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Designing Game-based Analytics Training Models for Smart Business Decision-Making: Evidence from Vietnam

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Abstract

The rapid diffusion of smart business technologies and data-driven management practices has intensified organizational demand for graduates with strong quantitative and analytical decision-making capabilities. Despite the growing emphasis on business analytics, many emerging economies continue to face persistent gaps between formal quantitative education and the applied analytics readiness of professionals. This study proposes and evaluates a game-based analytics training model designed to support the development of statistical reasoning and decision-making skills relevant to smart business environments. Using a design-based research approach, the model integrates game-based simulations, technology-enabled formative analytics tools, and authentic business-oriented assessment tasks within undergraduate quantitative courses at a Vietnamese higher education institution. Longitudinal evidence across multiple cohorts indicates improvements in learner engagement with business data, applied statistical performance, and collaborative decision-making confidence. The study contributes a context-sensitive framework for analytics capability development and offers practical implications for business schools, organizations, and smart enterprises seeking to strengthen data-driven human capital.

Keywords: *Business analytics, Smart business, Decision-making, Game-based simulation, Statistical analytics, Vietnam*

1. Introduction

Smart-business environments increasingly depend on analytics-enabled decision processes—spanning forecasting, optimization, customer intelligence, and operational control—creating sustained demand for graduates who can translate data into defensible managerial action[1]. Empirical work in information systems and analytics research shows that decision performance is shaped not only by data availability but also by data analytics competency, domain knowledge, and the ability to integrate analytic outputs into organizational decision routines [2][3][7]. Studies on business analytics capability further indicate that analytics-driven value creation is mediated by information quality, innovative

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capability, and the organization's ability to operationalize insights in dynamic environments [3][5].

Despite this strategic emphasis, firms frequently report gaps between formal quantitative preparation and workplace-ready analytics reasoning—particularly regarding uncertainty handling, hypothesis-based inference, and applied interpretation of results for decision quality and decision efficiency [2][7]. In parallel, evidence from big data and analytics research suggests that analytics investments influence decision-making and performance through complex pathways involving forecasting capability, decision speed, and organizational performance mechanisms [5][6].

In emerging economy contexts, these gaps are often amplified by language and learning environment constraints. In Vietnam's internationalized higher education sector—where English-Medium Instruction (EMI) is increasingly common—students may face additional cognitive load and anxiety that can suppress participation and undermine confidence in technical, quantitatively intensive business courses [10][11]. This context makes it strategically relevant to treat quantitative business education as a pipeline for analytics-capable human capital, rather than a purely pedagogical problem.

To address analytics readiness and decision confidence, research across higher education suggests that gamified and simulation-based learning environments can increase engagement, deepen conceptual processing, and support iterative learning via feedback and error-tolerant practice [1][8]. In business education specifically, simulation-based interventions have been associated with improvements in learners' competence development and applied learning outcomes [4]. Building on these insights, this study proposes and evaluates a game-based analytics training model for undergraduate quantitative business courses in Vietnam, with an explicit focus on developing applied statistical reasoning and decision-making capability aligned to smart business needs [2][3][12].

2. Literature review

2.1. Analytics capability and decision-making performance in smart business

A central theme in smart business and business intelligence research is that analytics-driven advantage depends on capabilities that connect data, tools, and human judgment to decision outcomes. At the firm level, data analytics competency has been conceptualized as a multidimensional construct encompassing data quality, analytical skills, domain knowledge, and tool sophistication. It has been empirically linked to decision quality and decision efficiency [2]. Complementary work indicates that business analytics capabilities contribute to agility and performance by improving information quality and fostering innovation, with environmental turbulence influencing the strength of these effects [3].

Beyond capability constructs, research on analytics-driven decision processes emphasizes organizational routines and contexts. Qualitative and mixed-methods work on analytics-based decision-making proposes structured process models (e.g., staged decision routines) and identifies recurring implementation challenges, including integration into managerial workflows and governance of analytic outputs [7]. Large-sample evidence also suggests that strategic emphasis on business analytics supports the development of analytical decision-making cultures, influencing how data is used across decision phases and reshaping authority patterns via information asymmetry dynamics [13].

Empirical research further links big data analytics to decision-making and performance outcomes through mechanisms such as forecasting capabilities, improved decision processes, and firm-level performance effects [6][9]. At the conceptual boundary of "data-driven decision-making," studies also caution that decision outcomes are shaped by how analytical evidence is combined with intuitive reasoning, indicating the need for training environments that explicitly develop interpretive judgment rather than only computational proficiency [8].

2.2. Game-based and simulation-based learning for business analytics capability development

Within higher education, gamified learning and Game-Based Learning (GBL) have been systematically reviewed as approaches that can increase motivation and engagement when appropriately designed, while also presenting challenges related to alignment, assessment, and variability of effects across contexts [1]. In business education, simulation games have been studied as competence-development tools, with evidence that participation can improve learning outcomes and skills development—though effects may vary across learner groups and implementation designs [4].

More recent empirical research in business simulation contexts links simulation participation to competence-related outcomes and learner perceptions, including nuanced patterns across age and prior experience [4]. Studies using flow theory in business simulation games suggest that learner experience states relate to learning outcomes, underscoring the importance of calibrating challenge, feedback, and learner skill levels in simulation design [12].

In management and business curricula, online simulation-based learning has also been evaluated using quasi-experimental and time-series approaches, with findings indicating improvements in applied skill use (e.g., strategy formulation and execution within simulated environments) [14]. In parallel, recent work specifically examining game-based learning in business decision contexts reports positive effects on decision-making skills and systems thinking, reinforcing the relevance of game-based designs for decision capability development rather than only content coverage [15].

2.3. Vietnam and emerging-economy constraints in analytics-oriented business education

When analytics capability development is situated in emerging economies, contextual constraints—language, prior preparation, and participation norms—become part of the capability development problem. In Vietnam, research on English-Medium Instruction (EMI) highlights implementation challenges and learning impacts, indicating that EMI may introduce barriers for both instructors and learners that can affect classroom participation and comprehension [10]. More targeted evidence in Vietnamese business administration contexts shows that EMI motivation and anxiety can shift over a semester, reinforcing that language-mediated learning conditions may influence engagement in quantitatively intensive business subjects [11].

Accordingly, a business-education intervention aimed at analytics readiness in Vietnam should be designed not merely to “increase engagement,” but to reduce avoidable cognitive load, create error-tolerant spaces for probabilistic reasoning, and strengthen interpretive judgment under uncertainty. This framing aligns with capability-based analytics research emphasizing decision quality and efficiency [2], and with emerging evidence on the role of analytics culture and capability in decision-making performance [16].

3. Research design and context

3.1. Research design

This study adopts a Design-Based Research (DBR) approach, drawing conceptually from design science traditions in information systems and business analytics research. DBR is particularly suitable when the research objective is to develop, implement, and iteratively refine an artifact—in this case, a game-based analytics training model—while simultaneously generating transferable design knowledge relevant to organizational and educational contexts.

Rather than testing a single isolated intervention, the design-based approach emphasizes:

- iterative development and refinement,
- close alignment between theory and practice,
- and systematic reflection on observed outcomes across multiple implementation cycles.

Within smart business and analytics research, such an approach is increasingly used to study decision-support mechanisms, analytics-enabled processes, and capability development initiatives where controlled experimentation may be impractical. Still, theoretical contribution remains essential [2][7]. The present study, therefore, focuses on how a game-based analytics training model functions as a capability development mechanism, rather than on causal inference alone.

3.2. Research context: Smart business and analytics education in Vietnam

The research was conducted at an international higher education institution in Vietnam that offers undergraduate business programs delivered primarily in English. Vietnam represents a relevant emerging smart-business context, characterized by rapid digitalization, growing adoption of analytics-driven decision-making in organizations, and increasing demand for analytics-capable graduates.

At the same time, several contextual constraints shape the development of analytics capabilities in this environment. First, most learners operate in English as a second language, which can increase cognitive load in quantitatively intensive business subjects. Second, many students enter university with limited prior exposure to applied statistics or data-driven decision scenarios, having experienced more examination-oriented instructional systems. Prior research on English-medium instruction and business education in Vietnam highlights how these factors may influence participation, confidence, and engagement, particularly in analytically demanding courses [10][11].

From a smart business perspective, these contextual conditions make Vietnam an appropriate setting for examining how analytics training models can be designed to:

- reduce avoidable barriers to analytical reasoning,
- support decision-making under uncertainty,
- and strengthen readiness for data-intensive business roles.

3.3. Participants and analytics training setting

Participants were undergraduate students enrolled in quantitative business courses, such as Business Statistics and Quantitative Methods. These courses function as foundational components of the business analytics capability pipeline, preparing learners for subsequent coursework and professional roles involving data interpretation, forecasting, and decision support.

Instructional delivery emphasized applied analytics tasks rather than procedural calculation alone. Learners engaged in individual and group-based activities that required them to interpret data, justify assumptions, evaluate outcomes, and communicate analytical reasoning—competencies widely recognized as critical for effective business decision-making [2][3].

While the primary unit of analysis in this study is the analytics training model, learners' engagement patterns, performance trends, and interaction with simulated business data served as indicators of capability development.

3.4. Data sources and analytical strategy

Data were collected longitudinally across multiple semesters to capture patterns associated with the introduction and refinement of the game-based analytics training model. Consistent with design-based research principles, multiple data sources were triangulated to support interpretive validity.

The primary data sources included:

1. Aggregated performance trends on applied quantitative and analytics-oriented assessment tasks, emphasizing interpretation and decision justification rather than rote computation.
2. Classroom observation records documenting learner engagement, participation in analytics simulations, and collaborative decision-making behavior.
3. Learner feedback and reflective comments regarding confidence in statistical reasoning, perceived relevance to business decision-making, and engagement with analytics tasks.
4. Instructional design reflections, used to iteratively refine simulation structure, feedback mechanisms, and task alignment with business analytics objectives.

The analytical strategy was descriptive and comparative, focusing on identifying consistent patterns across cohorts and instructional iterations. Given the study's design orientation, findings are interpreted as evidence of plausible effectiveness and design relevance, rather than as causal claims.

3.5. Ethical and methodological considerations

The study relied on aggregated and anonymized data derived from routine instructional and evaluation processes. No personally identifiable information was collected or reported. The analysis focused on trends and patterns rather than individual-level outcomes, ensuring compliance with ethical standards for educational and organizational research.

From a methodological standpoint, the study acknowledges limitations related to the absence of randomized control groups and formal experimental manipulation. However, these limitations are consistent with design-based and design science research in analytics and decision-support contexts, where the objective is to generate actionable design knowledge rather than universal causal laws [7][16].

4. Game-based analytics training model

This section elaborates on the proposed game-based analytics training model and explains how its components function as an integrated mechanism for developing analytics capabilities in smart business environments. Building on the research design outlined in Section 3, the model is conceptualized as a structured pathway linking simulation-based analytics inputs to decision-oriented business outcomes.

4.1. Conceptual framework and model overview

Figure 1 presents the conceptual framework underlying the game-based analytics training model. The framework adopts a capability-based perspective, widely used in business analytics and information systems research, to explain how analytics competencies are developed through structured interaction with data, decision scenarios, and feedback mechanisms.

As illustrated in Figure 1, the framework is organized into three interrelated layers: input, process, and output. The input layer consists of game-based analytics simulations and technology-enabled analytics tools that expose learners to business-relevant quantitative problems. These inputs activate a set of core process mechanisms—cognitive engagement with business data, statistical reasoning and analytical judgment, and collaborative decision-making—which operate through iterative decision cycles. The output layer captures the resulting business-relevant capabilities, including enhanced decision quality, increased decision confidence, and improved analytics readiness for smart business contexts.

By explicitly linking instructional design elements to analytics and decision outcomes, the framework positions quantitative training as a human capital development pipeline rather than a pedagogical intervention alone.

Figure 1 illustrates the proposed game-based analytics capability development framework, which conceptualizes quantitative training as a decision-oriented capability pipeline for smart business environments. The framework links game-based analytics simulations and technology-enabled tools to core capability development mechanisms—cognitive engagement with business data, statistical reasoning, and collaborative decision-making—culminating in improved decision quality, decision confidence, and analytics readiness.

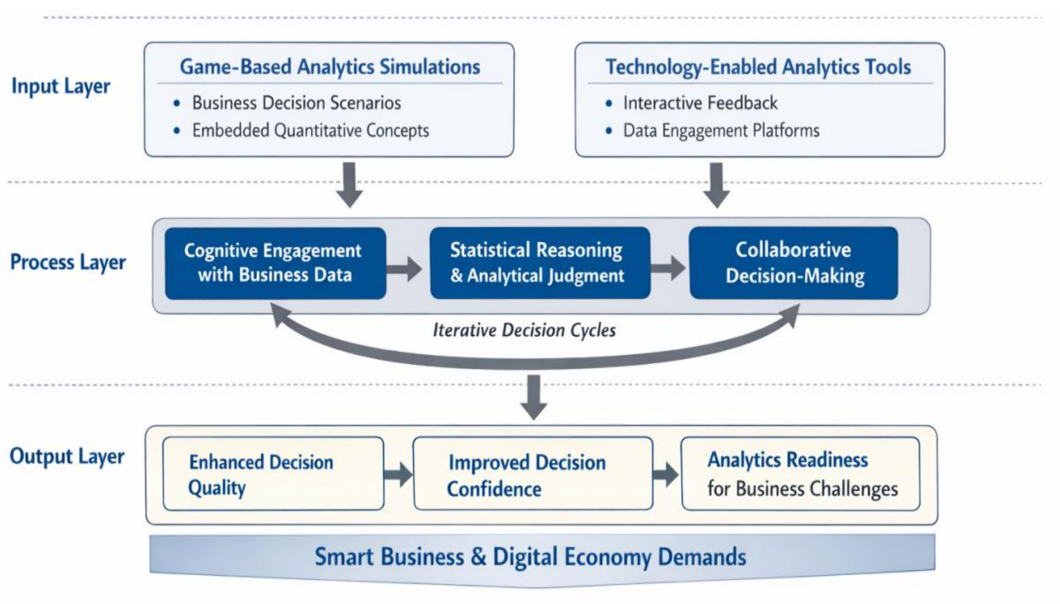

Figure 1. Conceptual framework for game-based analytics capability development in smart business contexts

4.2. Input layer: Game-based analytics simulations and analytics tools

The input layer of the model (Figure 1) comprises two complementary components: (1) game-based analytics simulations and (2) technology-enabled analytics tools. Together, these components create an interactive environment in which learners engage with quantitative concepts embedded in realistic business decision scenarios.

Game-based analytics simulations are designed to represent simplified yet authentic business contexts characterized by uncertainty, risk, and trade-offs. Quantitative concepts such as probability, hypothesis testing, confidence intervals, and regression analysis are embedded within these scenarios, requiring learners to interpret data, test assumptions, and justify decisions using statistical evidence rather than procedural calculation alone.

Technology-enabled analytics tools—such as real-time polling systems, interactive quizzes, collaborative data collection platforms, and visualization dashboards—support these simulations by providing immediate feedback and enabling active engagement with data. As shown in Figure 1, these tools function as decision-support mechanisms, mirroring the role of analytics technologies in smart enterprises.

Table 1 summarizes the model's primary input components and their intended analytical capabilities.

Table 1. Input components of the game-based analytics training model

Input Component	Operational Description	Embedded Analytics Concepts	Decision Context Simulated	Analytics Capability Targeted
Game-based analytics simulations	Structured, rule-based scenarios representing simplified business environments	Probability, hypothesis testing, estimation, regression	Risk evaluation, quality control, and market uncertainty	Decision framing under uncertainty
Scenario-driven decision tasks	Sequential decision problems requiring assumption testing and outcome evaluation	Null/alternative hypotheses, confidence levels	Go/no-go decisions, process validation	Evidence-based decision logic
Physical & digital randomization tools	Dice, random generators, and sampling tools are used to model stochastic behavior.	Sampling distributions, randomness	Demand fluctuation, operational variability	Intuition for probabilistic processes
Technology-enabled analytics tools	Real-time polling, quizzes, and collaborative data platforms	Descriptive statistics, inference	Rapid feedback loops	Real-time analytics interpretation
Data visualization elements	Charts, tables, and dashboards integrated into tasks	Trend analysis, comparative metrics	Performance monitoring	Insight extraction and sensemaking
Collaborative analytics interfaces	Group-based problem-solving environments	Shared datasets, peer comparison	Cross-functional decision contexts	Collaborative analytics reasoning
Formative analytics feedback	Immediate system-generated or peer feedback	Error diagnostics, result validation	Iterative decision refinement	Learning from analytics feedback
Authentic business datasets	Realistic or anonymized datasets drawn from business contexts	Applied statistics	Market, operations, finance scenarios	Transferability to real-world analytics

4.3. Process layer: Analytics capability development mechanisms

The process layer represents the core mechanisms that underpin the development of analytics capabilities, as depicted in Figure 1. This layer emphasizes how learners think and decide when interacting with business data, rather than what content is covered.

First, cognitive engagement with business data occurs as learners actively manipulate datasets, interpret outputs, and evaluate alternative decision options. This engagement shifts the focus from formula application to sensemaking, a key requirement in analytics-driven organizations.

Second, statistical reasoning and analytical judgment are developed through tasks that require learners to articulate assumptions, assess the strength of evidence, and justify conclusions using quantitative logic. These activities align closely with real-world analytics practices, where decisions must be defended under uncertainty.

Third, collaborative decision-making is fostered through group-based simulations in which learners negotiate interpretations, challenge assumptions, and converge on shared decisions. As shown in Figure 1, collaboration functions as a critical mediator between individual analytics reasoning and collective decision outcomes in business settings.

The framework highlights iterative decision cycles as a defining feature of the process layer. Learners repeatedly test assumptions, observe outcomes, receive feedback, and refine their reasoning—mirroring analytics workflows in smart enterprises where insights are continuously updated.

4.4. Output layer: Business-relevant analytics outcomes

The framework's output layer (Figure 1) captures the business-relevant outcomes of the analytics training model. These outcomes are conceptualized as capabilities rather than short-term performance indicators.

The first outcome is enhanced decision quality, reflected in more accurate, evidence-based, and context-aware analytical decisions. Learners demonstrate improved ability to select appropriate analytical methods and interpret results in relation to business objectives.

The second outcome is decision confidence, particularly in situations involving uncertainty, probabilistic reasoning, and incomplete information. Increased confidence is critical for enabling analytics adoption in organizational settings.

The third outcome is analytics readiness, defined as the ability to transfer quantitative reasoning skills to real-world business challenges, including forecasting, performance evaluation, and decision support.

Table 2 maps these output capabilities to observable indicators used in the study.

Table 2. Business-oriented analytics capability outcomes

Capability Dimension	Business-Oriented Definition	Observable Indicators	Decision-Making Relevance	Smart Business Alignment
Decision quality	Accuracy and robustness of analytics-based decisions	Correct method selection; justified conclusions	Reduces decision error and bias	Supports data-driven governance
Decision confidence	Willingness to engage with analytics under uncertainty	Active participation; assumption defense	Encourages analytics adoption	Enables organizational analytics culture
Statistical reasoning	Ability to interpret probabilistic and	Explanation of p-values, intervals	Improves evidence interpretation	Strengthens analytical maturity

	inferential results			
Analytical judgment	Integration of data, context, and business logic	Assumption articulation; trade-off analysis	Improves strategic and operational decisions	Aligns analytics with business goals
Analytics readiness	Transferability of skills to novel business problems	Performance on authentic tasks	Enhances employability	Builds analytics-ready workforce
Collaborative decision-making	Shared reasoning and consensus-building using analytics	Quality of group justifications	Supports cross-functional decisions	Reflects smart enterprise teamwork
Decision process efficiency	Speed and clarity of analytics-based decisions	Reduced hesitation; structured reasoning	Improves responsiveness	Supports agile organizations
Error tolerance & learning	Ability to revise decisions based on feedback	Iterative refinement behavior	Reduces fear of analytics failure	Encourages an experimentation culture

4.5. Alignment with smart business and digital economy demands

As illustrated at the base of Figure 1, the model is situated within broader demands for smart business and the digital economy. The integration of simulations, analytics tools, and iterative decision cycles reflects the realities of analytics-enabled organizations, where employees must continuously interpret data, collaborate across functions, and adapt decisions in response to changing information.

By aligning quantitative training with these demands, the model positions higher education as a strategic contributor to the development of analytics-ready human capital. This alignment enhances the model's relevance to business schools, organizations, and policymakers concerned with workforce preparedness in data-intensive economies.

5. Findings: Analytics capability development outcomes

This section reports the study's findings using the analytics capability dimensions outlined in Table 2 as analytical lenses. Consistent with the design-based research approach, the findings focus on patterns of capability development observed across multiple implementation cycles of the game-based analytics training model rather than on causal inference. The results are interpreted in relation to the conceptual framework presented in Figure 1, which links simulation-based analytics inputs to decision-oriented business outcomes.

5.1. Decision quality

Evidence from aggregated assessment outcomes and decision-task evaluations indicates an improvement in decision quality following the introduction of the game-based analytics training model. Learners demonstrated greater accuracy in selecting appropriate analytical methods and improved ability to justify decisions using statistical evidence rather than relying solely on procedural calculations.

Consistent with the output layer in Figure 1, decision-quality improvements were most evident in tasks that required interpreting probabilistic outcomes, hypothesis testing, and regression-based reasoning. Learners increasingly articulated assumptions and limitations when presenting decisions, suggesting a shift toward more robust, evidence-based analytical reasoning. These patterns align with business analytics research emphasizing the role of interpretive judgment in decision effectiveness.

5.2. Decision confidence under uncertainty

A notable finding concerns the development of decision confidence, particularly in contexts involving uncertainty and incomplete information. Classroom observations and learner feedback indicate increased willingness to engage with analytics-driven tasks, ask questions, and defend analytical conclusions in group discussions.

As illustrated in Figure 1, the iterative and error-tolerant nature of game-based analytics simulations appears to play a central role in reducing analytics-related anxiety. Learners reported greater comfort revising decisions based on feedback, an outcome critical to analytics adoption in organizational settings where decision-making is often iterative and probabilistic rather than deterministic.

5.3. Statistical reasoning and analytical judgment

Improvements were also observed in statistical reasoning and analytical judgment, particularly in learners’ ability to explain the meaning and implications of statistical outputs. Over successive implementation cycles, learners demonstrated increased competence in interpreting confidence intervals, p-values, and regression coefficients within business contexts.

Rather than treating statistical outputs as results, learners increasingly engaged in sensemaking behaviors, connecting numerical results to business objectives and contextual constraints. This pattern corresponds to the process layer of the framework in Figure 1, where cognitive engagement with data and analytical judgment mediate the relationship between analytics tools and decision outcomes.

5.4. Collaborative analytics and group decision-making

The findings also highlight gains in collaborative analytics capability, an increasingly important dimension of smart enterprise decision-making. Group-based simulations encouraged shared interpretation of data, debate over assumptions, and consensus-building around final decisions.

Observation records indicate that collaborative decision quality improved over time, with groups moving from surface-level agreement to more structured reasoning processes. This shift reflects the collaborative decision-making pathway depicted in Figure 1, where individual analytical reasoning is integrated into collective business decisions through structured interaction.

5.5. Analytics readiness and transferability

Finally, evidence suggests enhanced analytics readiness, defined as the ability to transfer quantitative reasoning skills to novel and authentic business problems. Learners demonstrated greater facility in working with unfamiliar datasets and framing analytical approaches without explicit procedural guidance.

This transferability supports the conceptualization of analytics capability as a dynamic and reusable asset, consistent with the output layer of Figure 1 and the outcome dimensions in Table 2. Importantly, analytics readiness was observed not as a one-time achievement but as an evolving capability reinforced through repeated exposure to simulated decision contexts.

5.6. Summary of capability development patterns

Taken together, the findings indicate that the game-based analytics training model supports the development of multiple, interrelated analytics capabilities relevant to smart business environments. Improvements in decision quality, confidence, statistical reasoning, collaboration, and readiness were mutually reinforcing, suggesting that analytics capability development is best understood as a systemic process rather than as isolated skill acquisition.

These findings provide empirical support for the capability-based framework proposed in Figure 1 and operationalized in Tables 1 and 2, reinforcing the value of simulation-driven analytics training for preparing decision-makers in data-intensive business contexts.

6. Discussion

This study set out to examine how a game-based analytics training model functions as a capability development mechanism for smart business decision-making, particularly within an emerging economy context. By interpreting the findings through the conceptual framework presented in Figure 1 and the capability dimensions operationalized in Table 2, several theoretically meaningful insights emerge for business analytics and decision-support research.

6.1. Analytics capability as a decision-oriented construct

The observed improvements in decision quality, decision confidence, and analytics readiness reinforce the view that analytics capability should be conceptualized as a decision-oriented construct, rather than as a narrow set of technical or computational skills. Prior analytics literature emphasizes that value from analytics investments materializes only when analytical outputs are effectively integrated into decision processes. The findings of this study support this position by demonstrating that repeated exposure to simulated decision contexts strengthens learners' ability to interpret evidence, justify assumptions, and act under uncertainty.

Importantly, the results suggest that analytics capability development is inherently iterative, aligning with analytics process models that depict decision-making as a cyclical activity involving hypothesis formation, testing, feedback, and refinement. The iterative decision cycles embedded in the game-based simulations mirror analytics workflows in smart enterprises, where insights are continuously updated as new data becomes available.

6.2. Bridging the gap between analytics tools and human judgment

A persistent theme in analytics research concerns the gap between sophisticated analytical tools and their effective use by decision-makers. The findings related to statistical reasoning and analytical judgment contribute to this literature by illustrating how simulation-based engagement can strengthen the interpretive layer of analytics use.

Rather than treating analytics outputs as objective truths, learners increasingly engaged in sensemaking behaviors—evaluating the relevance, limitations, and implications of statistical results. This behavior is consistent with recent decision-support research emphasizing the interplay between data-driven evidence and managerial judgment. The results thus support theoretical perspectives that view analytics not as a substitute for human judgment, but as an enabler of more informed and reflective decision-making.

6.3. Collaborative analytics and smart enterprise decision-making

The findings on collaborative analytics capability extend the analytics literature by foregrounding the social and collective dimensions of data-driven decision-making. While much analytics research focuses on individual cognition or organizational infrastructure, the present study highlights how collaborative simulations can enhance shared understanding and consensus-building around analytics outputs.

This insight aligns with emerging research on analytics culture and cross-functional decision-making in smart enterprises, where value creation depends on coordinated interpretation across organizational units. The collaborative mechanisms depicted in Figure 1 thus contribute to a more holistic understanding of analytics capability as a distributed organizational asset, rather than an individual competency.

6.4. Contextualizing analytics capability development in emerging economies

The Vietnamese context of this study provides an important boundary condition for research on analytics capability. Emerging economies often face structural constraints related to language, prior preparation, and uneven exposure to analytics practices. The findings suggest that simulation-based, error-tolerant analytics training can mitigate some of these constraints by lowering barriers to engagement and reducing anxiety associated with quantitative reasoning.

From a theoretical standpoint, this supports calls within analytics and information systems research to account for contextual variation in capability development. The study demonstrates that analytics capability is not universally transferable but must be cultivated through designs that reflect local cognitive, cultural, and institutional conditions.

6.5. Implications for analytics capability theory

Taken together, the findings contribute to analytics capability theory in three ways. First, they empirically support a capability-based framework in which decision quality, confidence, and readiness emerge through structured interaction with analytics tools and decision scenarios. Second, they highlight the roles of simulation and gamification as underexplored mechanisms for developing analytics capabilities, complementing existing tool- and infrastructure-focused research. Third, they underscore the importance of process-level mechanisms—such as iterative decision cycles and collaborative reasoning—in translating the potential of analytics into decision value.

These contributions reinforce the relevance of the proposed framework (Figure 1) as a theoretically grounded model for understanding how analytics capabilities are developed and enacted within smart business environments.

7. Conclusion

This study examined the design and implementation of a game-based analytics training model to develop analytics-ready decision-making capabilities in smart business environments. Grounded in a design-based research approach and situated within an emerging economy context, the study reframed quantitative training as a capability development pipeline that links simulation-based analytics inputs to decision-oriented business outcomes.

The findings indicate that structured engagement with game-based analytics simulations can support the development of interrelated analytics capabilities, including decision quality, decision confidence under uncertainty, statistical reasoning, collaborative analytics, and analytics readiness. By operationalizing these capabilities through the framework presented in Figure 1 and the outcome dimensions summarized in Table 2, the study provides empirical support for a capability-based perspective on analytics education and training.

From a theoretical standpoint, the study contributes to business analytics and decision-support literature by demonstrating how process-level mechanisms—such as iterative decision cycles, feedback-rich environments, and collaborative reasoning—mediate the relationship between analytics tools and decision value. The results reinforce the view that analytics capability is not merely a function of technical proficiency, but an emergent property of how individuals and groups interact with data within structured decision contexts.

Practically, the proposed model offers a scalable approach for business schools, corporate training units, and smart enterprises seeking to strengthen analytics capability development. By aligning analytics training with authentic decision scenarios and error-tolerant experimentation, organizations can reduce barriers to analytics adoption and foster a culture of evidence-based decision-making.

The study also highlights the importance of contextual sensitivity in developing analytics capabilities. The Vietnamese setting illustrates how conditions in emerging economies—such as language constraints and limited prior exposure to analytics—shape capability development and underscore the need for adaptable, simulation-driven designs.

Future research may extend this work by applying the model in organizational training settings, conducting cross-country comparisons, or incorporating objective performance metrics from workplace decision environments. Such extensions would further refine the understanding of how analytics capabilities evolve and how they can be systematically cultivated to support smart business transformation.

7.1. Limitations and future research

While this study contributes a capability-based framework for analytics training in smart business contexts, several limitations should be acknowledged and point to productive directions for future research.

First, the study adopts a design-based research approach, emphasizing interpretive insights and design relevance rather than causal inference. Although longitudinal patterns across multiple cohorts provide plausible evidence of effectiveness, the absence of randomized control groups limits the ability to attribute observed improvements in capability exclusively to the game-based analytics training model. Future research could complement the present approach with quasi-experimental or experimental designs to isolate specific mechanisms and estimate causal effects.

Second, the study relies primarily on aggregated performance trends, observational data, and learner feedback as indicators of analytics capability development. While these measures are appropriate for capturing process-level capability formation, future studies may incorporate objective organizational or workplace performance metrics, such as decision accuracy in simulated enterprise systems or analytics adoption rates in professional settings, to strengthen external validity.

Third, the research context is limited to a single national and institutional setting within an emerging economy. Although Vietnam represents a strategically relevant smart business context, analytics capability development is shaped by cultural, institutional, and industry-specific factors. Comparative studies across countries, industries, or organizational contexts help assess the generalizability of the proposed framework and identify its boundary conditions.

Fourth, the present study focuses on analytics capability development at the individual and group levels, without explicitly modeling organizational-level dynamics such as analytics governance, data infrastructure maturity, or leadership support. Future research may extend the framework by integrating multi-level perspectives, examining how individual analytics capabilities interact with organizational systems to influence decision performance and business outcomes.

Finally, future research could explore technological extensions of the model, including the integration of artificial intelligence–driven decision-support systems, adaptive analytics platforms, or immersive simulation environments. Such extensions would further align analytics training models with the evolving technological landscape of smart enterprises and digital economies.

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