Designing a Layered Learning Infrastructure with a Digital Twin Component

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The increasing availability and complexity of data across professional domains require decision-makers to integrate diverse information in uncertain situations, highlighting the role of professional education in developing data-informed decision-making competence. While digital twins are widely used to model and optimise complex systems, their potential as pedagogically structured learning environments remains underexplored. This study presents the design of a layered learning infrastructure for data-informed decision-making, in which a digital twin functions as a component within a simulation-based learning environment. The study proposes a reconceptualisation of digital twins as components of learning processes. Drawing on multi-professional co-creation process in a smart agriculture context, the study suggests that pedagogical orchestration makes learners' reasoning visible by supporting multi-source data integration, trade-off evaluation, and engagement with uncertainty. The paper contributes a design-oriented framework and argues that the educational value of digital twins depends on pedagogical orchestration that renders decision-making processes explicit and open to reflection.

Keywords:
data-informed decision-making,
digital twin,
simulation-based learning,
professional education,
smart agriculture

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1 Introduction

Across data-intensive professional sectors such as smart farming, decision-making increasingly requires the integration of heterogeneous data sources under conditions of uncertainty (Wolfert et al., 2017; Zhang et al., 2016). Smart farming refers to the use of digital technologies, data analytics, and automation to enhance agricultural productivity and sustainability (Wolfert et al., 2017; Klerkx et al., 2019). In this context, professionals are expected not only to access data, but also to interpret it, weigh alternatives, justify decisions, and reflect on consequences (Klerkx et al., 2019; Eastwood et al., 2019).

While the terms are often used interchangeably in the literature, some scholars distinguish data-driven decision-making as emphasising systematic data processing and analytic infrastructures, whereas data-informed decision-making highlights professional judgement, contextual interpretation, and ethical considerations (e.g., Brazauskienė, 2025). As decision-making in increasingly complex data-rich environments requires specific forms of professional competence, evidence suggests that data literacy training initiatives, for example in education, prioritise data analysis and interpretation, while the explicit development of decision-making competence remains less systematically addressed (e.g. Sandoval-Rios et al., 2025). Developing these competences has become a central challenge spanning individuals, organisations, and the education systems responsible for preparing and upskilling professionals (e.g. Sandoval-Rios et al., 2025; Coners et al., 2025; Brazauskienė, 2025).

Accordingly, this study adopts a data-informed decision competence (DIDC) perspective framing decision-making as a human, reflective competence rather than a purely technological process. Through intensified digitalization, AI-driven analytics become increasingly embedded in professional systems, research has raised concerns about over-reliance on AI models (Lai et al., 2021). This development highlights the need to preserve and strengthen human decision-making competencies (Comez et al., 2025).

Across sectors such as healthcare, engineering, energy, and smart agriculture, decision-making increasingly relies on multiple data sources. In smart agriculture, for example, decisions related to fertilisation strategies, harvesting timing, or investment planning increasingly rely on multiple data sources, including production, economic, environmental, and contextual indicators (Wolfert et al., 2017). To support decision-making in such complex data-rich contexts, digital twins (DT) are increasingly used to model, monitor, and simulate complex systems, supporting analysis, optimisation, and strategic decision-making (Pylianidis et al., 2021; Jans-Senegacnik et al., 2023). However, modelling capability alone does not automatically translate into decision competence. Although digital twins are increasingly discussed in educational contexts (Bachmann et al., 2024), their conceptualisation as pedagogically structured learning infrastructures remains under-theorised. This paper conceptualises DTs as pedagogically embedded modelling environments. It presents the design and exploratory evaluation of layered learning infrastructure in a smart agriculture context.

Smart agriculture provides a prototypical example of a data-intensive sustainability domain characterised by multi-source data integration and systemic uncertainty (Wolfert et al., 2017). Decisions in this context must balance economic performance, environmental impact, and system resilience, underscoring the need for structured opportunities to practise decision-making without immediate real-world economic consequences.

The study makes three contributions

First, it reframes DTs not merely as immersive or adaptive learning technologies, but as components of pedagogically orchestrated learning infrastructures aimed at developing decision competence. **Second,** it proposes a layered learning infrastructure that integrates a DT modelling environment with structured decision–consequence–reflection cycles. **Third,** it offers exploratory empirical insights into how these cycles can scaffold decision practice in sustainability-oriented, data-intensive contexts.

Accordingly, the study is guided by the following research question:

RQ How can a digital twin component be pedagogically orchestrated within a simulation-based learning environment to structure and scaffold data-informed decision competence through iterative decision–consequence–reflection cycles?

By shifting the focus from technological optimisation to pedagogical orchestration, this study extends the discourse on DTs as learning environments that intentionally develop human competence in complex data-rich systems.

2 Theoretical Background

2.1 Data-informed decision competence in data-rich environments

Data-informed decision-making extends beyond access to data or the ability to interpret isolated indicators. While data-driven approaches emphasise systematic data utilisation and predictive analytics in complex agricultural systems, for example (Agbonika et al., 2025), data-informed decision-making integrates professional judgment, digital evidence, and ethical considerations (Brazauskienė et al., 2025). Professional judgment incorporates experiential insight, domain-specific expertise, and theoretical understanding (Schön, 1983), often emerging through distributed interaction rather than individual cognition. In complex socio-technical systems, decision-makers must compare alternatives, evaluate data reliability, and interpret trade-offs across temporal and systemic scales.

In this study, DIDC is conceptualised as a professional competence that enables decision-makers to (1) integrate heterogeneous data and knowledge sources, (2) critically evaluate the reliability and relevance of available data, (3) reason transparently under conditions of uncertainty, and (4) articulate and justify decisions through explicit reflection on potential consequences.

While maturity models such as Cech et al. (2018) conceptualise data capability primarily at the organisational level, we extend the developmental logic to the level of professional decision competence. In smart agriculture, data-driven approaches are often framed in technological and optimisation terms (e.g., McBratney et al., 2005; Sáiz-Rubio et al., 2020), with limited attention to how decision-making competence can be systematically developed in data-intensive environments. Consequently, there remains a conceptual gap between data-driven agriculture infrastructures and pedagogically structured competence development. Although data-driven infrastructures are increasingly sophisticated, explicit pedagogical models for human decision competence development within such environments seem under-theorised.

Such competence is particularly relevant in sustainability-oriented and data-rich decision contexts, such as smart farming, where economic, environmental, and systemic considerations interact and often conflict (Klerkx, Jakku & Labarthe 2019). In these contexts, integrated data does not eliminate tensions between alternative priorities; rather, decision-makers must interpret information, compare projected consequences, and justify trade-offs across temporal and systemic scales. Because DIDC involves interpretative and distributed reasoning, its development requires learning environments that make reasoning processes visible and open to critical examination.

2.2 Simulation pedagogy and decision–consequence–reflection cycles

Simply presenting integrated datasets or modelling system behaviour does not automatically support competence-oriented learning. Learning environments must provide structured opportunities for articulating decisions, comparing alternatives, and reflecting on consequences.

Simulation-based learning (SBL) has been widely used in professional education to create structured environments where learners can experiment with decisions and examine outcomes in a controlled setting (Lateef, 2010). Meta-analysis across 145 empirical studies demonstrates a large positive overall effect on the development of complex skills in higher education, particularly when SBL is combined with appropriate scaffolding (Chernkova et al., 2020). From an experiential and reflective learning perspective (Kolb, 1984; Schön, 1983), SBL may provide a structured framework within which processes associated with DIDC can be enacted, examined, and discussed. Evidence indicates that SBL is particularly effective when supported by appropriate scaffolding and instructional structuring (Chernikova et al., 2025).

Through structured engagement with integrated data and comparison of alternative interpretations, learners can practise multi-source reasoning, trade-off evaluation, and uncertainty awareness. Structured debriefing and guided reflection provide key mechanisms for examining assumptions and reconsidering decisions (e.g., Dieckmann, 2009; Cheng et al., 2014). Iterative decision–consequence–reflection cycles are particularly relevant because they make reasoning processes visible and open to examination, thereby supporting explicit justification of data-informed choices.

From an experiential learning perspective (Kolb, 1984), modelling environments, such as DTs, can provide a structured environment for concrete experimentation. However, the possibility to run DT-enabled simulations does not in itself constitute simulation pedagogy. By enabling learners to test decisions, observe simulated consequences, and revise their assumptions, DT environments can function as platforms for iterative transitions between experience, reflection, conceptualisation, and renewed action, positioning digital twins not only as technological tools but as pedagogically structured learning environments.

2.3 Digital twins as pedagogically orchestrated modelling environments

DTs are commonly conceptualised as dynamic digital representations of physical systems that integrate heterogeneous data sources to enable monitoring, simulation, and predictive analysis (Tao & Zhang, 2017). In agricultural contexts, digital twin approaches combine production, environmental, machinery, and economic data into system-level models that support scenario-based exploration of alternative decisions (Verdouw et al., 2021; Pylianidis, C., Osinga, S., & Athanasiadis, 2021; Peladarinos et al., 2023). More broadly, digital twin technologies are associated with data-intensive system monitoring, predictive analysis, and scenario-based modelling in contexts such as autonomous farming and smart agricultural technologies (Papadopoulos et al., 2025).

Recent research has explored the integration of DTs with virtual learning environments to enhance experiential and simulation-based learning, particularly in manufacturing education (e.g., Karanam & Hartman, 2025). Such work demonstrates the potential of DT-based immersive and adaptive learning environments. Nevertheless, comparatively less attention has been given to how DT environments can be pedagogically structured to support the development of human decision competence. From an educational perspective, the central question is not how accurately a DT represents a system, but how it can be embedded within pedagogical orchestration that structures decision-making processes and reflection. For the purposes of this study, DT is thus understood as a data-integrating modelling environment that enables scenario-based simulation. This perspective positions DTs as pedagogically orchestrated environments that can support the development of data-informed decision competence.

3 Methodological Approach

This study adopts a design-oriented exploratory approach focusing on the development and evaluation of a layered learning infrastructure. The design and evaluation were conducted across iterative cycles of design, implementation, reflection, and refinement. It examines how DT-based modelling environments can be intentionally integrated with structured pedagogical processes to scaffold DIDC within simulation-based learning environment.

The development followed a multi-professional co-creation process involving domain experts, vocational educators, pedagogical specialists, technical developers, and potential end-users. Workshops were organised to identify stakeholder expectations, perceived benefits, needs, and key decision-making challenges across different user groups (Aksovaara, et al. 2025). During this process, for example, learner personas were collaboratively developed to articulate anticipated user needs and the practical value the environment should provide. The workshops also included facilitated discussions to inform explicit competence objectives tailored to the learner personas, emphasising multi-source data integration, transparent justification of decisions, evaluation of uncertainty, and reflective examination of projected consequences across economic, environmental, and systemic dimensions.

In parallel with the workshops, a pedagogical orchestration layer was implemented within a learning management system (LMS) as part of the intervention design to structure iterative decision–consequence–reflection cycles. Core design outputs included (1) competence objectives for DIDC, (2) scenario-based decision tasks and related prompts, and (3) a DT simulation interface for testing solutions and exploring consequences. Based on these stakeholder-driven objectives, relevant data sources were identified and integrated into the DT modelling environment. Scenario-based decision tasks were constructed to represent realistic sub-decisions and their projected consequences.

Pilot session setup and participants

The first pilot was implemented as a six-hour group-based training session in a dual-platform learning environment consisting of a LMS and the DT simulation interface. The pilot was implemented in a hybrid format, combining an online webinar with on-site group-based decision-making activities on campus. Participants were farmers (N = 5), recruited through the project network and participating on a voluntary basis. Their ages ranged from 30 to 65 years; two had over 20 years of experience in agriculture, while the others had shorter professional experience. Participants demonstrated moderate but uneven experience with digital tools: most used basic farm management and financial software (4/5), whereas fewer reported using advanced data-driven technologies such as sensors, automation, or telemetry (1–2/5).

The session comprised (1) an introduction to the DT simulation interface, which provided visualisations of key variables such as yield, cost, and environmental indicators, enabling comparison of alternative decision scenarios, (2) two to three decision rounds where participants selected and justified sub-decisions (e.g., fertilisation strategy and timing) using multiple data sources, (3) simulation of consequences in the DT, and (4) structured debriefing and reflection. The pedagogical orchestration layer in the LMS provided structured written prompts for decision justification and post-round reflection and served as a repository for participant artefacts.

Evaluation of the pilot session

Evaluation data included written participant reflections, collaboratively produced decision justifications, and survey responses. The analysis focused on examining how participants justified decisions, engaged with data, and reflected on consequences. The material was analysed using an iterative, theory-informed interpretative approach focusing on how participants articulated decisions, justified trade-offs, and engaged with uncertainty across the decision cycles. The analysis focused on recurring patterns, tensions, and illustrative examples in how participants used data, justified decisions, and engaged with uncertainty. The findings informed refinements to the pedagogical orchestration and supported examination of how decision-making processes became visible in practice. Insights were synthesised into relationships between pedagogical design, learner activity, and decision-process visibility, forming the basis of the conceptual model presented in the following section. Given the exploratory, design-oriented pilot, the small sample size was deemed appropriate for generating initial process-level insights.

4 Results

4.1. Layered learning infrastructure

The infrastructure developed in this study comprises two analytically distinct yet functionally interconnected layers (Figure 1): (1) a DT modelling layer and (2) a pedagogical orchestration layer.

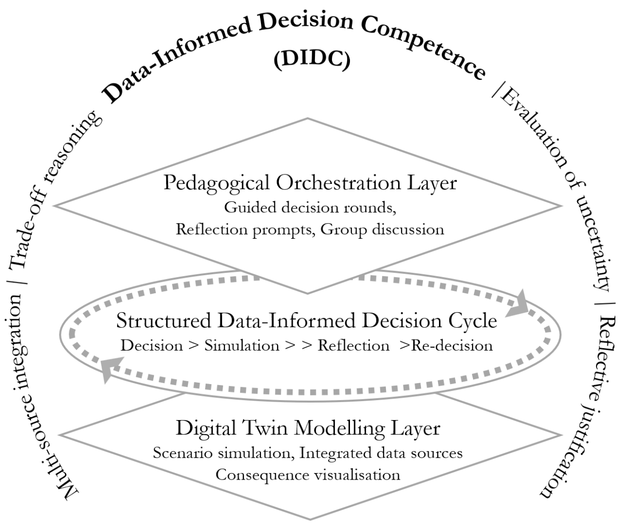

Figure 1: A layered learning infrastructure for data-informed decision-making with a digital twin component

The DT modelling layer functions as a virtual representation of the target system. It integrates production-related, economic, environmental, weather, and contextual data into a unified and temporally structured dataset. This enables scenario-based simulation of alternative decisions and examination of their projected consequences. By visualising outcomes across multiple criteria and time horizons, the DT renders systemic interdependencies and trade-offs analytically observable. The modelling environment itself does not prescribe how data should be interpreted or how decisions should be justified. Rather than a static analytics interface, the DT functions as an epistemic experimentation environment that externalises consequences and makes system dynamics visible

The pedagogical orchestration layer structures how the modelling environment is used within SBL. Implemented within a learning management system, it organises learning into iterative decision–consequence–reflection cycles. Within these guided rounds, learners articulate and justify sub-decisions based on multi-source data, implement and test alternatives within the DT environment, and engage in structured reflection. Reflection prompts and facilitated discussion make reasoning processes explicit, highlighting assumptions, uncertainty, data reliability, and trade-offs. A concluding reflection phase supports synthesis across decision rounds and connects simulated outcomes to broader sustainability-oriented system dynamics. Overall, the architecture creates structured opportunities for collaborative reasoning and examination of trade-offs in data-intensive contexts.

The interaction between the modelling and pedagogical layers forms an iterative learning cycle. Decisions are informed by integrated data, consequences are explored through the DT simulation interface, and reasoning is critically examined before proceeding to subsequent rounds. In relation to the RQ, the layered learning infrastructure illustrates how a DT component can be pedagogically orchestrated within a simulation-based learning environment, where the orchestration layer structures iterative decision–consequence–reflection processes.

4.2. Exploratory observations from the first pilot test

During the first six-hour pilot training session implemented as group-based learning, participants reported positively on the possibility to test alternative decisions and observe simulated consequences. The qualitative responses suggest engagement in processes associated with the components of DIDC.

Participants described how DT modelling outputs made system dynamics visible (e.g., "*It was interesting to see what kinds of results can be predicted through calculations – everything affects everything*"; "*The modelling made the relationships clearly visible*"). Decision-making drew on multiple heterogeneous data sources, including weather, soil sensor data, and historical data. Reflections such as *"We gained insights into variations in field growing conditions based on soil sensor data"* illustrate engagement in data-based reasoning.

The DT was explicitly described as a learning resource: *"I learned to use simulation comparison – it was a useful tool*", "*The simulation supported my own thinking*", and "*Through the simulations, we were able to compare alternatives.*" Participants also reflected critically on modelling outputs and data reliability (e.g., "*Historical data is not a law*," "*The computer can also be wrong*"), suggesting awareness of uncertainty and model limitations.

Trade-off reasoning between yield, costs, and environmental conditions was frequently articulated: "A *surprisingly high price is needed to reach break-even in grain farming*," "*Even if everything is done well, market prices can still make the outcome unprofitable*," and "*Fertilisation does not always increase yield.*" Observations such as "*Inputs affect the final outcome*" and "*An optimum must be sought between yield and costs*" indicated comparative evaluation of alternatives. Reflective comments "*One must dare to make unconventional decisions,*" "*It is worth thinking more broadly when selecting seed varieties*" further pointed toward explicit articulation and justification of decisions. Peer interaction played a central role in the learning process. Participants emphasised the importance of discussion and shared reasoning "*We made decisions together as a team,*" "*The team's support was important*", indicating that decision-making was enacted collaboratively despite the strong presence of technological tools.

These observations provide empirical indications supporting the proposed design principles rather than generalisable findings. In relation to the research question, the findings suggest that pedagogically orchestrated decision–consequence–reflection cycles, with the digital twin functioning as a modelling and experimentation resource, can create conditions for practising processes associated with data-informed decision competence. In particular, the layered learning infrastructure appears to make multi-source reasoning, trade-off evaluation, uncertainty awareness, and explicit justification of decisions more visible within a simulation-based learning process. In the present pilot, these processes were enacted collaboratively, which may have further supported the articulation and externalisation of reasoning.

5 Discussion and conclusions

This study conceptualised DT as a component of pedagogically structured learning environments that make the consequences of decisions visible over time and enable learners to explore alternative options. The proposed layered learning infrastructure integrates a DT simulation interface with pedagogically orchestrated decision–

consequence–reflection cycles. This integration enables learners to test decisions, observe simulated consequences, and reflect on their reasoning in a structured manner, making decision-making processes explicit and open to examination. A key contribution of this study is the distinction between the modelling layer and the orchestration layer, which clarifies how competence-oriented learning depends on pedagogical structuring in addition to DT simulation interface capability. The exploratory examination of participant materials indicates that the pedagogically orchestrated decision–consequence–reflection cycles created conditions in which learners articulated and examined their reasoning in relation to multi-source data and projected system outcomes. Initial observations suggest that sustainability-oriented contexts, such as smart farming, amplify the need for practicing DIDC through structured articulation of assumptions, comparison of alternatives, and guided reflection. When decisions involve trade-offs across economic, environmental, and temporal dimensions, integrated data does not automatically resolve tensions. Instead, learners must interpret, prioritise, and justify their reasoning. The layered infrastructure appears to make these processes more visible and open to examination.

This exploratory study suggests that digital transformation requires advanced modelling technologies alongside pedagogical solutions. Although developed in a smart agriculture context, the learning infrastructure may be transferable to other data-intensive domains to support data-informed decision competence. Coupling DTs with scalable pedagogical orchestration may support structured engagement with decision processes across diverse domains characterised by uncertainty.

Despite these contributions, this study has limitations. The exploratory pilot involved a small sample (N=5), and the findings are based on interpretative analysis rather than formal qualitative coding, and should therefore be understood as indicative rather than generalisable. Future research should examine how pedagogically orchestrated DT environments, potentially augmented with AI, support the development of data-informed decision-making competence in larger and more diverse contexts.

End notes

Use of Generative AI in the Writing Process. Generative AI was used solely for language editing. All research design, data analysis, modelling decisions, and interpretation represent the authors' independent intellectual contributions. The authors take full responsibility for the content of this manuscript.

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