Beyond Linear Thinking: Investigating Business-IT Alignment through Complexity Science

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Abstract: Complexity science offers a powerful perspective for studying process theory in Information Systems (IS). Process theory explores how events, actions, and interactions evolve over time. Although complexity science is well-established in other fields, its use in IS research remains limited. In this study, we apply complexity-based methods, particularly mathematical modelling, to deepen our understanding of IS processes. We focus on business-IT alignment as a case example. By building and analysing a dynamic model, we show that alignment follows complex, nonlinear patterns, such as feedback loops, tipping points, and oscillations, that traditional research methods often miss. Our findings highlight how system dynamics and complexity science can reveal hidden structures in IS processes and provide new tools for researchers.

Keywords: Research methodology, Complexity science, Business-IT alignment, System dynamics modelling.

1. Introduction

Process theory in Information Systems (IS) research centres on understanding how events, activities, and interactions unfold over time within IS contexts (Burton-Jones et al., 2011; Langley, 1999). It contrasts with variance theory, which typically focuses on identifying relationships between variables and their effects, often using static, cross-sectional data to determine causal links (Burton-Jones, McLean, and Monod, 2015). While variance theory seeks to explain *what* factors lead to particular outcomes by assessing their relative influence, process theory emphasises *how* and *why* these outcomes emerge through sequences of actions and interactions.

When viewed through a complexity science (CS) lens, process theory can be enriched by recognising that many IS phenomena exhibit complex dynamics (Allen and Varga, 2006; Merali, 2006). Processes often involve feedback loops, adaptations, and emergent patterns that cannot be fully explained by static models (Benbya et al., 2020). Despite its maturity in other fields, CS tools of investigation remain underutilised in IS research. While exceptions exist, such as Agent-Based Modelling (ABM) or system dynamics, the broader toolkit of nonlinear dynamics and mathematical modelling has yet to permeate mainstream IS methodologies (Benbya et al., 2020; Fang et al., 2018).

This gap raises the following research question: *How can complexity science modelling approaches enhance our understanding of complex IS processes and provide new methodological tools for IS research*? To address this question, we focus on investigating how a complexity science-inspired research methodology, system dynamics modelling, can contribute to deeper understanding of IS processes, using business-IT alignment as an exemplar case. Business-IT alignment, a persistent challenge for organizations, exemplifies a process that defies static analysis, as it is not a fixed state but a dynamic equilibrium shaped by recursive interactions, delayed feedback, and contextual turbulence (Benbya and McKelvey, 2006; Chan and Reich, 2007).

The present study adopts a mixed-methods, iterative methodology grounded in complexity science. The research integrates longitudinal case analysis with computational modelling to formalise observed dynamics through five key steps: (1) literature review to identify candidate variables and their hypothesised relationships; (2) exploratory case study spanning 36 months to refine variables, map interdependencies, and identify critical feedback mechanisms; (3) development of a system dynamics model expressed through nonlinear equations; (4) iterative testing of alternative mathematical formalisations against case data; and (5) analysis of process trajectories under varying conditions.

This study makes two key contributions. First, it advances theoretical understanding of business-IT alignment by revealing its inherent nonlinear dynamics, including path dependence, delayed feedback, and tipping points. Second, it demonstrates how CS methodologies, particularly system dynamics modelling, can bridge qualitative and quantitative approaches in IS research, offering new tools for studying emergent, context-dependent processes.

2. Literature review

2.1 Complexity science: foundations and methodologies

Process theory provides valuable insights into how IS phenomena unfold but often relies on narrative descriptions or qualitative categorisations (Langley, 1999). While useful for identifying key phases and transitions, these approaches struggle to capture the underlying mechanisms driving emergent patterns, feedback loops, and nonlinear change. Complexity science complements process theory by offering formal tools to analyse these dynamic processes (Benbya et al., 2020).

Complexity science studies systems characterised by multiple interacting elements, nonlinear relationships, and emergent behaviours that cannot be predicted from individual components alone (Anderson, 1999). These systems exhibit self-organization, adaptation, and sensitivity to initial conditions. Unlike reductionist approaches that focus on isolated elements, complexity science emphasises interconnections and feedback loops (Merali, 2006).

CS methodological toolkit includes different techniques. Agent-based modelling (ABM) simulates the interactions among autonomous agents to observe emergent system-level patterns (Merali & McKelvey, 2006). For instance, ABM has been used in financial markets to model trader behaviour and in supply-demand simulations (Axtell & Farmer, 2022). System dynamics modelling, developed by Forrester (1995), employs stocks and flows to represent system structures and analyse feedback loops, proving valuable in urban dynamics, supply chains, and ecology systems (Sterman, 2001). Mathematical modelling formalises complex behaviour through systems of equations (Strogatz, 2018), widely applied in fields such as biology, physics, and economics (May, 1976).

2.2 Complexity science and process phenomena

Organizational processes exhibit characteristics of complex systems, making CS methodologies particularly suitable for their investigation (Langley, 1999). These processes involve multiple interdependent actors whose interactions generate emergent patterns that defy linear cause-and-effect explanations. Feedback loops shape future conditions, creating dynamic patterns of change, while historical dependencies constrain future trajectories (Merali, 2006).

A complexity perspective on IS processes emphasises the interactions between organizational actors and technological components (Merali, 2006). Complexity science methodologies enable researchers to capture temporal dynamics and feedback mechanisms that variance-based approaches (which focus on static relationships between variables) might overlook. They allow for formalisation and testing of process theories, moving beyond descriptive narratives to explanatory models. Moreover, they uncover counterintuitive effects of interventions, helping organizations anticipate unintended consequences (Benbya et al., 2020).

2.3 Business-IT alignment as a complex process

Business-IT alignment is the ongoing harmonisation of organizational strategies, processes, and technologies (Henderson & Venkatraman, 1993). Rather than a static achievement, alignment is a dynamic process involving continuous adjustments between strategy, structures, and IT capabilities (Karpovsky & Galliers, 2020).

Several characteristics make alignment inherently complex (Allen & Varga, 2006; Benbya & McKelvey, 2006). It involves multiple interconnected elements (technology, organizational structure, processes, and human factors) that interact through feedback loops - e.g., improved IT capabilities enabling new business strategies, which in turn drive further IT investments. Alignment also exhibits time delays - IT implementations take time to yield business value, while organizational adaptation to new systems occurs gradually. Furthermore, small changes in factors like user resistance or management support can have disproportionate effects on outcomes.

Recent studies highlight the dynamic nature of alignment (Luftman et al., 1999; Reich & Benbasat, 2000; Alaceva & Rusu, 2015). Some researchers explore alignment as a gradual process or one characterised by abrupt transitions (Sabherwal et al., 2001). However, these perspectives lack a rigorous description of the mechanisms driving alignment and its corresponding dynamics.

Despite its theoretical promise, the practical application of complexity science in alignment research remains limited. Some notable exceptions exist; Zhang et al. (2019) used ABM to validate co-evolutionary principles in alignment, showing how individual actors' decisions lead to emergent alignment patterns. Peppard & Breu (2003) applied system dynamics to reveal how feedback loops and time delays influence alignment trajectories. However, the use of other CS methodologies, such as mathematical modelling, nonlinear analysis, and simulation, remains largely unexplored.

3. Research methodology

3.1 Overview of research design

Our research methodology combines qualitative case study research with mathematical modelling, following a mixed-methods approach grounded in complexity science principles (Venkatesh, Brown, and Bala, 2013). This design enables us to capture both the rich contextual details of alignment processes and their underlying dynamic patterns. The methodology consists of five interconnected phases (Table 1): (1) development of an initial system dynamics framework, (2) longitudinal case study investigation, (3) system dynamics model construction, (4) dynamic analysis, and (5) test through comparison with empirical observations.

Table 1: Research Methodology.

Phase	Description	Contribution to the study
1. Initial system dynamics framework	Development of a conceptual model based on alignment literature and complexity science principles.	Identified key alignment factors (e.g., leadership commitment, resistance) and hypothesised feedback relationships.
2. Longitudinal case study	In-depth investigation of a multinational organization's alignment journey.	Grounded theoretical constructs in empirical data. Refined variables (e.g., resistance thresholds) and revealed real-world feedback loops (e.g., leadership complacency cycles).
3. Mathematical model construction	Translation of qualitative insights into nonlinear equations (stocks, flows, parameters).	Formalised dynamic relationships. Introduced nonlinearities (e.g., tipping points) observed in the case study.
4. Dynamic analysis	Analysis of the model and exploration of alignment dynamics under varying conditions.	Uncovered emergent patterns (e.g., oscillatory regimes, hysteresis) and tested counterfactual scenarios (e.g., delayed IT investments).
5. Empirical test	Comparison of results with the case organization's alignment trajectories.	Tested model realism (e.g., matching tipping points to leadership shifts). Refined parameters (e.g., resistance decay rates) to resolve discrepancies.

3.2 Case study selection and data collection

To investigate the research question of the study, we selected a large manufacturing company for an exploratory case study aimed at testing the feasibility of constructing a complexity-based model of alignment dynamics. This organization was chosen for four reasons. First, it underwent a significant business-IT alignment initiative spanning five years, providing a rich longitudinal context for studying alignment dynamics. Second, the organization experienced various alignment challenges and successes during this period, offering opportunities to observe both positive and negative feedback loops. Third, the organization's size and complexity provided a suitable context for observing complex dynamics typical of enterprise-wide alignment efforts. Fourth, the organization offered comprehensive access to informants across all organizational levels as well as an extensive collection of secondary sources, including internal documents, project files, and performance metrics.

Data collection spanned 36 months, from mid 2019 to mid 2022, and involved multiple sources to ensure triangulation. Primary data came from 18 semi-structured interviews with key stakeholders across business and

IT functions, including senior executives, middle managers, and operational staff. Each interview lasted 60-90 minutes and was recorded and transcribed. Secondary data sources included internal documents (strategy papers, project reports, meeting minutes), alignment assessment reports, and organizational performance metrics. This rich dataset allowed us to track the evolution of alignment processes over time and identify key variables and relationships influencing alignment dynamics.

3.3 Model development

The development of the mathematical model followed an iterative process that moved between empirical observations and theoretical formulation. Initially, we used a system dynamics approach to identify key stocks (accumulated variables like IT capability, organizational resistance, and alignment level) and flows (rates of change in these stocks). These were derived from both our case study observations and existing alignment literature.

The mathematical formalisation of these relationships involved several steps. First, we translated qualitative relationships identified in the case study into mathematical constructs, using equations to represent change processes. For example, we modelled resistance to change as a stock variable influenced by various flows such as implementation pace, communication effectiveness, and perceived benefits. Second, we incorporated nonlinear relationships observed in the data, such as threshold effects in adoption patterns and diminishing returns in capability development. Third, the model's stocks and variables were operationalised using data from the case study, ensuring empirical grounding.

The modelling process was inherently iterative. As we developed mathematical representations, we frequently returned to the case data to verify and refine our assumptions. This led to several model revisions as we discovered additional feedback loops and refined our understanding of key relationships.

3.4 Model analysis

The analysis phase involved analysis of the model's properties and nonlinear dynamics. Employing techniques from dynamical systems theory (Strogatz, 2018), we first identified equilibrium points (steady states where alignment, resistance, and commitment stabilise) and assessed their stability. This revealed whether equilibria acted as attractors (stable states the system tends toward) or repellors (unstable states the system diverges from), providing insights into long-term behavioural patterns.

Bifurcation analysis further uncovered critical thresholds (e.g., leadership commitment levels) where qualitative shifts occurred, such as transitions from stable alignment to collapse. These methods collectively showed how the system's behaviour evolves under varying conditions, emphasising nonlinear phenomena like tipping points and regime shifts.

3.5 Test and theory development

Model test occurred through multiple mechanisms. We compared analysed trajectories with observed patterns from our case study, focusing on whether the model could reproduce key qualitative features of the alignment process. Then, we presented our model and preliminary findings to key informants from the case organization to verify that the dynamics captured matched their experience.

The insights gained from model analysis were then used to develop theoretical propositions about alignment processes. These propositions focused on the dynamic nature of alignment, the role of feedback loops, and the conditions under which different alignment patterns emerge. The combination of rich empirical data and formal mathematical analysis allowed us to develop theory that is both based on real organizational experience and formally rigorous in its specification of causal mechanisms.

4. Results: model-based analysis of business-IT alignment dynamics

4.1 Case study narrative

The case organization, a multinational manufacturing firm operating in a stable market with long-term client contracts, began its alignment journey in 2016 with a fragmented IT landscape. Production sites relied on heavily customised legacy systems, while corporate IT lacked governance mechanisms, resulting in ad hoc solutions and minimal integratio.

The 2017 leadership overhaul marked a strategic change. New executives prioritised the integration of IT and business operations, launching ERP consolidation and standardising workflows. From 2017 to 2019, initial improvements in data visibility and operational efficiency created a positive feedback loop: leadership commitment spurred IT initiatives, which in turn enhanced alignment. However, this progress also generated resistance. Employees accustomed to legacy workflows voiced growing frustrations, while department heads observed declines in productivity, early signs of the paradox of progress, where advancements in alignment led to discord.

By 2019, tensions peaked. Supplier integration issues and end-user complaints surged. IT investments took months to translate into operational benefits. Leadership's sustained commitment during this crisis phase proved critical, temporarily offsetting resistance through symbolic actions like CEO-led training programs. Gradually, benefits emerged, standardised interfaces eased supplier collaboration, and improved process efficiency began winning over skeptics.

The 2020–2021 stabilisation phase revealed hysteresis in reverse where overcoming resistance required persistent effort, but visible gains eventually reinforced leadership commitment. Successes enabled expansion to international subsidiaries, demonstrating how alignment can propagate, but only after crossing critical thresholds of trust and capability.

By 2022, alignment exhibited cyclical dynamics. Periods of progress alternated with setbacks as the organization balanced standardisation with local flexibility. This oscillation shows alignment as a dynamic equilibrium, where stability emerges not from stasis but from continuous adaptation to feedback loops.

4.2 System structure: key stocks and flows

Through analysis of the case data, we identified four main stock variables in the alignment process:

- A(t) - Alignment level: Measuring the degree of harmony between business strategies and IT capabilities.
- T(t) - Top Management commitment: Representing leadership's active engagement in alignment initiatives, manifested through resource allocation and strategic prioritization.
- I(t) - IT Implementation actions: Encompassing the portfolio of technical and organizational initiatives aimed at improving alignment.
- R(t) - Organizational resistance: Capturing the collective resistance to change, influenced by historical experiences and organizational culture.

These stocks interact through feedback loops that drive or hinder alignment. For example, Top management commitment (T(t)) fuels IT actions (I(t)), which enhance alignment (A(t)). However, rising alignment reduces commitment over time as complacency sets in, a pattern observed in the case organization between 2010 and 2017, when perceived success led leadership to deprioritise IT initiatives. Meanwhile, organizational resistance (R(t)) moderates these relationships, as seen during the 2019 alignment push: employee complaints surged due to skill gaps and process disruptions, slowing progress despite increased IT actions. The interactions of stocks are influences by alignment parameters, such as the efficacy of the IT actions and the Leadership commitment. For each stock and parameters, proxies from the case study were identified (Table 2). For example, A(t) was observed based on feedback provided by C-level managers, R(t) was based on the complaints presented by the end users and collected by the IT department, the Strength of IT department actions on alignment (α) was based on the number of alignment projects launched by the IT department.

Table 2: Stocks and parameters in the model and how they have been assessed.

Stock/parameter	Description	Case study proxy	Data sources
A(t)	Degree of business-IT alignment	C-level managers' alignment ratings (periodic strategic reviews)	Interviews' transcripts, survey data
I(t)	IT department alignment actions	Number of active alignment projects (e.g., ERP upgrades, workflow standardisation)	Project portfolios, meeting minutes
R(t)	Personnel resistance to change	End-user complaints (IT service tickets)	IT support logs, end-user survey on IT satisfaction
T(t)	Top management commitment	Percentage of leadership meeting time and budget allocated to alignment initiatives	Meeting minutes, financial reports
α	Strength of IT actions on alignment	Correlation between project launches and alignment score improvements	Project timelines, alignment scores
γ	Effectiveness of commitment on IT actions	Ratio of budget allocated to alignment projects vs. total IT budget	Budget documents, project records
δ	Resistance growth rate	Increase in complaints per alignment score unit increase	Complaint logs, alignment scores
η	Leadership's mitigation of resistance	Frequency of leadership-led initiatives (e.g., training, external consultants support hours)	Meeting minutes, event calendars
ϵ	Complacency effect (commitment decay)	Change in the proportion of leadership meeting time allocated to alignment activities as alignment scores increase	Meeting minutes, alignment scores

3. Model formulation: a nonlinear system

The dynamic interactions between alignment variables were formalised through a system of nonlinear equations. The model is in discrete time, as we observed in the case study that the key events and actions that shape alignment (e.g., budget formulation for IT projects, launch of alignment initiatives, etc.) occur in specific moments in the life of the organization. The model captures key relationships observed in the case study as well as the role of some alignment variables.

$A(t+1)=A(t)+\alpha\cdot I(t)\cdot(1-R(t))$ (Alignment grows via IT Actions, hindered by Resistance)

$I(t)=\gamma\cdot T(t)\cdot(1-R(t))$ (IT Actions depend on Leadership Commitment, hindered by Resistance)

$R(t+1)=R(t)+\delta\cdot A(t)\cdot(1-R(t))-\eta\cdot T(t)$ (Resistance grows with Alignment but is mitigated by Leadership)

$T(t+1)=T(t)-\epsilon\cdot A(t)$. (Leadership commitment declines as Alignment improves)

Alignment at a certain time A(t+1) depends on the previous state of alignment A(t) and the IT department actions I(t), which are moderated by Personnel resistance R(t). In the model, the variables represent:

- α: Strength of IT department actions on alignment.
- $(1-R(t))$: Moderating effect of Personnel resistance.

The IT Department Actions I(t) depend on Top management commitment T(t) (since budget for IT projects is proportional to T) and on Personnel resistance R(t), which hinders IT actions. The variables represent:

- γ: Strength of Top management commitment on IT actions.
- $(1-R(t))$: Moderating effect of Personnel resistance.

The Personnel resistance R(t+1) depends on the previous state of resistance R(t), the Top management commitment T(t), which reduces resistance, and the current level of alignment A(t), which increases resistance (due to complacency or fatigue). The variables represent:

- δ: Strength of alignment's impact on resistance.
- η: Strength of Top management commitment's impact on reducing resistance.

Top Management commitment T(t+1) depends on the previous state of commitment T(t) and on the current level of alignment A(t), which reduces commitment (as alignment improves, the urgency to pursue further alignment decreases). In the model, the variable ϵ represents the Strength of alignment impact on reducing Top management commitment.

4.4 Nonlinear dynamics and emergent behaviours

Analysis of the model revealed some nonlinear dynamics that characterise the alignment process. First, alignment growth exhibits diminishing returns, where initial improvements yield rapid benefits but face increasing resistance as changes penetrate deeper into organizational routines. In the case study, early IT actions (e.g., ERP consolidation) boosted alignment rapidly, but resistance grew proportionally, slowing progress. Beyond a threshold value, Personnel resistance outweighed gains, mirroring the case's 2020 stagnation.

Second, organizational resistance shows hysteresis effects: once resistance passes a certain threshold, it becomes self-reinforcing and increasingly difficult to reverse. In the case study, when resistance reached a high level, reducing it required much greater Top management commitment than before. This was clearly visible in 2021, when the organization had to invest heavily in employee retraining to restore alignment momentum.

Third, Top management commitment shows critical threshold behaviour, where commitment below certain levels can trigger rapid deterioration in alignment initiatives. Below a certain value of the Top management commitment, alignment collapses irreversibly, reflecting the case's near-breakdown in 2017 when leadership attention shifted prematurely.

4.5 Model test: comparing model analysis and observed dynamics

The model's dynamics showed correspondence with observed patterns in the case organization. We identified several key parallels.

Positive feedback dynamics. The initial phase of the transformation program mirrored the model's positive feedback dynamics. Strong leadership commitment, exemplified by the new CEO publicly supporting IT modernisation, triggered a virtuous cycle: budgetary approvals accelerated IT projects (e.g., ERP consolidation), which delivered quick wins (e.g., streamlined reporting). These successes, in turn, reinforced leadership's confidence, unlocking further resources. Just as the model predicted, early momentum created a self-reinforcing "alignment engine," where trust in IT strategic role grew alongside measurable progress.

Negative feedback effects and the paradox of progress. As alignment improved, resistance to change grew, especially among employees who were comfortable with the existing systems. This resistance created a self-limiting feedback loop that eventually slowed further progress. The model captured this dynamic: rising alignment (A) increased resistance (R), which in turn limited future gains. By 2020, the organization faced this paradox directly, as the improvements achieved through earlier efforts began to stall due to widespread "change exhaustion."

Tipping points and critical transitions. The model analysis identified threshold points where the system's behaviour changed significantly, matching patterns observed in the organization. In the case study, leadership became prematurely satisfied with the alignment progress and shifted focus toward market expansion. As a result, commitment dropped below a critical level. This reflected the model's predicted tipping point, where reduced leadership attention triggered a rapid decline in alignment. IT projects lost priority, resistance grew stronger, and the organization came close to collapse.

Oscillatory behaviour and cycles of crisis and complacency. The model highlighted the cyclical nature of alignment efforts, where periods of strong leadership focus were followed by phases of reduced attention. This pattern reflected the organization's own experience with crisis-driven IT governance. The company often responded to urgent issues, such as production scheduling problems after acquiring major new customers, but then returned to a state of complacency once the immediate crisis had passed. The model reproduced these oscillatory patterns, showing how alignment gains during leadership-driven initiatives, like post-crisis audits, tended to fade during quieter periods, creating a recurring reactive cycle.

6. Discussion

In the present study, we use complexity science as a methodological foundation to explore how the process of business-IT alignment in organizations evolves over time. Guided by the question of how complexity-based modelling can enrich our knowledge of IS processes, we developed and tested a nonlinear system dynamics model grounded in a longitudinal case study. The model shows that alignment emerges from the interaction of competing forces. Leadership commitment pushes the process forward, but progress also generates resistance that slows further improvement. This interplay creates complex dynamics that traditional, linear approaches often fail to capture. Our findings contribute both to alignment theory and to IS research methodology by showing how system dynamics can reveal hidden structures in organizational processes.

6.1 Contributions to understanding business-IT alignment

The first contribution of the study is a deeper understanding of the alignment process in organizations, moving beyond current conceptualisations of alignment as either a gradual, linear process (Chan and Reich, 2007) or one characterised by punctuated equilibrium (Sabherwal et al., 2001). The mathematical description of alignment developed in our study challenges conventional views of alignment as a stable target, instead revealing it as a dynamic equilibrium shaped by interconnected forces.

Our analysis reveals that alignment progress often creates its own obstacles. Early successes in alignment initiatives, such as ERP consolidation, generate momentum but simultaneously trigger unintended resistance. As employees become overwhelmed by rapid changes, they may disengage from the process, creating self-limiting dynamics where alignment's very progress undermines its sustainability. This paradoxical relationship helps explain why organizations often plateau despite increased IT investments, a phenomenon not fully explained by previous static models of alignment (Henderson & Venkatraman, 1993).

Furthermore, our study identifies a critical hysteresis effect in alignment processes, where resistance, once established, demonstrates remarkable persistence. This finding extends previous process-based views of alignment (Chan & Reich, 2007) by showing how historical paths constrain future possibilities. The case organization expensive efforts to rebuild trust after early missteps, such as delayed leadership engagement with training programs, demonstrates how reducing entrenched resistance demands significantly greater effort than preventing its initial emergence. This temporal asymmetry highlights the importance of proactive, rather than reactive, governance mechanisms.

The study reveals a paradoxical trajectory of leadership commitment: while a strong initial focus drives early gains, accumulating progress can lead to complacency, creating vacuums where resistance flourishes. Our model identifies critical thresholds where diminished leadership commitment can trigger rapid alignment collapse. This extends previous research on the role of leadership in alignment (Luftman et al., 1999) by specifying the dynamic mechanisms through which leadership influences operate. Additionally, this finding enhances the complex adaptive systems view of alignment (Benbya & McKelvey, 2006) by offering a more nuanced understanding of the nonlinear dynamics involved.

Furthermore, the study insights bridge the gap between "alignment as a state" (emphasising alignment factors) and "alignment as a process" (focusing on temporal evolution). By formalising how factors interact dynamically, the model explains why organizations oscillate between harmony and discord, a pattern that static models struggle to capture.

The deeper understanding of the complexity of the process offers valuable suggestions for practitioners. Organizations can utilise these insights to identify critical factors in their alignment process, leveraging positive feedback loops while mitigating negative ones. C-level executives may also use the insights of the model to assess in a more insightful way the alignment trajectories of their organizations and define effective actions. For example, when faced with a reduction in alignment, understanding whether the dynamics are caused by ineffective actions or are the result of a complex evolution which alternates alignment and misalignment helps executives make more informed decisions.

6.2 Contribution to IS research methodologies

The second major contribution of our study lies in extending the methodological toolkit available to IS process researchers. Beyond alignment, this study shows how complexity science methodologies can advance IS research more broadly. Traditional approaches, whether qualitative (e.g., case studies) or variance-based (e.g., regression analysis), struggle to capture the recursive and context-sensitive nature of IS processes (Merali, 2006). Our model addresses these limitations by revealing hidden patterns and clarifying causal mechanisms through proactive exploration.

Nonlinear analysis uncovered dynamics invisible to static methods, such as delayed feedback (e.g., IT investments taking months to impact workflows) and oscillatory regimes (e.g., crisis-driven "firefighting" followed by complacency). By forcing explicit links between variables (e.g., how top management commitment mitigates resistance), the model moves beyond what factors matter to why and when they matter. This approach extends prior work on complex adaptive systems in IS research (Allen and Varga 2006; Benbya and McKelvey 2006; Merali 2006) by providing a more granular understanding of the interplay between various alignment factors and how they shape the alignment process.

The model serves as a "virtual lab" to test interventions (e.g., staggered IT rollouts vs. big-bang implementations), offering insights into leverage points and unintended consequences. This capability addresses the call for more dynamic and adaptive approaches to studying IS phenomena (Benbya et al., 2020; El Sawy et al., 2010).

This methodological contribution shifts IS research from post-hoc explanation to generative understanding, where processes are studied as systems of interacting forces rather than linear sequences. For contemporary phenomena like digital transformation or AI adoption, where outcomes depend heavily on adaptation and emergence, complexity-aligned methodologies offer a lens for understanding organizational dynamics.

This study has some limitations. It is based on a single case and relies on perceptual measures, such as assessments of leadership commitment, which restrict the generalisability of the findings. Future research could address this limitation by conducting multi-case studies and incorporating sensor-based data, such as workflow telemetry, to capture organisational dynamics more objectively. Although our focus was on business-IT alignment, the modelling approach is adaptable. Similar methods could be applied to other complex IS processes, including cybersecurity incident response and platform ecosystem governance, where feedback, adaptation, and nonlinear change also play critical roles.

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AI declaration: AI was not used for the creation of the present paper, EditGPT was used for text proofreading.

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