



# Micro-change as Macro-Catalysts: Non-linear Dynamics of Leadership Behaviour: Cultural Emergence, and System Outcomes in Adaptive Organisations

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## Abstract

The persistent failure of linear, plan-driven models to effect lasting organisational transformation necessitates a paradigm shift. Contemporary organisations, particularly in high-stakes environments such as healthcare, do not function as predictable machines but as Complex Adaptive Systems (CAS), in which change is inherently non-linear and emergent. This longitudinal, mixed-methods study investigates the central premise that micro-changes in leadership behaviour, such as subtle, sustained adjustments in daily practice, can act as a critical catalyst, precipitating significant and often discontinuous shifts in organisational culture and performance. Designed as a 24-month longitudinal mixed-methods study within a Malaysian healthcare organisation, this research will synthesise CAS theory, transformational leadership, and organisational culture theory to track the co-evolution of leadership and culture. A key methodological innovation will be the application of Cusp Catastrophe Modelling to formally test for threshold-based, non-linear transitions. Quantitative and qualitative data will be collected in parallel across four waves (Baseline, Month 8, Month 16, and Month 24) to map broad trends and probe lived experiences and mechanisms of change. The study is designed to address contemporary calls for rigour in microfoundations and in embedding research. The findings aim to advance theory by empirically modelling cultural emergence as a dynamic system and provide practitioners with a nuanced, evidence-based framework for fostering genuine adaptability in complex environments.

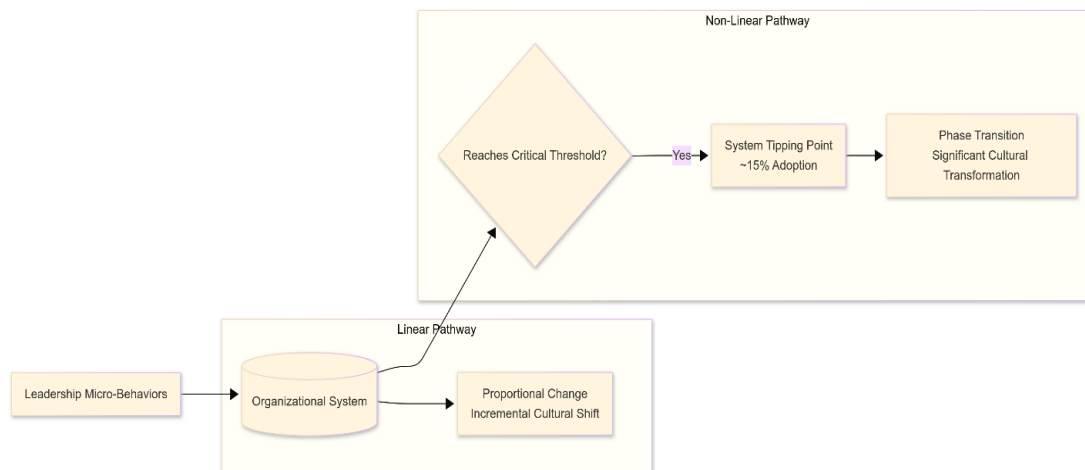
**Keywords:** emergent culture; micro-behaviours; non-linear dynamics; organisational emergence; threshold effects

## 1. Introduction

For decades, the prevailing approach to organisational change has been linear and managerialist, characterised by staged models that promise predictable outcomes from large-scale interventions. These models assume a direct and proportional relationship between the extent of leadership intervention and the magnitude of the resulting cultural change (Kotter,

1996; Burnes, 2017). This paradigm, while comforting in its illusion of predictability and control, has consistently failed to account for the dynamic, interconnected, and inherently emergent nature of contemporary organisations, particularly in complex, knowledge-intensive sectors such as healthcare. The fundamental flaw lies in the misapprehension of the organisational form itself. A growing body of research has redefined organisations as Complex Adaptive Systems (CAS). These are dynamic networks of interconnected agents whose ongoing interactions generate new patterns at the system level that cannot be understood from examining the individual parts alone (Plsek & Greenhalgh, 2001; Uhl-Bien & Arena, 2018; Zimmerman et al., 2008).

Within the CAS framework, change is understood as a fundamentally non-linear process. Small, seemingly inconsequential inputs, which we term micro-changes, can accumulate within the organisational fabric, their effect remaining latent and below the threshold of observable impact for an extended period. This incubation continues until a critical tipping point is reached, at which the system undergoes a sudden, often irreversible phase transition, reconfiguring itself into a qualitatively new state (Gladwell, 2000; Schelling, 1971). This perspective poses a profound challenge to conventional leadership and change management doctrines, suggesting that transformative shifts may not necessitate grand, top-down initiatives but instead be catalysed by the precise, sustained application of subtle behavioural nudges at pivotal junctures (Centola, 2021). This perspective is visualised in Figure 1, which contrasts linear, proportional change with a non-linear pathway featuring a tipping point.



*Figure 1: Conceptual model of linear versus non-linear pathway in leadership-driven cultural change. The diagram illustrates the core proposition: incremental leadership micro-behaviours may initially yield little visible change until a critical adoption threshold (approximately 15%) is reached, after which a phase transition triggers disproportionate cultural transformation.*

*Source: Generated by the authors*

The domain of leadership behaviour presents a critical arena for exploring this non-linear dynamic. While transformational leadership theory effectively outlines broad behavioural dimensions such as inspiration, motivation, and intellectual stimulation (Bass & Riggio, 2006), it often glosses over the daily, micro-level adjustments through which these dimensions are enacted. These include a slight shift towards more open-ended questioning in meetings, increased transparency in communicating difficult decisions, and a more consistent provision of personalised feedback. Concurrently, organisational culture, defined as a deep-seated pattern of shared assumptions that guides perception and behaviour (Schein, 2017), is widely recognised as the ultimate determinant of an organisation's adaptability and performance (Cameron & Quinn, 2011). The precise mechanism linking these granular leadership

behaviours to macroscopic cultural shifts remains poorly understood. This gap is particularly acute regarding non-linear pathways, which are empirically underexplored.

Therefore, this study aims to address the pivotal research question: How do micro-changes in leadership behaviour function as non-linear catalysts for significant shifts in organisational culture and system-wide performance outcomes within a complex adaptive system? By integrating the meta-theory of CAS with established theories of transformational leadership and organisational culture, we propose that a leader's subtle, daily behavioural adjustments serve as critical control parameters within a dynamic social system. We posit that as these parameters are gradually adjusted, the organisation's cultural status may remain in a stable equilibrium, resisting visible change until a specific threshold is crossed. Once this tipping point is crossed, the system becomes unstable. It can jump discontinuously to a new cultural attractor state, manifesting as a sudden, widespread transformation in norms, values, and collective behaviour (Guastello, 2013; Olthof et al., 2023).

The impetus for this research is to transcend the metaphorical use of complexity science and provide rigorous longitudinal evidence of these dynamics within the complex context of a healthcare organisation, thereby offering leaders a more nuanced, evidence-based, and practical framework for nurturing genuine adaptability in an era of perpetual volatility.

### **1.1. Theoretical Integration and Hypothesis Development**

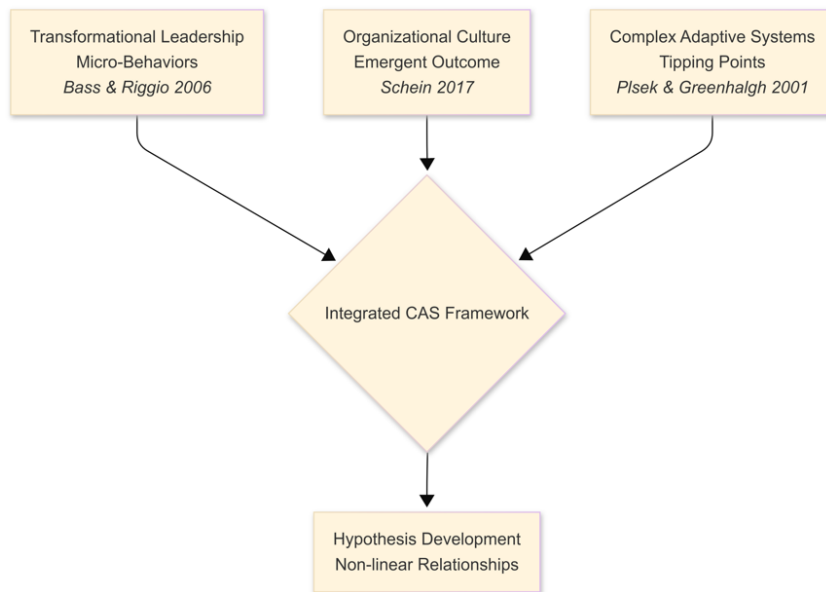
The investigation is grounded in a deliberate synthesis of three complementary theoretical perspectives, thereby creating an integrative framework for rigorously examining non-linear change.

The foundational lens will be provided by the theory of Complex Adaptive Systems (CAS). This perspective reconceptualises organisations as ecologies of interacting agents capable of self-organisation, co-evolution, and emergent order (Plsek & Greenhalgh, 2001; Schneider & Somers, 2006). Within such systems, outcomes are path-dependent and sensitive to initial conditions, and changes are rarely smooth or proportional. Instead, it is characterised by feedback loops, punctuated equilibria, and bifurcation points, at which systems choose among alternative futures (Uhl-Bien & Arena, 2018). This theory moves us away from a reductionist, engineering view of change towards one that acknowledges the inherent unpredictability and the potential for small causes to have disproportionately large effects.

This systems view will be integrated with the specific behavioural focus of Transformational Leadership Theory. Transformational leaders inspire followers to go beyond self-interest through idealised influence, inspirational motivation, intellectual stimulation, and individualised consideration (Avolio et al., 1999). Our research will deliberately zoom in from these broad constructs to their micro-manifestations: the tangible, daily “nudges” and subtle behavioural shifts that constitute the practice of leadership on the ground. This aligns with recent microfoundations research, which emphasises that organisational outcomes are built from the actions and interactions of individuals and groups, exploring how micro-variables configure into firm-specific dynamic capabilities (Wilkins & Sprafke, 2019).

The third pillar is the Organisational Culture Theory, which defines the primary emergent outcome of interest. Drawing on Schein's (2017) layered model (from artefacts to espoused values to basic assumptions) and Cameron and Quinn's (2011) Competing Values Framework, we treat culture not as a static variable to be managed but as a dynamic emergent property that is continuously produced and reproduced through social interaction and leadership behaviour (Schein, 2017). We pay particular attention to cultural types associated with adaptability, specifically the Adhocracy (characterised by dynamism, entrepreneurship, and innovation) and Clan (characterised by collaboration, trust, and mentorship) quadrants, as these are the most

conducive to thriving in volatile environments. The integration of these three theoretical streams forms the foundational framework for this study, as depicted in Figure 2.



*Figure 2: Integrated theoretical framework for investigating non-linear cultural change. The diagram synthesises three core theoretical perspectives: complex adaptive systems (Plsek & Greenhalgh, 2001) provide the dynamic systems lens; transformational leadership theory (Bass & Riggio, 2006) focuses on micro-behavioural input; and organisational culture theory (Schein, 2017) defines the emergent outcome. Their integration provides a basis for hypothesising non-linear tipping-point dynamics in leadership-driven cultural transformation. Source: Generated by the authors.*

As shown in Figure 2, the integration of CAS meta-theory, transformational leadership, and organisational culture theory provides the foundation for our core theoretical proposition: the relationship between leadership micro-behaviours and cultural outcomes is non-linear. This relationship can be modelled as a non-linear dynamic with threshold effects, as illustrated in Figure 1 (conceptual comparison) and mathematically formalised in the cusp catastrophe framework presented in Figure 5 (Guastello, 2013), which will be tested in this study.

This integrative, micro-focused approach is situated within a growing empirical literature on organisational microfoundations, which seeks to explain macro-level outcomes by aggregating individual and small-group actions (Felin et al., 2015). An empirical study by Wilkens & Sprafke (2019) categorised the microfoundations of dynamic capabilities into four critical fields, namely leadership behaviour, team interaction, individual abilities, and job characteristics. Their cross-firm analysis reveals that while certain factors, such as “access to resources or information” and “team learning”, function as cross-firm commonalities, the specific configuration of micro-variables that drive organisational renewal is often firm-specific. This finding directly supports our study’s premise that the aggregate effect of leadership macro-behaviours is contingent on the organisational context and cannot be understood in isolation from other interacting micro-level factors.

The healthcare sector, a quintessential CAS, provides a critical context for examining these dynamics. Recent empirical studies have begun applying complexity principles to understand cultural and safety transformations. For example, a large-scale ethnographic study of speaking up in intensive care units revealed the complex, socially embedded nature of safety culture, showing how daily micro-interactions such as gentle pre-emptions, strategic use of humour, or quiet words function as informal systems of social control that can prevent errors and enforce norms (Tarrant et al., 2017). This study underscores the non-linear, context-dependent relationship between individual actions and system-wide culture. However, attempts to

engineer such cultural shifts often encounter deliberate systemic resistance. A recent process evaluation of a “hybrid” patient involvement intervention found that, despite its design for adaptability, pressured ward environments led to “taskification”, a stable state where staff merely delivered fixed components without engaging in the creative, flexible practices needed for genuine culture change (Hampton et al., 2025). This illustrates the common “plateau” where systems resist visible change until a critical threshold is crossed. Extending this view to strategic initiatives, a central scoping review by Mogensen et al. (2026) systematically conceptualised cultural change as a primary metric of impact. Their resulting PPI Culture Change (PPI-CC) model provides a critical theoretical scaffold, framing change as a dynamic, non-linear process across the micro (user socialisation), meso (organisational commitment), and macro (regulatory assumptions) levels. This multi-level, complexity-informed model directly complements the CAS perspective central to our study, offering a structured lens for interpreting the emergent cultural outcomes we aim to measure.

Further emphasising the role of granular actions, a systematic review by Sfantou et al. (2017) on leadership in healthcare found that the transformational leadership style was consistently associated with improved quality-of-care measures, underscoring the practical importance of leadership behaviours in complex clinical environments. This supports our micro-behavioural focus. To model the non-linear dynamics that such behaviours may create, methodological advances beyond traditional regression are required. Recent methodological advances, such as Latent Change Score models, enable more sophisticated detection of discontinuous growth patterns in organisational phenomena (McNeish & Matta, 2018).

Concurrently, methodological advancements are enabling more sophisticated detection of the very non-linear dynamics theorised by CAS, including longitudinal studies that can model complex temporal changes (Ployhart & Vandenberg, 2010). Furthermore, recent studies employing complex systems approaches have demonstrated how to model non-linear dynamics and emergence in social systems (Olthof et al., 2023). This study builds on these trends by applying catastrophe theory, a rigorous framework for modelling phase transitions, to the specific domain of leadership-driven cultural change. In this mathematical model, the organisation's cultural state (the outcome) is determined by the interplay between two control parameters. The first is the level of demonstrated adaptive leadership behaviour. The second is a contextual asymmetry factor, such as environmental volatility or internal stress levels. The cusp model depicts a folded surface on which the system can reside in one of two possible states (e.g. a traditional hierarchy versus an adaptive network) within a specific range of parameter values. As leadership behaviour improves, the system moves towards the fold line. At this critical threshold, even a minuscule additional change can cause the cultural state to “catastrophically” shift from one basin of attraction to another, explaining the common organisational experience of protracted stability (“the plateau”) followed by sudden, breakthrough change. The core non-linear proposition is illustrated in Figure 5.

From this integrative proposition, we derive the following testable hypotheses to structure the longitudinal enquiry. H<sub>1</sub> posits that transformational leadership will show a statistically significant positive trend over 24 months, reflecting leaders’ adaptive behavioural changes. H<sub>2</sub> proposes that organisational culture will exhibit significant positive changes in its adaptive and emergent qualities over the same period. H<sub>3</sub> suggests that improvements in leadership behaviour are significantly associated with positive shifts in organisational culture. H<sub>4</sub> states that enhanced adaptive leadership and emergent clinical attributes will be significantly correlated with improvements in non-financial outcomes, such as employee satisfaction and operational effectiveness. Finally, H<sub>5</sub>, central to our non-linear thesis, proposes that minor changes in leadership behaviours will lead to significant and unexpected shifts in organisational

culture over time, demonstrating non-linear, threshold-based dynamics best explained by a cusp catastrophe model.

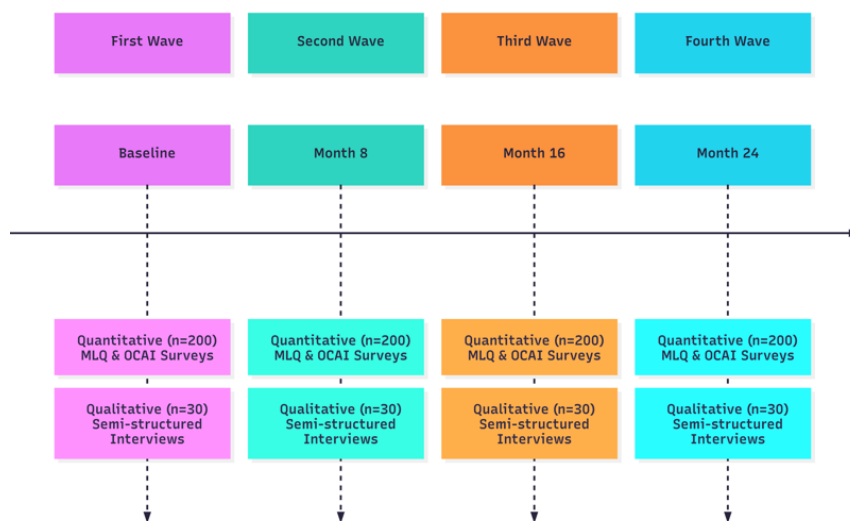
These hypotheses collectively frame the investigation of micro-changes as potential macro-catalysts within a single adaptive healthcare organisation, with H<sub>5</sub> seeking to provide direct empirical evidence for the tipping-point dynamics and non-linear change processes at the heart of our theoretical model.

## 2. Proposed Research Design and Methods

To adequately capture the dynamic, process-oriented, and potentially non-linear nature of the research questions, a longitudinal embedded mixed-methods design will be deployed within a single healthcare organisation in Malaysia. This approach will enable intensive tracking of the co-evolution of variables over time, establishing temporal sequences, and, most importantly, uncovering the underlying mechanisms and subjective experiences that produce quantitative trends.

### 2.1 Longitudinal Mixed-Methods Approach

This study will be implemented as a 24-month longitudinal investigation embedded within a single healthcare organisation in Malaysia. This setting provides a context of high interdependence, professional complexity, and constant pressure for adaptive change, a classic CAS environment (Plsek & Greenhalgh, 2001), in which the phenomena of interest are likely to be salient. The design will be sequential and iterative. Iterative quantitative surveys will map broad trends and relationships, while concurrent qualitative interviews and open-ended survey responses will probe the meanings, narratives, and lived experiences behind those statistical patterns. This synergy will facilitate an understanding of both what is changing and a thorough exploration of how and why these changes occur. The overarching longitudinal mixed-methods design is shown in Figure 3.



*Figure 3: Proposed longitudinal mixed-methods research design. The diagram outlines the 24-month study timeline, showing the parallel collection of quantitative (MLQ and OCAI) and qualitative (semi-structured interviews) data across four waves (Baseline, Month 8, Month 16, and Month 24), along with the integrated analysis plan. Secondary outcome measures (UWES-3 and operational effectiveness metrics) are collected at all four waves but are not shown in the figure to maintain visual clarity; see Section 2.1.4 for complete measurement details.*

Source: Generated by the authors.

<sup>1</sup>To account for anticipated 20% attrition, 250 quantitative participants were recruited at baseline (target 200 per wave) and 38 qualitative participants were recruited at baseline (target 30 per wave), with replenishment sampling at Waves 2, 3, and 4 for both cohorts.

### **2.1.1 Study Context and Participants**

The study will be conducted in a comprehensive healthcare organisation in Malaysia comprising multiple clinical departments, nursing units, and administrative divisions. The participant groups will include a leadership cohort of approximately 30 mid- to senior-level clinical and administrative leaders and a staff cohort of approximately 200 clinical and administrative personnel. From these groups, a qualitative subsample of 30 will be purposively selected for in-depth engagement, ensuring representation of leaders exhibiting notable behavioural change and staff from units experiencing significant cultural shifts.

### **2.1.2 Feasibility and Risk Mitigation**

To ensure the feasibility of this 24-month study, several strategies will be implemented to address the key operational risks.

**Attrition.** The study site is a private healthcare organisation, a context characterised by high workforce mobility. Peer-reviewed research consistently documents nurse retention as a persistent challenge in private healthcare settings in Malaysia. A study by Krishnamoorthy et al. (2020) found that promotional opportunities, manageable workload, and work environment significantly influenced nurses' intention to stay. As of 2013, an estimated 7,000 to 8,000 Malaysian nurses worked in Saudi Arabia, reflecting substantial international migration. Similarly, Zain et al. (2025) surveyed 532 nurses across three private hospitals in Malaysia and found that only 48.41% intended to remain with their current organisation, with job satisfaction identified as the most significant predictor of retention ( $R^2 = 0.534$ ). Ariffin and Yee (2022) further confirmed these challenges, reporting that factors such as training and development, work-life balance, and reward and recognition policies critically affect nursing staff's intention to remain in Malaysian private hospitals. Although these studies focus specifically on nurses, they reflect a broader pattern of elevated staff turnover across clinical and administrative roles in the private healthcare sector. We anticipate a participant attrition rate of approximately 20% over the 24-month period. This estimate aligns with established benchmarks for longitudinal research, where an attrition of up to 20% is considered acceptable before introducing substantial bias (Fewtrell et al., 2008), and it conservatively accounts for higher mobility observed in the private healthcare workforce. To maintain adequate statistical power (target  $N = 200$  at baseline), we will initially recruit 250 staff members to account for the expected dropouts. For the qualitative subsample ( $n = 30$ ), we will recruit 38 participants at baseline. To safeguard against attrition across the four waves, we will implement participant replenishment at Waves 2, 3, and 4, recruiting new participants as needed to maintain a target sample of approximately 30 per wave.

This replenishment strategy is methodologically supported by longitudinal research, which demonstrates that refreshment samples (new participants selected using the same criteria as the original sample) lead to lower relative bias, greater efficiency, and higher statistical power than not supplementing for missing participants (Taylor et al., 2020). Empirical evidence from the MIDUS national longitudinal study successfully reinstated 651 dropouts (31.4% of those contacted), improving sample representativeness (Song et al., 2021). Similarly, the ITC Netherlands Survey found that tailored replenishment samples effectively compensated for attrition effects, with only minimal demographic differences between waves (Zethof et al., 2016). In qualitative longitudinal research, systematic retracing strategies after extended gaps have been shown to enhance retention rates (Ellis et al., 2023).

**Leader Turnover.** Leadership behaviour is measured through staff ratings of the leaders they regularly interact with. In a dynamic organisational environment, leader turnover is an expected phenomenon. If a leader departs during the study period, subsequent staff ratings will reflect the behaviour of the incoming leader. This does not compromise the validity of the study;

rather, it reflects the real-world complexity of leadership dynamics in adaptive organisations. Our analytical strategy for H<sub>3</sub> and H<sub>4</sub>, using the Random-Intercept Cross-Lagged Panel Model (RI\_CLPM; Hamaker et al., 2015), inherently accounts for changes in the predictor variable (leadership ratings) over time, whether those changes result from behavioural shifts in the same leader or from leader replacement. This allows us to model the effects of changes in leadership inputs on culture and outcomes rather than treating leadership as a static entity. Additionally, the qualitative interviews will explicitly probe how staff experience leadership transitions and whether such transitions create discontinuities in cultural emergence. This dual approach, the quantitative modelling of change plus qualitative exploration of transitions, ensures that leader turnover is treated as a meaningful organisational dynamic rather than a methodological nuisance. Consistent with recommendations for longitudinal research in dynamic organisational contexts, we treat leader turnover as a naturally occurring variation in the leadership input variable rather than a threat to internal validity (Antonakis et al., 2010).

**Access to Administrative Data.** The asymmetry composite requires access to aggregated anonymised administrative data. A data access agreement has been drafted with the organisation's senior management and ethics committee, stipulating that all data will be aggregated at the departmental level, anonymised before being shared with the research team, and used solely for this study. The organisation's designated data custodian will oversee the extraction and de-identification processes.

**Departmental Sample Sizes for Clustering.** We anticipate approximately 12-15 departments, such as clinical wards, nursing units, and administrative divisions. With a baseline staff sample of 200, this yields an average cluster size of 13-17 individuals per department. While some departments may be smaller, this distribution is sufficient for multilevel modelling, as simulation studies suggest that a sample of 15 groups with 10 individuals per group provides adequate power to detect moderate cross-level effects (Gelman & Hill, 2006). We will also employ robust standard errors to account for unequal cluster sizes.

### **2.1.3 Acknowledging Design Constraints and Analytical Considerations**

The single-site, embedded design is a strength in depth and context, but imposes constraints on generalisability. Furthermore, the data are inherently nested (individuals within teams/departments within the organisation), introducing potential non-independence that must be methodologically addressed to avoid biased parameter estimates and incorrect inferences (Bliese & Ployhart, 2002; Henry & Muthén, 2010). This nested structure violates the assumption of independent observations, which is fundamental to traditional regression techniques, and can lead to underestimation of standard errors, Type 1 errors, and biased parameter estimates if not properly modelled (Liu, 2026; Bliese & Ployhart, 2002). Research on mixture modelling with nested data has demonstrated that ignoring this clustering can significantly impact the identification of latent subgroups and the interpretation of model results, underscoring the importance of appropriate model specifications (Musci et al., 2024).

While our primary cusp catastrophe analysis treats the organisation as the primary system-level unit of analysis (by appropriately aggregating leadership and culture scores), we will employ supplementary multilevel modelling (MLM) to account for nesting in the preliminary linear analyses of H<sub>1</sub>-H<sub>4</sub> (Bliese & Ployhart, 2002). To address the level-of-analysis concern in cusp catastrophe modelling, we clarify that the analytic N for the primary cusp model will be 200 individuals (staff members), each providing four waves of data, resulting in 800 observations for analysis, rather than four organisational-level aggregate time points. This individual-level repeated-measures approach aligns with established cusp modelling practices in organisational research, where the system under investigation is conceptualised at the individual level, focusing on psychological and behavioural responses to leadership stimuli (Guastello, 2013;

Olthof et al., 2023). To account for the nested structure of these data (repeated measures within individuals, individuals within departments), we will (a) include department as a clustering variable in the cusp model using robust standard errors, and (b) conduct sensitivity analysis using group-level aggregated data to verify the robustness of findings across levels of analysis. This multi-level approach to cusp modelling addresses recent methodological guidance on handling nested data in non-linear dynamical systems analysis (Liu, 2026; Musci et al., 2024). To incorporate the repeated-measures structure and explore nested dynamics, we will also explore person-centred approaches, treating each department's longitudinal trajectory as a potential case for qualitative comparative analysis (QCA) alongside the primary model, as suggested for studying non-linear dynamics in nested contexts (Olthof et al., 2023).

#### **2.1.4 Measurement Strategy**

The quantitative and qualitative data arms will operate in parallel, with planned data collection at four waves: Baseline, Month 8, Month 16, and Month 24.

The design consistently employs four waves of data collection: Baseline, Month 8, Month 16, and Month 24. All references to data collection waves in the manuscript, Sections 2.1, 2.1.4, and 2.2, and Figure 3, have been verified and harmonised to reflect this four-wave structure. The qualitative component will similarly collect data at all four waves from the purposive subsample, enabling the temporal matching of quantitative trends with lived experiences of change at each critical juncture.

This four-wave longitudinal design reduces the respondent burden while providing sufficient data points for dynamic modelling (Ployhart & Vandenberg, 2010). It also enables the temporal separation of measurements and utilises a multi-source approach to mitigate common method bias (Podsakoff et al., 2012).

We address common method bias through five strategies (Podsakoff et al., 2024). First, although the same staff cohort rates both leadership (MLQ) and culture (OCAI), the constructs have different referents (specific leaders versus organisation-wide culture), reducing percept-percept inflation (Cruz, 2022). Second, temporal separation within each wave (distractor items, different response formats) and the cross-lagged longitudinal design (leadership at T predicting culture at T+1) preclude contemporaneous bias (Podsakoff et al., 2012; Podsakoff et al., 2024). Third, the OCAI uses forced-choice ipsative scaling, reducing acquiescence and halo effects (Meade, 2004). Fourth, statistical diagnostics include Harman's single-factor test and the unmeasured latent method factor (ULMF) approach, although we acknowledge the limitations of Harman's test (Podsakoff et al., 2024; Fuller et al., 2016). Fifth, qualitative interviews triangulate survey findings (Jick, 1979).

The quantitative arm will employ validated instruments at each wave. Transformational leadership will be measured using the Multifactor Leadership Questionnaire (MLQ 5X-Short; Bass & Avolio, 1995), with staff rating their direct supervisors' leadership behaviour. Organisational culture will be assessed using an adaptation of the Organisational Culture Assessment Instrument (OCAI; Cameron & Quinn, 2011), contextualised for healthcare with a focused analysis of Adhocracy and Clan culture types. The OCAI's ipsative, forced-choice format is deliberately selected because it is less susceptible to common bias, such as acquiescence and halo effects, which can inflate relationships in Likert-scale measures (Meade, 2004). This is a critical advantage for a study in which leadership and culture are measured by the same respondents. However, we acknowledge the known caveats of ipsative data for longitudinal analysis, particularly its limitations for traditional confirmatory factor analysis (CFA) due to the inherent dependence among scale items. As Moeller (2015) notes, ipsatisation changes the covariance matrix, rendering the data unsuitable for traditional CFA and structural equation modelling. To manage this, we will not perform CFA on the OCAI scores. Instead,

we will test for longitudinal measurement invariance using a structural approach recommended for ipsative data. This structural approach aligns with recent methodological guidance for forced-choice questionnaire data (Sieber, 2024) and extends established methods for analysing ipsative measurement invariance across groups (Cheung & Chan, 2002; Cheung, 2004). This involves (a) analysing the four OCAI subscale scores (Clan, Adhocracy, Market, and Hierarchy) separately as dependent variables in longitudinal models, and (b) using a multinomial logistic regression approach to test for shifts in the dominant culture profile over time, a method that is robust to the ipsative constraint. This approach aligns with the theoretical focus on the organisation's dominant cultural orientation (Cameron & Quinn, 2011). Methodologically, this strategy is supported by recent guidance on analysing ipsative data within the Competing Values Framework, including compositional data analysis with log-ratio coefficients (Sieber, 2024) and nonparametric bootstrap tests with permutation methods (van Eijnatten et al., 2015).

Employee satisfaction will be assessed using a validated engagement survey subscale, the ultra-short Work Engagement Scale (UWES-3; Schaufeli et al., 2019). The UWES-3 will be administered to the full staff cohort (n=200) at all four waves (Baseline, Month 8, Month 16, and Month 24) to track work engagement as a secondary longitudinal outcome. Operational effectiveness metrics (innovation and error rates) will be collected across all four waves from administrative sources as exploratory secondary outcomes that support H4. Innovation is measured by the monthly count of staff-proposed and implemented process improvements. Error rates are measured by monthly aggregated clinical and administrative incident reports. To ensure the psychometric integrity of our longitudinal comparisons, we will test for measurement invariance (configural, metric, and scalar) of the MLQ factor structure across the four time points using multigroup Confirmatory Factor Analysis (CFA) in AMOS, following established reporting conventions (Putnick & Bornstein, 2016). As noted above, the OCAI's ipsative format precludes traditional CFA invariance testing. Instead, we will rely on the multinomial logistic regression and compositional approaches described previously to assess cultural stability and change over time. Failure to establish invariance for the MLQ would necessitate a cautious interpretation of mean-level changes. Establishing at least scalar invariance is a prerequisite for meaningfully comparing latent means across time and for testing longitudinal hypotheses (Putnick & Bornstein, 2016).

The qualitative component at each wave will involve semi-structured interviews with purposive subsamples (n = 30). The interview protocol will be carefully crafted using Bloom's taxonomy (Anderson & Krathwohl, 2001) to structure the cognitive progression in questioning, moving from descriptive recall to evaluative synthesis. This structured approach is designed to elicit rich, layered data on perceived causal mechanisms, the experience of threshold effects, and the nature of reinforcing or balancing feedback loops within the organisation.

This four-wave longitudinal design provides a robust framework for testing hypotheses H<sub>1</sub>-H<sub>4</sub>. For H<sub>1</sub> (leadership trend) and H<sub>2</sub> (culture trend), latent growth curve modelling (LGCM) will be applied to the four time points to estimate linear and non-linear trajectories over 24 months (Preacher et al., 2008). For H<sub>3</sub> (leadership-culture association) and H<sub>4</sub> (leadership/culture-outcome relationship), random-intercept cross-lagged panel models (RI\_CLPM) will be used to examine within-person changes and bilateral effects across waves while controlling the nested data structure (Hamaker et al., 2015). Measurement invariance testing across the four waves is a prerequisite for these longitudinal comparisons (Putnick & Bornstein, 2016).

The study received full ethical approval, and all data will be anonymised and stored on encrypted, password-protected servers, with access strictly limited to the research team.

While the single-site, observational nature of this study precludes definitive causal claims, we employ multiple analytical and design strategies to strengthen causal inference and address endogeneity concerns (Antonakis et al., 2010).

First, the longitudinal design with temporal separation, in which the predictor is measured at Time  $t$  and the outcome at Time  $t+1$ , establishes temporal precedence. The use of random-intercept cross-lagged panel models (RI-CLPM) explicitly models within-person change over time, allowing us to examine whether changes in leadership behaviour precede subsequent changes in organisational culture while controlling for stable between-person differences (Hamaker et al., 2015).

Second, we will incorporate time-varying covariates to control for alternative explanations. For instance, a dummy variable will be included for major concurrent organisational initiatives to statistically control for their influences on outcomes (Balasubramanya et al., 2018). The qualitative interview protocol will explicitly probe for other significant change events during the study period, and we will maintain a study journal to document major external and internal events.

Third, we will explore the possibility of a natural experiment within the single-site design. Should an unexpected exogenous event occur during the study period, we will treat it as a quasi-experimental shock to examine its impact on the leadership-culture dynamic (Sieweke & Santoni, 2020). This approach can provide stronger evidence for causal effects than a purely observational analysis. Natural experiments, including instrumental variables and regression discontinuity designs, offer rigorous opportunities to infer causal relationships in leadership research, where randomised controlled trials are infeasible (Sieweke & Santoni, 2020). Quasi-experimental designs, while lacking random assignment, remain valuable for testing causal hypotheses in field settings where researcher control is constrained (Podsakoff & Podsakoff, 2019).

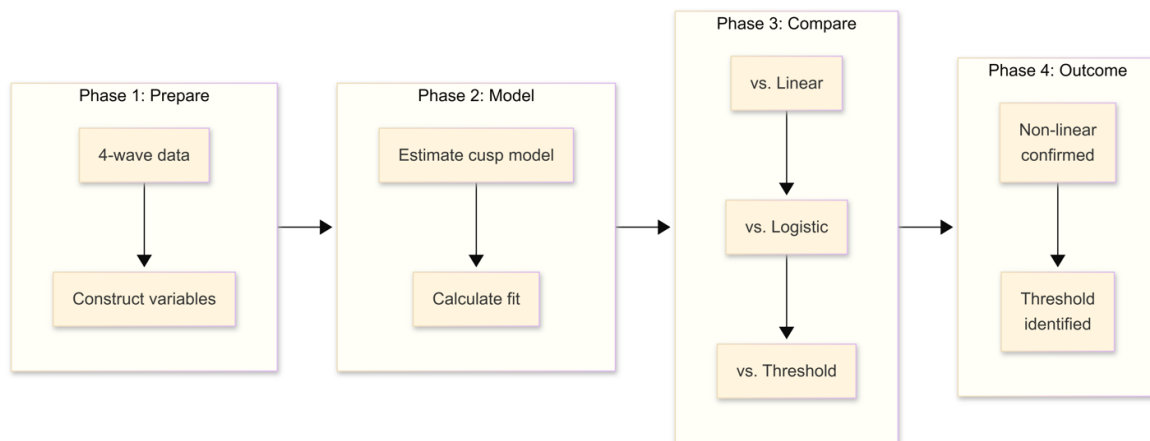
Fourth, to address unobserved time-invariant heterogeneity, we will supplement our primary analyses with fixed-effects panel models, where appropriate, which use each individual as their own control (Wooldridge, 2010; Antonakis et al., 2010).

Fifth, to ensure robustness to time-varying shocks, we will conduct sensitivity analyses by testing our cusp model findings with and without periods of documented major organisational or external disruptions (Lombardi et al., 2025).

Finally, the core non-linear hypothesis,  $H_5$ , will be tested using cusp catastrophe modelling, which explicitly models the system's dynamics as a function of its control parameters (Guastello, 2013). This approach provides a more rigorous test of our theoretical proposition than simple linear models, which are particularly vulnerable to omitted bias in complex systems (Antonakis et al., 2010).

## **2.2. Analytical Innovation: Cusp Catastrophe Modelling**

A key methodological contribution of this study is the planned application of Cusp Catastrophe Modelling (Guastello, 2013) to formally test for the non-linear, discontinuous change predicted by  $H_5$ . This technique is uniquely suited for operationalising the dynamics of complex adaptive systems, in which control parameters can drive a system past a tipping point into a new attractor state (Olthof et al., 2023). Catastrophe theory provides a robust mathematical framework for modelling sudden state transitions arising from smooth and continuous changes in the underlying control parameters. Catastrophe models have proven effective in capturing such non-linear, threshold-based dynamics in other complex organisational contexts, such as regional innovation networks (Zeng et al., 2024). The sequential analytical pathway for testing the non-linear Hypothesis  $H_5$  is outlined in Figure 4.



*Figure 4: Sequential analytical pathway for testing the non-linear hypothesis  $H_5$ . The flowchart details the analytical process from data preparation (4-wave data and variable construction) through cusp model estimation and fit calculation, followed by comparative model testing against linear, logistic, and threshold alternatives, culminating in confirmation of non-linear dynamics and threshold identification.*

*Source: Generated by the authors.*

All analyses described in Section 2.2, including the cusp catastrophe modelling, will utilise the full four waves of data collected at Baseline, Month 8, Month 16, and Month 24. This consistent four-wave structure across both quantitative and qualitative strands ensures methodological coherence and provides sufficient temporal density to detect non-linear change patterns (Ployhart & Vandenberg, 2010).

### 2.2.1 Specification of Cusp Model Variables

For our proposed model, the variables are specified as follows to align with the catastrophe theory framework.

Following catastrophe theory conventions (Guastello, 2013; Cobb, 1981), we specify the cusp model variables as follows to ensure consistency across the manuscript: The bifurcation (or normal) variable represents the factor that pushes the system toward the bifurcation set and determines the system's position along the folded surface of the bifurcation set. In our model, this will be the aggregate transformational leadership score from the MLQ, reflecting the behavioural input that drives the system toward a potential phase transition. The asymmetry (or splitting) variable governs the susceptibility of the system to discontinuous changes and creates the potential for two distinct system states. This will be operationalised as a composite index combining external volatility metrics, such as the frequency of regulatory changes, and internal stress indicators, such as aggregated workload measurements. The state variable, or outcome, represents the system's position on the cusp surface and will be the composite score for the adaptive organisational culture derived from the OCAI. This specification aligns with the mathematical foundation of the cusp catastrophe model, in which the bifurcation variable (leadership) and asymmetry variable (contextual stress) jointly determine the system's state through the canonical equations:  $-\partial V(z; \alpha, \beta) / \partial z = z^3 - \beta z - \alpha = 0$ , where  $z$  represents the state variable,  $\beta$  the bifurcation variable, and  $\alpha$  the asymmetry variable (Grasman et al., 2009; Cobb & Zacks, 1985). Before analysis, these component metrics will be standardised and combined in accordance with established psychometric practices (Kline, 1994) and theoretical justifications.

### 2.2.2 Construct Definition and Validation Plan for the Asymmetry Composite

The asymmetry parameter represents the net contextual pressure that creates a potential for bifurcation (Guastello, 2013). Conceptually, it is specified as a formative composite index (Hair et al., 2021), meaning that its indicators are understood as distinct causes that collectively

define the construct rather than as the interchangeable effects of a single latent trait (Jarvis et al., 2003; Koivunen et al., 2022).

We define the asymmetry composite as a formative index comprising two distinct domains: (a) Environmental Volatility: A standardised score combining monthly counts of major new regulatory directives affecting organisation and sectoral volatility indices; and (b) Internal Operational Stress: A standardised score derived from monthly aggregated, anonymised data on patient-to-staff ratios, overtime hours, and incident report volumes.

These components reflect exogenous shocks and endogenous strains, which are theorised to amplify the system's susceptibility. Following the methodological frameworks for formative index development (Diamantopoulos & Winklhofer, 2001), the validation of this composite will follow a structured, multi-step process similar to that employed in recent index development studies (Ebbinghaus et al., 2025). Recent systematic reviews of healthcare algorithmic applications have emphasised the importance of rigorous composite construction, particularly when combining administrative and environmental data sources (Mackin et al., 2025). In their extended umbrella review of post-processing bias mitigation methods, Mackin et al. (2025) demonstrated that composite indices integrating multiple data streams require explicit validation protocols to ensure construct integrity and their predictive utility. This validation approach, outlined below, incorporates the recommendations for assessing multicollinearity, conducting sensitivity analyses, and testing external validity.

Data sources and collection frequency for the asymmetry composite will be operationalised as follows:

1. Environmental Volatility Component
  - a. Regulatory changes: Monthly counts of new Ministry of Health Malaysia circulars, guidelines, and policy directives applicable to the organisation. Data will be sourced from the official Ministry of Health Malaysia e-Surat Pekeliling database and the organisation's policy compliance unit's records.
  - b. Sectoral volatility: Monthly healthcare sector volatility index derived from media monitoring of healthcare policy announcements, funding changes, and major sectoral disruptions reported in national news media, such as Berita Harian and The Star healthcare sections. A structured content analysis protocol will be applied to ensure systematic coding (Krippendorff, 1986).
2. Internal Operational Stress Component
  - a. Patient-to-staff ratios: Monthly aggregated departmental data from the organisation's human resources and patient admission systems
  - b. Overtime hours: Monthly aggregated overtime records by department from the payroll system
  - c. Incident report volumes: Monthly counts of clinical incidents, near misses, and safety reports from the organisation's risk management database.

Missing data handling for administrative data sources will follow the hierarchical approach below:

- For missing monthly data points (< 5% expected), linear interpolation will be applied using adjacent months.
- For systematic missingness in specific indicators (>10%), we will examine patterns and, if missing completely at random (MCAR), proceed with available cases
- Sensitivity analyses will be conducted by comparing the results with and without imputed data to assess robustness (Graham, 2009).

As detailed in Section 2.1.2, all administrative data will be anonymised at the source, with formal data access agreements and a data transfer protocol established with the organisation's data governance committee to ensure compliance with ethical and confidentiality standards. These monthly indicators will be aggregated to correspond with the four survey waves (averaged over the periods preceding each wave), enabling temporal alignment between the objective contextual pressure composite and the subjective survey measures collected at Baseline, Month 8, Month 16, and Month 24.

The composite will be calculated as an equally weighted sum of standardised scores. We will assess its validity and robustness using the following three key steps:

- (1) Examination of Multicollinearity: We will assess multicollinearity among components using Variance Inflation Factors ( $VIF < 5$  indicates acceptable levels; Kock & Lynn, 2012).
- (2) Sensitivity Analyses: We will test alternative weightings, such as entropy weighting and component selections, to ensure that the findings are not an artefact of a single operationalisation, a key step in the formative index validation (Ebbinghaus et al., 2025; Espinosa & Porter, 2011).
- (3) Assessment of External Validity: We will evaluate the composite's correlation with independent, theoretically related measures.

Unlike reflective constructs, formative indices are not validated through internal consistency metrics but through theoretical grounding and predictive utility (Koivunen et al., 2022). This is a fundamental departure from the validation of reflective scales, such as the Self-Efficacy in Clinical Performance Scale, which relies on confirmatory factor analysis and internal consistency measures, such as Cronbach's alpha, to establish reliability and construct validity (Olaussen et al., 2025). This comprehensive validation plan ensures that the asymmetry composite is a robust, theoretically sound representation of contextual pressure for use in the cusp catastrophe model.

### **2.2.3 Measurement Invariance Testing Across Waves and Nested Units**

Before testing longitudinal hypotheses  $H_1$  to  $H_4$ , we will establish measurement invariance of the MLQ instrument across the four time points and across nested departmental units. Due to the ipsative nature of the OCAI, traditional CFA-based invariance testing is inappropriate. As detailed in Section 2.1.4, we will instead manage the OCAI's psychometric caveats by analysing its subscales separately and testing for changes in dominant cultural profile using multinomial logistic regression. For the MLQ, we will conduct standard measurement invariance testing. Following established guidelines (Putnick & Bornstein, 2016; Vandenberg & Lance, 2000), we will conduct multigroup confirmatory factor analysis (CFA) in AMOS v30 and test sequentially as follows:

- Configural invariance: Same factor structure across time points/departments (unconstrained model).
- Metric invariance: Equal factor loadings across time points/departments (constrained loadings).
- Scalar invariance: Equal indicator intercepts across time points/departments (constrained loadings and intercepts).
- Strict invariance: Equal indicator residuals across time points/departments (constrained loadings, intercepts, and residuals).

Model fit will be assessed using  $CFI \geq 0.90$ ,  $RMSEA \leq 0.08$ , and  $SRMR \leq 0.08$  (Hu & Bentler, 1999). Invariance is supported if  $\Delta CFI \leq -0.01$  and  $\Delta RMSEA \leq 0.015$  between successive models (Chen, 2007). For the nested data structure, with individuals within departments, we

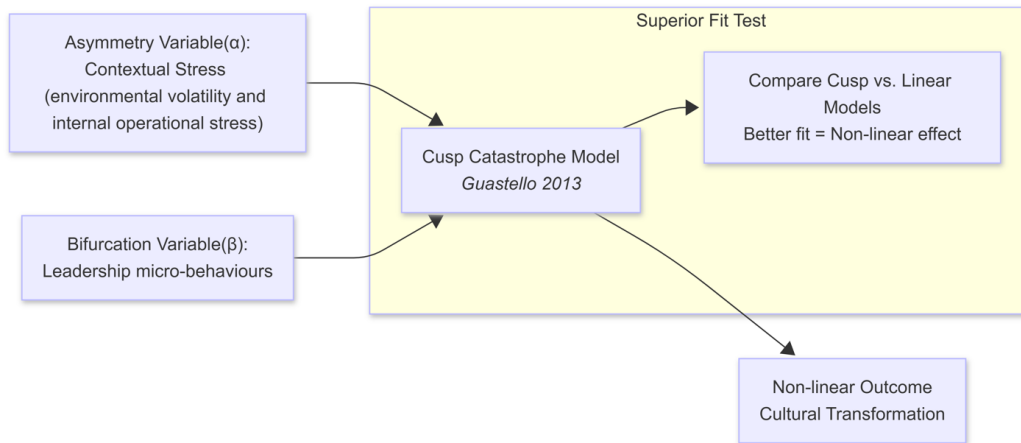
will employ multilevel CFA (MI-CFA) using Mplus 9.0 to partition within-group and between-group variance and test invariance simultaneously at both levels (Muthén, 1994; Im et al., 2016; Leitgöb et al., 2023). This approach addresses potential non-independence and ensures that construct validity holds across the organisational hierarchy (Ryu, 2014). Establishing at least scalar invariance is a prerequisite for meaningful latent mean comparisons across time and for testing cross-lagged relationships (Hamaker et al., 2015; Putnick & Bornstein, 2016).

#### **2.2.4 Analytical Procedures, Power and Robustness Check**

The analytical implementation will involve a rigorous multi-stage process. Before the final participant recruitment, a Monte Carlo simulation power analysis for the cusp model will be conducted using the cusp package in R (Grasman et al., 2009), based on effect size estimates derived from leadership meta-analyses (Rudolph et al., 2020), to ensure sample size adequacy ( $n = 200$ ) for detecting non-linear effects. For  $H_1$ - $H_4$ , power is ensured by a four-wave repeated-measures design, which increases sensitivity to detect change and associations over time. The Sample size ( $N = 200$ ) and four time points provide sufficient degrees of freedom for the multilevel and cross-lagged models (Muthén & Muthén, 2002). Using the cusp package in R (Grasman et al., 2009), we will fit the cusp model to the longitudinal dataset.

To ensure analytical robustness, we will conduct a priori power analyses for cusp modelling, implement Full Information Maximum Likelihood (FIML) estimation to handle any missing data, assuming it is missing at random (MAR), and design sensitivity analyses to test the construction of the asymmetry variable. Finally, we will perform a rigorous model comparison; the fit of the cusp catastrophe model will be statistically evaluated against a suite of nested and alternative models, including not only linear, quadratic, and logistic models but also more flexible non-linear alternatives such as a two-threshold autoregressive model and a regime-switching model, using likelihood-ratio tests and information criteria (AIC, BIC; Burnham & Anderson, 2004; Vrieze, 2012) to determine the best representation of the underlying change process (Guastello, 2013; Olthof et al., 2023). This comparative approach ensures that the selected model best represents the underlying change process.

A well-fitting cusp model that demonstrates statistical superiority over simple linear or logistic alternatives would provide compelling evidence that cultural change in this organisation occurs not merely through gradual accretion but through sudden phase transitions or “catastrophe” when leadership behaviours and contextual pressures cross critical thresholds. This represents a significant advance, moving beyond correlational statistics to model the dynamic process of change. The framework for this analysis is illustrated in Figure 5.



*Figure 5: Analytical framework for cusp catastrophe modelling in leadership-culture research. The diagram illustrates the cusp model variables: leadership micro-behaviours function as the bifurcation parameter( $\beta$ ), and contextual stress (environmental volatility and internal operational stress) functions as the asymmetry variable ( $\alpha$ ). These factors jointly influence the system’s cultural state. The superior fit of this model relative to the linear alternatives confirms the presence of a non-linear, threshold-based dynamics.*

*Source: Generated by the authors based on Guastello (2013) and Grasman et al. (2009).*

### 3. Expected Contributions and Implications

#### 3.1 Theoretical contributions

This study is positioned to make several meaningful contributions to organisational theory and practice. Theoretically, it aims to empirically ground CAS theory within the specific domains of leadership and cultural dynamics, moving it from a powerful but often metaphorical lens to a framework with testable and mathematical predictions about organisational behaviour (Plsek & Greenhalgh, 2001; Uhl-Bien & Arena, 2018). It will aim to refine and advance theories of cultural emergence by formally modelling culture as a dynamic system capable of abrupt, non-linear reorganisation, rather than portraying it as a slow-moving, monolithic variable that changes only through concerted, massive effort (Schein, 2017). Furthermore, by introducing Cusp Catastrophe Modelling as a novel and rigorous analytical tool for organisational research, it will provide a methodological pathway for other scholars to detect and validate the existence of tipping points and discontinuous change in complex social systems (Olthof et al., 2023; Zeng et al., 2024), responding directly to calls for more sophisticated non-linear analyses in management research.

#### 3.2 Practical Implications for Leaders

If the study’s hypotheses are supported, the findings will have significant implications for leadership practice, necessitating a shift towards a “Complexity-Informed Playbook” for change. The playbook encompasses several key principles. It advocates precision in leadership development, shifting the training focus from broad competencies to the identification, practice, and reinforcement of specific, high-leverage micro-behaviours known to influence system dynamics. It would cultivate threshold sensitivity among leaders and change agents, teaching them to recognise the subtle leading indicators that a system is approaching a tipping point, such as increased informal networking, heightened discourse about values, or the viral spread of small pilot projects (Centola, 2021). This awareness would allow for timely and targeted reinforcement to catalyse the desired phase transition. Furthermore, leaders can cultivate the ability to consciously identify and leverage these reinforcing feedback loops. By identifying micro-behaviours that initiate virtuous cycles, such as how increased transparency fosters greater trust, which in turn encourages more information sharing and improved decision-making, leaders can strategically seed and nurture these loops to accelerate positive

cultural transformation. Finally, and perhaps most critically, the model would validate the necessity of strategic patience during plateaus. Leaders can be equipped to recognise that periods of high investment with little visible return are not failures but often essential incubation periods for developing the latent potential required for a phase transition, thereby preventing the premature abandonment of promising change initiatives (Errida & Lotfi, 2021).

#### **4. Conclusion**

This paper outlines a proposed research study design to investigate the non-linear dynamics through which micro-level changes in leadership catalyse macro-level cultural and performance shifts within a single healthcare organisation. By framing the healthcare organisation as a complex adaptive system and employing a longitudinal mixed-method design enhanced by cusp catastrophe modelling, this study seeks to uncover the mechanisms of tipping points and emergent feedback loops. This research promises to advance the theoretical understanding of cultural emergence in healthcare and equip healthcare leaders with a scientifically grounded, actionable framework for fostering genuine adaptability, thereby contributing to the critical discourse on sustainable culture change in healthcare (Bianco-Mathis & Burrell, 2023) in an increasingly volatile world. Ultimately, this challenges healthcare leaders to reconsider the scale of the intervention required for transformation, suggesting that profound change often begins with the most minor behavioural adjustments at the leadership level.

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