Towards a Gamification-Enhanced Agent-Based Simulations for the Digital Transformation Process

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Abstract. *This paper presents a novel approach to digital transformation simulation using agent-based modelling within intelligent virtual environments. We propose a three-phase architecture integrating ontology-based modelling, customised implementation, and optionally-gamification-enhanced, more nuanced and interactive simulation. Unlike traditional token-based simulations, our approach leverages artificial agents' social and interactive nature to provide richer feedback on planned business process transformations. We demonstrate the application of our architecture using two scenarios from a production planning and scheduling use case. This method offers digital transformation experts a powerful tool for evaluating transformation strategies, predicting resource requirements, and observing emergent behaviours in digitised business processes.*

Keywords. digital transformation, artificial intelligence, artificial agents, multiagent systems, gamification, digital twins, simulation

1 Introduction

Digital transformation is a "thorough transformation of business that includes innovative changes in key organizational activities, processes, products/services, and business models, with the aim of utilizing the potential provided by digital technologies" (Pihir et al., 2019). It involves innovative changes in organisational activities, processes, and business models through the use of digital technologies. A critical early step is accurately describing the business process to be digitised. Digital twins, representing real-life entities, serve as intermediate products in this transformation, providing a test bed for proposed modifications.

Artificial agents, entities that can act upon and receive input from their environment (Russell and Norvig, 2022), can be considered digital twins in multiagent systems (MASs). These systems offer practical testing grounds for simulating business processes before real-world implementation.

The authors argue for using ontologies to describe business processes in terms translatable to artificial agents to facilitate this process. This enables the generation of a simulation-ready MAS blueprint, specifically an intelligent virtual environment (IVE) comprising agents and interactive objects.

This paper proposes introducing artificial agents within simulation-ready IVEs can enhance the digital transformation process. This approach allows for more nuanced simulations with agents behaving and interacting in a dynamic environment, possibly influenced by various gamification-based reward systems, unlike the more abstract currently often used token-based simulations.

This paper describes how formal business process descriptions, ontologies, and agent-run ontology-based simulation environments can be combined to provide an active, interactive, and reactive feedback loop in the digital transformation process.

The rest of the paper is organised as follows. Section

2 provides an overview of recent research and necessary definitions in the related domains. The example use case laid out in Sec. 3 is used to illustrate the proposed agent-based simulation architecture (presented in Sec. 4) using two scenarios described in Sec. 5. The approach proposed in this paper is discussed in Sec. 6, followed by plans for future research laid out in Sec. 7.

2 Related Work

2.1 Intelligent Agent

Artificial intelligent agents are systems capable of environmental perception and action to achieve specified objectives (Russell and Norvig, 2022; Wooldridge, 2009; Wooldridge and Jennings, 1995). These agents are designed for inter-agent cooperation and information exchange to enhance functionality. The key characteristics of intelligent agents include social ability, autonomy, reactivity, adaptability, proactiveness, and goal-orientated behaviour. They are frequently employed in implementing distributed systems, social systems, and systems with autonomous components (Schatten et al., 2017). Modelling social dynamics and phenomena using artificial agents provides a safe methodology for generating valuable data without human risk (Chopra and Singh, 2018).

Multi-agent systems (MAS), consisting of multiple intelligent agents, are gaining prominence with ongoing advancements in smart cities, smart home simulations and large-scale artificial intelligence models. In MAS, intelligent agents can be organized into groups, coordinating and delegating tasks to achieve goals. Figure 1 depicts the definition of an intelligent agent (i) organized into specialized MAS groups (ii) that communicate to achieve common goals in an intelligent virtual environment (IVE), which requires different abilities to achieve the goals (iii).

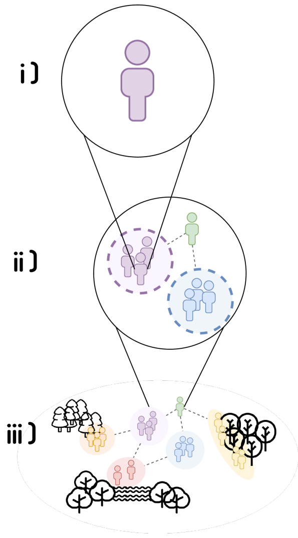

Figure 1: Artificial agents on different grouping levels: i) an intelligent agent; ii) a multiagent system; iii) an intelligent virtual environment

2.2 Intelligent Virtual Environments

Intelligent Virtual Environments (IVEs) represent a sophisticated fusion of high-fidelity environmental simulations and artificial intelligence (Luck and Aylett, 2000a). Central to the functionality of IVEs is the deployment of intelligent agents equipped with cognitive abilities designed to operate and interact within virtual spaces. This combination of virtual landscapes with intelligent agents enables the simulation of lifelike scenarios, enhancing the capability for complex decision-making processes.

By incorporating intelligent agents into these virtual settings, a new layer of dynamic interaction is achieved that transcends the limitations of static simulations. This dynamic allows for a deeper exploration and understanding of interactions between systems, entities, and users in a controlled digital context. Such technology is increasingly being applied in a wide range of fields, from agricultural advancements (Gutiérrez Cejudo et al., 2024) to sectors including robotics, the Internet of Things (IoT), and urban development (Luck and Aylett, 2000b).

The Flexible IVE Designer (FIVE) is an example of a framework built on Unity and SPADE agents that streamlines the creation of custom IVEs by facilitating the import of 3D models (Carrascosa et al., 2023). Users can construct IVEs through modifications to text files. This platform is equipped with a helper tool that automatically generates 3D virtual environments by allowing users to select real-world locations from an interactive satellite map.

2.3 Digital Twin Definition and Background

A digital twin (DT), first proposed in 2003, is defined as making full use of the data such as physical model, sensor update, operation history, etc., and integrating the simulation process with multi-disciplinary, multi-physical quantities, multi-scale, and multi-probability to realise the mapping that can be completed in virtual space, to use it to reflect the corresponding entity equipment life cycle process (Wang and Wu, 2020). The concept is credited to Michael Grieves (Grieves, 2014), who pioneered its development along with John Vickers. The digital twin is meant as the virtual and computerised counterpart of a physical system that can be used to simulate it for various purposes, exploiting a real-time synchronisation of the sensed data coming from the field; such synchronisation is possible thanks to the enabling technologies of Industry 4.0 and, as such, the DT is deeply linked with it (Negri, Fumagalli, and Macchi, 2017).

2.4 Digital Transformation Journey: Towards a Process Digital Twin

Technological changes affect the transformation of traditional production processes and their management (Jiang et al., 2024; Liu et al., 2020; Negri, Fumagalli, and Macchi, 2017; Sakr et al., 2021). The era of Industry 4.0 has led to the incorporation of collaborative communication and virtual work in production engineering, and one of the significant paradigms in this domain is Cyber-Physical Systems (CPS) (Negri and Abdel-Aty, 2023; Uhlemann et al., 2017). Production equipment and systems are no longer just physical elements; they have become digital elements that are just as important as representations of the physical system. The digital transformation of the production system is based on drivers such as cloud services and resource virtualisation, virtualisation of shop floor devices, high availability and policy-based security in production (Borangiu et al., 2020). In the context of transformation, data recording, storage, and analysis are increasingly important within the enterprise production system, and embedded systems at the plant level, operations, production execution and resource planning form the basis for a digital twin in a smart factory (Uhlemann et al., 2017). Industry 4.0 and technologies have enabled a vision for the industry of the future based on cyber-physical production systems that provide flexible, dynamically reconfigurable real-time control of strongly connected processes. The information and operational technologies of production systems are merged, and the physical reality of the factory has become a mirror to virtual counterparts, digital twins that represent abstract entities specific to the production domain, taking into account products, orders, and resources (Borangiu et al., 2020).

The application of DT in production refers to CPS whose constant interaction and communication should enable production flexibility (Barthelmey et al., 2019; Jiang et al., 2024; Negri, Fumagalli, and Macchi, 2017; Sakr et al., 2021). For CPS to fulfil its purpose, it is necessary to merge the physical object with its representation in the digital world (Albo et al., 2021; Jiang et al., 2024; Rocha and Barata, 2021; Szabo et al., 2019), that is, the previous creation of a production DT (Barthelmey et al., 2019; Sakr et al., 2021) using different technologies such as Industrial Internet of Things (IIoT) (Sakr et al., 2021), Big Data (Albo et al., 2021), Cloud Computing (Liu et al., 2020), etc., where simulation is an indispensable part of the twins' functioning (Liu et al., 2020; Rocha and Barata, 2021). Simulation enables offline testing, planning and experiments (Albo et al., 2021), while digital twins support the synchronous performance of activities (Liu et al., 2020) and processes and their modification (Rocha and Barata, 2021; Sakr et al., 2021). The aforementioned leads to complementation, optimization, monitoring and control of the production process through the digital world (Jiang et al., 2024; Liu et al., 2020; Rocha and Barata, 2021; Sakr et al., 2021; Szabo et al., 2019), whereby the features of the digital can be used to enrich the physical production counterpart in parallel (Albo et al., 2021; Liu et al., 2020). The concept of DT is based on the two-way exchange of large amounts of production data (Negri, Fumagalli, and Macchi, 2017; Szabo et al., 2019) between a physical and a digital object, whereby changes in one affect changes in the other (Liu et al., 2020) enabling two-way synchronization and real-time updates (Negri, Fumagalli, and Macchi, 2017). This emphasizes the ability of digital twins "to collect and manage information about the system operations, its history, its behaviour and its current state" (Liu et al., 2020).

The production process is subject to uncertainty factors (Jiang et al., 2024; Rocha and Barata, 2021; Wang and Wu, 2022) such as occasional material shortages, changes in customer orders, equipment failures, or deviations in final product quality. Such factors will make it impossible to execute the production process on time. To prevent the same, digital twins can provide a kind of technical support for production (Liu et al., 2020). In the process of production and deployment, digital twins have a two-sided focus – they look at what actually happens in the process (Albo et al., 2021; Rocha and Barata, 2021), but also enable understanding of what may happen in the future (Rocha and Barata, 2021; Sakr et al., 2021).

Despite the many positive aspects of DT, the authors warn of increasing cybersecurity vulnerabilities such as physical tampering, supply chain attacks and sabotage (Jiang et al., 2024), which requires special attention. For this reason, digital twins can be used to find vulnerabilities in the production system (Rocha and Barata, 2021) and simulate attacks to strengthen the cyber security of the production sector (Jiang et al., 2024).

2.5 Digital Twin Classification

Since digital twins are virtual synchronised representations of physical entities that aim to mirror their real-world counterparts as closely as possible, they become novel tools for industries (Purcell and Neubauer, 2023), promising real-time insights and improved decision-making for physical assets.

According to Kritzinger et al. (2018), there are three distinct levels of integration in the implementation of DT, each characterised by the depth and directionality of data flow: digital model (DM), digital shadow (DS), and digital twin (DT). Figure 2 illustrates the difference between them.

A **digital model** exhibits no automated data transfer between the physical entity and its virtual model. Interaction is manual, limiting the potential for real-time analytics and adaptation. Data of a **digital shadow** flow unidirectionally and automatically from the physical entity to the virtual model at this stage. This allows for some level of monitoring and simulation based on

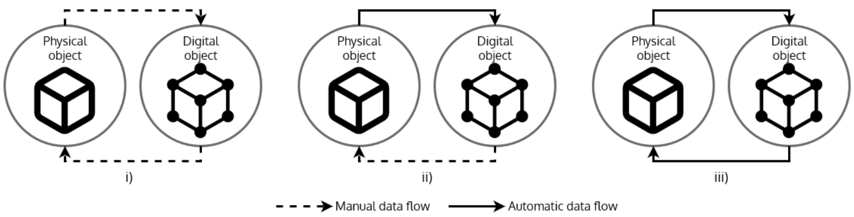

Figure 2: i) digital model; ii) digital shadow; iii) digital twin

real-time data, but without reciprocal interaction from the virtual to the physical. A **digital twin** represents the most integrated level, where data exchange is bidirectional. Changes in the virtual model are immediately reflected in the physical entity and vice versa. This dual interaction facilitates enhanced simulation, real-time feedback, and preemptive decision-making.

3 Example Use Case

The process of production planning and production capacity scheduling in typical production organisations includes the activities of the production, procurement, and storage departments. Process is intertwined with a series of activities in the above mentioned departments. Roughly presented by the authors, production planning and capacity scheduling can be divided into four fundamental phases that include multiple activities and, in a digital context, the creation of algorithms (Figure 3):

Phase 1: **Planning** involves scheduling production processes, raw materials, and resources to produce products for consumers within predetermined time frames. It determines what needs to be produced and how much work should be done. The goal is to ensure that products are processed efficiently and on time. Effective production planning impacts critical parts of a manufacturing organisation, such as capacity planning, supply chain management, production lead time, and material requirements planning. This phase includes processing input data (data store) based on the planned needs of the established demand, information on the product's technical characteristics, and the basis for setting up algorithms for planning needs for purchase and production. Phase input is a data store (inventory status, final product inventory status, planned incoming inputs, bill of materials, etc.) consisting of: 1. Standardisation of material factors: defining and establishing all the settings of the products that are planned to be produced, respecting the quality standards of the resources that are obtained for production purposes; 2. Technical documentation preparation: checking and determining the correctness of the technical documentation of the products that are planned to be produced, taking into account documents such as bills of material for products; 3. Orders generation: material requirement planning algorithm. Phase outputs are documents (work orders, purchase orders, recommendations for replanning purchase or production).

Phase 2: **Preparation** includes collecting all necessary documents for production planning and determining the current state of the production process. Phase input: Documents (work orders, purchase orders, recommendations for replanning purchase or production) containing: 1. Draft production planning: defining the time period for which the plan is made, collecting work orders, determining the approximate needs for materials; 2. Final production planning: defining the final production needs in the planned periods, defining the type, quantity, and terms of purchase of materials, and creating the final production plan. Phase output: Documents (production plan, purchase plan).

Phase 3: **Scheduling** of production focuses on planning how many capabilities (production resources) are needed and when they must be ready for production. It specifies who will perform the operations and when those operations will take place. By combining production needs with available resources cost-effectively, production scheduling ensures that the manufacturing process runs as smoothly as possible. Phase input: Documents (production plan, purchase plan) contains data on: 1. Checking the status of production capacities: within this activity, the available resources (such as machinery, labour, and materials) are allocated to meet production demands. Capacity planning ensures the right resources are in place to handle the workload. It considers factors like production capacity, lead times, and resource availability; 2. Planning production capacities occupation: Production schedules are created once the resources are allocated. This involves determining the sequence of production orders, assigning time slots for each operation, and coordinating activities across different departments. The goal is to optimise production flow and minimise idle time. Phase output: Document (occupation plan on capacities).

Phase 4: **Implementation** of production activities is carried out according to the schedules during the implementation phase. Capacities are occupied with work orders, and production activities have started. Managers monitor progress, track performance metrics, and make adjustments as needed. Phase input: Document (occupation plan on capacities) detailing: 1. Execution of orders on production capacities: work orders are scheduled on capacities based on the occupation plan, and they are processed during the production time. Phase output: Database updates (inventory status, final product inventory status, etc.).

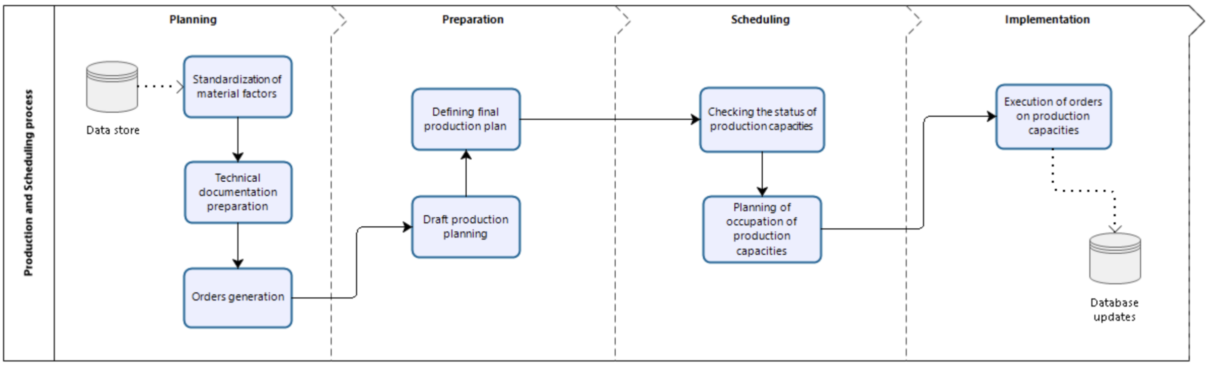

Figure 3: Diagram of the four phases in production planning and capacity scheduling.

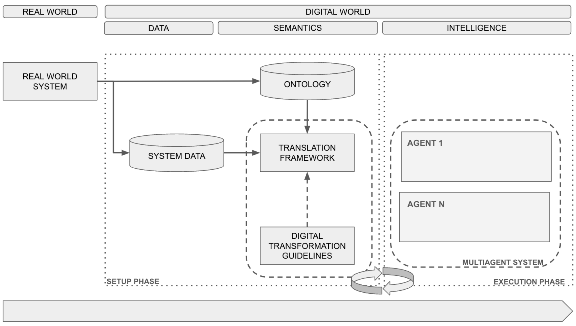

Figure 4: Conceptual model of the agent-based simulation architecture for digital transformation, leveraging ontologies and artificial agents to simulate real-world scenarios.

4 Proposed Architecture

This paper proposes a conceptual model of the non-specified work-in-progress architecture of an agent-based approach to simulation for the digital transformation process that uses entities in intelligent virtual environments. This approach is divided into the following phases: i) setup phase, ii) customised implementation phase, iii) execution phase (Figure 4).

In the setup phase, real-world elements are matched to intelligent virtual environment components using an ontology being developed based on (Okreša Đurić et al., 2019). This ontology aims for necessary expressiveness without over-constraining applicability. The phase models the real-world scenario using IVE concepts, ensuring initial validity. Validation occurs through the initial simulation run post-implementation, with the setup phase repeated if deemed invalid. The modelled system is valid if the outcomes match the expected behaviour of the real-world system. In the context of digital transformation of business processes, this involves abstracting processes as agents or introducing actor agents that perform the modelled processes. A novel approach of modelling agents as processes for specifying inter-agent communication flow (Peharda et al., 2023) could be applied to convert business processes to artificial agents or facilitate their communication.

The implementation phase consists of translating the ontology-based model of the first phase into an implementation blueprint. This phase uses the in-development framework to translate selected concepts of the chosen ontology into Python implementation blueprints. This blueprint contains the basic implementation of the modelled system, similar to the process described in (Okreša Đurić, 2017). The blueprint is expected to be further specified by a developer based on the domain of the observed real-world system, the goals and guidelines of digital transformation, and the expected comprehensiveness of the simulation, which is the crucial part of phase iii).

Once the IVE and the incorporated agents representing the modelled elements of the world are implemented, system data inputs are used during the simulation phase to describe the real world and to perform the tasks for which the agents were commissioned. Therefore, the agents and objects within the simulation can be observed as digital twins. Furthermore, based on the customised implementation phase, the agents can be observed on any of the three levels of digital twin integration presented in Sec. 2.5. We consider the ever-evolving nature of the digital twin to match and refine the required functionalities, which requires an iterative process where, for each new version, the setup phase may need to be re-run to execute the new environment being deployed.

Gamification techniques are proposed to enhance the natural interaction of simulated agents, complementing their core features. By implementing gamification beyond basic points and badges, agents' behaviour can be subtly modified to reflect nuanced changes in real-world human behaviour. Techniques such as rewarding goal-oriented interaction, encouraging grouping, and incentivising efficiency can be applied depending on simulation requirements. While these essentially form reward systems for agents, framing them as gamification concepts facilitates their application and translation to real-world human agents.

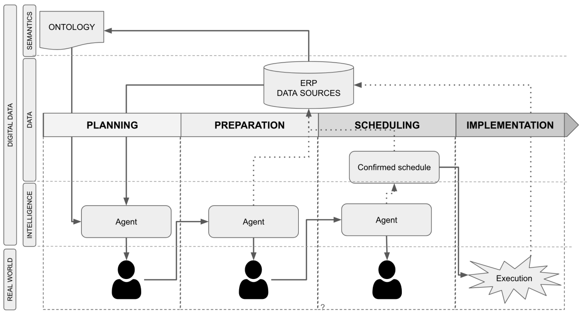

Figure 5: Integration of the proposed agent-based simulation architecture to illustrate the application of the digital transformation process.

5 Applying the Proposed Architecture to the Example Use Case

Digital transformation of the process described in Sec. 3 is presented here in two distinct possible scenarios: i) digital transformation of Planning (phase 1) and Preparation (phase 2) production process; ii) digital transformation of Scheduling (phase 3) and Implementation (phase 4) production process (Figure 5). Only the simulation stage of the digital transformation process is described in this section, following the three phases of the agent-based approach presented in Sec. 4. The setup phase is the same in both scenarios since both scenarios are observed within the same system.

5.1 The First Scenario

In phase 1 (Planning), customer orders are received, which serve as the basis for production planning. Upon the arrival of customer orders, work orders are generated and forwarded in digital form to phase 2 (Preparation). With digital transformation, inputs (material stocks) are synchronised in real time and allocated to work orders. All documents are digital, updated in real-time, and forwarded to subsequent stages. Additionally, due to changes in the inventory status, material requirements are generated in real-time, ensuring constant updates on how much to order from suppliers. The production plan is digitally synchronised in real-time, making production requirements dynamically swiftly to changing market conditions, minimising bottlenecks, and achieving higher efficiency.

The setup phase of this scenario should be customised with additional agents and artefacts related to the observed concepts that play the leading roles of this scenario. For example, should the digital transformation expert wish for a detailed and highly customisable simulation, they may choose to model both customer and work orders as separate agents. Furthermore, an overseer agent can be modelled to oversee the two described phases of the business process. The process of forecasting production needs can be modelled as a separate agent. Inventory status, material stocks, and material requirements can be modelled as simple data inputs or IVE artefacts within the system. Ultimately, suppliers may be modelled as agents, as other entities, or as simple data flows, depending on the desired abstraction and interaction level.

Various behaviours can be implemented in the customised implementation phase, granting different levels of intelligence and autonomy to the included agents; e.g., additional agents may be included that behave as forecasting agents. When the simulation is run, the behaviour of the observed system can be deduced from the individual and emergent interactions of the included agents. Running the simulation is expected to give the digital transformation expert an estimate of, for example, various resource consumption. Such data is predicted to be valuable in the digital transformation decision-making process.

5.2 The Second Scenario

In phase 3 (Scheduling), digital work orders are allocated to capacities, i.e., included in the occupation plan of work orders on capacities. The plan is digital and changes in real time, according to the enterprise's defined algorithms (rules). At any moment, the current workload, available capacities, their status, and the capacity requirements for the working day are known. As a result, the need for overtime work and additional human resources is determined. In phase 4 (Implementation), digital work orders are distributed to capacities (machines), and the production preparation time, the production flow, and the completion of the production are determined. In the event of a potential failure or other incidents that affect the normal production flow, the digital process allows feedback on previous stages and enables replanning according to new requirements. The role of the human factor is reduced to a minimum in the entire process, i.e., the human has only a controlling role.

The setup phase of this scenario should include agents that can play the role of work orders and capacities. Based on the desired level of interaction and precision, the amount of work, overtime work, and human resources could be modelled as simple data flows. The forecasting process can be implemented as an individual agent.

Various behaviours can be implemented as available to the simulation agents, e.g., the forecasting agent forecasts daily production capacity, determines the need for extra shifts, and calculates the required workforce for task completion. Upon running the simulation, the results of the agent interaction provide the digital transformation expert with valuable input.

6 Discussion

The approach presented in this paper is expected to provide digital transformation experts with valuable feedback on the benefits of the planned transformation of the initial business process. These benefits may be observed, e.g., as quantified results, emergent behaviour, or relative change of used resources compared to the initial real-world process. The benefit of utilising artificial agents in a simulation instead of the traditional toke-based simulations is the social and interactive nature of the concept of intelligent artificial agents by default.

Interaction that stems from the fundamental features of artificial agents is argued here to be able to provide different and possibly much more valuable feedback than token-based simulations. Furthermore, implementing intelligent agents is a way of introducing modern methods and algorithms of artificial intelligence into the equation of digital transformation and transformation suggestions or guidelines. Finally, influencing agents' behaviour using gamification techniques can allow digital transformation experts to observe the seemingly natural evolution of the initial model.

7 Conclusion & Future Research

The agent-based approach to digital transformation simulation presented in this paper offers several advantages over traditional methods. By utilising intelligent artificial agents within IVEs, our architecture enables more dynamic and interactive simulations that better reflect the complexities of real-world business processes.

Key contributions of this work include 1. a flexible three-phase architecture that combines ontology-based modelling, customised implementation, and gamification-enhanced simulation; 2. integration of artificial intelligence and multiagent systems into the digital transformation process, allowing for more sophisticated modelling of business processes and human factors; 3. the use of gamification techniques to influence agent behaviour, providing a novel way to simulate subtle changes in human behaviour within transformed business processes; 4. a demonstration of the architecture's applicability through two scenarios in a production planning and scheduling use case.

Our approach addresses the limitations of token-based simulations by incorporating the social and interactive nature of intelligent agents. The stated allows digital transformation experts to observe emergent behaviours, quantify resource requirements, and comprehensively evaluate planned transformations' potential benefits.

Future research directions include, but are not limited to, further development and refinement of the ontology for describing business processes and IVE components, expansion of the gamification techniques applied to agent behaviour to model more complex human factors, integration of machine learning algorithms to enhance agent decision-making and adaptability within simulations, empirical validation of the proposed architecture through real-world case studies across various industries, development of visualisation tools to better represent simulation outcomes and aid in decision-making for digital transformation strategies.

By providing a more nuanced and interactive simulation environment, our agent-based approach has the potential to significantly improve the planning and implementation of digital transformation initiatives across diverse business domains.

Acknowledgement

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