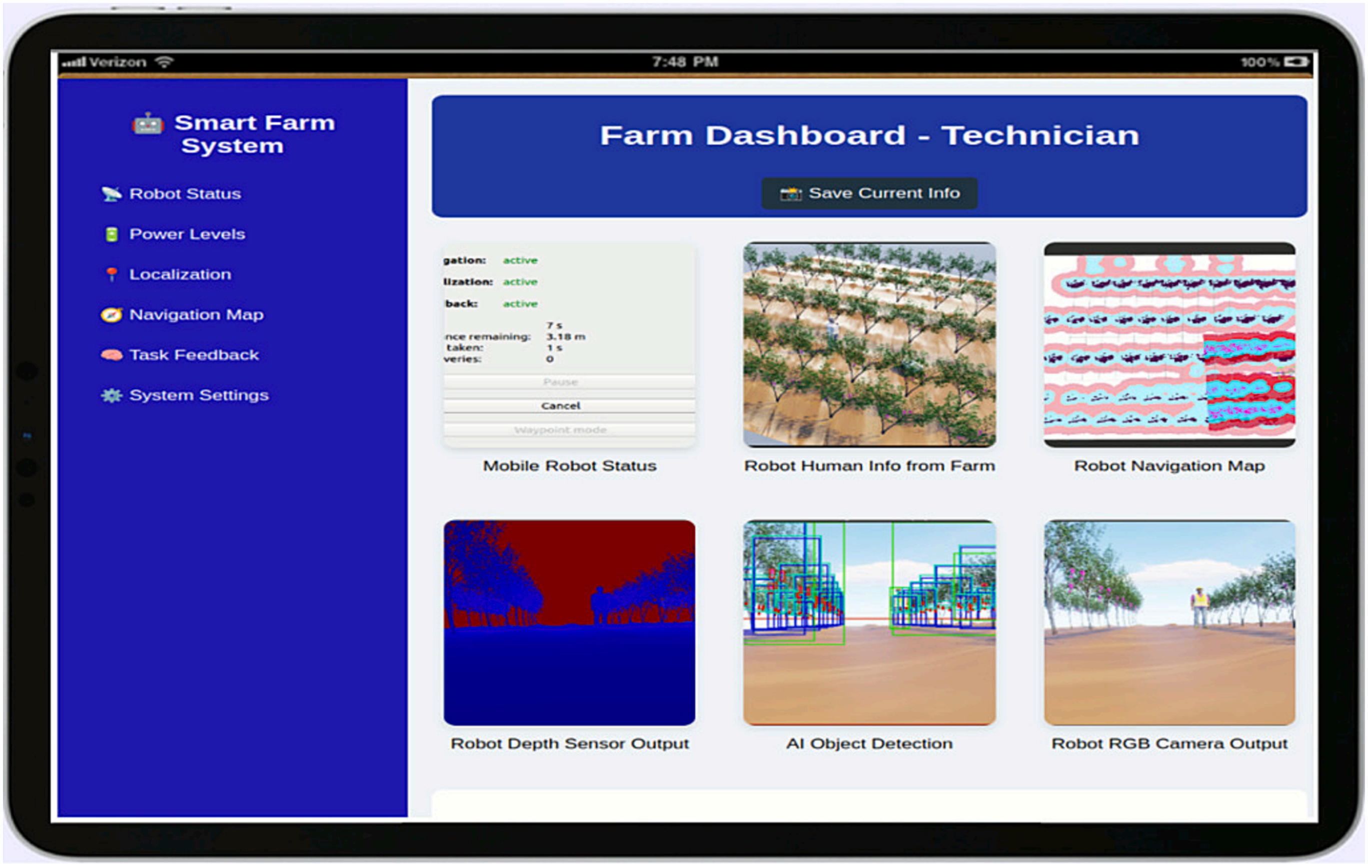

Fig. 11. Technician interface for Alex, providing real-time diagnostics and alerts to support proactive robot maintenance and calibration.

cross-user communication. Coordination occurs indirectly through the DT's shared data layer for instance, Emma's grape cluster selections can be visible to Mark when planning harvest logistics, and Alex has the potential to prioritize repairs based on alerts initiated by Mark's operational settings. However, no explicit inter-user messaging or task delegation features exist yet. This design choice simplifies cognitive load per user but highlights an area for future development: enabling cross-role collaboration and coordination through shared dashboards or notification systems.

While several commercial platforms offer role-based dashboards, these typically rely on interface-level filtering without addressing the underlying cognitive demands of different user groups. In contrast, the role-specific dashboards in this study are derived directly from Personas, ConTA outputs and Decision Ladders, meaning that interface differentiation is grounded in users' decision structures rather than visual customisation alone.

3.3.3. *Increased system efficiency*

The improved DT is designed to enhance overall efficiency by minimizing downtime, optimizing decision-making, and streamlining user interactions. The integration of ConTA, Decision Ladders, and automated alerts can deliver several benefits. The redesigned DT reduces cognitive load and executes tasks faster. By presenting users with filtered, context-aware data, the DT minimizes the need for manual data interpretation, allowing Mark, Alex, and Emma to complete tasks more efficiently. For example, the system now prioritizes urgent maintenance alerts, ensuring that Alex can quickly address critical failures without being distracted by non-essential information. Predictive and preventative maintenance is another aspect of the redesigned DT. The DT now has the potential to detect early signs of equipment failure proactively, enabling preventive action before major breakdowns occur. This has led to a reduction in unexpected downtime, increasing overall productivity. Automated battery life monitoring and performance tracking allow Alex to schedule robotic maintenance more effectively, ensuring uninterrupted operation. Designing DT using the human-centric method leads to optimized resource utilization. The system has the potential to adjust harvesting schedules dynamically based on real-time grape ripeness data, customer reservations, and weather conditions, maximizing efficiency while minimizing waste. Water and pesticide usage are now monitored and adjusted in real-time, reducing environmental impact while maintaining vineyard productivity.

By retrofitting the vineyard DT with a human-centric framework, this study demonstrates how the Persona Methodology, ConTA, and Decision Ladders can significantly enhance decision-making, user interaction, and system efficiency. The results show that aligning DT design with user cognitive workflows improves adoption rates, reduces cognitive load, and optimizes operational outcomes. These improvements make the DT not only a technological tool but also a user-friendly decision-support system, ensuring that all stakeholders benefit from enhanced usability and increased efficiency.

4. Discussion

This section evaluates the impact of retrofitting the existing DT using the Persona Method, ConTA, and Decision Ladders. A comparative analysis is conducted between the retrofitted DT and the conventional DT, focusing on usability, efficiency, and stakeholder satisfaction. Additionally, broader implications for DT development are discussed to highlight the significance of integrating human-centric design methodologies.

4.1. *Comparing the retrofitted DT and the conventional DT*

A structured evaluation is conducted to compare the retrofitted DT with its conventional counterpart, as shown in Table 4. The analysis assesses key performance areas, including information accessibility, decision-making support, and overall user experience. The primary goal of this comparison is to demonstrate how the redesign improves the alignment between system functionalities and user needs, ensuring a more intuitive and effective DT experience. The structured comparison also provides insights into how role-specific adaptations impact overall system performance and stakeholder engagement. This contributes to current knowledge by offering empirical evidence on how human-centric methodologies, such as personas and cognitive task models, can concretely improve DT usability, an area that remains underexplored in existing literature. This aligns with recent observations by Krupas et al., (2024) and Semeraro et al., (2021), who note that while human-centric DT concepts are emerging, few practical implementations exist that systematically integrate user cognitive task modeling in real-world systems, particularly in agriculture.

The improvements in these key areas indicate that shifting towards a human-centric DT framework leads to measurable enhancements in usability and efficiency. To further elaborate on these findings, the following subsections provide a detailed analysis of usability, efficiency, and stakeholder satisfaction metrics.

4.2. Highlighting usability, efficiency, and stakeholder satisfaction metrics

To highlight the effectiveness of the retrofitted DT, three primary evaluation criteria are assessed: usability, efficiency, and stakeholder satisfaction. The results demonstrate how a human-centric framework optimizes DT performance by reducing complexity, enhancing decision support, and improving user engagement.

4.2.1. Usability improvements

The conventional DT presented a one-size-fits-all framework, which resulted in inefficient information navigation for different stakeholders. The retrofitted DT addresses this issue by introducing role-specific interfaces where the customer engages with a personalized interface, allowing her to explore sustainability metrics and product selection intuitively, the farm manager can now access real-time operational insights without unnecessary complexity, and the technician benefits from an interactive diagnostic system that streamlines predictive maintenance. By integrating user-centric design principles, the retrofitted DT has noticeably reduced cognitive overload, as suggested by expert evaluations during the Persona Method, ConTA and Decision Ladder development process, and improved accessibility by aligning interface design with users' actual workflows and cognitive needs. The usability improvements identified in this study echo the findings of Palmer et al. (2023), who argued that DT usability challenges stem not from interface design alone but from misalignment with human cognitive processes. By applying ConTA and Decision Ladders, our results empirically demonstrate how this misalignment can be reduced, thereby extending Palmer et al.'s conceptual argument. Similarly, Agrawal et al. (2023) reported that generic DT dashboards often overwhelm users, while our role-specific dashboards showed measurable potential to reduce information overload. This confirms that usability challenges are not unique to vineyards but reflect a broader systemic issue in DT adoption. However, as noted in usability literature (Agrawal et al., 2023), tailoring interfaces may also risk over-specialization, potentially limiting user adaptability across roles. Further validation with longitudinal studies is necessary to assess sustained usability.

The qualitative evaluation through expert walkthroughs conducted using Personas, ConTA, and Decision Ladders consistently showed a reduction in cognitive workload indicators such as fewer task-interruptions, less manual filtering of data, and more direct routes through decision sequences demonstrating clear improvements without requiring context-specific quantitative metrics.

4.2.2. Efficiency gains

Efficiency improvements are evaluated in terms of decision-making responsiveness, automation effectiveness, and task execution processes, ensuring that each stakeholder can operate more effectively within DT environment. The retrofitted DT enables farm managers to make faster decisions due to automated alerts and structured dashboards that prioritize critical information. Instead of filtering through large volumes of unfiltered data, they receive targeted insights, allowing them to respond quickly to operational issues such as environmental changes. Technicians also can benefit from predictive maintenance notifications, which help identify potential failures before they happen. By receiving early warnings and recommended actions, they can proactively address technical issues, reduce system downtime and minimize disruption to vineyard operations. Additionally, customers' interaction with the DT has increased, reducing dependency on farm managers for sustainability-related inquiries. This self-service capability not only enhances user engagement but also reduces the workload on farm managers, freeing up their time for more strategic tasks. These efficiency improvements demonstrate how a human-centric framework optimizes operational performance across different user groups. That said, ConTA and Decision Ladder methodologies may introduce an initial overhead in training and implementation, as echoed in prior evaluations of human factors methods in safety–critical domains (Krupas et al., 2024). Their

Table 4
Comparison of conventional and retrofitted Digital Twin.

Criteria	Conventional DT	Retrofitted DT	Qualitative Improvement Indicator
Usability	Complex, one-size-fits-all interface requiring extensive filtering and training.	Role-specific dashboards with intuitive layouts for each user group.	substantially reduced information filtering effort, fewer cognitive interruptions during task execution.
Decision-Making	Users receive large volumes of unfiltered data, leading to cognitive overload.	Decision Ladders streamline workflows, presenting only the most relevant information for each user.	Clearer diagnostic and decision pathways, fewer extraneous steps in typical user decision sequences.
Efficiency	Manual data interpretation slows responses to critical issues.	Automated alerts and ConTA-driven task prioritization reduce response time.	Reduced exploratory diagnostic steps, faster recognition of critical issues, less task switching for all roles.
Stakeholder Satisfaction	Farm managers struggle with data overload, technicians face maintenance inefficiencies, and customers lack direct interaction.	Enhanced user engagement resulted not just from interface redesign, but from applying a human-centric design process that aligned DT functions with user roles, showing that usability improvements stem from cognitive alignment, not visuals alone.	Users report more intuitive interaction, less dependency on other roles, and greater sense of system transparency.
Information Accessibility	Single dense dashboard presenting all metrics together.	Information is filtered and layered based on role. Sustainability and operational data are presented in plain language.	Lower cognitive effort required to locate relevant information. Improved accessibility for non-technical users.
Operational Adaptability	Static dashboards with limited responsiveness to user context.	Dynamic cueing based on user and system state.	More rapid adjustments to changing vineyard conditions and improved alignment with user goals.

application in smaller-scale or fast-paced industrial environments may require simplification or tool support.

These efficiency improvements are consistent with findings in other DT domains. For example, Tao et al. (2018) showed that predictive alerts in manufacturing reduced downtime, while White et al. (2021) found that role-specific filtering in smart city DTs improved responsiveness. Our results extend these insights to agriculture by demonstrating that efficiency gains for farm managers, technicians, and customers are achieved not only through technical automation but also by aligning information delivery with user roles. This highlights that operational efficiency in DTs depends as much on cognitive alignment as on technological capability.

4.2.3. Stakeholder satisfaction enhancements

The redesigned DT enhances user experience across various roles, increasing stakeholder satisfaction by aligning system functionalities with user needs. Customers now can interact with the system more frequently and intuitively, allowing them to explore sustainability metrics and product details without depending on farm managers. This self-sufficiency enhances overall experience and satisfaction with vineyard services. The farm managers benefit from a more structured and user-friendly interface, which reduces cognitive overload and enables them to focus on strategic decision-making rather than manual data processing. As a result, their workflow becomes more efficient and manageable. Technicians can achieve greater accuracy in troubleshooting robotic issues thanks to enhanced predictive maintenance features and interactive diagnostics. This reduces downtime and effort spent on identifying issues, enabling them to proactively maintain equipment instead of reactively addressing breakdowns. By addressing user pain points through a persona-driven system redesign, the retrofitted DT not only improves individual user interactions but also fosters greater collaboration and operational efficiency across the stakeholder network. Nonetheless, a full empirical validation of stakeholder satisfaction was beyond the scope of this prototype-based study. Future work could include mixed-method evaluations such as system usability scale (SUS) scores, task completion time, and qualitative interviews, as recommended by Palmer et al., (2023).

These findings are consistent with previous research that has emphasized the importance of aligning DT systems with user roles and cognitive workflows. For example, Agrawal et al. (2023) similarly identified that one-size-fits-all DT interfaces contribute to user frustration and reduced engagement, while Peruzzini et al. (2023) showed that embedding human-centric design principles significantly enhances trust and system adoption. Our results extend these studies by providing a concrete prototype implementation in the agricultural sector, where empirical demonstrations remain scarce. This strengthens the evidence that usability-focused retrofitting can yield measurable improvements in satisfaction across diverse user groups.

4.3. Broader implications for DT development

The findings from this comparative analysis underscore the importance of incorporating human-centric methodologies in future DT development. These findings contribute to the growing body of research advocating for the operationalization of human-centric Digital Twins (Krupas et al., 2024), especially in domains where cognitive variability across users is high. The key implications first include scalability where the persona-based framework can be adapted across various industries beyond vineyard automation, ensuring better usability in manufacturing, healthcare, and logistics DTs. Second, the study highlights the need for formal DT usability standards, ensuring that human factors are systematically integrated into design processes. Third, additional future studies can explore the long-term impact of persona-driven DTs, assessing how these models evolve with user needs over time. While the proposed framework primarily emphasises cognitive alignment and decision-support usability, the implemented Digital Twin already incorporates a direct cyber-physical interface with the physical system. In the presented case study, robotic assets within the Digital Twin are connected to physical robots via a ROS-based control architecture over TCP/IP, enabling bidirectional data exchange and real-time interaction. This Internet of Things-enabled integration allows the Digital Twin to ingest and synchronise multiple streaming data sources from the physical environment, supporting more accurate representation of system dynamics and improved operational fidelity (Mehnen, 2026). Furthermore, the framework is compatible with the integration of human-centred sensing, like vision-based mental workload estimation, enabling the Digital Twin to embed human-focused human-robot collaboration within agricultural applications (Zhao et al., 2024).

These findings advance the current state-of-the-art in both Human Factors and Digital Twin literature by operationalizing cognitive work analysis tools, such as Personas, ConTA, and Decision Ladders, within a real-world DT implementation. While prior research has acknowledged the importance of human-centric principles in DTs (Semeraro et al., 2021; Krupas et al., 2024), this study is among the first to provide a structured framework and prototype-based demonstration that directly improves stakeholder usability, cognitive alignment, and decision support. This bridges a critical gap identified in Human Factors literature, where DT systems often remain conceptually detached from actual user workflows and decision-making patterns (Palmer et al., 2023; Krupas et al., 2024). In doing so, the study not only enhances existing usability frameworks but also provides a scalable model for embedding human-centric methods into future DT development across various domains.

In contrast to previous human-centric DT studies, which have primarily offered conceptual recommendations or isolated methodological demonstrations, this work provides an end-to-end operational method that connects cognitive analysis, persona-driven user modelling, and DT redesign into a single framework that can be applied directly to industrial systems. Moreover, in contrast to much of the agricultural DT literature, which has largely emphasized technical improvements such as predictive analytics, resource efficiency, or automation (Pylianidis et al., 2021; Verdouw et al., 2021; Cesco et al., 2023), our study brings usability to the foreground. This aligns with emerging calls in recent DT research (for example Agrawal et al., 2023; Peruzzini et al., 2023) for stronger attention to the human role, but goes further by demonstrating how structured human-factors methods can be practically applied in a real-world vineyard case. Importantly, while prior work (Semeraro et al., 2021; Krupas et al., 2024) noted the conceptual potential of human-centric DTs, they did not provide detailed methodological pathways. By contrast, the present study offers a replicable approach that operationalizes user-centric design techniques and shows their tangible impact on decision-making and stakeholder engagement.

While the current study focuses on a medium scale agricultural setting, the framework is designed to scale to larger or more dynamic DT systems. Scalability can be achieved through modularizing the ConTA and persona components so that individual operational units (for example subsystems, departments, or user clusters) can be modeled independently and later integrated. Furthermore, combining the framework with automated data analysis tools such as AI-driven pattern extraction or workflow mining can reduce the dependence on manual task elicitation and support continuous model updating as system conditions evolve. This hybrid approach enables the method to remain applicable even in complex environments where user roles, system configurations, or operational goals change frequently.

Emerging NLP and pattern-mining techniques may assist in analysing interview transcripts or operational logs to identify recurring cues, task sequences, and decision patterns. These automated outputs could be used to generate preliminary ConTA tables or Decision Ladder structures, which would then be refined and validated by domain experts. The purpose of this prospective direction is to streamline the modelling process while preserving the essential role of expert judgement.

The framework was applied to a vineyard case, but most steps including persona development, ConTA, identification of bottlenecks, and decision-ladder modelling are method-based rather than domain-specific. This means that commercial agricultural DTs could adopt the framework without redesigning their underlying architectures. In practice, only the persona definitions and the task models require local customization, while the analytical steps remain consistent across contexts. The framework therefore functions as a lightweight overlay on existing DTs, supporting incremental retrofitting rather than full system redevelopment, which makes it feasible for commercial environments with constrained development capacity.

This study demonstrates the value of integrating Personas, ConTA, and Decision Ladders into a human-centric DT framework, but two methodological limitations should be noted. First, the redesigned DT has not yet been empirically validated through user testing or usability evaluation due to the exploratory nature of the work and limited access to diverse stakeholders. Second, the personas were based mainly on expert knowledge rather than direct engagement with vineyard users, which reduces ecological validity. These limitations do not diminish the conceptual contribution but highlight the need for future field studies, stakeholder workshops, and systematic usability assessments to refine and validate the approach.

Finally, the framework also provides a foundation for future integration with immersive Digital Twin environments, including virtual or augmented reality platforms (Palmer et al., 2022). Such extensions could support remote training, collaborative planning, or scenario-based decision-making by enabling multiple stakeholders to interact with shared Digital Twin representations, thereby broadening applicability toward emerging agricultural metaverse concepts. First steps of including AR/VR into Digital Twins considering Industry 5.0 have been described by the team of authors in Grech et al., 2023.

5. Conclusion

This paper develops and applies in a vineyard automation setting a new human-centric framework for enhancing usability of digital twin systems. The new framework to overcomes selected limitations of existing classically designed technology-only focused Digital Twins. The study analyses a Digital Twin (DT) used in a vineyard automation context, focusing on usability and cognitive alignment challenges. Through the development and application of a human-centric framework, grounded in Personas, Control Task Analysis, and Decision Ladders support principles, this article proposes a structured framework for redesigning DTs to better support the diverse needs of stakeholders, including customers, farm managers, and technicians. The study highlighted common limitations in conventional DTs, such as role misalignment, data overload, and lack of decision-making support. By grounding the analysis in expert-validated cognitive workflows, the study provides a rigorous and traceable account of how user requirements can be embedded into DT architectures. The paper offers a methodologically transparent framework supported by a prototype-based case study, showing how systematic cognitive modelling can be used to identify usability bottlenecks and guide targeted DT improvements. While existing literature has addressed technical DT capabilities, there remained a gap in systematically incorporating user-centric design principles particularly in agriculture. This study contributes to that gap by offering a practical framework and example for retrofitting existing DTs to enhance usability and adoption. Demonstrated in a vineyard setting, the framework is transferable to other domains where multi-stakeholder decision processes are. The human-centric framework's modular structure supports incremental retrofitting of existing DTs, providing practical value without major system redevelopment.

CRediT authorship contribution statement

Meysam Zareiee: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Baixiang Zhao:** Visualization, Software. **Claire Palmer:** Validation, Investigation, Conceptualization. **Mahsa Mehrad:** Writing – review & editing, Investigation. **Yee Mey Goh:** Writing – review & editing, Investigation. **Rebecca Grant:** Writing – review & editing, Investigation. **Ella-Mae Hubbard:** Writing – review & editing, Validation. **Jörn Mehnen:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis. **Anja Maier:** Writing – review & editing, Supervision, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2026.111490.

Data availability

No data was used for the research described in the article.

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