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Abstract:

Digitization provides entirely new affordances for our economies and societies. This leads to previously unseen design opportunities and complexities as systems and their boundaries are re-defined, creating a demand for appropriate methods to support design that caters to these new demands. Conceptual modeling is an established means for this, but it needs to advance to adequately depict the requirements of digitization. However, unlike the actual deployment of digital technologies in various industries, the domain of conceptual modeling itself has not yet undergone a comprehensive renewal in light of digitization. Therefore, inspired by the notion of Industry 4.0, an overarching concept for digital manufacturing, in this commentary paper, we propose Modeling 4.0 as the notion for conceptual modeling mechanisms in a digital environment. In total, 12 mechanisms of conceptual modeling are distinguished, providing ample guidance for academics and professionals interested in ensuring that modeling techniques and methods continue to fit contemporary and emerging requirements.

Keywords: Conceptual Modeling, Digitization, Industry 4.0, Mechanisms.

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

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1 Introduction

Conceptual modeling is a critical activity in systems analysis and design. IS professionals develop graphical representations to describe relevant aspects of a real-world domain for understanding, communicating, and reasoning about it (Mylopoulos, 1992). These representations are called conceptual models. They are developed using modeling grammar, methods, and tools (Wand & Weber, 2002). Several studies have shown that IS professionals use conceptual modeling for various purposes related to gaining a better understanding of current systems and articulating new design options (Bourque & Fairley, 2014; Brambilla et al., 2017; da Silva, 2015). In particular, conceptual models are deployed for large-scale software engineering (Hutchinson et al., 2014; Whittle et al., 2014); open-source software development (Robles et al., 2017); in agile projects (Moyano et al., 2022); as well as to assist with business analytics (Moyano et al., 2022); and big data initiatives (Storey & Song, 2017). More recently, conceptual models are also used in professionals' work with AI (Lukyanenko, Castellanos, et al., 2019; Nalchigar et al., 2021); to describe the Internet of Things (IoT) solutions (Yuan et al., 2019); or to conceptualize robotic process automation (Völker and Weske, 2021).

Formal or semi-formal representations have been used by system designers, business analysts, process analysts, and software developers to design and analyze systems and visualize datasets or processes. However, traditional conceptual models provide static representations of focal real-world phenomena and are explicitly specified at design time (Benslimane et al., 2009). Their maintenance is challenging in terms of the costs and time of change management and often inadequate in terms of version and release management so that evolutions of these models are not represented appropriately.

Digitization provides new affordances for our economies and societies. This includes, among others, the ability to access and analyze real-time data of large scale, advanced sensing capabilities providing access to new data sets, sophisticated forms of visualization that facilitate advanced comprehension, and the ability to personalize cost-effectively. As a result, new frameworks and entire paradigms, such as smart manufacturing with personalized batch size one production or the metaverse with its digital twinning and engagement opportunities, are emerging.

As such, digital technologies reinstate and combine manufacturing practices, industrial platforms, production planning, and control with the affordances of digital technologies and smart automation. Various digital technologies converge to build and empower intelligence, connectivity, and cognitive automation in a contemporary manufacturing and industrial landscape using advanced machine-to-machine interactions, the Internet of Things (IoT), sensors, smart systems, and actors. New levels of sophisticated communication and self-monitoring arise and change the nature of current information systems (Lasi et al., 2014). For example, hybrid, i.e., physical-digital manufacturing systems emerge, and existing manufacturing systems are becoming decentralized, integrated, and autonomous, whereas product and service development become individualized (Dalenogare et al., 2018; Lasi et al., 2014).

Conceptual modeling still remains relevant to represent essential features of highly intertwined digital technologies (Recker et al., 2021). However, digital technologies are changing the domains and context of modeling, which requires a new modeling paradigm. For instance, agile technologies challenge the utility and efforts needed to develop models (Erickson et al., 2005), and the constantly changing nature of digital technologies challenges the maintenance and accuracy of conceptual models (Frisendal, 2016; Hills, 2016). We, therefore, argue that conceptual modeling requires a new set of capabilities tailored to the affordances of digital technologies (Jabbari et al., 2018). For example, digital technologies need to be comprehended in terms of their scale and continuous change, catalyze new environments that need to be modeled (e.g., intelligent systems), and provide new ways to model (e.g., augmented modeling). Thus, digitalization affects *why* we model, *what* we model, and *how* we design and use models. Therefore, future research on conceptual modeling needs to consider the emerging technology adoption to address the evolving requirements of information systems developers and users (Storey et al., 2023). In light of this context, our commentary proposes new design principles and mechanisms that reflect these requirements. Our proposed design principles depict *fundamental assumptions of modeling in the digital age,* and our mechanisms capture *modeling requirements in digital environments*. Our proposed principles and mechanisms can act as a foundational reference for researchers delving into the dynamic landscape and evolving nature of conceptual modeling. Moreover, they offer guidance in formulating essential requirements for tool providers and process analysts when developing and configuring new concept modeling environments.

To achieve these aims, we first provide a longitudinal conceptualization of the core stages of conceptual modeling to derive what we call the notion of *Modeling 4.0*. Then, we draw on the main principles of Industry 4.0, i.e., modularity, interoperability, real-time capability/response, virtualization, decentralization, and service orientation. We argue that an analogous adoption of the capabilities of a digital environment is required for conceptual modeling. Consequently, we call this *"Modeling 4.0",* an umbrella term used to capture the mechanisms of conceptual modeling needed to deal with a digitalized, smart, and autonomous environment. Modeling 4.0 suggests that traditional models should be adapted to be interoperable, virtual, decentralized, real-time, service-oriented, and robust to cope with the changes induced by the uptake of digital technologies.

2 The Four Stages of Conceptual Modeling

Conceptual models are defined as representations of an individual's or group's understanding of a real-world domain and the features or phenomena in that domain (Kung & Sølvberg, 1986; Mylopoulos, 1992; Wand & Weber, 2002). Information Systems (IS) professionals such as systems designers, software developers, and business and process analysts use conceptual models to develop integrated data schemas, design current and intended models of business processes, or conceptualize entire information systems. They use semi-formal graphical representations, which are developed using conceptual modeling grammar. Grammars provide a set of constructs and the rules by which to use the constructs to represent real-world phenomena (Wand & Weber, 2002).

Before conceptual modeling was introduced to capture conceptual structures of a domain in notations that a programmable computer can manipulate, humans were using graphical representations to model systems and relevant elements of their environment. Such models were considered some of the earliest universal characteristics of human activity (Funkhouser, 1937). The ideographic drawings of the cave dwellers indicate that humans - from the early stages – employed graphical representations to communicate their thoughts. The communication languages of Babylonian, Mayan, and Egyptian civilizations were essentially graphical symbols (Funkhouser, 1937). As the sciences emerged and developed, graphical aids continued to be used to facilitate better understanding, and their application evolved to manage a series of tasks required to achieve a particular objective. For instance, harmonograms – the early root of Gantt charts – were used as graphical solutions to production problems as they were used to present diagrams of workflow networks (Marsh, 1975). We call this era "**Modeling 1.0**". In this stage, the basic fundamentals of modeling emerged; models were not formally structured, and modeling grammars were not yet formally defined to be used as a standard in developing models.

Modeling 2.0 was the era between the 1970s and 1980s marked as a golden age of invention in programming languages and databases. It was when information systems developers recognized the importance of conceptual modeling in eliciting and articulating user mechanisms, understanding the different properties of domains, and providing insights into data and design processes. In this era, conceptual modeling as we know it today was invented, and structured grammars such as the Entity Relationship Diagram to present static aspects (e.g., things and their properties) (Chen, 1976) or Petri Nets to represent dynamic aspects (e.g., events and processes) (Petri, 1962) were invented. Their syntax, semantics, and notations were formally specified (e.g., in the form of meta-models), and formal approaches to represent different aspects of phenomena and ontologies as meta-theories evolved (Wand & Weber, 2002). Based on this foundation and the rising need for a shared language, more formal modeling methods were proposed (Mylopoulos, 1992, 1998). In the mid-1990s, practices like object-oriented analysis and design created another wave of conceptual modeling research in which new methods and grammar were developed (Vessey & Conger, 1994). Modeling 2.0 is therefore characterized by the existence of well-defined, meta-model grammars that facilitate the representation of a specific aspect of the real-world (e.g., data, objects, processes).

Modeling 3.0 is the era when the previously separate grammars were consolidated into overarching, integrated frameworks. Advanced modeling techniques such as Unified Modeling Language (OMG, 2011), Model Driven Architecture (MDA) (Kleppe et al., 2003; Soley, 2000), ArchiMate (The Open Group, 2012), or the Architecture of Integrated Information Systems (ARIS) (Scheer, 1994) emerged by combining different conceptual modeling grammars to provide a holistic and cohesive view of the domain in interest. These modeling frameworks enabled designing, storing, exchanging conceptual models, and integrated modeling-in-the-large on distinct levels of abstraction. Entire enterprise architectures were populated, and the interplay between elements, such as data being input and output of processes became a focus of models. Moreover, advanced modeling tools enforced the grammatical correctness of these models and facilitated the developing and testing of conceptual models. Modeling 3.0 involved the development of conceptual modeling tools and grammars for broader purposes covering business analysis, organizational redesign, or risk and compliance assessments in addition to systems development. This era also involved the development of domain-specific grammars that incorporated concepts to represent domain-specific knowledge (Van Deursen & Klint, 2002) as well as the design of comprehensive, domain-specific reference models such as ITIL (IT management), eTOM (telecommunication), or SCOR (supply chain management). Modeling 3.0 is, to a large extent, the current state of conceptual modeling.

However, Modeling 3.0 often resulted in rather complex integrated models that required a high cognitive load to interpret, create, and update a plethora of integrated models manually. While in this era, some computer tools were developed to manage the process of designing and using conceptual models, they still raised concerns with regard to practicability and efficiency, such as the lack of tool interoperability and integration with emerging technologies (e.g., AI, blockchain, etc.) and methods (e.g., agile and rapid development). Furthermore, the increased capabilities and sophistication of digital technologies meant that the models available as part of Modeling 3.0 are no longer able to cater adequately to the changing demands. For example, conceptual models can now be developed, maintained, and consumed by digital agents, artifacts like algorithms, autonomous tools, bots, APIs, and generative engines (Recker et al., 2021). Current modeling grammars and tools cannot capture machine-to-machine communication channels, human and machine safety, collaboration regulations, digital models of manufacturing execution, and constraints (Rehse et al., 2018). For performance and conformance reasons, organizations are expected to monitor, control, and evaluate activities, their interdependencies, and performances; enable timely decisions based on big data analytics; learn from experiences and propose solutions; be flexible and adapt to the changes in agile environments. Integrating agile and model-driven development approaches emphasizes making modeling easier and faster (Karagiannis et al., 2022).

As digital technologies transform how we work, communicate, organize, and live, the capabilities of Modeling 3.0 are no longer sufficient. No longer is the manual design of integrated, large-scale, and rather static models conforming to enterprise architecture and digitalization-specific concepts adequate (Rehse et al., 2018). Rather, new levels of agility, real-time capabilities, finer levels of granularity, and new real-world phenomena require a set of conceptual modeling capabilities. We call this stage **Modeling 4.0.** Before we describe its core mechanisms in Section 4, we will introduce the well-defined and widely deployed principles of Industry 4.0 as a point of reference for our development of Modeling 4.0 principles.

3 Main Principles of Industry 4.0

The fourth industrial revolution expedites a new fundamental paradigm shift in industrial production. It provides a consolidating framework for various digital technologies and their use in the context of manufacturing. Thus, we argue that the uptake and success of Industry 4.0 serve as a compelling benchmark and provide rich stimuli to develop an analog Modeling 4.0. In the following, we briefly review the main principles of Industry 4.0 before deploying these in the context of Modeling 4.0. Detailed reviews of these principles are provided by (Hermann et al., 2016; Lasi et al., 2014).

Interoperability: The seamless flow of contextual information is a crucial principle of Industry 4.0. In the factories of the future, smart systems and things, human workers, internal and external data sources, external ecosystem participants, and objects are integrated (Hermann et al., 2016). Therefore, seamless interoperability and continuously exchanging information are important for the entire system to perform. Different components of cyber-physical systems need to be integrated and aggregated to read and transform data to derive meaningful information (Thuemmler & Bai, 2017).

A seamless flow of information across systems requires information consistency and completeness. This ensures consistent representations of data throughout. Solutions such as interworking proxies have been used to enable interoperability between two communication domains. At each point, a server maintains a set of information. The interworking proxy guarantees the consistency of this information between two servers. Each time information is updated in one domain (e.g., in the manufacturing operating system of a producer), the same update must be reflected in the other domain (e.g., the scheduling system of the supplier) and vice versa (Cavalieri, 2021).

Another important element of interoperability across heterogeneous sources of information is expandability. The expandability of information is the ability to access any or all related information across multiple servers (Barata et al., 2018). Expandability in Industry 4.0 supports tracing and tracking and enables controlling products (Bougdira et al., 2020). It allows to recall reactions and supports adaptable systems with flexible lines in which machines perform necessary actions through information exchange and sensors embedded into them (Frank et al., 2019).

Virtualization: Developing a virtual copy of the physical world (e.g., a digital twin) based on data collected from various sensors is important to monitor the physical processes as well as presenting conditions of all cyber-physical systems. Virtualization technologies are based on Augmented and Virtual-Reality tools that enable the integration of a computer-supported representation of a real-world situation with additional and valuable information (Salkin et al., 2018). Industry 4.0 relies on the cooperation of humans with leading virtualization technologies. Virtual reality flourishes this collaboration by representing a virtual model of a real-life situation representing all necessary information (Hermann et al., 2016). This facilitates modifications and customizations and helps to detect flaws during the production lifecycle without needing physical prototypes (Fei et al., 2018; Frank et al., 2019). In other words, virtual information can be encompassed in real-world presentations to enrich the human perception of reality with virtual objects and elements.

Virtualization includes developing a digital twin of the physical world and augmenting the physical world with digital information. Unlike virtual reality, augmented reality extends the physical world without replacing it (Masood & Egger, 2019). Augmented-reality (AR)-based systems support collaborators with interactive and real-time guidance to improve decision-making (Scurati et al., 2018). It can be used in a different range of applications such as operation, manufacturing, guidance and training systems, quality assurance, or maintenance. In all these applications, AR can intuitively display real-time information when operators depend on this information. It enables workers to be smoothly integrated into the digital environment.

Decentralization: In the evolving digital environments, faster decision-making procedures are necessary to ensure specific conditions are immediately attended (Lasi et al., 2014) and to address individualization requirements (Smit et al., 2016). Therefore, organizational hierarchies need to be reduced. Embedded computers enable cyber-physical systems to make decisions on their own. Therefore, central planning and controlling are no longer needed, and decision authority can be delegated to the edges. Distributed cyber-physical systems work independently and make autonomous decisions. However, they remain aligned toward a single ultimate goal (Napoleone et al., 2020). Distributed systems autonomously process information for decision makings using technologies such as data mining, artificial intelligence, or machine learning. Thus, decentralization enables more reactive approaches and eliminates the long-time span of feedback loops in centralized approaches (Lasi et al., 2014; Meissner et al., 2017).

Decentralization also positively impacts production quality as data is gathered immediately where it occurs on the shop floor. For design and customization, that means modifications can be made based on the information collected to reach customer needs and wants (Brettel et al., 2017). The autonomous decision within the system or process enables the product to be manufactured without the need for central interference. Therefore, control is moved towards the edges of the system, i.e., the lowest levels of decision making to ensure minimal decision latency (Lasi et al., 2014). Unlike traditional structures where decisions are made centrally and often based on experience, knowledge, and ultimately confidence, in the decentralized approach, decisions are made evidence-based using information gathered from the shop floor. This decision process is further assisted by self-optimizing and knowledgeable systems (Atzeni et al., 2010).

Real-Time Capability: It refers to zero-latency capabilities that allow an immediate reaction to changes, customizations, or product failures (Smit et al., 2016). Data are collected and analyzed in real-time. Therefore, the status of products, business operations, and changes are permanently tracked to manage, and any response strategies or alternative actions can be activated immediately (Gattullo et al., 2019). Technical documents such as product specifications need to be kept updated in real-time to drive insights immediately (Hofmann & Rüsch, 2017). Therefore, the system is able to detect any changes and reacts with minimum latency, ensuring the functionality and quality of the production (Napoleone et al., 2020).

Sensors and smart devices gather real-time data, and advanced analytical tools enable monitoring and forecasting of potential failures, problems, and capabilities to provide predictive maintenance to avoid downtimes (Frank et al., 2019). This real-time recognition of individualized mechanisms in a distributed manner is a key success factor of industry 4.0.

Service Orientation: Customer-centered service aggregation is an important component of smart factories where smart devices, things, and objects add to a set of individualized aggregated services. Hermann et al. (2016) give a high-level overview of “customer-centered” service aggregation where the

IoT, the Internet of Service (IoS), and the Internet of People (IoP) add to a set of individualized aggregated services in smart factories. On the product level, services are closely interlinked with customization and other services to “predict product degradation” (Liu and Xu, 2017). Examples of these services include on-demand manufacturing (Zhong et al., 2017) or manufacturing-as-a-service (Xu et al., 2018). At its core, Industry 4.0 strategies empower organizations to evolve from manufacturers to service providers, allowing growing amounts of individualization and personalization in customer service. The industrial production of high-tech products must be leveraged between the satisfaction of heterogeneous customer needs through individualization and the realization of scale effects along the value chain. The related dilemma between the economies of scale and scope can be addressed by the concept of Mass Customization (MC) (Fogliatto et al., 2012). MC is a strategy that focuses on the affordable production of personalized mass products (Barata et al., 2018). Recent developments in Industry 4.0 have heightened the need for mass customization in a wide range of industries. Mass personalization is provisioned by key technologies, including Cloud, IoT, AR, and AM, through an iterative, incremental process enabling an affordable personalization that was previously unattainable (Aheleroff et al., 2020).

Modularity: Modular systems can flexibly adapt to changing requirements by replacing or expanding individual modules. For that reason, modular systems can be easily adjusted in case of seasonal fluctuations or changed product characteristics. Modularity is the capability to flexibly change and reconfigure in response to rapidly changing customers’ requirements and product changes through modularized systems. Thus, modularity allows system independence, making it capable of adopting more flexibility (Napoleone et al., 2020). Modularity reduces the impact of changes to a minimal level, the level limited to the impacted module. By flexibly adjusting the combination of standardized modules, the speed of new product development drastically increases, and as a result, time-to-market can be shortened significantly (Baldwin et al., 2000; Brettel et al., 2017).

These six main principles of Industry 4.0 are a rich source of inspiration for a contemporary conceptualization of the future of modeling in a highly digitized environment. Labeled Modeling 4.0, we will, in the following, use these six principles to present a total of twelve mechanisms, two per principle, to finally derive a new framework for Modeling 4.0.

4 Design Principles and Mechanisms for Modeling 4.0

Based on the six principles of Industry 4.0, we propose twelve mechanisms for Modeling 4.0 to articulate the new set of requirements for conceptual modeling in the digital world. Figure 1 represents these mechanisms.

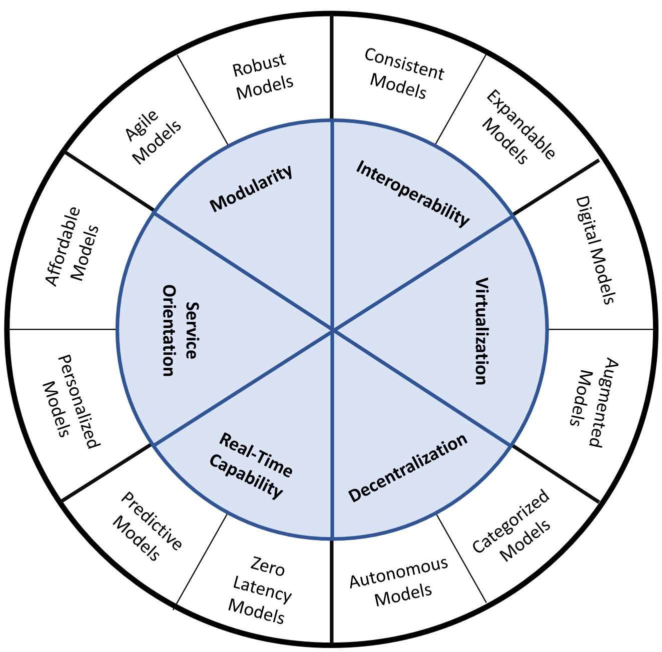

Figure 1. Principles and Mechanisms of Modeling 4.0

4.1 Design Principle 1: Interoperability

In the digital world, seamless interoperability is important to enable different systems and their components to exchange information and use the functionality of one another continuously (Chen et al., 2008). In the context of Modeling 4.0, interoperability refers to the capability of conceptual models to be aggregated and integrated and to be able to communicate with each other. Therefore, standardization is required because different models have to interact with each other (Napoleone et al., 2020; Ruppert et al., 2018). Interoperability enables accessibility to the representations of diverse and heterogeneous systems components, application solutions, business processes, and the business context (Berre et al., 2007; Lu, 2017). Thus, we define two mechanisms, consistent and expandable models, as part of the interoperability principle.

4.1.1 Mechanism 1: Consistent Models

Interoperability between conceptual models requires consistency. Consistency refers to faithful and coherent representations of different components of systems throughout multiple conceptual models. Due to modern systems' evolving complexity and multi-dimensionality, multiple, complementary, and overlapping models are required to represent different aspects of the systems holistically. Consistent models ensure that changes in one model are reflected in other models that are impacted by this change.

Prior studies have focused on controlling model consistencies (Boufares & Bennaceur, 2004; Klare et al., 2021), and some tools developed the capabilities to check the accuracy of the models[1] by validating relationships and verifying connectivities or enable consistency checking between two models[2] such as between process models and enterprise architecture diagrams. However, existing tools fail to ensure *that changes in one model are reflected in other models*. Consistent models consistently correct, adjust and update their constructs to reflect variations in any system aspect. Such consistency requirements can vary. For example, an update in one entity type (e.g., change the name from 'customer' to 'client') requires immediate updates in corresponding process models (e.g., change 'Contact customer' to 'Contact client'). Another request for consistency would be that business rules in a process model (e.g., the use of an exclusive or split) align with the corresponding decomposition in the related data model (needs to be disjunct and not overlapping) (Boot et al., 2022). As these two examples have shown, ensuring that modeling systems support this type of advanced consistency is not always easy to implement, as complex grammatical and semantic rules must be interrelated across different models. However, the integrity, overall quality, and trust in these integrated models are compromised without such consistency mechanisms. As a result, mechanisms to ensure consistent models attract substantial attention. Earlier studies proposed rules (Liu et al., 2002) and methods such as transformational languages (Bergmann et al., 2015) to deal with inconsistencies. But they have focused on *detecting* inconsistency.

Consistent models in Modeling 4.0 emphasize the need to *preserve* consistency across multiple models. For instance, research methods such as the *Vitruvius* approach propose using reaction and mapping languages to ensure consistency across different models in developing software-intensive systems (Klare et al., 2021), and the Agile Modeling Method Engineering (AMME) approach proposes consistency preservation to deal with Multi-view consistency challenges in Enterprise Modelling (Karagiannis, 2022).

4.1.2 Mechanism 2: Expandable Models

Interoperability requires an entire set of models to be correlated with each other. This enables users to be able to access corresponding information across multiple models. Different models represent distinct perspectives of a domain. Expandable models integrate these different perspectives and provide a holistic domain view. This is important, as model users usually find it complicated to have a complete view of a complex domain as they can only process partial information about the domain. This aspect is partially supported by existing tools[3] as they offer the capabilities to create links and dependencies between different models and elements in the models or to add hyperlinks[4] to give access to external resources. However, expandable models enable users to navigate more seamlessly through a set of models, mine deeper into specific elements and search for additional information, view different perspectives of the domain, and integrate information to form a whole understanding of the domain. For example, users can

[1] e.g., Sparxsystems and IBM Rational Software Architect
[2] e.g., ARIS and Astah
[3] e.g., Visual Paradigm, ARIS, Lucichart or Astah
[4] e.g., Draw.io

navigate from a data model capturing the taxonomy of customers to those business processes that deal with a selected sub-type of customers (e.g., seeing only those processes that are unique to international customers). This way, the data analyst expands their data-centric view with a process view. In return, a process analyst might want to identify and better understand the data (entity types and their attributes) that trigger the need for a specific business process variant. This might point to the cost drivers of the process, and dealing with these will be one way of streamlining the process. Numerous studies and findings highlighted the necessity of developing multi-view models (Cicchetti et al., 2019; Jabbari & Recker, 2017). However, prior studies mainly focused on detecting and avoiding inconsistencies between models (Feldmann et al., 2019; Spanoudakis & Zisman, 2001; Van Der Straeten et al., 2003), integrating and identifying correspondences between models (Jabbari et al., 2022; Kim et al., 2000; Persson et al., 2013), or evaluating the capability of multiple models to present a complete and clear representation of a domain (Recker & Green, 2019). Expandable models in Modeling 4.0 extend the capabilities of multi-view modeling by enabling users to navigate through multiple models without changing the modeling tool, platform, or environment. This requires new methods and tools to enable horizontal and vertical integration of multiple models in a unified modeling environment. Early steps for expandable models have been suggested by SUM-based approaches (Atkinson et al., 2013; Sztipanovits et al., 2014).

4.2 Design Principle 2: Virtualization

Virtualization is an inseparable and conjoined part of the digital world as it enables the simulation of processes and digital manufacturing (Fei et al., 2018). In the context of Modeling 4.0, virtualization allows the developing virtual assistants to model and virtual simulation of the behavior of the system, for example, to stress-test it or to anticipate emerging challenges in light of changing demand patterns (Babiceanu & Seker, 2016; Napoleone et al., 2020). Digital models enable virtual simulation of the system, merging the physical and the corresponding digital world. Digital models have various benefits and have already been shown to reduce error rates and completion time (Masood & Egger, 2019). Virtual assistants use digital technologies to automate modeling processes. Therefore, we define two mechanisms, digital models and augmented models, as part of the virtualization principle.

4.2.1 Mechanism 3: Digital Models

Current tools support the digital creation of conceptual models. However, the developed models are mainly static or, in a few cases, can simulate a predefined scenario to identify bottlenecks, inefficiencies, and potential improvements[5]. Digital models extend these capabilities and argue the need to develop context-aware, autonomous, and adaptive models that allow traceability, adjustability, and communication feedback from the digital world back to the physical world. Similar concepts have been developed in the manufacturing field, where digital models provide representative behavior of an equipment's status based on context acquired from the condition of the working equipment (Aivaliotis et al., 2023).

Digital models provide a semi-realistic view of a system to check and evaluate system behavior in a digital world. They allow all system elements to be fully traceable throughout their lifecycle, from design to operational and improvement phases (Negri et al., 2020). These models are connected to the real physical world and allow traceability, adjustability, and communication feedback from the digital world to the physical world. Digital models represent the physical systems and monitor and perform on physical systems based on the simulation results (Cimino et al., 2019). Digital models are *connected to various data sources* to support context-aware model generation, such as using IoTs to simultaneously capture the system data, e.g., a change in temperature and trends of these changes, and visualize systems transitions in response to these changes, e.g., transitions in the thermostat's status in response to the environment temperature. These models enable designing digital representations that can simulate corresponding real-world artifacts. For instance, digital models can highlight non-compliant elements or how external changes (such as an upcoming tropical storm) affect internal arrangements (e.g., demand patterns for the call center for an insurance company). Unlike traditional models that represent static aspects, digital models represent *stream semantics* of the physical world (Siau et al., 2022) and enable digital channels to interact with the model, e.g., voice-embedded capabilities.

Initial efforts have been made to adopt conceptual modeling to emerging contexts such as digital twins, self-regulating and adaptive systems, and AI-based cognitive systems (Lukyanenko et al., 2022). Digital models are required to be adequately accurate to be trusted and, at the same time, require the minimum

[5] Bizagi, Signavio, ARIS BPM

possible effort for development, as well as for operation and maintenance. Digital models represent an on-the-fly view of the system using data from smart devices, various hardware, and services and rely on continuous synchronization between the physical world and virtual models (Qiu et al., 2019). Digital models are used to represent the varying parameters of systems or disturbances acting on the system. For instance, to represent the system's behavior and tolerance level against external turbulences.

4.2.2 Mechanism 4: Augmented Models

Augmented models are virtually assisted models involving humans and machines in the act of modeling. Advanced technologies such as machine learning, natural language processing, and artificial intelligence can be used to (semi)automate designing and implementing models. A few of the existing tools[6] offer automation through scripting and plugins. However, augmented modeling involves a smart and even autonomous modeling process. For instance, AI could help discover "design references" and provide a new form of content experience (e.g., by changing the size of model elements based on their context-specific significance), comprehend models in their physical context (e.g., by projecting a conceptual model of passenger flows to the real-world environment of an airport), to guide the analyst in the design of the model (e.g., by adding recommendations such as how to overcome a bottleneck in a process) and to communicate the model to a broader audience (e.g., by adding an animated narrative on top of the model such a customer with all related experiences along a sales process) (Nee et al., 2012).

Emerging deep learning algorithms and artificial intelligence offer great potential to identify users' needs, analyze mechanisms, generate content, and evaluate designed artifacts (Buchmann & Karagiannis, 2017; Tang et al., 2019). These powerful computing models enable non-human (artificial) intelligence to co-create novel and meaningful content (Oh et al., 2018) and promote inspiration (Chen et al., 2019). Implementing AI could help discover "unexpected design references" and provide a new form of content experience (Liao et al., 2020). Emerging studies motivate the development of new AI-based tools to assist existing conceptual modeling tools in targeting a specific problem and suggesting new conceptual modeling approaches to be combined with the emerging automated solutions (Bork, 2022; Feltus et al., 2021; Wu et al., 2021). Conceptual modeling by nature requires creativity and different contextual and individual factors such as thinking patterns, working styles, or tool literacy. Accordingly, assisted modeling needs to take into account the difference between individual preferences and contextual variations.

A few methods have been proposed as virtual assistants to evaluate conceptual model quality automatically. For instance, emerging approaches propose using machine learning and image processing to extract features from UML class diagrams to automate quality assurance (Bergström et al., 2022) and suggest that assisted models can be integrated with DevOps toolchain. Gupta and Poels (2022) propose that agile methodologies use auto-generated conceptual models from user stories. They proposed assisted modeling that enables automatic requirements elicitation and dealing with complexity managing and understanding user stories.

4.3 Design Principle 3: Decentralization

In Industry 4.0, decentralization refers to the shift away from centralized control systems to self-organized and decentralized control entities (Lasi et al., 2014). Decentralized entities autonomously process information and make decisions. In the organizational context, decentralization refers to distributed production systems and processes, connected materials with plug-and-play capabilities, and adaptability (Sanders et al., 2016; Sommer, 2015). Decentralization refers to replacing traditional top-down structures with more distributed and collaborative models. Pre-requisites for decentralization are distributed, autonomous entities with connected goals, goods, and materials (Beier et al., 2020). Therefore, for Modeling 4.0, we define two mechanisms, autonomous models and categorized models, as part of the decentralization principle.

4.3.1 Mechanism 5: Autonomous Models

Unlike the traditional approach of modeling, which follows a top-down approach by presenting a domain in general (e.g., in the form of a value chain) and decomposing it into smaller models (e.g., fine-granular process models in the BPMN notation) that present specific aspects of the domain, autonomous models start from bottom-up with specialized aspects of a domain before aggregating and generalizing these. The

[6] e.g., Visual Paradigm or ARIS

existing studies have proposed bottom-up modeling (e.g., Grau et al., 2008; Pijpers et al., 2012; Pohjalainen, 2011). Some tools[7] support model repositories and version control, but they don't offer merging sub-models into a single model. Autonomous modeling refers to modeling specific components and parts of a more complex whole that share common characteristics to assemble all models into a larger model. Each model represents specific aspects of a system, and all models combine to represent the overall system. This could be a particular sequence of tasks for a certain type of purchase order or a highly specialized entity type (e.g., a narrowly defined customer category) that can be composed of more general entity types (customer categories). Thus, decentralized autonomous models represent specific operations and structures of an organization but, at the same time, are designed for generalization (Turetken & Demirors, 2011).

The decentralization of models and modeling creates new user experiences. Autonomous models facilitate adoption and change management by allowing changes to be performed on the individual model rather than on a central system. The concept of bottom-up and decentralized modeling was proposed a while ago. For instance, methods such as “viewpoints” or “role-based modeling” (Cicchetti et al., 2019; Turetken & Demirors, 2011) describe approaches to develop decentralized models, each with a partial representation of the overall domain. However, these models are outdated once they are merged into a general model and are usually not maintained as separate entities from then on. Any changes in the system are supposed to be presented in the integrated model. In these approaches, tools and automated support for bottom-up modeling and their maintenance are mostly missing (Töpel & Kaczmarek-Heß, 2022). Process mining is an emerging example of decentralized, bottom-up modeling. Process mining uses event logs, i.e., data related to an activity performed in a system, such as data elements, timestamps, sequence, and resources, to discover and produce a model without using any a priori information (Van Der Aalst, 2012). The concept of process mining provides capabilities to mitigate some of the problems with traditional model-driven approaches. It offers a semi-automated approach to discovering models without having predefined directions. But still, the important aspects of autonomous models, the *ability to facilitate adaptation and change management*, are missing in current modeling tools and methods.

Autonomous models extend the existing bottom-up modeling approaches and propose new modeling capabilities to develop decentralized autonomous representations that independently represent different bottom-up aspects of the domain at the lowest level of detail but facilitate autonomous change management and adaptation and can be integrated with other models. The integrated model can be at the lowest level of detail or the highest level, but any updates or changes are managed independently in the decentralized models.

4.3.2 Mechanism 6: Categorized Models

Categorized models address the need to identify applicable models for a specific context that share the same goals, goods, and materials. For instance, to identify where smart contracts can be used (e.g., as part of a human resources process) and what series of actions and set of conditions are required to be met in that context (e.g., geo-specific identification of those relevant COVID policies that guide sick leave). Categorized models are standalone but context-dependent, i.e., they exist in isolation but are categorized based on the same context they share. For instance, models can be categorized based on the resources they share. Therefore, categorized models enable the identification of otherwise independent models (e.g., process models) that are dependent on the same resource. Categorized models provide capabilities for model users and decision-makers to answer what-if scenarios; for example, which processes will be affected if a certain resource needs to be maintained or upgraded?

Emerging methods such as business process repositories (Leyer et al., 2020) enable categorizing models based on their activities (e.g., labels) and behavioral and structural features, creating packages, organizing models into folders, or grouping models based on users' preferences[8] . However, these tools are limited to process models, are manual, or are not context-based. Other model repositories have been proposed to enable model reuse in model-driven system development and support the specifications, definitions, and packaging of a set of modeling artifacts (Hamid, 2017). However, existing techniques enable the retrieval and reusing of model components from repositories and the preparation of new models based on their similarities and dependencies (Liu et al., 2017). Categorized modeling extends the

[7] e.g., Sparx Systems Enterprise Architect, Visual Paradigm or ARIS
[8] e.g., Sparx Systems Enterprise Architect, Visual Paradigm, ARIS, Lucidchart, Astash

current approaches and specifies the need to categorize different independent models based on specific contexts. Modeling 4.0 tools support the context-dependent categorization of various models, such as relevant processes, their related data, and customer journey map. This capability allows the smart utilization of models, identifies integrable models, and suggests relevant models address emerging inquiries.

4.4 Design Principle 4: Real-time Capability

The capability to acquire and analyze real-time data is a key requirement of cyber-physical systems that detect changes in the physical world and react in real-time to ensure the systems' functional and safe operation (Napoleone et al., 2020). For Modeling 4.0, real-time capability refers to the capability of models to represent the domain's real-time state and predict the system's future behavior or state.

4.4.1 Mechanism 7: Zero latency models

Zero latency models address the time-to-model issue and eliminate the delay between the occurrence of a change in the real world and its representation in the conceptual model. Existing debates on conceptual modeling question the speed and quality with which conceptual models can be developed and stress the issues with the maintainability of conceptual models. Traditional conceptual modeling, especially in realistic large-scale settings, requires a lot of time and cost (Indulska et al., 2009). Studies identified the effort and time required to understand and use complex conceptual modeling tools as a barrier to conceptual modeling (Fettke, 2009). While tools play an important role in improving the efficiency of conceptual modeling through the complete modeling lifecycle, existing tools struggle with flexibility when it comes to customizing the modeling processes (Davies et al., 2006). There is a lack of integration. While some tools provide limited capabilities to handle collaborative modeling[9], there is limited support for concurrent editing, real-time collaboration (David et al., 2021; Jiang et al., 2016), or version control. Current modeling tools lack comprehensive validation capabilities or advanced analysis features, making it difficult to identify modeling errors, inconsistencies, or potential design flaws on a real-time basis during the modeling process.

Zero latency models reduce the time to model and enable representing relevant information as fast as possible to the users who need to act quickly to emerging information and modifications of the requirements. Using computational intelligence, integrated with big data analysis, business informatics, and communication technologies in self-organizing modeling methods, can be used to develop and maintain zero latency models. For example, during COVID, frequently changed policies for airports have meant that airport providers had to frequently and quickly update their processes (e.g., check-in or security procedures) – the lower the latency of these updates, the lower the risk and the costs of non-compliance (Yuan et al., 2019).

4.4.2 Mechanism 8: Predictive models

Predictive models refer to models that represent future aspects of a domain. Unlike traditional modeling, where modelers use approaches such as process mining to derive the current state of the domain (Van Der Aalst, 2012) and use process reengineering techniques to improve this current state (Mohapatra, 2012), predictive models build on weak signals and emerging trends and anticipate the future model before it materializes in the real world (Poll et al. 2018). Thus, predictive models have a negative latency, i.e., the model is ahead of reality, whereas, under the previous mechanism, we referred to the real world being ahead of the model.

For instance, predictive models present where a new activity (e.g., check eligibility) can be added to the process when new requirements are emerging in the physical world (e.g., policies to encourage triple vaccination). Predictive models require gathering experts' knowledge about the domain being modeled, understanding the inherent variation in the response and taking steps, collecting relevant data to address desired requirements, and utilizing a variety of solutions to have the best chance of uncovering possibilities (Kuhn & Johnson, 2019). Recent studies for predictive process analytics are often underpinned by deep learning techniques (Wickramanayake et al., 2022). In Modeling 4.0, predictive models suggest new modeling approaches that enable representations of predictions. For example,

[9] For example, Lucidchart, Visual Paradigm, and Draw.io offer collaborative modeling features that enable teams to work together. Other more general tools such as Conceptboard, Cacoo, and MURAL are online collaboration platforms that can also facilitate creating and editing visual diagrams.

predictive models represent the domain knowledge and objects shared across distributed and heterogonous systems and show how processes can change if the behavior of other system components changes, e.g., a predictive process model can represent how the process of flight allocations can change if new requirements have emerged for international travelers.

4.5 Design Principle 5: Service-Orientation

Customer-oriented service aggregation is another design principle of Industry 4.0, where products and services are created based on the customer's specifications. This design principle provides significant economic potential (Lu, 2017) and allows flexible and lean production systems to produce different varieties, i.e., in small lots, of affordable customized products (Aheleroff et al., 2020; Brettel et al., 2017). For Modeling 4.0, service orientation refers to personalized and affordable models.

4.5.1 Mechanism 9: Personalized Models

Personalized models are customized to individual needs. In personalized models, individuals are able to add meaningful constructs to the available constructs of the models to address specific and temporary scenarios. For instance, individuals are able to comprehend specific features they are interested in from the information presented in a model, such as features of COVID-safe processes, how to address a deviation, or how to handle evolutions that may require occasional or permanent modifications in the schemas.

Traditionally, models were developed to be used by a group of stakeholders with specific individual characteristics such as their roles, level of experience, domain knowledge, or familiarity with modeling concepts. However, individuals with different interests (e.g., software development versus quality assurance) use models. Thus, model readers should be able to personalize the model's contents (e.g., refer to quality standards). Therefore, personalized models increase their usefulness and lead to high model acceptance (e.g., Bouwers et al., 2014).

Personalized models can also enable personalized model conversion. So, people with different capabilities, knowledge, and skills can use models in different formats. For instance, model users should be able to convert large and complex business process models to simple pictorial flowcharts that are understandable by managers. Similarly, visually impaired people should be able to convert visual models to audible models. These increase ease-of-script use and, with this, a second essential factor of model acceptance.

4.5.2 Mechanism 10: Affordable Models

Conventional conceptual modeling approaches often suffer from drawbacks such as high cost or time of modeling. Conventional conceptual modeling grammars, methods, and tools typically require highly skilled developers/designers and, therefore, are highly dependent on advanced modeling skills. These drawbacks limit the opportunities to draw useful insights about the system from domain experts and become less useful for smaller projects because of time and money restrictions. For instance, process models were typically made by hand by trained modelers. However, new techniques such as process mining use data trails, so-called event logs, to analyze, discover, and model business processes (Van Der Aalst, 2012). Therefore, the cost of developing a high-quality model can be reduced.

In addition to the cost of creating new models, the cost of changing, updating, and maintaining an established model tends to be high. Developed models may require changes due to emerging mechanisms and the evolution of technologies. New techniques, such as process query (Polyvyanyy et al., 2017), can be developed to decrease the cost of maintaining developed models in a model repository and improve the efficiency of updating or changing models in the repository in terms of time and money. However, process modeling is still considered an expensive task. Despite emerging automated technologies, process modeling remains a manual, cognitively demanding task, making it time-consuming, labor-intensive, and error-prone (Beerepoot et al., 2023). Besides, it is expensive to train expert modelers, and it is not reasonable to expect that models are developed by experts only (Recker et al., 2021). This is where new technologies such as AI can be used as an enabling technology to support non-experts in modeling (Feltus et al., 2021).

Affordable models require adequate and usable modeling tools to adapt modeling languages efficiently. Advanced modeling tools that provide a feature-rich, feature-proof, and efficient foundation for state-of-the-art interaction and visualization methods can speed up the model development process and improve the ease of use of the tools (De Carlo et al., 2022).

4.6 Design Principle 6: Modularity

Modular systems have the capability to adapt to changing requirements, for example, in case of changes in product characteristics or contextual factors such as seasonal fluctuations (Gattullo et al., 2019). Modular systems adapt themselves by exchanging or altering discrete modules (Smit et al., 2016), and this makes dealing with the uncertainties that lie ahead easier. For Modeling 4.0, modularity refers to robust and agile models.

4.6.1 Mechanism 11: Robust Models

Robust models are decoupled and standalone models that are focused on internal robustness rather than interaction with other models. Decoupled models are robust models that do not change with changes in other models representing the system or the external changes in the real world, as their level of granularity is higher than the level of real-world change. A robust model stays valid and provides correct and relevant information under various conditions. A decoupled representation of physical products can help more effectively capture product-related information, thereby preventing clean production defects (Preuveneers et al., 2018). Decoupled robust models ensure acceptable representations under ordinary conditions and conditions not anticipated in advance (Schuster, 2008).

In a digital world, any system is inevitably subject to uncertainty. Robust models represent the uncertainty of alternative scenarios and provide information and potential solutions with acceptable quality for all scenarios (Marla et al., 2020). Different robust modeling methods have been developed based on existing design theories. For example, using principles of axiomatic design (Suh, 1998) for robustness (Kuo & Wang, 2019) where axiom independence is applied to develop high-quality designs. Once multiple high-quality designs are developed, the robustness concept is employed to select the most appropriate design by the information axiom (Duan, 2021; Park et al., 2006). In a similar way, a method can be applied in robust models to provide a robust representation of a changing domain.

4.6.2 Mechanism 12: Agile Models

Agile models adapt and update their constructs and behavior in response to unexpected changes (Rezk & Gamal, 2019). Agile models are iterative, incremental, self-organizing, and adaptive, and the structure, constructs, and behavior adapt according to the situation. They permit cost-effective responses to unpredictable requirement changes and support rapid and responsive systems development tailored to meet changing users' desires. Agile models represent real-time interaction between physical and cyberspace (Aheleroff et al., 2021). These models are inductive, similar to agile design and manufacturing in Industry 4.0, and they stress simultaneous leading-edge solutions that surpass emerging changes with real-time responses (Lu, 2017; Shafiq et al., 2015).

One of the main characteristics of Industry 4.0 is to have responsive systems (ElMaraghy et al., 2017). Responsive systems often comprise many units that can be highly heterogeneous (Sanderson et al., 2015). These systems are deductive, and their heterogeneous units can be replaced to enable different operations and behavior in such a way that they can respond to emerging perturbations. For models to be responsive, similar characteristics such as scalability and convertibility should be comprised, enabling models to be context-aware. Frameworks have been proposed to adhere to agile principles in conceptual modeling[10] (Gupta et al., 2022; Moyano et al., 2022) or to use domain-specific conceptual modeling to obtain a diagrammatic view in Jira projects (Floruț & Buchmann, 2022).

Agile models in Modeling 4.0 focus on conceptual models' agility and argue that agile models consist of a set of alternative models. Depending on the real-world change, the relevant model is activated. Such context-aware models require tight coupling between the external state and the metadata of the models. For example, a process model might only be activated during the state of a pandemic when online interactions (for retailing or lecturing) need to be in place while physical processes are hibernated.

[10] For example, Sparx Systems Enterprise Architect, Visual Paradigm, or Lucidchart enable iteratively creating and refining conceptual models

5 Discussion and Conclusion

Our society now functions in an ever-expanding digital world, with many human activities mediated or shaped by digital technologies (Recker et al., 2021). Conceptual models are no exception, but so far, the impact of digitization on conceptual modeling has not been sufficiently captured. Thus, this paper proposes six design principles and describes twelve mechanisms for conceptual models in a digital world. In themselves, some of these mechanisms are not entirely new. For instance, the concept of collaborative conceptual modeling (Recker et al., 2013), applying agile principles in conceptual modeling (Floruț & Buchmann, 2022), or using computational tools such as natural language processing to automate conceptual modeling (Gupta et al., 2019) have been proposed by previous studies that explored some of these principles in detail. Motivated by the principles of Industry 4.0, the twelve mechanisms provide opening premises for how the next generation of conceptual models needs to adapt to the new requirements of the digital world and meet the challenges of developing and understanding smart, automated, and highly personalized systems.

Previous studies have used different theories to provide the fundamental basis for conceptual modeling – modeling grammars. For instance, different ontologies, a branch of philosophy that studies what exists in reality, have been used to evaluate the quality of conceptual models, such as clarity, comprehensiveness, and completeness (Saghafi & Wand, 2020). Our proposed mechanisms call for further measurements to evaluate the capabilities of conceptual modeling grammars and developed models based on those grammars, such as their expandability, robustness, agility, and zero latency. These may require new or expansions of current ontological foundations of conceptual modeling (Eriksson & Ågerfalk, 2022; Lukyanenko et al., 2021).

Our proposed characteristics also target the costs of modeling and call for a new generation of conceptual modeling grammars that make conceptual modeling the development, deployment, and entire model lifecycle management more efficient. The new generation of modeling grammars should make conceptual modeling accessible and understandable for people with minimum or no pre-required training and skills. Traditionally, conceptual models were developed and used by IT professionals (Recker et al., 2021); however, more and more socially developed conceptual models are used to understand and develop information systems. The new generation of conceptual modeling grammars needs to allow those not familiar with predefined modeling rules to develop and use conceptual models (Lukyanenko, Parsons, et al., 2019). This also requires more flexible conceptual modeling grammars that enable the use of new formats or tentative components to represent digital and social world characteristics. Our principles also suggest affordable and augmented models, which ultimately highlight the need to use more advanced computational techniques to generate conceptual models, automatically or semi-automatically, based on user inputs in a variety of formats (Storey et al., 2023).

Our proposed principles and mechanisms can guide the development of new conceptual modeling tools. Existing modeling tools are mature and established applications. Research over a long period actively contributed to their fundamental basis, extensions, and features (De Carlo et al., 2022; Rittgen, 2009). However, these tools are not compatible with state-of-art technologies such as decentralized collaboration, data-driven platforms, or cyber-physical systems. We argue that our proposed mechanisms for Modeling 4.0 can be used as a basis to explore requirements for designing advanced modeling tools that could speed up the model development process, facilitate their maintainability, and improve usability and ease of use of the tools and comprehension of conceptual models by humans (De Carlo et al., 2022). Future modeling tools should enable timely model development based on big data analytics, learn from experiences and propose solutions, be flexible, and adapt to the changes in agile environments. We argue that next-generation conceptual models are not limited to static artifacts representing predefined characteristics of the physical world but rather also allow ongoing adaptation and interaction with users, developers, and their context. Weber (2020) suggests that the next generation of modeling tools will provide specific and personalized support adaptable to users' needs. For instance, modeling environments can collect multi-modal data and constantly analyze the collected data to adapt models based on emerging insights or assess the users' cognitive load and adapt the difficulty of the materials provided accordingly (Weber, 2020). With the emerging computation techniques, conceptual models can offer a variety of new capabilities that will enhance the current limitations of generic and non-personalized conceptual models.

Systems analysis and design methods and tools are evolving with emerging technologies, their new affordances and capabilities (Siau et al., 2022), and, therefore, the role of conceptual modeling. The majority of studies on conceptual modeling have focused on developing and evaluating conceptual modeling grammars and tools (Recker et al., 2021). Our proposed mechanisms trigger the need for research on modeling pragmatics, such as their construction and use. For example, future research requires investigating how conceptual models should be designed and used in dynamic and heterogeneous contexts if traditional modeling is applicable in the current digital setting. There is also a need to meet the requirements of evolving systems analysis and design methods and expectations. We argue that future conceptual modeling should follow dynamic and iterative approaches, as we explained in our proposed mechanisms for agile, autonomous, zero-latency, and robust models. Emerging technologies, their affordances, and capabilities, such as AI and machine learning, can aid, facilitate, and automate conceptual design modeling, as explained in the mechanisms for autonomous, augmented, digital, and affordable models. Future conceptual models should enable the use of models for different purposes and by different users, including human and digital agents, as we explained in our machinimas for expandable, personalized, categorized, and predictive models. As emerging systems' requirements and complexity continue to grow, we propose mechanisms for consistent, agile, and robust models to ensure that systems are well-designed and well-executed.

In summary, we have proposed twelve mechanisms for conceptual modeling to capture and adequately design tomorrow’s digital environments. Our mechanisms facilitate a type of modeling that can deal more appropriately with the current affordances of a digital environment. What we did not provide, though, is the detailed requirements of how these mechanisms can be applied. Future research, therefore, is encouraged to use our Modeling 4.0 framework to develop detailed functional and non-functional requirements to ensure that conceptual modeling remains a relevant and contemporary approach, helping us to understand and shape the world we live in.

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