Systemic design requirements for sustainable Digital Twins in precision livestock farming

Chapter · November 2022

3 authors, including:

Kevin Mallinger
SBA Research
13 PUBLICATIONS **3** CITATIONS
SEE PROFILE

Warren Purcell
TU Wien
5 PUBLICATIONS **3** CITATIONS
SEE PROFILE

Systemic design requirements for sustainable Digital Twins in precision livestock farming

K. Mallinger[1,2]*, W. Purcell*[1]*, T. Neubauer*[1,2]
[1]*Information and Software Engineering Group, TU Wien, Vienna, 1040, Austria*
[2]*SBA Research gGmbH, Floragasse 7/5.OG, Vienna, 1040, Austria*
kmallinger@sba-research.org

Abstract

Facing the manifold sustainability challenges (GHG emissions, eutrophication, social welfare, etc.) in livestock farming, Digital Twins can help farmers to use available feed and nutrients efficiently, monitor livestock health, and control emissions to air, soil, and water. Combined with current precision livestock farming (PLF) technologies, Digital Twins (DT) enable real-time monitoring, simulation, and automation capabilities through real-world models and a two-way flow of information. As current applications are mostly focused on closed and highly regulated systems, this paper investigates the systemic challenges and associated design implications of DTs in complex PLF settings. By integrating a STES (social-technical-ecological system) design approach, the authors argue to foster design strategies that serve sustainable livestock governance and enable a sound and flexible basis for balancing associated engineering requirements such as privacy, security, ethics, and inclusion. We will use a qualitative assessment approach, discuss multi-disciplinary requirements for Digital Twins, and consolidate them in a high-level road-map.

Keywords: Digital Twins, Sustainability, Precision Livestock Farming, Technology Assessment, Systemic Challenges

Introduction

A Digital Twin (DT) is a virtual representation of a product, process, or environment with a bilateral exchange of information. By incorporating novel advances in Artificial Intelligence, IoT (Internet of Things), big data analytics, cloud, and edge computing, Digital Twins use the enhanced capacities of data storage, processing, and visualization to track, predict, and optimize the behavioural traits of its subject. Current successful applications of Digital Twins can be found particularly in closed and controlled environments such as industrial and engineering fields (Erol et al., 2020; Ibrion et al., 2019; Uhlenkamp et al., 2019). As the processes in these settings are easier to monitor and the external variables are limited, the reduced complexity allows faster development of robust DT models and therefore, a higher return of investment (Neethierajan and Kemp, 2021).

Recent reviews have been conducted to summarize the potential benefits of DTs for precision livestock farming (PLF) such as risk reduction, enhanced flexibility, and efficiency gains (Neethierajan and Kemp, 2021; Pylianidis et al., 2021). The same research also highlights the novelty of DTs and the so far limited number of prototypes in precision livestock farming, but also in other dynamic biological and ecological systems. Although first promising results have been achieved in more open environments

(Pylianidis et al., 2021; Ford et al., 2020), swift progress is hindered by the many design challenges that arise by working with different stakeholder needs and complex multi-variate systems causing a high degree of uncertainty, as well as through different and sometimes conflicting objectives (e.g., cost-reduction vs. animal well-being, animal health vs. ecological footprint, model fairness vs. model accuracy).

By connecting the biophysical realm with the virtual domain (models) under the prerequisite of stakeholder needs, the design of a Digital Twin is inherently co-dependent on ecological, social, and technological parameters. Therefore, sound development must refer to the individual requirements and standards of each perspective, but also include the complex feedback mechanisms that result from the practical application of DTs. To achieve this, the authors introduce a socio-technical-ecological systems (STES) approach (Ahlborg et al., 2019) for DTs that guides the incorporation of the manifold human-environment relationships in the design and development phase. By highlighting the systemic requirements that come with such an integrated approach, we aim to display some of many needed aspects for fair, inclusive, reliable, and sustainable technology development. As a complete overview of all possible challenges would go beyond the scope of this paper, we will highlight and exemplify design aspects that specifically address prominent effects of complex STES systems such as cascading error propagation, single points of failures, or unwanted emergent behaviour of DTs, but also foster multi-value effects for achieving sustainability from various perspectives.

Material and methods

This paper is following a *Requirement Engineering* approach, with its primary focus to generate a set of multi-disciplinary and inter-systemic requirement specifications that represent stakeholder needs (Braun et al., 2015). As defined by the IEEE (2010), *requirement* will be interpreted as the condition or capability of a system or a person to solve a certain problem or to reach an objective. In the scope of this paper, the objectives are defined in the results section and represent exemplified systemic interdependencies that arise through STES dynamics. Therefore, the requirement analysis follows a STES framework introduced by Ahlborg (et al., 2019) to analyze i) how technologies shape specific human–nature relations and with what consequences, for whom, and where; ii) how emergent pressures in complex socio-technical-ecological systems are interlinked and; iii) how intentional and unintentional technical mediation may result in ambiguous outcomes and feedbacks. The preliminary and potential systemic implications of different Digital Twin designs will be assessed by literature review. This will be complemented by incorporating known systemic risks of the fundamental technologies Digital Twins are based on. Thus, the qualitative assessment is practice-inspired, focusses on generalizing Digital Twin design requirements based on the various systemic threats and opportunities in PLF settings, and formulates the next steps for generating sustainable DT designs as a roadmap.

Results and Discussion

Challenges

Digital Twins incorporate a wide range of novel technologies to achieve high-fidelity virtual replication and optimization through the consolidation of large volumes of real-time data from distributed sources, simulation-driven insights, and feedback mechanisms which enables the user to replicate and manage entities with complex life cycles (Jones et al., 2020). As the DT is optimizing the biophysical realm set by the user's goals, the level of precision and success to achieve these goals is directly and indirectly linked to ecological and social feedbacks (see figure 1 and table 1) as well as to the capability of the DT design to process and display such (e.g., its visualization of information, automated management strategies). Therefore, the DT is in the very center of various dependencies, with the goal to mediate individual feedbacks and requirements (legal, technical, social, ethical, etc.). Because of its virtual and physical entanglement, it is extremely difficult to define external and internal boundaries of a Digital Twin. Defining challenges, requirements, and goals of DTs without acknowledging the intertwined feedback mechanisms will ultimately lead to designs that lack the flexibility, adaptability, and processing capacities to handle uncertainty and to manage complex real-world systems sustainably.

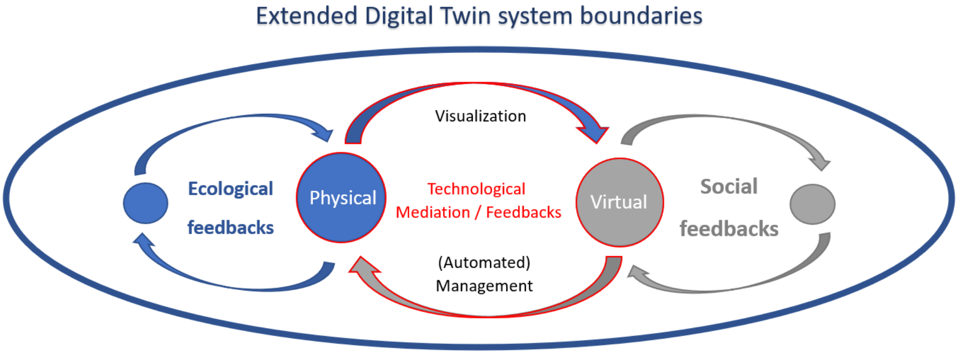

Figure 1: This representation shows the extended system boundary of a Digital Twin to capture the physical and virtual entanglement as well as the direct and indirect coupled dynamics that govern it.

As DTs build on the capacities and flaws of existing technologies, its hyper-connected design not only inherits those systemic connections (Fuller et al., 2020), but further intensifies existing dependencies. If not addressed properly in the early design phase, Digital Twins may accelerate current attitudes and barriers of PLF technology adoption such as the lack of trust and usability, the fear of a low return on investment, issues of interoperability, privacy, and security, as well as concerns about complexity and external dependencies (Boothby and White, 2021, Makinde et al., 2020; Drewry et al., 2019).

Following a STES approach, we distinguished the systemic dependencies of Digital Twins in the form of social, technological, and ecological perspectives and associated challenges (see table 1). As Digital Twins are at the intersection of all three areas (and many more), some dependencies can be assigned to several perspectives at once (such as data vendor lock-in). To avoid duplication, we chose to display certain dependencies only once and exemplify categories in more detail below.

Table 1: An exemplified overview of categorical dependencies that need to be examined to create sustainable Digital Twins and design strategies to manage systemic effects.

Social — Vendors, users, designer, third-party entities, farming community

- **Drivers:** multi-user vs. single user design, lack of technological knowledge, technological blindness, cash-crop specialization, unclear data ownership, need of data sovereignty, economic scalability, etc.
- **Effects:** monopolisation and low diversity, large-scale fragility, single-points of failure, increased external dependencies, loss of technological know how and economic autonomy

Technological — Data, algorithmic, visualization, physical infrastructure

- **Drivers:** internal and external data dependencies, algorithmic layering, lack of transparency, diversity of adjacent PLF infrastructure, low understandability of output, high complexity of multidirectional data streams, etc.
- **Effects:** single-points of failure, cascading error propagation, unwanted emergence, difficulties of achieving independent modules, unmanageable connections (technological debt and low maintainability)

Ecological — Livestock, biophysical farming environment

- **Drivers:** unexpected behaviour of animal, environmental redeployment, integration of indirect environmental effects, unknown & hidden biophysical feedbacks, etc.
- **Effects:** cascading error propagation, unwanted emergent effects, unknown ecological dependencies

In order to balance qualitative attributes like usability, maintainability, and legal adherence, **social** dependencies and interactions based on stakeholder incentives must be carefully explored. As many design aspects are driven by individual economic incentives, the deployment of DTs has the potential to accelerate prominent issues of data ownership, maintenance responsibilities, and the balance between scalability and use-case specific design (Fuller et al., 2020). Centralized data storage at the vendor site (Vendor-Lock in), infrastructure and technological know-how monopolization, and the primary focus on multi-user design and cash-crops, can lead to unwanted systemic effects that ultimately hinder sustainable farming (see table 1). Without carefully balancing the needs, incentives, and dependencies of the stakeholders, profit-driven DT design could increase single-points of failures, loss of crop diversity, lack of trust in technologies, and societal imbalances. The technological design must therefore acknowledge social feedback mechanisms and enable a careful balance of values without further deepening existing dependencies.

On the **technical** side, a critical aspect of Digital Twin designs is the automated information flow, data processing, or even decision making (Mallinger et al., 2021), which is often based on machine learning models. An unfit design might incorporate unknown biases (by insufficient modelling of use-case domains such as lack of health metric incorporation to enhance productivity) that can reinforce unwanted effects of animal production (animal mismanagement and lower yields) by algorithmic feedback loops. This situation is being aggravated by the combination of multiple and co-depended machine learning models that focus on individual but interconnected aspects of the animal and its environment. As the explainability and transparency of a single model is already very limited (Birhane et al., 2021), building a Digital Twin that exchanges data between multiple models and then uses model outputs further as input for other models, correlations, and calculations, creates an incredibly complex information flow. These direct and hidden machine learning dependencies lower the transparency of the system and in turn effect maintainability, error tracking, and may lead to unwanted emergent effects and feedback processes (Sculley et al., 2015).

Within its **ecological** environment, the DT is inherently linked with its physical entity/subject by monitoring and adjusting the state based on predefined goals. Therefore, any changes on either side (virtual or physical) create feedback mechanisms that alter the state of both. This is further complicated, as the DT farming environment is not a closed system. Any changes on the subject may lead to unforeseen systemic or even cascading effects of its environment. Designing algorithms and data streams without carefully assessing the individual DT environments, can therefore lead to direct or hidden feedbacks and unwanted emergent effects (Ibrion et al., 2019). Creating algorithms and architectures that are flexible enough to cope with such uncertainties and enable robust but also cost-efficient redeployment is therefore one of the biggest systemic challenges for sustainable DT development.

High-level roadmap

Balancing these interdependent social, technical, and ecological requirements is vital to truly realise multi-stakeholder Digital Twins in agriculture and Precision Livestock Farming. As such, the following high-level roadmap in the form of core milestones is outlined:

Milestone One: The alignment of Precision Livestock Farming use-cases and technologies. The arrival of low-cost sensors, cloud computing, and Artificial Intelligence has enabled considerable automation in animal monitoring, and other time-consuming tasks (e.g., automatic feeding, calving detection, etc). Although, many of these systems sit in isolation and data is often used for bespoke applications or singular decision-making tasks (Jayaraman et al., 2016; Neethirajan & Kemp. 2021) we can say with certainty that Digital Twins for Precision Livestock Farming are feasible (Jo et al., 2018). Limited examples in the area demonstrate that research has not fully matured, as the applications which do exist often mirror the technological use-case on which they are built (Neethirajan & Kemp. 2021; Verdouw et al., 2021). To fully leverage the benefits of Agricultural and PLF Digital Twins, data from multiple use-case dependant sources should be collected, combined, and modelled. Although these benefits are easily justified, a more complex task is the reconciliation of intermediate dependencies that must first be overcome to enable these benefits. These include questions pertaining to data privacy and processing. AI models are by their very nature data dependent, and farms are privately owned complex non-uniform environments. Therefore, data privacy and data processing should be considered a prerequisite for large scale data collection, owning to the sensitivity of the domain. For example, stakeholders may want to keep ownership or at least control over sensitive data, avoiding vendor-lock-in or undesirable data use. An initial step might be to research data management approaches which satisfy these privacy concerns, while allowing models to be leveraged for other purposes, or even by other stakeholders. Federated Machine Learning could be one such solution, allowing models to be shared while maintaining data sovereignty and privacy (Ramu et al., 2022). However, these consideration and requirements must be investigated in full and appropriate solution found for true use-case alignment and data consolidation to take place.

Milestone Two: Model modularity, fidelity & validation. Current examples of Digital Twins for PLF are tightly coupled in terms of design, technology, and use-case. An effect of this is that validation, and by extension assessment of model fidelity, is often complex and non-trivial, or overlooked entirely. Expert validation, although adequate for proof of concept and other simpler applications, can lead to significant problems as applications grow in scale and complexity. As current methods do not adhere to concrete methodologies or metrics by which an analytical comparison can be effectively and efficiently made, it will become increasingly difficult to identify models which accurately ensure fidelity, both in unknown and adverse conditions. To overcome these issues, methodological protocols and key performance metrics must be developed to ensure comparability through a set of concise design requirements, enabling standardised approaches for in-depth assessment and understanding of model behaviour and limitation. Such requirements and approaches could enable both decision-safety and ethical concerns to be assessed, and undesirable model behaviour to be mitigated.

The widespread availability of pre-validated modularised and standalone (i.e., single use-case) models would further facilitate such goals. These models would provide users with measured and known failure modes and expected behaviour, allowing Digital Twins to be developed safely and quickly for new applications without needing to undertake cumbersome validation processes (Mahmud et al., 2021; García et al., 2020).

Milestone Three: A FAIR Digital Twin Framework, the FAIR (Findability, Accessibility, Interoperability, and Reuse) principles are ubiquitous in the world of data, forming the conceptual underpinning of current state-of-the-art data management and open system design methodologies (Research Data Alliance, 2020). The Digital Twin as a concept is uniquely positioned to gain significant value from the FAIR methodology. If modular, validated, and use-case aligned Digital Twins are to be fully leveraged, their accessibility to industrial practitioners and the wider research community is a prerequisite. A methodological design framework which adheres to the FAIR principles would be a logical next step in this process. Although the value of such a framework is immediately evident, developing and implementing the required standardised methodological approaches may prove a formidable and complex challenge, requiring the integration and assessment of not only technological criteria, but social, privacy and ethical requirements. The involvement of these distinct and intersecting groups must be ensured, if coherent and applicable guidelines are to be developed and widely adopted.

Conclusions

Digital Twins in agricultural settings are specifically prone to various risks (e.g., single points of failure, cascading errors, unwanted emergence) due to their manifold technological, ecological, and social dependencies. Without proper management, the systemic implications of those risks negatively impact various design requirements simultaneously (e.g., reusability, scalability, maintainability, privacy, security, ethical, etc.) and ultimately, hinder technology adoption. Therefore, defining key design characteristics and management techniques that acknowledge these complex feedback mechanisms and enable flexible and robust DT development are key for sustainable farming, specifically in PLF settings. The authors acknowledge that these interdisciplinary challenges cannot be met by design decisions alone and are a matter of extensive regulatory efforts. Nevertheless, early identification of STES requirements can serve as a multiplier effect for technological and ecological sustainability and foster an environment for balancing economic and ecologic incentives. To achieve this, we identified three milestones that are necessary to manage systemic dependencies and lay the foundations for sustainable DT development. Firstly, the alignment of Digital Twin use-cases, requirements, technology and definitions with those of Precision Livestock Farming (PLF). Secondly, standardised criteria for the development and validation of subsequent models. Finally, the creation of a FAIR principle driven design framework which promotes Digital Twin accessibility.

Acknowledgements

The authors acknowledge the funding of the project “DiLaAg – Digitalization and Innovation Laboratory in Agricultural Sciences”, by the private foundation “Forum Morgen, Austria”, the federal state of Lower Austria and by Project AI4CROPR, No. 877158 funded by the FFG, Austria.

References

Ahlborg, H., Ruiz-Mercado, I., Molander, S., & Masera, O. (2019). Bringing technology into social-ecological systems research—motivations for a socio-technical-ecological systems approach. Sustainability, 11(7).

Birhane A. (2021): Algorithmic injustice: a relational ethics approach. - Patterns 2 (2): 1-9.

Boothby, A. L., & White, D. R. (2021). Understanding the Barriers to Uptake of Precision Livestock Farming (PLF) in the UK Sheep Industry. Agricultural Engineering AgEng2021, 572.

Braun, R., Benedict, M., Wendler, H., & Esswein, W. (2015, May). Proposal for requirements driven design science research. In International Conference on Design Science Research in Information Systems (pp. 135-151). Springer, Cham.

Drewry, J. L., Shutske, J. M., Trechter, D., Luck, B. D., & Pitman, L. (2019). Assessment of digital technology adoption and access barriers among crop, dairy and livestock producers in Wisconsin. Computers and Electronics in Agriculture, 165, 104960.

Erol, T., Mendi, A. F., & Doğan, D. (2020, October). Digital Transformation Revolution with Digital Twin Technology. In 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) (pp. 1-7). IEEE.

Ford, D. N., & Wolf, C. M. (2020). Smart cities with digital twin systems for disaster management. Journal of management in engineering, 36(4), 04020027.

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access, 8, 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

García, R., Aguilar, J., Toro, M., Pinto, A., & Rodríguez, P. (2020). A systematic literature review on the use of machine learning in precision livestock farming. Computers and Electronics in Agriculture, 179, 105826. https://doi.org/10.1016/j.compag.2020.105826

Ibrion, M., Paltrinieri, N., & Nejad, A. R. (2019, October). On risk of digital twin implementation in marine industry: Learning from aviation industry. In Journal of Physics: Conference Series (Vol. 1357, No. 1, p. 012009). IOP Publishing.

IEEE: Systems and software engineering. Vocabulary. ISO/IEC,IEEE 24765:2010(E) (Dec 2010) 1-418.

Jayaraman, P., Yavari, A., Georgakopoulos, D., Morshed, A., & Zaslavsky, A. (2016). Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt. Sensors, 16(11), 1884. https://doi.org/10.3390/s16111884

Jo, S. K., Park, D. H., Park, H., & Kim, S. H. (2018, October). Smart livestock farms using digital twin: Feasibility study. In 2018 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 1461-1463). IEEE.

Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, 29, 36-52.

Mahmud, M. S., Zahid, A., Das, A. K., Muzammil, M., & Khan, M. U. (2021). A systematic literature review on deep learning applications for precision cattle farming. Computers and Electronics in Agriculture, 187, 106313. https://doi.org/10.1016/j.compag.2021.106313

Makinde, A. (2020). Investigating perceptions, motivations, and challenges in the adoption of precision livestock farming in the beef industry (Doctoral dissertation, University of Guelph).

Mallinger, K., Schatten, A., Sendera, G., Klemen, M., & Tjoa, A. M. (2021). Potential Threats of Human Digital Twins for Digital Sovereignty and the Sustainable Development Goals. UN IATT Report.

Neethirajan, S., & Kemp, B. (2021). Digital twins in livestock farming. Animals, 11(4), 1008.

Pylianidis, C., Osinga, S., & Athanasiadis, I. N. (2021). Introducing digital twins to agriculture. Computers and Electronics in Agriculture, 184, 105942.

Ramu, S. P., Boopalan, P., Pham, Q.-V., Maddikunta, P. K. R., Huynh-The, T., Alazab, M., Nguyen, T. T., & Gadekallu, T. R. (2022). Federated learning enabled digital twins for smart cities: Concepts, recent advances, and future directions. Sustainable Cities and Society, 79, 103663. https://doi.org/10.1016/j.scs.2021.103663

Research Data Alliance FAIR Data Maturity Model Working Group. (2020). FAIR Data Maturity Model: Specification and guidelines. https://doi.org/10.15497/RDA00050

Uhlenkamp, J. F., Hribernik, K., Wellsandt, S., & Thoben, K. D. (2019, June). Digital Twin Applications: A first systemization of their dimensions. In 2019 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1-8). IEEE.

Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. Agricultural Systems, 189, 103046. https://doi.org/10.1016/j.agsy.2020.103046