Experiences in Developing Configurable Digital Twin-assisted xR Applications for Industrial Environments

Richard May
Harz University of Applied Sciences
Wernigerode, Germany
rmay@hs-harz.de

Simon Adler
Harz University of Applied Sciences
Wernigerode, Germany
simonadler@hs-harz.de

Abstract

The integration of digital twins, i.e., virtual replicas of physical systems, is increasingly transforming manufacturing by enhancing efficiency through real-time monitoring, simulation, and optimization. The 3D-visualization of their data as a core functionality of xR applications (e.g., Virtual Reality) extends their usefulness and can be used as an important tool for teaching, training, and support. However, in addition to already known and well-discussed challenges (e.g., data representation), developing digital twin-assisted xR applications poses various variability challenges due to the complexity of manufacturing processes, data models, and the need for configurability across various scenarios and platforms. In this paper, we share our experiences in developing such applications, focusing on the gap of handling variability. Based on the DigiLehR research project, which also includes three industrial use cases as configurable products of an xR application family, we describe challenges we faced during development and essential lessons learned. Here, we particularly focus on platform specifics, immersion and interaction, digital twin-related data fragmentation, accessibility, and security. Overall, our work aims to create awareness for practitioners and researchers about the challenges of developing digital twin-assisted xR applications and their configurations, encouraging discussions on their efficient application in industrial settings.

CCS Concepts

• Software and its engineering → Reusability; **• Computer systems organization → Embedded and cyber-physical systems**; **• Human-centered computing → Interaction paradigms**.

Keywords

extended reality, virtual reality, augmented reality, digital twins, configuration, modularization, manufacturing, industry 4.0

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1 Introduction

With the rise of Industry 4.0, information and communication technologies are increasingly being integrated into manufacturing processes. The value added by industrial machines now extends beyond the manufactured product to include the generation of digital data during manufacturing [36, 38]. This data can be used for various new fields and associated applications, with *digital twins* standing out as an area of particularly high potential. Digital twins are comprehensive virtual replicas of physical systems that facilitate real-time monitoring, simulation, and optimization of manufacturing processes [40, 42]. In more detail, they typically denote a quality criteria about the digital data which should at least reflect the current state of industrial machines but could also include historical signal data, documents, or process data [1, 11]. By utilizing such data, companies can gain valuable insights into their manufacturing processes, leading to significant enhancements in efficiency and productivity, for example, based on predictive maintenance [30, 37].

Although 3D-visualizations are not a key requirement for digital twins, they offer another way to effectively utilize their data [16, 45]. Such visualizations can be particularly valuable for teaching, training, or supportive purposes [23, 39] with a high potential for mobile as well as EXtended Reality (xR) applications, i.e., typically Virtual Reality (VR) and Augmented Reality (AR) [43, 49]. This is why, there is already numerous research on such applications, their challenges, and potentials, ranging from educating students [39] to supporting practitioners in industrial environments [25]. For example, Hazrat et al. [17] reported on utilizing digital twins in engineering education to facilitate the training of human-centric decision-making and Kuts et al. [22] developed a VR-based digital twin-assisted factory environment for learning purposes. Calandra et al. [7] proposed an xR application, which allows collaboratively programming a digital twin-assisted robot. Moreover, Kaarlela et al. [19] presented scenarios of digital twin-assisted safety and emergency training.

Overall, we argue that developing xR applications relying on digital twins is highly challenging — not only due to their increasing complexity (e.g., manufacturing processes, data models, data visualization) [2, 20, 48], but also due to growing demands to efficiently adapt the xR application to dynamic scenarios and users, as well as to deploy them on different platforms (e.g., VR, AR, and mobile devices) [12, 13]. Consequently, digital twin-assisted xR applications must be highly configurable to address such requirements, leading to various common challenges in handling variability, such as valid configurations and their effective verification [8, 21, 32] or reliable and secure evolution [28, 33]. However, due to the unique peculiarities of digital twins (e.g., data fragmentation [14]) and xR technologies (e.g., 3D-visualization [34]), they pose additional challenges in efficiently handling their features.

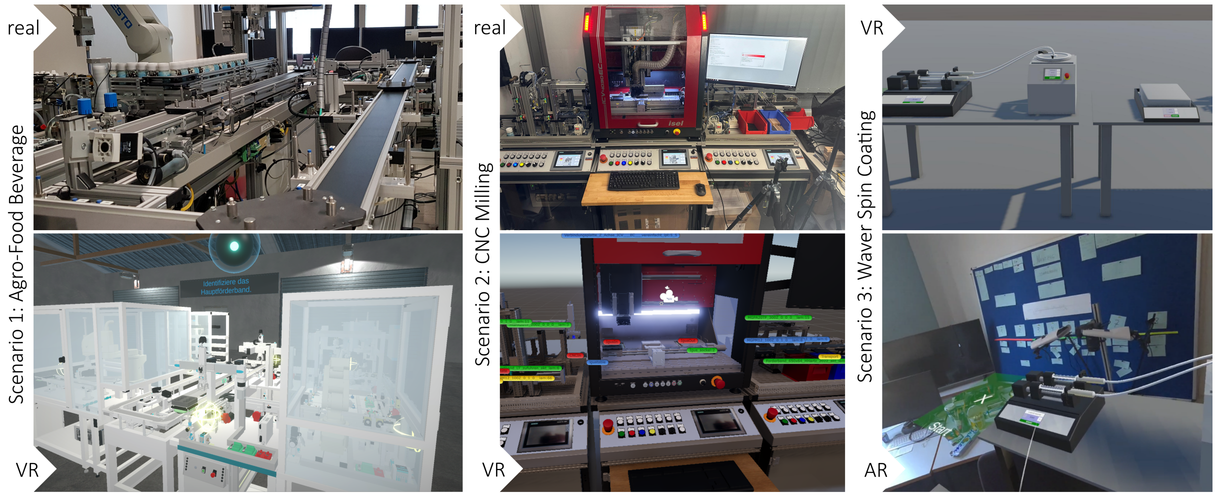

Figure 1: Scenario overview for agro-food beverage (Scenario 1), CNC milling (Scenario 2), and spin coating (Scenario 3).

Although there is not only extensive research related to digital twin-assisted xR applications for Industry 4.0 but also related to managing variability in industrial environments [24, 31, 44], we are not aware of work focusing on both properties, i.e., digital twin-assisted xR applications in Industry 4.0 and their variability. The closest work to ours is by Fernandes and Werner [12, 13] who focused on a web xR application software product line for software engineering education. However, digital twin technology was not part of their study, highlighting the value of our goals. **To address this gap, we aim to share our experiences by reporting challenges we faced and lessons we learned during the development of a family of configurable (i.e., variable) digital twin-assisted xR applications for industrial environments.**

Our insights are based primarily on a research project called *Digital Teaching and Learning in Augmented Realities (DigiLehR)* that investigates the potential of utilizing xR technologies for teaching, training, and supportive purposes. In this context, different industrial scenarios were enhanced by digital twin-assisted xR, including *agro-food beverage*, *CNC milling*, and *waver spin coating* (cf. Sec. 2). To enable reusability of variable features and to restrict additional efforts in resources, we roughly followed a software product line approach [3], i.e., leading to several similar, but adapted applications. Overall, we aim to contribute the following:

- Insights into variability handling in applications for industrial scenarios utilizing both xR and digital twin technologies.
- Challenges and lessons learned in developing configurable digital twin-assisted xR applications.

With our work, we aim to increase the awareness of variability in applications based on xR and digital twin technologies and to spur discussions on handling it efficiently.

2 Industrial Scenarios

While xR applications themselves are already quite complex, the deployment for different scenarios and platforms taking into account digital twin data resulted, not surprisingly, in large efforts. This is why a configurable approach to reuse features was used, which, starting from a basic product with mandatory (i.e., transferable) features and additional optional features, ensured significantly more efficient development. Generally, all scenarios rely on a feature model (Fig. 2) and are implemented based on Unity as well as the xR Interaction Toolkit.

Scenario 1: Agro-Food Beverage *(VR, mobile).* The application consists of an agro-food beverage (AFB) (Fig. 1, left) machine, including seven assembly units, driven by Siemens S300 PLC each. It realizes a circular process with a bottle storage and a module to extract filled, and return empty bottle packages. In addition, it mainly contains discrete actuators and sensors to assert the automated process. With xR-AFB, users should first understand the machine, its parts, their purpose, and how to put the machine into operation. The order in which to start the assembly units is arbitrary; but they depend on each other. So, one learning goal is to differentiate between regular behavior, usual failures, and failures that require expert consultations. For xR the scene is spatially large and geometrically complex. Users must be able to navigate and select components on VR and mobile devices.

Scenario 2: CNC Milling *(VR, mobile).* Here, a CNC milling machine (Fig. 1, middle) was realized, consisting of four assembly units: three are controlled by a Siemens S1500 PLC; one is the isle-CNC main unit. The machine has an input assembly unit with material magazines. Operators can choose a type of material and a drilling recipe. Conveyors will transport the material to the CNC. After completion, the product is transported to an output storage. The operation is standardized, but users must be aware of small steps, that can easily overseen (e.g., hatch must be closed before powering the CNC). The main goal of xR-CNC is the training of operation and how to drill products. The xR scene is less complex than in Scenario 1, but the operation is controlled by human-machine interaction (HMI). Virtual HMI can be easily used on mobile devices by touch gestures; care must be taken in VR due to their small scale.

Scenario 3: Waver Spin Coating *(VR, AR, mobile).* This application contains a waver spin coater (Fig. 1, right), which is a batch processing with manual tasks, including four independent stations. First, users pick up a waver to place it in the spin coater; and select

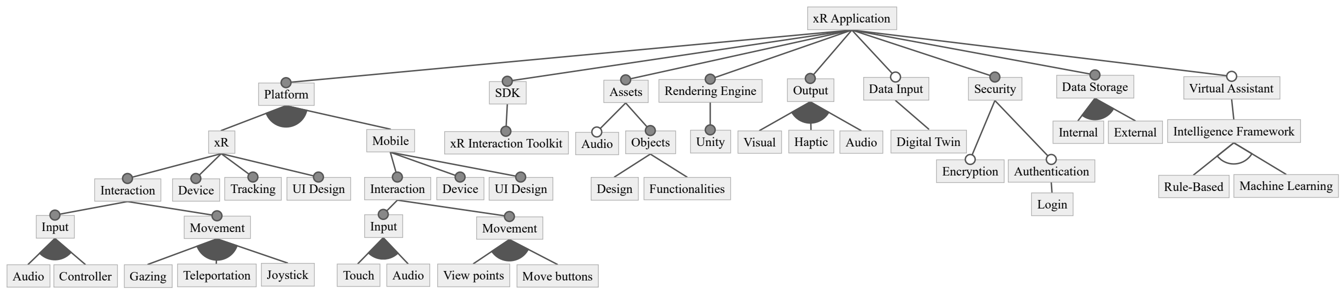

Figure 2: Simplified feature model for configurable xR applications.

a type and amount of liquid from a connected pump station, which will drop the liquid on the waver. Then, users select the temperature, duration, and speed in which the waver will be rotated to distribute the liquid. Finally, the coating quality is measured after selecting the temperature and duration for drying the waver.

Even with professional equipment, each step has variance σ, influencing the outcome. So, users can train how to balance settings (i.e., via HMI), to achieve a result within requirements without wasting material. The experiments are recorded in a protocol monitored live by trainers, if required. The interaction in VR is mostly two-handed (e.g., opening the spin coater with one hand and placing the waver with the other hand). In VR the placement is done manually, for mobile devices animations are used.

3 Challenges and Lessons Learned

Next, experiences and lessons learned we have made during development, in particular related to variability issues, are explained. Fig. 2 provides a general overview of relevant features of the xR applications we relied on. For reasons of simplicity, cross-tree constraints have been excluded here, however, this does not mean that there are none (e.g., joystick movement and mobile platforms).

3.1 Platform Specifics

Challenges. Deploying 3D-visualizations in xR environments and traditional mobile platforms, presents diverse challenges rooted in the individual scenario requirements but also in the distinct hardware capabilities associated with each platform. Even when employing identical visualizations and data, these platforms often require distinct interaction modalities and specific user interface (UI) elements. For instance, VR might require high-resolution graphics, spatial audio, and real-time 3D-rendering to maintain immersion, utilizing motion controllers for interaction with simulated real-world objects [10, 50]. In contrast, AR focuses on overlaying digital information onto the physical environment and typically relies on touchscreens or simple gestures [5, 50]. Meanwhile, mobile devices prioritize touch interactions and responsive design, often employing more traditional 2D-UI elements within simplified 3D-spaces [46]. These differences require the development of platform- as well as device-specific interaction modes, posing challenges in maintaining uniformity in usability and functionality. Integrating and synchronizing these variants while ensuring accurate and consistent data visualization across platforms during evolution adds additional layers of complexity to the development process.

Lessons Learned. To address these challenges, a significant lesson learned is the advantage of using standardized frameworks, such as questionnaires, as a foundation for designing interactions. By categorizing interactions that correspond to assessable questionnaire answers oriented towards each scenario (e.g., CNC milling in Scenario 2), developers can establish structured, platform-specific interaction patterns. This strategy allows the abstraction of essential user engagement components, such as selecting options and navigating environments, which can then be tailored to various input methods available on each platform. Note that although configurability is achieved through questionnaires, the actual possibilities for interaction are limited. Furthermore, leveraging transferable UI technologies (e.g., buttons) through at best platform-independent SDKs (e.g., xR Interaction Toolkit) and engines (e.g., Unity) helps to harmonize interactions and visualizations across devices.

3.2 Immersion and Interaction

Challenges. Typically, xR environments are distinguished by their degree of immersion. High immersion means that user perceive and accept the simulation as realistic and themself as part of the simulation [6]. For this perception of presence, natural interaction methods must be used – in contrast to traditional UIs, which are characterized by more static elements such as buttons and menus [41]. In virtual environments, users can interact, for example, by gestural manipulation of virtual objects, spatial navigation via bodily movements, and virtual assistant support. In this context, there is a high complexity and variability implementing these interactions. Accurate detection and interpretation of variant-rich input modalities requires reliable tracking systems. Furthermore, developers must meet stringent performance demands, balancing high-quality environmental rendering with the need for seamless, responsive interaction processing (cf. Scenario 1).

Lessons Learned. To address these challenges, Hunicke et al. [18] proposed the MDA-framework at concept level, differentiating the development process in phases of Mechanics, Dynamics, and Aesthetics. Developers start by developing mechanics to allow users some dynamics, because users should get into a specific mood. On the other hand, users try to perform a interaction because of a mood and search for mechanics or objects to do so. The processes of developers and users are therefore in contradiction.

Managing variability within the MDA-framework is crucial for accommodating diverse user preferences and device capabilities. This is achieved through user-centric configuration, where users are able to adjust settings like sensitivity or control schemes for personalized experiences, or adaptive systems semi-automatically modifying mechanics based on user behavior to optimize interaction. Reusable designs, objects, and functions that support high immersion facilitate the efficient coverage of variant-rich scenarios.

3.3 Data Fragmentation and Association

Challenges. Developing digital twin-assisted systems is challenging due to the fragmentation of data, their different sources (e.g., different machines or parts of them), and the association between datasets. Because of data fragmentation it is difficult to ensure that data is consistently and accurately represented within the digital twin [14]. Data is collected in multiple formats and update frequencies [51], complicating (real-time) integration into xR applications. So, digital twins and their associated data have a high degree of variability that must be managed accordingly.

Lessons Learned. In our project, different platforms were treated as variants of a Unity base scenario to ensure a centralized data integration. This enables consistent management of data, relationships, and (cross)dependencies between multiple configurations and platforms. Implementing standardized data schemes and APIs facilitate seamless data exchange and transformation. Leveraging middleware solutions (i.e., C# scripts) to harmonize formats allows to create a unified data pipeline within the digital twin framework.

3.4 User Accessibility

Challenges. Motion sickness, or the (temporal) availability of the required xR hardware, requires alternatives to accommodate a diverse user base. This makes configurability an essential requirement in xR applications to tackle this variability issue. Thus, a great challenge is to integrate configuration options into the development project, ensuring that features remain accessible to all users or industrial scenarios regardless of their individual constraints (e.g., grabbing items, such as a waver in Scenario 3).

Lessons Learned. One strategy is to implement visualization techniques guiding users through xR by highlighting interaction targets and providing visual cues (e.g., using specific colors, lights). This makes environments more navigable and less challenging for users prone to motion sickness, as they can control the pacing and intensity of their interactions. We also offered users to switch between xR and offline-working mobile apps, based on their comfort level and restrictions. Additionally, by providing options for different interaction methods based on different platforms as well as additional support by configurable conversational agents [29] we tried to ensure that all users, regardless of their physiological responses or device constraints, can effectively use all scenarios. In our perception, this configurability not only enhanced user satisfaction but also helps in reducing potential discrimination against people.

3.5 Security

Challenges. While digital twins as counterparts to safety-critical machines are known for their ability to reduce functional safety risks [4], there are several challenges related to security, including associated privacy risks. These are typically more related to integrated digital twins based on real-time data than to those based on fixed datasets. Real-time digital twins in xR applications usually involve the continuous collection, processing, and visualization of detailed operational and potentially sensitive data. Such dynamic data streams are vulnerable to unauthorized access, possibly leading to data breaches and compromised system integrity [9, 15]. Additionally, integrating xR applications and digital twins with additional (critical) industrial systems may increase the attack surface even more, making the systems more vulnerable to potential attacks. Even more potential threats can arise due to common configurability issues, ranging from (cross-)dependency issues over unwanted feature interactions to misconfiguring applications [27, 28, 47]. So, the more complex and configurable the system, the greater the attack surface and thus the number of possible attacks [28].

Lessons Learned. To address security challenges, a security engineering approach is recommended, i.e., integrating security into the development process as phase between domain and application engineering [26]. For real-time digital twin-assisted xR applications, implementing a layered security architecture with dynamic encryption and authentication protocols helps mitigate dynamic risks. In non-real-time applications, securing stored data with encryption, access controls (e.g., account systems), and isolating particularly sensitive data is key. Effective dependency and configuration handling as well as defensive configuring prevent configuring issues and helps maintaining system confidentiality, integrity, and availability in different scenarios [35]. In our case, performing not only feature-/product-based verification (i.e., testing), but also family-based verification was useful for addressing issues that originate from the xR application family (e.g., core assets). In addition, isolating (i.e., modularizing) essential features and their source code under consideration of information hiding and optional encryption may reduce the attack surface and associated privacy risks.

4 Conclusion

In this paper, we shared our experiences in developing digital twin-assisted xR applications for industrial environments and efficiently handling their variability. We presented challenges and associated lessons learned, including platform specifics, immersion and interaction, digital twin-related data fragmentation, accessibility, and security. Configurability of xR applications is a key requirement to efficiently develop related variants, which, however, can lead to various issues to be addressed. Several additional research directions arise, taking into account the unique properties of digital twins, xR applications, and industrial environments. For instance, developing guidelines based on software product lines for handling configurability, enhancing data integration and synchronization across platforms, investigating influences related to no-code / low-code, or strengthening security measures tailored to occurring feature interactions and (cross)configurations.

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References

[1] S. Adler and E. Bayrhammer. 2019. Engineering model linking and ontology linking for production. In *European Conference on Smart Objects, Systems and Technologies (Smart SysTech)*. 1–6.

[2] S. Alizadehsalehi and I. Yitmen. 2023. Digital twin-based progress monitoring management model through reality capture to extended reality technologies (DRX). *Smart and Sustainable Built Environment* 12, 1 (2023), 200–236.

[3] S. Apel, D. Batory, C. Kästner, and G. Saake. 2013. *Feature-oriented software product lines.* Springer.

[4] M. Attaran and B. G. Celik. 2023. Digital twin: Benefits, use cases, challenges, and opportunities. *Decision Analytics Journal* 6 (2023), 100165.

[5] M. Billinghurst. 2021. Grand challenges for augmented reality. *Frontiers in Virtual Reality* 2 (2021), 578080.

[6] P. Cairns, A. Cox, and A. I. Nordin. 2014. Immersion in digital games: Review of gaming experience research. *Handbook of Digital Games* (2014), 337–361.

[7] D. Calandra, F. G. Pratticò, A. Cannavò, C. Casetti, and F. Lamberti. 2022. Digital twin-and extended reality-based telepresence for collaborative robot programming in the 6G perspective. *Digital Communications and Networks* (2022), 315–327.

[8] T. Castro, L. Teixeira, V. Alves, S. Apel, M. Cordy, and R. Gheyi. 2021. A Formal framework of software product line analyses. *ACM Transactions on Software Engineering and Methodology* 30, 3 (2021), 1–37.

[9] A. J. G. de Azambuja, T. Giese, K. Schützer, R. Anderl, B. Schleich, and V. R. Almeida. 2024. Digital twins in Industry 4.0 — Opportunities and challenges related to cyber security. *Procedia CIRP* 121 (2024), 25–30.

[10] A. C. C. dos Santos, M. E. Delamaro, and F. L. S. Nunes. 2013. The relationship between requirements engineering and virtual reality systems: A systematic literature review. In *Symposium on Virtual and Augmented Reality*. IEEE, 53–62.

[11] M. Eisenträger, S. Adler, and E. Fischer. 2019. Rethinking software development for collaboration technologies. In *International Conference of Engineering, Technology, and Innovation (ICE/IEE ITMC)*. 1–9.

[12] F. A. Fernandes and C. M. L. Werner. 2022. A scoping review of the metaverse for software engineering education: Overview, challenges, and opportunities. *PRESENCE: Virtual and Augmented Reality* 31 (2022), 107–146.

[13] F. E. Fernandes and C. M. L. Werner. 2022. Software product line for metaverse: Preliminary results. In *Smartworld, Ubiquitous Intelligence & Computing, Scalable Computing & Communications, Digital Twin, Privacy Computing, Metaverse, Autonomous & Trusted Vehicles (SmartWorld/UIC/ScalCom/DigitalTwin/PriComp/Meta)*. IEEE, 2413–2420.

[14] G. Fortino and C. Savaglio. 2023. Integration of digital twins & internet of things. In *The Digital Twin*. Springer, 205–225.

[15] S. Guikema and R. Flage. 2024. Digital twins as a security risk. *Perspective* 121 (2024), 1–5.

[16] Z. Han, Y. Li, M. Yang, Q. Yuan, L. Ba, and E. Xu. 2020. Digital twin-driven 3D visualization monitoring and traceability system for general parts in continuous casting machine. *Journal of Advanced Mechanical Design, Systems, and Manufacturing* 14, 7 (2020), 1–15.

[17] M. A. Hazrat, N. M. S. Hassan, A. A. Chowdhury, M. G. Rasul, and B. A. Taylor. 2023. Developing a skilled workforce for future industry demand: The potential of digital twin-based teaching and learning practices in engineering education. *Sustainability* 15, 23 (2023), 16433.

[18] R. Hunicke, M. Leblanc, and R. Zubek. 2004. MDA: A formal approach to game design and game research. *AAAI Workshop - Technical Report* 1 (01 2004).

[19] T. Kaarlela, S. Pieskä, and T. Pitkäaho. 2020. Digital twin and virtual reality for safety training. In *International Conference on Cognitive Infocommunications (CogInfoCom)*. IEEE, 115–120.

[20] H. M. Kamdjou, D. Baudry, V. Havard, and S. Ouchani. 2024. Resource-Constrained eXtended reality operated with digital twin in industrial Internet of Things. *Open Journal of the Communications Society* (2024).

[21] E. Kuiter, A. Knüppel, T. Bordis, T. Runge, and I. Schaefer. 2022. Verification strategies for feature-oriented software product lines. In *International Working Conference on Variability Modelling of Software-Intensive Systems (VaMoS)*. ACM, 1–9.

[22] V. Kuts, T. Otto, E. G. Caldarola, G. E. Modoni, and M. Sacco. 2018. Enabling the teaching factory leveraging a virtual reality system based on the Digital Twin. In *EuroVR Conference*. VTT Technology.

[23] A. Liljaniemi and H. Paavilainen. 2020. Using digital twin technology in engineering education–course concept to explore benefits and barriers. *Open Engineering* 10, 1 (2020), 377–385.

[24] S. Malakuti. 2021. Emerging technical debt in digital twin systems. In *International Conference on Emerging Technologies and Factory Automation (ETFA)*. IEEE, 01–04.

[25] A. Martínez-Gutiérrez, J. Díez-González, P. Verde, and H. Perez. 2023. Convergence of virtual reality and digital twin technologies to enhance digital operators' training in industry 4.0. *International Journal of Human-Computer Studies* 180 (2023), 103136.

[26] R. May, C. Biermann, A. Kenner, J. Krüger, and T. Leich. 2023. A product-line-engineering framework for secure enterprise-resource-planning systems. In *International Conference on ENTERprise Information Systems*. Elsevier, 1–8.

[27] R. May, C. Biermann, J. Krüger, and T. Leich. 2025. Asking security practitioners: Did you find the vulnerable (mis)configuration?. In *International Workshop on Variability Modelling of Software-intensive Systems (VaMoS)*. ACM, 1–10.

[28] R. May, C. Biermann, X. M. Zerweck, K. Ludwig, J. Krüger, and T. Leich. 2024. Vulnerably (mis)configured? Exploring 10 years of developers' Q&As on Stack Overflow. In *International Workshop on Variability Modelling of Software-intensive Systems (VaMoS)*. ACM, 112–122.

[29] R. May and K. Denecke. 2024. Conversational agents in healthcare: A variability perspective. In *Working Conference on Variability Modelling of Software-Intensive Systems (VaMoS)*. ACM, 123–128.

[30] R. May., T. Niemand., P. Scholz., and T. Leich. 2023. Design patterns for monitoring and prediction machine learning systems: Systematic literature review and cluster analysis. In *International Conference on Software Technologies (ICSOFT)*. SciTePress, 209–216.

[31] K. Meixner, K. Feichtinger, H. S. Fadhlillah, S. Greiner, H. Marcher, R. Rabiser, and S. Biffl. 2024. Variability modeling of products, processes, and resources in cyber–physical production systems engineering. *Journal of Systems and Software* 211 (2024), 112007.

[32] M. Nieke, C. Seidl, and S. Schuster. 2016. Guaranteeing configuration validity in evolving software product lines. In *International Workshop on Variability Modelling of Software-intensive Systems (VaMoS)*. ACM, 73–80.

[33] C. Quinton, M. Vierhauser, R. Rabiser, L. Baresi, P. Grünbacher, and C. Schuhmayer. 2021. Evolution in dynamic software product lines. *Journal of Software: Evolution and Process* 33, 2 (2021), e2293.

[34] E. M. Raybourn, W. A. Stubblefield, M. Trumbo, A. Jones, J. Whetzel, and N. Fabian. 2019. Information design for xr immersive environments: Challenges and opportunities. In *International Conference on Virtual, Augmented and Mixed Reality. Multimodal Interaction (VAMR)*. Springer, 153–164.

[35] S. Samonas and D. Coss. 2014. The CIA strikes back: Redefining confidentiality, integrity and availability in security. *Journal of Information System Security* 10, 3 (2014).

[36] G. Schuh, M. Riesener, A. Gützlaff, C. Dölle, S. Schmitz, J. Ays, S. Wlecke, J. Tittel, and Y. Liu. 2022. Industry 4.0: Agile development and production with internet of production. In *Handbook Industry 4.0: Law, Technology, Society*. Springer, 367–390.

[37] G. Schuh, P. Scholz, T. Leich, and R. May. 2020. Identifying and analyzing data model requirements and technology potentials of machine learning systems in the manufacturing industry of the future. In *ITM)*. IEEE, 1–10.

[38] G. Schuh, P. Scholz, and M. Nadicksbernd. 2020. Identification and characterization of challenges in the future of manufacturing for the application of machine Learning. In *International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS)*. IEEE, 1–10.

[39] S. M. E. Sepasgozar. 2020. Digital twin and web-based virtual gaming technologies for online education: A case of construction management and engineering. *Applied Sciences* 10, 13 (2020), 4678.

[40] M. Singh, E. Fuenmayor, E. P. Hinchy, Y. Qiao, N. Murray, and D. Devine. 2021. Digital twin: Origin to future. *Applied System Innovation* 4, 2 (2021), 36.

[41] D. Stone, C. Jarrett, M. Woodroffe, and S. Minocha. 2005. *User interface design and evaluation.* Elsevier.

[42] F. Tao, B. Xiao, Q. Qi, J. Cheng, and P. Ji. 2022. Digital twin modeling. *Journal of Manufacturing Systems* 64 (2022), 372–389.

[43] X. Tu, J. Autiosalo, R. Ala-Laurinaho, C. Yang, P. Salminen, and K. Tammi. 2023. TwinXR: Method for using digital twin descriptions in industrial eXtended reality applications. *Frontiers in Virtual Reality* 4 (2023), 1019080.

[44] M. P. Uysal and A. E. Mergen. 2021. Smart manufacturing in intelligent digital mesh: Integration of enterprise architecture and software product line engineering. *Journal of Industrial Information Integration* 22 (2021), 100202.

[45] E. Van Der Horn and S. Mahadevan. 2021. Digital twin: Generalization, characterization and implementation. *Decision Support Systems* 145 (2021), 113524.

[46] P. Weichbroth. 2020. Usability of mobile applications: a systematic literature study. *IEEE Access* 8 (2020), 55563–55577.

[47] T. Xu and Y. Zhou. 2015. Systems approaches to tackling configuration errors: A survey. *Comput. Surveys* 47, 4 (2015), 1–41.

[48] C. Yang, X. Tu, J. Autiosalo, R. Ala-Laurinaho, J. Mattila, P. Salminen, and K. Tammi. 2022. Extended reality application framework for a digital-twin-based smart crane. *Applied Sciences* 12, 12 (2022), 6030.

[49] Y. Yin, P. Zheng, C. Li, and L. Wang. 2023. A state-of-the-art survey on augmented reality-assisted digital twin for futuristic human-centric industry transformation. *Robotics and Computer-Integrated Manufacturing* 81 (2023), 102515.

[50] T. Zhan, K. Yin, J. Xiong, Z. He, and S.-T. Wu. 2020. Augmented reality and virtual reality displays: Perspectives and challenges. *iScience* 23, 8 (2020).

[51] H. Zhang, Q. Yan, and Z. Wen. 2020. Information modeling for cyber-physical production system based on digital twin and AutomationML. *The International Journal of Advanced Manufacturing Technology* 107, 3 (2020), 1927–1945.