Understanding Process Dynamics in Digitized Processes: Foundational Methods and Theory Development

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Abstract

Process dynamics research aims to explain stability and change in business processes. A common approach is to analyze process behavior by assessing how process complexity changes over time. Such an approach has contributed novel and relevant insights, including observations of sudden high-complexity states in digitized processes. However, the validity of the underlying measurement procedure has received limited attention. This doctoral thesis contributes to the understanding of process dynamics in digitized processes by strengthening the methodological foundations and building upon these foundations in a theory-building study. The three methodological contributions of this thesis strengthen the validity of existing change measurement approaches and introduce a novel approach to assess process dynamics. The overarching theory-building study builds on these methodological advances to develop theoretical explanations of process stability and change. This doctoral consortium submission outlines the relevance of the thesis contributions and presents the corresponding research roadmap.

Keywords

Process Dynamics, Process Complexity, Process Change

1. Introduction

Business processes are dynamic in the sense that their structure changes over time [1]. These changes result from exogenous influences, such as the COVID-19 pandemic, or from endogenous factors, such as emerging workarounds [2, 3]. Process mining research provides a rich toolbox for detecting, locating, and characterizing process drifts based on event logs (e.g., [4, 5, 6]). Yet these methods for analyzing change do not explain the underlying mechanisms by which processes remain stable or change over time. Understanding these mechanisms is a central objective of process dynamics research, as such understanding may ultimately enable organizations to anticipate and influence process change [1].

One approach to studying process dynamics is to analyze changes in process complexity over time (e.g., [7, 8]). This approach partitions an event log into consecutive trace windows and calculates a complexity score for each window [9]. Changes in the resulting time series are then interpreted as indicators of behavioral change [1]. Complexity-over-time analyses have produced relevant findings about process dynamics, including initial evidence for so-called bursts of complexity, which are sudden transitions into highly chaotic process states [10].

This thesis addresses two problems within this domain. First, the validity of complexity-based process dynamics analysis has received only limited attention. Validity entails that measurements represent the underlying concept rather than artifacts of the measurement process [11], in this case process complexity. Valid measurement of complexity is therefore foundational for substantiating empirical observations about process change. Second, complexity-based analyses of process dynamics have produced inconclusive findings regarding the dynamics of change. Empirical evidence for bursts of complexity remains mixed, with some studies observing this behavior [8] and others not [7]. These mixed findings indicate that further research is required to explain how and why process change unfolds.

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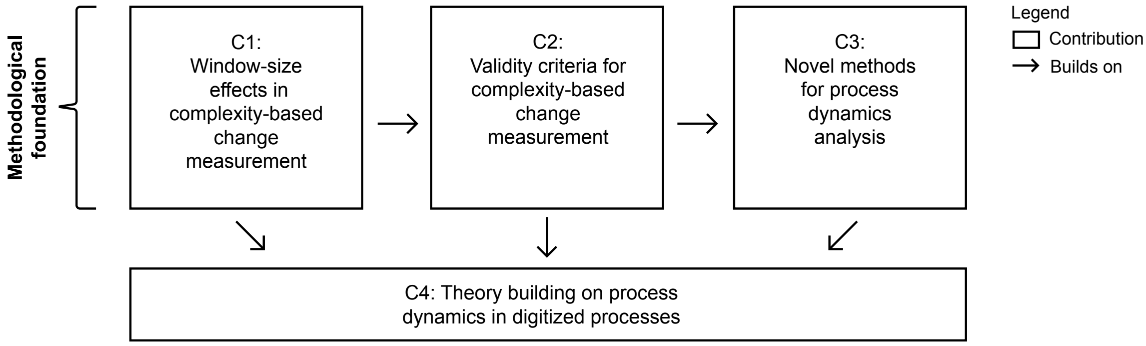

Figure 1: Structural overview of the doctoral thesis

Accordingly, this thesis aims to strengthen the methodological foundations of process dynamics research and to build on these foundations to improve our understanding of how business processes remain stable or change over time.

The thesis comprises three methodological contributions and one theory-building contribution, as summarized in Figure 1. C1 examines the effect of window size, a core parameter in complexity-over-time analyses, on the validity of complexity measurement. Building on these findings, C2 broadens the analysis from window size to the complete observation pipeline, comprising event-log sampling, windowing, and complexity calculation. It develops validity criteria for assessing the responsiveness, robustness, and reliability of complexity measures. C3 develops a complementary method for process dynamics analysis that does not rely on observation windows, avoiding window-size dependencies investigated in C1. Finally, C4 builds on the methodological insights from C1-C3 to develop theory about the underlying mechanisms that generate stability and change in digitized processes.

The remainder of this paper is structured as follows. Section 2 introduces the background and related work, leading to the research gap. Section 3 presents the research roadmap, structured around the four contributions of this thesis. Finally, Section 4 discusses the implications and remaining challenges.

2. Background and related work

2.1. Observation pipeline

This section summarizes how complexity-based change analysis is typically performed (e.g., see [1]), as our later discussion of related work and our contributions build upon this understanding. The observation pipeline consists of three consecutive steps. In the first step, an event log is created. The system-supported execution of process activities creates digital traces which can be used to construct process mining event logs [12].

In the second step, the event log is partitioned into a sequence of sub-logs, referred to as trace windows [9, 1]. These windows may either contain a fixed number of traces [9] or correspond to predefined time intervals, such as one-month periods [7, 1]. Windows may overlap, such that a trace may be part of multiple windows [9].

In the third step, a scalar complexity value is calculated for each window, resulting in a time series of complexity values [9, 1]. The measures take as input a set of traces from a trace window and then either perform counts, compare traces, or construct graphs from which measures are derived [13]. Changes in the level of complexity are then interpreted as indications of behavioral change [1].

2.2. Related work

We present state-of-the-art related work from the three research streams most relevant to this thesis: concept drift detection, process complexity measurement, and process dynamics.

Concept drift detection provides approaches for detecting, locating, and characterizing process changes based on event logs [4]. Most approaches rely on statistical comparisons of trace observations across different windows [14]. Accordingly, prior work has proposed different windowing strategies, including fixed-size windowing, in which all windows have a predetermined size, and adaptive windowing, in which window sizes may vary within a given range [15]. In fixed-size settings, similar to those commonly used in process dynamics analysis, window size is a critical parameter that affects drift detection results [14].

Process complexity measurement constitutes the second related stream. The business process management and routine dynamics communities have developed event-log-based process complexity measures (e.g., [16, 17, 13]). These measures primarily target the control-flow perspective of a process, although initial efforts have extended them to additional perspectives [18]. Control-flow complexity measures capture different notions of complexity, including size (e.g., *number of events*), variation (e.g., *estimated number of acyclic paths*), and distance (e.g., *average edit distance*), or combinations of these [13]. Process dynamics studies predominantly apply variation measures to quantify process complexity (e.g., [10, 8, 7]). With regard to validity, routine dynamics research has developed complexity measures from organizational theory to ensure that they reflect meaningful notions of routine complexity (e.g., [16, 17]). In business process management, complexity measures have been designed to satisfy desirable characteristics, such as discriminative power [13]. Furthermore, an empirical study by Cardoso [19] has investigated the relationship between complexity measures and perceived process model complexity.

The third stream, process dynamics research, seeks to explain stability and change in business processes [1]. A key finding from a simulation study by Pentland et al. [10] suggests that business processes may transition through different phases, including periods of high variation resembling chaotic behavior. An empirical case study of a financial institution observed spikes in process complexity, which the authors attributed to preceding reorganization efforts [8]. In contrast, a case study of a manufacturing company did not observe comparable spikes, despite known COVID-19-related organizational changes [7].

In summary, prior work provides established approaches for detecting process change and measuring process complexity. However, the validity of complexity-based change analysis has only received limited attention, especially considering the impact of the observation pipeline on computed complexity scores. Furthermore, the mechanisms through which process change unfolds remain insufficiently understood. These gaps motivate the contributions presented in the following section.

3. Research roadmap

3.1. C1: Window-size effects in complexity-based change measurement

The first contribution investigates the effect of the window-size parameter on the construct validity and reliability of process complexity measures. It addresses the research question: *How does the observation window size relate to the validity of process complexity measures?* (RQ1)

Construct validity refers to the extent to which a measure reflects the underlying concept rather than artifacts of the measurement process [11]. Reliability captures the absence of random variation in a measure [20]. Because window size is a parameter of the measurement process, strong dependence on this parameter may threaten construct validity. The contribution investigates the effects of window size by analyzing how complexity measures change as window size increases, using simulated and real-world processes without process change.

The contribution finds that many commonly used complexity measures systematically depend on window size, such as the *estimated number of acyclic paths* used in [10]. Three underlying mechanisms are identified and used for categorizing the measures, i.e., *unbounded growth*, *discovery*, and *averaging*. Unbounded growth measures continuously grow with window size (e.g., number of traces), discovery measures converge as rare objects are observed (e.g., number of distinct traces), and averaging measures are least affected by window size (e.g., average trace length). Furthermore, the contribution suggests strategies for mitigating window size effects, depending on what aspect of process complexity practitioners or researchers aim to capture.

Status of contribution: Accepted for publication at the International Conference for Business Informatics (CBI) 2026 [21].

3.2. C2: Validity criteria for complexity-based change measurement

The second contribution extends the scope of C1 to the entire observation pipeline. It addresses the research question: *How can the validity of complexity-based change measurement be assessed?* (RQ2)

The contribution adopts a signal-processing perspective to distinguish between signal, i.e., variation in process complexity caused by process change, and noise, i.e., variation unrelated to process change. Based on this distinction, the concepts of responsiveness, robustness, and reliability are introduced to capture (a) the extent to which a complexity measure responds to process change, (b) its sensitivity to changes in the observation pipeline, and (c) the degree of random variation. Using simulated data with known drift points, these validity criteria are evaluated for a broad catalog of complexity measures.

A key finding of the contribution is that established complexity measures differ substantially regarding their signal-and-noise behavior. Some commonly used measures, such as the aforementioned estimated number of acyclic paths, have low responsiveness, robustness, and reliability. Few measures (e.g., avg. distinct activities per trace) show high robustness and reliability, as well as relatively high levels of responsiveness. However, responsiveness even for best-performing measures is only moderate. Overall, the contribution highlights that researchers and practitioners should consider the signal-and-noise characteristics of the underlying measure before interpreting changes in complexity scores as evidence of process change.

Status of contribution: Accepted for publication at the International Conference on Business Process Management (BPM) 2026 [22]. The conference paper may be extended into a journal article.

3.3. C3: Novel methods for process dynamics analysis

The third contribution introduces a novel approach to process dynamics analysis that does not rely on observation windows. It addresses the research question: *How can process dynamics be represented to identify behavioral patterns and provide insights into their underlying mechanisms?* (RQ3)

Motivated by the use of distributional analysis in linguistics and network theory (e.g., [23]), C3 explores whether distributions of trace variant frequencies point to underlying mechanisms such as process structure, composition, and change. First, the contribution introduces trace variant rank-frequency curves (RFCs) as a window-size-independent representation of variant frequencies. Second, the contribution analyzes RFCs from 24 real-world event logs, finding that these distributions frequently exhibit power-law-like behavior, among other characteristic regularities. Third, simulation experiments investigate the effect of process structure, composition, and change on RFC shapes. At its current state of development, the contribution presents a novel analysis approach that provides a basis for further investigations into the underlying mechanisms shaping trace variant RFCs.

Status of contribution: Accepted for publication at the Workshop on Change, Drift, and Dynamics of Organizational Processes (ProDy) at the International Conference on Business Process Management (BPM) 2026 [24]. Further development in the form of a conference paper or journal article is ongoing.

3.4. C4: Understanding process dynamics in digitized processes

The fourth and final contribution builds on the methodological advances from C1–C3 to develop a theoretical contribution on process dynamics. It addresses the research question: *How can process dynamics in digitized processes be identified and explained?* (RQ4)

C4 aims to develop explanatory theory [25] by applying robust analysis methods and connecting observed behavioral patterns to the mechanisms that generate them. The contribution's data may come from a specific case for which contextual information is available or from established process mining datasets (e.g., BPIC datasets). While a specific case allows for detailed contextual analysis, using the set of 20–30 publicly available event logs increases generalizability. Furthermore, simulation may be used to examine whether hypothesized mechanisms can generate the observed patterns, as demonstrated in our approach for addressing C3 [24]. The overall goal of this contribution is to advance our understanding of process dynamics by explaining observed phenomena and their underlying mechanisms.

Status of contribution: Study under development.

4. Implications and remaining challenges

The thesis, as proposed in this submission, has methodological, theoretical, and practical implications. The key methodological implication of C1 and C2 is a shift from discussing individual complexity measures to discussing the validity of the entire observation pipeline. The explicit treatment of event logs and trace windows as sample behavior closely aligns with an open world assumption [26]. Our observations on window size effects and the proposed validity criteria may also be transferable to other process mining tasks, such as concept drift detection or KPI measurement. Overall, our methodological contributions may improve the robustness and reliability of future process dynamics studies.

The theoretical contribution of this thesis lies in developing explanations of the mechanisms underlying process dynamics through C3 and C4. C3 enables novel theoretical explorations, such as investigations of mechanisms known from network theory. C4 may help to clarify previously conflicting findings, such as bursts of complexity [10] versus rather linear changes in complexity [7].

Improving the methods by which process dynamics are measured and advancing our understanding of the underlying mechanisms may in the long term also benefit practitioners. If process dynamics are sufficiently understood, practitioners can take actions to encourage desired change or prevent unexpected change. Desired change may include innovation or necessary adaptation in response to external events such as COVID-19. On the other hand, undesired change may lead to non-compliance with regulatory standards. Although the thesis mainly focuses on the methodological and theory-building level, there may be downstream implications on practical business management.

Several limitations and challenges remain. The first challenge concerns the generalizability of findings. To derive patterns in process behavior in C4, a large sample of different processes from diverse industries would be ideal. However, there are only 20–30 publicly available event logs mainly covering public-sector, finance, and IT service management processes. We address this challenge by substantiating findings with theory-based explanations. The second challenge concerns the potential case study in C4. Although we have access to data from a past case study, the collaboration with the organization has ended. Consequently, the study relies on previously collected field data and on its richness in providing sufficient contextual information. The third challenge is that real-world processes generally lack ground-truth information regarding their underlying structure and dynamics. This challenge can be addressed by applying approaches that estimate system-level quantities, such as the number of trace variants [27].

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Declaration on Generative AI

During the preparation of this work, the author used ChatGPT-5.5 in order to: (1) improve writing style and grammar and (2) perform spelling checks. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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