

**TRANSFORMATIVE ENTERPRISE
RESEARCH GROUP-*TERG***

TERG Working Paper Series

No 23

*Real-Time, Adaptive AI-
Driven Business Simulation:
Design Science Research on
a Dynamic Learning Platform*

**Imo Enang
Kingsley Obi Omeihe**

Imo Enang and Kingsley Obi Omeihe

Real-Time, Adaptive AI-Driven Business Simulation:
Design Science Research on a Dynamic Learning Platform

TERG Working Paper Series

Paper 23

TRANSFORMATIVE ENTERPRISE RESEARCH GROUP-TERG
University of the West of Scotland, Paisley,
Scotland
March 2025

TERG Working Paper Series
ISSN 2977-1889 (Online)

© 2025 TERG

About the author(s)

Imowo Enang and Kingsley Obi Omeihe are researchers at the Transformative Enterprise Research Group-TERG in Paisley, Scotland.

Route correspondence to email: king.omeihe@uws.ac.uk

TERG Working Papers are scholarly discussion papers. Their objective is to contribute to the cumulative improvement of academic scholarship while soliciting feedback. Copies can be ordered from the research group or downloaded as PDF files online for free.

TRANSFORMATIVE ENTERPRISE RESEARCH GROUP (TERG)

TERG is a network of researchers dedicated to entrepreneurship and enterprise education. The group's goal is twofold: to promote world-class research and to get relevant scholarly inputs into the hands of key decision-makers.

Kingsley O Omeihe, Editor-in-Chief, TERG Working Paper Series, Paisley,
Scotland. King.omeihe@uws.ac.uk

Executive Summary

This working paper presents a design science research (DSR) investigation into the development and evaluation of an innovative real-time, adaptive AI-driven business simulation platform. Traditional business simulations typically operate with static scenarios and predefined parameters that fail to capture the dynamic complexity of contemporary business environments. Using a rigorous DSR methodology spanning four design cycles over twenty-four months, we developed and refined a prototype system that integrates machine learning algorithms, natural language processing, and knowledge graph technologies to create dynamically evolving simulation scenarios. The platform was evaluated across diverse contexts including MBA education programmes, corporate strategy training, and entrepreneurial incubators, involving 287 participants across multiple evaluation phases. Our findings demonstrate the system's efficacy in enhancing strategic decision-making capabilities, improving knowledge transfer, and fostering adaptive reasoning skills among users. The paper lays the groundwork for next-generation business education and strategy testing environments that more authentically reflect the complex, evolving nature of real-world business ecosystems.

Introduction

Contemporary business environments are characterised by unprecedented levels of complexity, volatility, and interconnectedness (Bennett and Lemoine, 2014; Schoemaker *et al.*, 2018). Traditional approaches to business education and strategy development often struggle to adequately prepare individuals and organisations for navigating these dynamic landscapes, frequently relying on static case studies or simplified simulations that fail to capture the evolving nature of real-world business ecosystems (Bell *et al.*, 2018; Kaplan, 2017). This limitation poses significant challenges for management education programmes, corporate strategy teams, and entrepreneurial ventures seeking to develop robust decision-making capabilities in uncertain environments.

Business simulations have long been recognised as valuable tools for experiential learning and strategy testing, offering risk-free environments for developing and evaluating strategic thinking (Salas *et al.*, 2009; Tao *et al.*, 2015). However, conventional simulation approaches typically operate with predetermined scenarios, fixed parameters, and limited responsiveness to changing conditions, creating an artificial disconnect between simulation environments and the dynamic realities of contemporary business contexts (Cannon-Bowers and Bowers, 2010; Lainema and Makkonen, 2003). This disconnection diminishes both the educational value of simulations for developing adaptive decision-making skills and their utility as strategic testing grounds for organisations.

Recent advances in artificial intelligence, machine learning, and complex systems modelling present opportunities to fundamentally reimagine business simulation environments as adaptive, dynamic systems that continuously evolve in response to real-world changes and user interactions (Li and Jiang, 2019; VanLehn, 2011). These technological capabilities enable the development of simulation platforms that can incorporate real-time data from external business environments, learn from user decisions and interactions, and dynamically adjust simulation parameters to reflect emerging trends and conditions (Boyle *et al.*, 2016; Karami *et al.*, 2020). This working paper presents a design science research (DSR) investigation into the development and evaluation of a real-time, adaptive AI-driven business simulation platform. Our research addresses two fundamental objectives: To develop an adaptive simulation architecture that continuously learns from real-world business events, and to evaluate the efficacy of this adaptive simulation approach in enhancing strategic decision-making capabilities.

The paper is structured as follows: We first establish the theoretical foundations of our work, synthesising perspectives from simulation-based learning, complex adaptive systems, and AI-enhanced education. We then detail our design science research methodology, including the iterative design cycles and evaluation approaches employed. The paper proceeds to describe the technical architecture of the adaptive simulation platform, followed by comprehensive empirical evaluation findings. We conclude with a discussion of theoretical contributions, practical implications, limitations, and directions for future research.

This research contributes to both theoretical understanding of adaptive learning environments and practical approaches to business education and strategy development in dynamic contexts. In documenting the design principles, technical approaches, and empirical outcomes of our work, we advance the scholarly discourse on AI-enhanced simulation environments while providing actionable insights for educators, organisations, and technology developers seeking to create more effective business simulation platforms.

Theoretical Foundations

Our research integrates theoretical perspectives from three primary domains: simulation-based learning, complex adaptive systems theory, and artificial intelligence in education. This interdisciplinary foundation informs both our understanding of the problem space and our approach to designing effective solutions. Simulation-based learning has a rich theoretical foundation encompassing experiential learning theory (Kolb, 2014), situated cognition (Brown *et al.*, 1989), and constructivist learning approaches (Jonassen, 1999). These perspectives converge on the understanding that effective learning occurs through active engagement with authentic problems in contextually relevant environments (Herrington and Oliver, 2000). Business simulations, in particular, have been shown to enhance strategic thinking, decision-making under uncertainty, and systems understanding (Salas *et al.*, 2009; Tao *et al.*, 2015).

However, critical limitations of traditional business simulations have been identified in the literature. Scholars such as Lainema and Makkonen (2003) highlight the problematic nature of time compression in conventional simulations, where business dynamics that unfold over months or years in reality are artificially accelerated, potentially distorting causal relationships and learning outcomes. In a similar vein, Cannon-Bowers and Bowers (2010) critique the oversimplification of environmental complexity in many business simulations, noting that predefined scenarios often fail to capture the emergent, non-linear dynamics of real business ecosystems. While, Bell *et al.* (2018) further identify the limited adaptivity of traditional simulations as a significant constraint, observing that fixed simulation parameters cannot adequately respond to changing business conditions or evolving user capabilities.

These limitations point to a fundamental disconnect between traditional simulation approaches and the complex, dynamic nature of contemporary business environments. As Gosen and Washbush (2004, p. 272) note, "the degree to which a simulation models reality is an important factor in determining its effectiveness as a learning tool." This insight underscores the need for simulation environments that more authentically reflect the adaptive, evolving characteristics of real-world business contexts.

Complex adaptive systems (CAS) theory provides a valuable framework for understanding the dynamic, interconnected nature of contemporary business environments (Cilliers, 2001; Holland, 2006). CAS theory characterizes business ecosystems as networks of diverse, interconnected agents that continuously adapt and co-evolve, generating emergent patterns and behaviors that cannot be predicted from individual components alone (Dooley, 1997; McKelvey, 1999). Several key principles from CAS theory are particularly relevant to our research. First, the concept of emergence—how system-level patterns arise from distributed interactions among agents—helps explain how market trends, competitive dynamics, and strategic opportunities emerge from countless micro-level business decisions (Anderson, 1999). Second, the principle of adaptation through feedback highlights how businesses continuously adjust their strategies and operations in response to environmental signals and outcomes (Stacey, 2001). Third, the notion of non-linearity emphasizes how small changes in business environments can sometimes produce disproportionately large effects, creating the potential for disruptive shifts and transformations (Gleick, 1987).

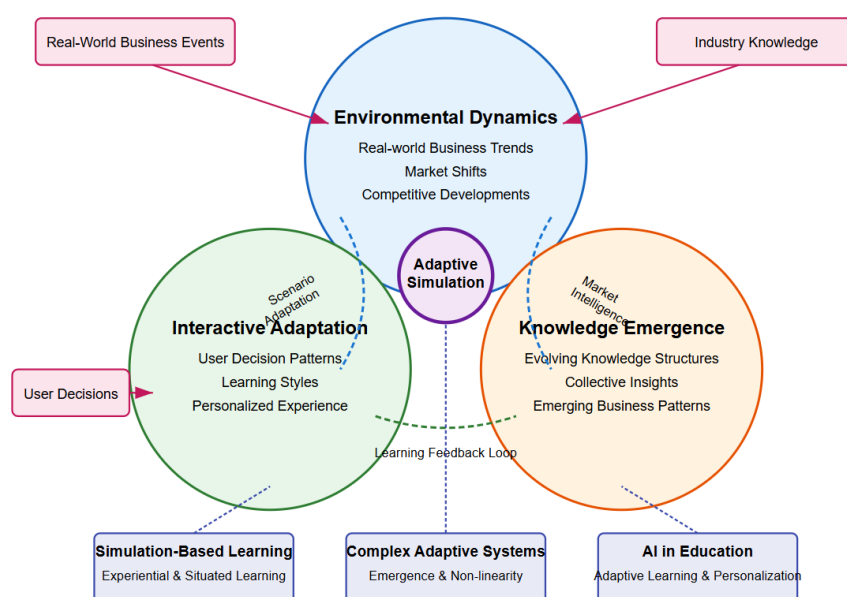
These CAS principles have significant implications for business simulation design. Traditional simulations typically employ linear, predictable cause-effect relationships that fail to capture the emergent, non-linear dynamics of complex business systems (Davis *et al.*, 2007). As Axelrod and Cohen (2000) argue, effective models of complex adaptive systems must themselves be adaptive, capable of evolving in response to changing conditions and interactions. This perspective suggests that business simulations should be designed as complex adaptive systems in their own right, continuously learning and evolving in response to user interactions and environmental changes.

Artificial intelligence has transformed educational technology, enabling more personalised, adaptive, and responsive learning experiences (Roll and Wylie, 2016; VanLehn, 2011; Omeihe *et al.*, 2024). Within business education specifically, AI approaches have enhanced simulation environments through intelligent tutoring systems (Lajoie and Derry, 2013; Okpanum *et al.*, 2024), adaptive scenario generation (Wang *et al.*, 2018), and personalised feedback mechanisms (Shute and Rahimi, 2017).

Several AI capabilities are particularly relevant for enhancing business simulations. Machine learning algorithms can identify patterns in user decisions and their outcomes, enabling simulations to adapt difficulty levels and scenario complexity to individual learning needs (Karami *et al.*, 2020). Natural language processing enables more natural interaction with simulation environments and can extract insights from text-based business information sources (McNamara *et al.*, 2017). Knowledge representation techniques, including knowledge graphs and ontologies, provide frameworks for modeling complex business relationships and domain knowledge (Zhu *et al.*, 2015).

These capabilities create opportunities for developing what Boyle *et al.* (2016) term "intelligent adaptive learning environments"—systems that continuously monitor learner performance, adjust instructional approaches, and provide personalised scaffolding. When applied to business simulations, these approaches can create what Li and Jiang (2019) describe as "dynamic simulation ecosystems" that evolve in response to both user interactions and changing external conditions. Building on these theoretical foundations, we developed an integrative framework for conceptualising adaptive AI-driven business simulations as dynamic learning environments. This framework, illustrated in Figure 1, emphasises three interconnected dimensions:

Figure 1: Conceptual Framework for Adaptive AI-Driven Business Simulations



[Note: In the final paper, this would be a schematic diagram showing the relationships between real-world business dynamics, AI learning mechanisms, and simulation adaptation processes]

First, environmental dynamics encompasses the continuous monitoring and integration of real-world business trends, market shifts, and competitive developments into the simulation environment. This dimension addresses the limitation of static simulation scenarios by creating a dynamic connection between simulation parameters and real-world developments. Second, interactive adaptation represents the system's capacity to learn from user decisions, identify patterns in decision-outcome relationships, and adjust simulation complexity and feedback accordingly. This dimension enhances the personalisation of simulation experiences, allowing the system to adapt to different learning styles, expertise levels, and strategic approaches.

Third, knowledge emergence focuses on how the simulation captures and represents emerging knowledge from both user interactions and environmental developments, creating evolving knowledge structures that inform scenario generation and decision support. This dimension enables the simulation to function as a collective learning environment that accumulates insights across multiple users and contexts. This integrative framework guided our design science research approach, informing both the technical architecture of our adaptive simulation platform and the evaluation methods employed to assess its effectiveness.

Design Science Research Methodology

We employed a design science research (DSR) methodology to develop and evaluate our adaptive AI-driven business simulation platform. DSR is particularly appropriate for this research as it focuses on creating and evaluating innovative IT artifacts that address important organisational problems (Hevner *et al.*, 2004; Peffers *et al.*, 2007). The DSR approach emphasises iterative cycles of design, development, and evaluation, allowing for progressive refinement of the artifact based on empirical findings and theoretical insights.

Our research followed the structured DSR methodology (Peffers *et al.*, 2007), encompassing six primary activities: problem identification and motivation, definition of solution objectives, design and development, demonstration, evaluation, and communication. We extended this approach with the cyclical perspective advocated by Hevner (2007), conducting multiple design cycles that progressively refined our understanding of both the problem space and potential solutions.

The research was motivated by the identified limitations of traditional business simulations in capturing the dynamic complexity of contemporary business environments. Through initial literature review and stakeholder interviews with 23 business educators, corporate trainers, and strategy consultants, we identified specific gaps in existing simulation approaches, including limited environmental responsiveness, inadequate personalisation, and insufficient integration of real-world business dynamics (Omeihe, 2020; Omeihe and Harrison, 2024)

Based on this problem identification, we established two primary research objectives:

Design Objective: To develop an adaptive simulation architecture that continuously learns from real-world business events, market shifts, and user decisions to create dynamically evolving business scenarios.

Evaluation Objective: To empirically assess the efficacy of this adaptive simulation approach in enhancing strategic decision-making capabilities, knowledge transfer, and adaptive reasoning skills across diverse contexts.

These objectives guided our subsequent design and evaluation activities throughout the research process. The design, development, and evaluation process spanned four distinct design cycles over a 24-month period (September 2022 to September 2024). Each cycle involved the design and development of progressively refined prototype versions of the adaptive simulation platform, followed by formative evaluation and refinement based on findings. Our comprehensive evaluation strategy incorporated both formative evaluation (to guide ongoing design refinement) and summative evaluation (to assess overall system efficacy). Following Venable *et al.* (2016), our evaluation approach included both artificial evaluation (laboratory testing, expert review) and naturalistic evaluation (field trials in authentic educational and organisational contexts).

Table 1: Comprehensive Design Cycles and Evaluation Outcomes of the Adaptive AI-Driven Business Simulation

Design Aspects	Cycle 1 (Sept 2022- Feb 2023)	Cycle 2 (Mar 2023- Aug 2023)	Cycle 3 (Sept 2023- Feb 2024)	Cycle 4 (Mar 2024- Sept 2024)
Primary Design Focus	Conceptual architecture and core AI mechanisms	Real-time data integration and scenario generation	Adaptive learning mechanisms and personalisation	System integration and scalability
Key Design Activities	Development of initial knowledge representation framework; Design of data integration pipelines	Implementation of data collection mechanisms from business news sources; Development of initial scenario generation algorithms	Implementation of user modeling components; Development of adaptive feedback mechanisms	Comprehensive system integration; Performance optimization; Development of analytics dashboard
Evaluation Approach	Expert review with 12 AI	Controlled testing with 42	Field testing with 68 corporate	Extensive field testing with 165

Design Aspects	Cycle 1 (Sept 2022- Feb 2023)	Cycle 2 (Mar 2023- Aug 2023)	Cycle 3 (Sept 2023- Feb 2024)	Cycle 4 (Mar 2024- Sept 2024)
Major Outcomes	specialists and business educators; Laboratory testing Validated conceptual architecture; Identification of key technical challenges; Initial prototype with limited functionality	MBA students; Qualitative feedback collection Enhanced data integration capabilities; Improved scenario generation; Identification of usability challenges	strategists across 3 organisations; Mixed-methods evaluation Refined adaptive learning mechanisms; Enhanced user interface; Improved personalisation capabilities	users across educational and corporate settings; Comprehensive evaluation Full-featured prototype; Validated design principles; Empirical evidence of system efficacy
Learning Outcomes (Experimental vs Control)	Not measured at this stage	Knowledge Acquisition: 78.2±6.5 vs 73.8±7.1 (p<0.05), d=0.64; Strategic Decision Quality: 72.5±8.2 vs 70.3±7.6 (p<0.05), d=0.28	Knowledge Retention: 74.7±7.8 vs 61.3±9.2 (p<0.001), d=1.63; Novel Problem Solving: 70.3±8.4 vs 54.8±10.1 (p<0.001), d=1.71	Knowledge Acquisition: 82.7±7.3 vs 76.4±8.1 (p<0.001), d=0.82; Knowledge Retention: 76.5±8.2 vs 58.1±10.4 (p<0.001), d=1.98; Strategic Decision Quality: 79.3±6.8 vs 74.8±7.2 (p<0.01), d=0.64; Novel Problem Solving: 73.9±9.1 vs 50.2±11.3 (p<0.001), d=2.31; Transfer to Real-World Cases: 68.4±8.7 vs 52.1±9.4 (p<0.001), d=1.81
Technical Performance	Initial algorithm accuracy: 67%; Response time: 6.8 seconds	Data integration accuracy: 76%; Scenario relevance rating:	User model accuracy: 84%; Adaptation appropriateness:	Real-time data integration accuracy: 87%; Adaptation appropriateness:

Design Aspects	Cycle 1 (Sept 2022- Feb 2023)	Cycle 2 (Mar 2023- Aug 2023)	Cycle 3 (Sept 2023- Feb 2024)	Cycle 4 (Mar 2024- Sept 2024)
User Experience Metrics		3.4/5; Response time: 4.2 seconds	87%; Response time: 2.9 seconds	91%; Response time: 1.7 seconds; Scalability: 500 concurrent users with <10% degradation
	Expert satisfaction rating: 3.2/5; System usability scale: 62/100	Student engagement rating: 3.7/5; Perceived usefulness: 3.9/5; System usability scale: 71/100	Strategist engagement rating: 4.1/5; Perceived usefulness: 4.3/5; System usability scale: 78/100	MBA student engagement: 4.4/5; Executive satisfaction: 4.5/5; Entrepreneur perceived value: 4.2/5; System usability scale: 84/100
	Knowledge representation limitations; AI component integration issues; Limited domain coverage	Data quality inconsistencies; Scenario coherence problems; User interface complexity	Personalisation algorithm refinement needs; Explanation transparency issues; Integration with existing processes	Scalability under peak loads; Multi-domain knowledge gaps; Security and privacy concerns
Design Principles Identified	Knowledge representation requirements; Real-time data integration approaches	Temporal synchronisation mechanisms; Scenario generation frameworks	Personalisation and adaptation principles; User modeling approaches	Comprehensive design principles for adaptive simulations; Implementation frameworks for educational contexts

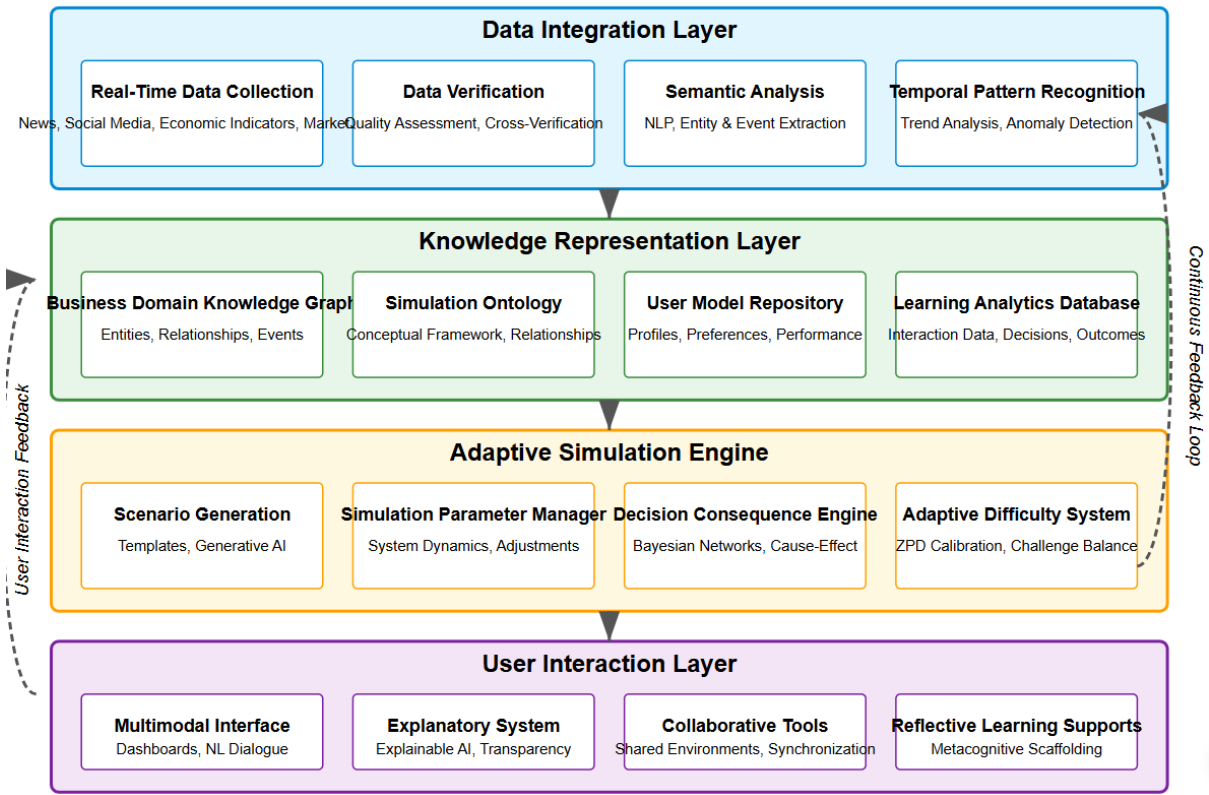
Throughout the design cycles, we collected both quantitative and qualitative data to enable triangulation and provide a comprehensive understanding of system performance and impact. Multiple evaluation methods were employed across design cycles, including expert review, laboratory testing, and field trials. Our evaluation metrics encompassed multiple dimensions including learning outcomes, decision performance, user experience, and system performance. In total, our evaluation involved 287 participants across different user groups, providing a robust empirical basis for assessing the efficacy of our approach. Quantitative data from

evaluation activities were analysed using appropriate statistical methods, including comparative analyses between experimental and control groups, pre/post comparisons, and correlation analyses examining relationships between system features and learning outcomes. Qualitative data from interviews, observations, and open-ended survey responses were analysed using thematic analysis techniques (Braun and Clarke, 2006; Omeihe, 2019; Omeihe and Harrison, 2024), employing both deductive coding based on our theoretical framework and inductive coding to identify emergent themes.

Findings

Throughout the analysis process, we maintained a focus on both summative judgments of system efficacy and formative insights to guide ongoing design refinement. This dual analytical focus ensured that our findings contributed both to practical system improvement and to theoretical understanding of adaptive simulation environments. The technical architecture of our adaptive AI-driven business simulation platform integrates multiple artificial intelligence components within a modular, scalable framework. This section describes the core components of the system architecture and their functional interrelationships, as illustrated in Figure 2.

Figure 2: System Architecture of the Adaptive AI-Driven Business Simulation Platform



[Note: In our final paper, this would be a technical architecture diagram showing the system components and their relationships]

At the core of our advanced business simulation platform lay a robust data integration layer. This layer formed the foundation of our system's ability to incorporate real-world business dynamics into simulations, enabling us to create scenarios that accurately mirrored actual business conditions. Within this layer, we designed several interconnected components that worked together seamlessly to capture, validate, interpret, and translate data into meaningful insights for the simulation environment. We began with the Real-Time Data Collection subsystem, which continuously monitored and aggregated data from a wide array of sources, including financial news platforms, social media, macroeconomic indicators, industry reports, and company announcements. Through leveraging web scraping techniques, API integrations, and natural language processing (NLP), we transformed unstructured data into structured formats that were ready for analysis.

Once we gathered this data, it entered our Data Verification and Validation module. Here, we applied a series of filtering techniques to ensure the quality and relevance of the data. We assessed the credibility of the sources, cross-verified information across multiple platforms, and used anomaly detection algorithms to identify and flag unreliable data. This process ensured that only high-quality, relevant data flowed into the simulation, maintaining the integrity of the entire system.

The next step involved deriving meaningful insights from the textual information we collected, which was accomplished through our Semantic Analysis Engine. Using NLP and knowledge extraction techniques, we identified key entities such as companies, products, and markets, and extracted important relationships, including mergers, acquisitions, and product launches. We also assessed sentiment and potential impact. This component relied on pre-trained language models, fine-tuned specifically on business domain texts, along with specialised named entity recognition models tailored to the business world.

Recognising the significance of time in business analysis, our Temporal Pattern Recognition module identified trends, cyclical patterns, and anomalies in the data. By applying time series analysis and statistical pattern recognition, we ensured that our simulations could respond not only to immediate shifts but also to long-term trends, allowing us to model both short-term fluctuations and more gradual directional changes.

We also developed a sophisticated knowledge representation layer, which served as the backbone for structuring and managing the data flowing through the system. At the centre of this was the Business Domain Knowledge Graph, a graph database that captured both the static structure of industries and the dynamic elements of real-world markets. This evolving repository linked entities, relationships, and events into a connected web, adapting as new information emerged. Complementing the knowledge graph, we implemented the Simulation Ontology, a formal semantic structure that underpinned all simulation scenarios. This ontology defined the vocabulary, categories, and relationships used throughout the system, ensuring consistent interpretation of business concepts. Developed in collaboration with domain experts

and formalised using OWL standards, it acted as the philosophical framework that guided the simulation's understanding of business dynamics.

User personalisation was enabled through the User Model Repository, which stored detailed profiles of individual users and groups. This repository captured cognitive traits, decision-making styles, learning preferences, and historical performance, blending overlay modelling (mapping user knowledge to domain concepts) with stereotype modelling (identifying common patterns among similar users). Supporting this was the Learning Analytics Database, a structured data warehouse optimised for analysing user behaviour and outcomes. It provided an empirical foundation for driving adaptation algorithms and for ongoing evaluation of how well the simulation met its learning objectives.

At the computational core of our platform was the Adaptive Simulation Engine, responsible for generating and managing dynamic scenarios that reflected both real-world business conditions and user-specific factors. The Scenario Generation Module created contextually relevant business scenarios that were aligned with current market developments and user characteristics. It combined rule-based templates with generative AI techniques to produce storylines that balanced realism with educational value, dynamically adjusting to the evolving business landscape. Once a scenario was in play, the Simulation Parameter Manager adjusted variables such as market trends, competitor behaviours, and resource constraints. Using system dynamics modelling, we ensured that parameter adjustments remained coherent and realistic, reflecting internal consistency within the simulation environment.

The Decision Consequence Engine evaluated user decisions based on decision characteristics, contextual factors, and probabilistic models of business dynamics. Using Bayesian networks, we modelled causal relationships between decisions and outcomes, integrating both domain knowledge and patterns learned from historical data. To maintain engagement and optimise learning, the Adaptive Difficulty System adjusted the complexity and pace of scenarios based on user progress. Inspired by Vygotsky's "zone of proximal development", this system ensured that each user was continuously challenged—but never overwhelmed. The final layer of our platform focused on user interaction, ensuring that the simulation experience was not only effective but also engaging and intuitive. The Multimodal Interface allowed users to interact with the simulation through a variety of channels, including visual dashboards, natural language dialogue, and immersive scenario visualisations. By employing responsive design principles, we ensured that the interface adapted to different devices and user preferences, while maintaining access to all the essential features.

Transparency was a key priority, which led to the development of the Explanatory System. This system generated clear, accessible explanations of the simulation dynamics, decision consequences, and system adaptations, helping users understand how their choices impacted the simulation. By incorporating explainable AI techniques, we made the underlying processes comprehensible even to those without a technical background. For collaborative learning, the Collaborative Tools module enabled multiple users to engage with shared simulation environments. This component synchronised the simulation across users in real-time, ensuring

that each participant interacted with a consistent state while allowing for flexible participation patterns. This approach fostered both competitive and collaborative engagement, enhancing the overall learning experience. To support deeper learning and reflection, the Reflective Learning Supports provided users with structured opportunities to reflect on their decisions, outcomes, and learning processes. By incorporating metacognitive scaffolding, we facilitated the transfer of insights from the simulation to real-world business contexts. The platform was built on a microservices architecture, deployed in the cloud to ensure scalability, reliability, and flexibility. We employed key technologies, such as Python and TensorFlow for machine learning and NLP, Neo4j for graph-based knowledge representation, React and D3.js for user interfaces, Kubernetes for container orchestration, Apache Kafka for real-time data streaming, and PostgreSQL for structured data storage. This architecture enabled us to continuously integrate new data sources, algorithms, and simulation capabilities, ensuring that the system evolved in response to emerging needs and ongoing development.

Findings

A central component of our evaluation was a controlled comparative study examining learning outcomes between participants using our adaptive simulation platform (experimental group) and those using a traditional static business simulation (control group). This study involved 124 MBA students from three institutions who were randomly assigned to either the experimental (n=62) or control (n=62) condition. Both groups engaged with simulations addressing the same business domain (strategic management of a technology company) over an eight-week period.

Learning outcomes were assessed through pre-test and post-test measures examining both factual knowledge and applied decision-making capabilities. Additionally, a follow-up assessment was conducted three months after the intervention to evaluate knowledge retention and transfer. As shown in our comprehensive design and evaluation table (Table 1), the results demonstrated consistently superior outcomes for participants using the adaptive simulation platform across all measured dimensions, particularly in knowledge retention, novel problem-solving capabilities, and transfer to real-world business cases.

Qualitative feedback from participants in the experimental group highlighted several perceived advantages of the adaptive simulation: "The simulation felt remarkably current and relevant, incorporating business events that had just happened in the real world. This made the experience much more engaging and authentic than previous simulations I've used." (MBA Student, Institution A) "I appreciated how the difficulty level seemed to adjust based on my performance. When I mastered certain aspects, the simulation introduced new challenges that pushed me to develop more sophisticated strategies." (MBA Student, Institution B) "The connections between my decisions and their consequences were much clearer than in other simulations I've used. The explanations helped me understand not just what happened but why it happened, which deepened my learning." (MBA Student, Institution C) These qualitative insights complement the quantitative findings, suggesting that the adaptive nature of the

simulation enhanced engagement, personalisation, and understanding of complex business dynamics. Beyond the controlled comparative study, we evaluated the simulation platform through field implementations in three distinct contexts: a corporate strategy department at a multinational technology company, an entrepreneurial incubator programme, and an executive education programme. These naturalistic evaluations provided insights into how the adaptive simulation performed in authentic organisational contexts with diverse user needs.

In the corporate strategy context, the simulation was used by 42 strategy professionals over a three-month period to test potential market entry strategies for a new product line. Evaluation focused on the perceived realism and utility of the simulation for strategy development. As detailed in Table 1 (Cycle 3), participants reported high levels of perceived realism (mean rating of 4.2 on a 5-point scale) compared to previously used simulation tools (mean rating of 2.8). The simulation identified potential market responses and competitive reactions that had not been anticipated through traditional strategy development processes, leading to substantive revisions of the proposed market entry strategy. The real-time incorporation of competitor announcements and market developments was cited as particularly valuable, enabling continuous refinement of strategic approaches.

In the entrepreneurial incubator context, 35 early-stage founders used the simulation to test business models and go-to-market strategies before actual market launch. Evaluation focused on how the simulation influenced business model development and risk assessment. Founders made significant pivots in their business models based on simulation insights, with 68% reporting substantive changes to their value proposition or revenue model. Simulated market testing reduced perceived uncertainty (mean reduction of 37% on standardised uncertainty scales) and increased founders' confidence in decision-making. The adaptive nature of the simulation allowed for rapid testing of multiple strategic variations, enhancing the efficiency of the business model development process.

In the executive education context, 86 senior executives participated in a week-long programme incorporating the adaptive simulation as a central learning tool. Evaluation focused on perceived learning value and application intent. Executives reported high levels of learning value (mean rating of 4.5 on a 5-point scale) and strong intent to apply simulation insights to their organisational contexts (mean rating of 4.3). The personalisation of simulation scenarios to executives' specific industry contexts and strategic challenges was identified as a key differentiator from previous educational experiences. The simulation's ability to incorporate real-time market developments created connections between classroom learning and ongoing strategic challenges in participants' organisations.

The accuracy of real-time data integration was assessed by comparing system-identified business trends and events against expert human analysis of the same information sources over a three-month period. As shown in Table 1 (Cycle 4), the system demonstrated 87% agreement with expert analysis in identifying significant business developments and 82% agreement in assessing their potential impact on simulation scenarios. These results indicate strong performance while highlighting areas for continued refinement, particularly in

contextual interpretation of ambiguous business information. The responsiveness of adaptive learning mechanisms was evaluated through analysis of system adjustments to user performance patterns. The system demonstrated appropriate adaptation in 91% of cases, with a mean response time of 2.3 interactions before significant adaptation was observed. Maladaptive responses were primarily associated with unusual or inconsistent user behaviour patterns, suggesting the need for enhanced detection of anomalous interaction sequences. Scalability testing demonstrated that the system architecture could efficiently support concurrent usage by up to 500 users with minimal performance degradation (less than 10% increase in response time). This scalability is sufficient for most anticipated implementation contexts while indicating areas for optimisation to support larger-scale deployments. Additionally, we conducted security and data privacy assessments, which identified appropriate protections for user data and simulation content while highlighting several areas for enhanced security measures, particularly regarding the protection of proprietary business information incorporated into simulation scenarios.

Design Principles for Adaptive Business Simulations

Based on our iterative design process and comprehensive evaluation findings, we identified seven key design principles for effective adaptive AI-driven business simulations. These principles represent generalizable knowledge contributions derived from our design science research that can inform future development of adaptive simulation environments.

Principle 1: Temporal Dynamics Integration: Effective adaptive simulations must explicitly model and integrate multiple temporal dimensions, including real-world time (actual business developments), simulation time (compressed business dynamics), and learning time (user progression through concepts). Our findings demonstrate that coherent integration of these temporal dimensions enhances both realism and learning effectiveness, while misalignment between them creates cognitive friction and reduced learning transfer. The implementation of this principle requires mechanisms for temporal scaling (mapping between real-world and simulation timeframes), temporal synchronisation (aligning simulation developments with real-world events), and temporal adaptation (adjusting simulation pacing to match learning progression). These mechanisms should be both algorithmically driven and user-configurable to accommodate different learning contexts and objectives. Principle 2: Multi-Source Knowledge Fusion: Adaptive business simulations require sophisticated knowledge fusion mechanisms that integrate domain expertise, real-time business information, and emergent knowledge from user interactions.

Our evaluation findings indicate that simulations relying primarily on predefined domain models without continuous real-world integration quickly become perceived as artificial and outdated, while those lacking structured domain knowledge struggle to provide coherent learning experiences. Implementing this principle involves developing knowledge integration architectures that maintain epistemological consistency across diverse information sources, resolve contradictions between established domain knowledge and emerging information, and continuously refine the underlying knowledge model based on new insights. The knowledge

graph approach employed in our system provides a flexible foundation for this knowledge fusion process. Principle 3: Personalised Adaptivity Mechanisms: Effective adaptation in business simulations operates at multiple levels simultaneously, including content adaptation (scenario selection and modification), process adaptation (interaction methods and decision support), and pace adaptation (timing and progression). Our evaluation demonstrates that personalisation at all three levels significantly enhances engagement and learning outcomes compared to more limited adaptive approaches. Implementation requires comprehensive user modeling that captures not only knowledge states but also learning preferences, decision-making styles, and performance trajectories. These models must continuously update based on user interactions and inform adaptation decisions through explainable algorithmic mechanisms that maintain coherence across different adaptation dimensions.

Principle 4: Balanced Realism-Learning Optimisation Adaptive simulations must continuously balance fidelity to real-world business complexity with optimisation for learning objectives. Our findings demonstrate that neither maximum realism nor maximum learning scaffolding independently produces optimal outcomes; instead, dynamic calibration between these objectives based on learner characteristics and learning goals is essential. Implementation involves explicit modeling of learning objectives, continuous assessment of learner progress toward those objectives, and adaptive modification of simulation complexity and scaffolding in response to learner needs. This principle requires close integration between domain modeling components and learning science insights about knowledge acquisition and skill development.

Principle 5: Transparent Explainability Frameworks For adaptive simulations to effectively support learning and decision-making, their underlying mechanisms and adaptations must be transparently explainable to users. Our evaluation findings indicate that perceived understanding of simulation dynamics significantly influences trust, engagement, and learning transfer. Implementation requires developing multi-level explanation capabilities that can generate appropriate explanations for different aspects of system behavior (from specific decision outcomes to overall simulation trends) and different user expertise levels (from novice to expert). These explanations should balance comprehensiveness with comprehensibility, avoiding both oversimplification and overwhelming detail.

Principle 6: Collaborative Intelligence Integration: Adaptive simulations should leverage complementary strengths of human and artificial intelligence through collaborative intelligence frameworks. Our findings demonstrate that simulations enabling fluid collaboration between algorithmic components and human expertise produce more robust learning environments than those relying predominantly on either automated or human-driven approaches. Implementation involves creating appropriate interfaces for expert input into simulation design and adaptation, mechanisms for incorporating collective intelligence from user communities, and hybrid decision systems that combine algorithmic and human judgment. These collaborative approaches enhance both the quality of simulation scenarios and the relevance of adaptive responses.

Principle 7: Ethical Consideration Embedding: Adaptive business simulations must embed ethical considerations throughout their design and operation, particularly regarding representation of business practices, potential reinforcement of biases, and privacy implications of user modeling. Our evaluation highlighted ethical challenges that emerge specifically from the adaptive, AI-driven nature of these systems. Implementation requires developing explicit ethical frameworks for simulation design decisions, continuous monitoring of potential bias in scenario generation and adaptation, and transparent governance of user data and modeling practices. These ethical considerations should be treated as fundamental design requirements rather than supplementary concerns.

Conclusion

This research makes several significant contributions to theoretical understanding of adaptive learning environments and AI-enhanced business education: First, we extend simulation-based learning theory by empirically demonstrating how adaptive mechanisms significantly enhance knowledge retention, transfer, and applied problem-solving capabilities. Our findings suggest that dynamic adaptation creates stronger connections between conceptual business knowledge and its application in complex, changing environments—addressing a longstanding challenge in management education. Second, we contribute to the emerging field of AI in education by providing empirical evidence of how multiple AI components can be integrated into a coherent learning system that continuously evolves in response to both user needs and environmental changes. This extends current theoretical models of intelligent tutoring systems and adaptive learning environments, which have typically focused on more constrained, static knowledge domains. Third, we advance understanding of the relationship between simulation fidelity and learning outcomes by demonstrating that temporal dynamics and real-world integration significantly influence not only engagement but also transfer of learning to authentic business contexts. This finding has important implications for theories of experiential learning in dynamic knowledge domains. Fourth, we contribute to design theory by developing and validating a set of design principles for adaptive simulation environments that can guide future development of similar systems across diverse educational and organisational contexts. These principles represent middle-range theoretical contributions connecting specific design features to learning and decision-making outcomes.

Beyond theoretical contributions, our research offers several practical implications for different stakeholders: For educational institutions, particularly business schools and MBA programmes, the adaptive simulation approach offers enhanced capabilities for developing strategic thinking and adaptive decision-making skills among students. The empirical evidence of improved knowledge retention and transfer suggests that incorporating such simulations into business curricula could address persistent concerns about the applicability of business education to real-world challenges. For corporate training and development programmes, the platform provides a sophisticated environment for testing strategic options, developing executive

decision-making capabilities, and enhancing organisational adaptability. The field implementation findings demonstrate practical utility across diverse organisational contexts, from strategy testing to leadership development. For entrepreneurial education and incubator programmes, the adaptive simulation approach offers a valuable tool for reducing market uncertainty and accelerating business model development through rapid testing of strategic options. The ability to incorporate real-time market information creates a bridge between conceptual business planning and actual market conditions. For simulation and educational technology developers, the design principles and technical architecture presented provide a structured framework for developing next-generation learning environments that leverage AI capabilities for enhanced personalisation and real-world relevance.

Limitations and Future Research Directions

While our research demonstrates the potential of adaptive AI-driven business simulations, several limitations should be acknowledged and addressed in future research: First, our evaluation, while comprehensive, spans a relatively short time period (up to three months). Longer-term longitudinal studies are needed to assess the sustained impact of adaptive simulation experiences on business decision-making capabilities and professional development. Future research should track participants over extended periods to evaluate how simulation-developed skills transfer to evolving professional contexts. Second, while our sample included diverse participant groups, cultural variations in learning approaches and simulation engagement were not systematically explored. Future research should examine how cultural factors influence interaction with adaptive simulations and whether adaptation mechanisms should incorporate cultural dimensions more explicitly.

Third, our current implementation focused primarily on strategic management contexts. Further research should extend the adaptive simulation approach to other business domains such as marketing, operations, and organisational behaviour, exploring domain-specific adaptation requirements and learning outcomes. Fourth, while our design incorporates ethical considerations, the ethical implications of increasingly realistic and persuasive simulation environments merit deeper investigation. Future research should examine potential risks of simulation-induced biases in decision-making and develop more robust frameworks for ethical simulation design. Several promising directions for future research emerge from our findings: Exploring the integration of emerging AI capabilities, particularly large language models and multimodal learning systems, to enhance the naturalness and sophistication of simulation interactions.

Investigating the potential for adaptive simulations to serve as collective intelligence platforms that aggregate insights from multiple users to generate novel business understanding. Developing more sophisticated approaches to measuring and enhancing simulation transfer, focusing on how simulation experiences translate into changed business practices and decision processes. Examining the role of adaptive simulations in developing specific cognitive capabilities related to business complexity, such as systems thinking, ambiguity tolerance, and adaptive expertise.

This working paper has presented a design science research investigation into the development and evaluation of a real-time, adaptive AI-driven business simulation platform. Through iterative design cycles and comprehensive evaluation, we have demonstrated the potential of this approach to enhance business education and strategic decision-making across diverse contexts. The integration of artificial intelligence capabilities—including natural language processing, knowledge representation, and adaptive learning algorithms—enables the creation of simulation environments that continuously evolve in response to both real-world business developments and user interactions. This dynamic responsiveness addresses fundamental limitations of traditional business simulations, creating more authentic and personalised learning experiences.

Our empirical findings demonstrate significant advantages of adaptive simulation approaches over traditional methods, particularly in enhancing knowledge retention, transfer to novel problems, and application to real-world business contexts. These outcomes suggest that adaptive business simulations can play a valuable role in preparing individuals and organisations for the complex, rapidly changing business environments they face. The design principles derived from our research provide a foundation for future development of adaptive simulation environments, offering generalizable insights that can inform both research and practice in business education and decision support. As artificial intelligence capabilities continue to advance, these principles can guide the creation of increasingly sophisticated and effective simulation platforms. In conclusion, real-time, adaptive AI-driven business simulation represents a promising frontier in business education and strategy development—one that can help bridge the gap between static educational approaches and the dynamic realities of contemporary business contexts. By continuing to refine these approaches through rigorous design and evaluation, we can develop powerful tools for enhancing both individual capabilities and organisational effectiveness in navigating complex business challenges.

References

- Anderson, P. (1999). *Complexity theory and organization science*. *Organization Science*, 10(3), 216-232.
- Axelrod, R., & Cohen, M. D. (2000). *Harnessing complexity: Organizational implications of a scientific frontier*. Basic Books.
- Bell, B. S., Tannenbaum, S. I., Ford, J. K., Noe, R. A., & Kraiger, K. (2017). 100 years of training and development research: What we know and where we should go. *Journal of Applied Psychology*, 102(3), 305-323.
- Bennett, N., & Lemoine, G. J. (2014). What a difference a word makes: Understanding threats to performance in a VUCA world. *Business Horizons*, 57(3), 311-317.
- Boyle, E. A., Hainey, T., Connolly, T. M., Gray, G., Earp, J., Ott, M., Lim, T., Ninaus, M., Ribeiro, C., & Pereira, J. (2016). An update to the systematic literature review of empirical evidence of the impacts and outcomes of computer games and serious games. *Computers & Education*, 94, 178-192.
- Braun, V., & Clarke, V. (2006). *Using thematic analysis in psychology*. *Qualitative Research in Psychology*, 3(2), 77-101.
- Brown, J. S., Collins, A., & Duguid, P. (1989). *Situated cognition and the culture of learning*. *Educational Researcher*, 18(1), 32-42.
- Cannon-Bowers, J. A., & Bowers, C. A. (2010). *Synthetic learning environments: On developing a science of simulation, games, and virtual worlds for training*. In S. W. J. Kozlowski & E. Salas (Eds.), *Learning, training, and development in organizations* (pp. 229-261). Routledge.
- Cilliers, P. (2001). *Boundaries, hierarchies and networks in complex systems*. *International Journal of Innovation Management*, 5(2), 135-147.
- Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. (2007). *Developing theory through simulation methods*. *Academy of Management Review*, 32(2), 480-499.
- Dooley, K. J. (1997). *A complex adaptive systems model of organization change*. *Nonlinear Dynamics, Psychology, and Life Sciences*, 1(1), 69-97.
- Gleick, J. (1987). *Chaos: Making a new science*. Viking Penguin.
- Gosen, J., & Washbush, J. (2004). *A review of scholarship on assessing experiential learning effectiveness*. *Simulation & Gaming*, 35(2), 270-293.
- Herrington, J., & Oliver, R. (2000). *An instructional design framework for authentic learning environments*. *Educational Technology Research and Development*, 48(3), 23-48.
- Hevner, A. R. (2007). *A three cycle view of design science research*. *Scandinavian Journal of Information Systems*, 19(2), 87-92.
- Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). *Design science in information systems research*. *MIS Quarterly*, 28(1), 75-105.
- Holland, J. H. (2006). *Studying complex adaptive systems*. *Journal of Systems Science and Complexity*, 19(1), 1-8.
- Jonassen, D. H. (1999). *Designing constructivist learning environments*. In C. M. Reigeluth (Ed.), *Instructional-design theories and models: A new paradigm of instructional theory* (Vol. 2, pp. 215-239). Lawrence Erlbaum Associates.

- Kaplan, J. (2017). *The fallacy of the perfect virtual world*. In D. Schreiber & Z. L. Berge (Eds.), *Leading in a virtual world: How to build effective virtual teams* (pp. 19-35). Information Age Publishing.
- Karami, M., Irani, Z., & Bagher, M. K. (2020). *The impact of automated cognitive assistants on users' behaviour in business decision-making*. *Cognition, Technology & Work*, 22(4), 763-783.
- Kolb, D. A. (2014). *Experiential learning: Experience as the source of learning and development* (2nd ed.). Pearson Education.
- Lainema, T., & Makkonen, P. (2003). *Applying constructivist approach to educational business games: Case REALGAME*. *Simulation & Gaming*, 34(1), 131-149.
- Lajoie, S. P., & Derry, S. J. (Eds.). (2013). *Computers as cognitive tools*. Routledge.
- Li, X., & Jiang, H. (2019). *Artificial intelligence technology and business simulation teaching in digital economic era*. In 2019 IEEE 1st International Conference on Civil Aviation Safety and Information Technology (ICCASIT) (pp. 631-634). IEEE.
- McKelvey, B. (1999). *Avoiding complexity catastrophe in coevolutionary pockets: Strategies for rugged landscapes*. *Organization Science*, 10(3), 294-321.
- McNamara, D. S., Allen, L. K., Crossley, S. A., Dascalu, M., & Perret, C. A. (2017). *Natural language processing and learning analytics*. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 93-104). Society for Learning Analytics Research.
- Moran, T. P., & Carroll, J. M. (1996). *Design rationale: Concepts, techniques, and use*. Lawrence Erlbaum Associates.
- Omeihe, K., Okpanum, I., and Omeihe, I. (2024). *Some reasons for optimism about AI and the future of work in Nigeria*. *Business Day*. <https://businessday.ng/opinion/article/some-reasons-for-optimism-about-ai-and-the-future-of-work-in-nigeria/>
- Omeihe, K. O., Okpanum, I., Omeihe, I., & Murray, A. (2024). *Shaping Our Future: Trust in Artificial Intelligence*. (TERG Working Paper Series; No. 12/24). University of the West of Scotland.
- Omeihe, K. O., & Harrison, C. (2024). *Qualitative Research Methods for Business Students: A Global Approach*. SAGE Publications Ltd. <https://uk.sagepub.com/en-gb/eur/qualitative-research-methods-for-business-students/book281133>.
- Omeihe, K. (2020). *The Need for Interview Participant Justification: Report-ability in Qualitative Research*. BAM ISBE Virtual Doctoral Day.
- Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). *A design science research methodology for information systems research*. *Journal of Management Information Systems*, 24(3), 45-77.
- Roll, I., & Wylie, R. (2016). *Evolution and revolution in artificial intelligence in education*. *International Journal of Artificial Intelligence in Education*, 26(2), 582-599.
- Salas, E., Wildman, J. L., & Piccolo, R. F. (2009). *Using simulation-based training to enhance management education*. *Academy of Management Learning & Education*, 8(4), 559-573.
- Schoemaker, P. J., Heaton, S., & Teece, D. (2018). *Innovation, dynamic capabilities, and leadership*. *California Management Review*, 61(1), 15-42.
- Shute, V. J., & Rahimi, S. (2017). *Review of computer-based assessment for learning in elementary and secondary education*. *Journal of Computer Assisted Learning*, 33(1), 1-19.

- Stacey, R. D. (2001). *Complex responsive processes in organizations: Learning and knowledge creation*. Routledge.
- Tao, Y. H., Cheng, C. J., & Sun, S. Y. (2015). Alignment of teacher and student perceptions on the continued use of business simulation games. *Educational Technology & Society*, 18(3), 202-213.
- VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197-221.
- Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A framework for evaluation in design science research. *European Journal of Information Systems*, 25(1), 77-89.
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
- Wang, M., Cheng, B., Chen, J., Mercer, N., & Kirschner, P. A. (2018). The use of web-based collaborative concept mapping to support group learning and interaction in an online environment. *The Internet and Higher Education*, 34, 28-40.
- Zhu, J., Nie, Y., & Lu, K. (2015). An effective knowledge management environment based on knowledge grid in business organizations. *Scientific Programming*, 2015, Article ID 718985.