# Opening the Interpretive Loop: A Human-Centered Approach to Derive Windows

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**Abstract.** Quantitative Ethnographic (QE) models such as Epistemic Network Analysis (ENA), Ordered Network Analysis (ONA), and Transmodal Analysis (TMA) represent human activity by modeling interdependency among events distributed across time. A central challenge in these approaches is determining how to determine the window lengths to represent the recent temporal contexts. Existing approaches often select windows based on predictive model performances, broad theoretical assumptions, or labor-intensive qualitative analysis. These approaches make it difficult to derive windows that are simultaneously process-oriented, interpretation-grounded, and computationally tractable. This paper introduces *Qualitative Parameter Triangulation* (QPT), a method to derive windows from human interpretations of local events and their surrounding contexts. Drawing on principles from Quantitative Ethnography, QPT *opens the interpretive loop* by treating interpretation as the starting point for parameter derivation, as a mirroring of closing the interpretive loop after the model is constructed. According to the procedures of QPT, researchers interpret and annotate meaningful connections around sampled anchor events, represent those interpretations as anchor networks, and use computational search to identify temporal windows that best reproduce human annotations. This paper presents the theoretical foundations of QPT, describes the complete workflow, and introduces an interactive software that supports window derivations for multimodal process models.

**Keywords:** Multimodal learning analytics · Windows · Transmodal Analysis · Epistemic Network Analysis · Ordered Network Analysis Analysis · Human-centered analytics

## 1 Introduction

Human activity unfolds as processes that are distributed across time. People engage in conversations, interact with technologies, and learn through experience. To understand and analyze these processes, researchers construct models to represent complex human activity. The selection of representations is grounded in theoretical assumptions about which aspects of a process matter and how they

should be represented. For example, diSessa conceptualizes learning as a process of making connections among ideas and experiences[1]. From this perspective, network representations provide a natural way to model learning because concepts can be represented as nodes and relationships as connections.

Within Quantitative Ethnography (QE), constructing a model involves more than selecting an appropriate representational form. A central principle of QE is that computational models should be aligned with qualitative evidence from the original activity so that the model is fair to data, community, theory, and subgroups [5]. A second principle is that interpretation is fundamentally contextual [6, 4]. Researchers rarely interpret isolated events. Instead, they examine local moments situated within surrounding activity and use deictic evidence to understand how meaning is constructed within the recent temporal context. In this paper, each focal moment selected for such interpretation is termed an *anchor event*.[3] These principles are reflected in widely used QE methods such as Epistemic Network Analysis (ENA) [4], Ordered Network Analysis (ONA) [9], and Transmodal Analysis (TMA) [7], which model processes through relationships among events distributed across time. These network approaches belong to a specific family of models called *state-dependent models* [7].

A persistent challenge across these approaches is determining how to represent the recent temporal context. Most state-dependent models operationalize context using sliding windows that specify how far back in time prior events remain relevant to interpreting an anchor event. Window lengths directly shape the resulting representation of a process, yet deriving particular window lengths remains difficult. Existing approaches typically rely on computational optimization, theoretical assumptions, or qualitative heuristics. While each approach offers advantages, none simultaneously provides strong process orientation, direct grounding in human interpretation, and computational tractability.

This paper introduces Qualitative Parameter Triangulation (QPT), a method for deriving temporal window lengths from human interpretations of local events and their surrounding contexts. Rather than using interpretation to evaluate model outputs after parameters have been selected, QPT begins with interpretation itself. Human interpretations are formalized as anchor networks and translated into temporal parameters through systematic computational search. By opening the interpretive loop, QPT provides a process-oriented, interpretation-grounded, and computationally tractable approach to deriving temporal parameters.

[3] An anchor event serves as a *focal* point for interpretation. Rather than interpreting an entire process at once, researchers ground their interpretation in a specific focal event and examine its prior events to understand with contexts. By examining a collection of anchor events sampled across a process, researchers accumulate locally grounded interpretations that support a broader interpretation of the process.

## 2 Theory

### 2.1 State-Dependent Models and Windows

Many computational models represent human activity as a sequence of interdependent events unfolding across time. Rather than treating observations as isolated units of analysis, these approaches assume that the meaning of an anchor event depends on events that occurred previously and, in turn, influences future activity. Such *state-dependent models* have been used to study discourse, collaboration, decision making, and learning because they provide a way to model activity as an evolving process rather than as a collection of independent observations.

Within Quantitative Ethnography, this perspective has motivated the development of several process-oriented modeling approaches. Epistemic Network Analysis (ENA) models patterns of connection among elements of discourse and practice [4]. Ordered Network Analysis (ONA) extends this approach by preserving temporal ordering among connected events [9]. More recently, Transmodal Analysis (TMA) extends state-dependent modeling to multimodal contexts by representing relationships across modalities, including discourse, action, and visual attention [7]. Although these approaches differ in their representations, they share a common assumption: understanding an event requires understanding the context created by prior events. Consequently, a central challenge for all state-dependent models is determining which prior events are relevant when interpreting the current moment.

The assumption that events are interdependent raises a fundamental question: which prior events should be considered relevant when interpreting an anchor event? Researchers rarely interpret an event in isolation. Instead, they examine surrounding activity to understand why the event occurred, what it meant to participants, and how it relates to prior interactions. Similarly, state-dependent models, such as ENA, ONA, and TMA, construct network representations based on fixed-length windows to determine the boundary of event-dependence and accumulate the co-occurrences of coded events across the sliding window. Thus, in both qualitative and computational approaches, meaning emerges not from individual events alone but from relationships among events distributed across time.

The notion that events derive meaning from context is often referred to as recent temporal context (RTC) [8, 4]. RTC represents the subset of prior events that remain relevant for understanding an anchor event.[4] Defining RTC becomes

[4] RTC is the focus of this paper; however, contextual relevance can extend beyond temporality to include semantic, structural, theoretical, and other forms of relationships among events. We focus specifically on temporal relevance because widely used QE methods, including ENA, ONA, and TMA, model relationships among events based on their temporal organization. Future work may combine QPT with complementary approaches to account for these alternative forms of contextual relevance (see Discussion and Conclusion). Such extensions, however, are beyond the scope of the present paper.

increasingly challenging in multimodal settings because different modalities often operate on different temporal scales and contribute different forms of information about an underlying process. A brief shift in visual attention may occur within milliseconds, whereas actions, conversational exchanges, or strategic decisions may unfold over substantially longer periods. Oviatt argues that modalities differ in their affordances, strengths, and functional roles in communication and cognition, suggesting that different modalities may contribute to meaning-making in fundamentally different ways. Consequently, the recent temporal context may differ across modalities, and multimodal models may require different temporal assumptions for different activity streams.

### 2.2 Windows Shape Interpretations and Representations: a Qualitative Illustration Example

**Table 1.** Illustrative Example of Recent Temporal Context in Collaborative Clinical Simulation

| # | Speaker | Modality | Description | Code |
|---|---|---|---|---|
| 1 | Team Leader | Dialogue | "Patient is in pulseless V-tach." | JointInfo-Processing |
| 2 | Defib | Action | Begin chest compressions. | IntManage |
| 3 | Airway | Dialogue | "Epi was administered two minutes ago." | JointInfo-Processing |
| 4 | Team Leader | Dialogue | "Continue following ACLS protocol." | Coordination |
| 5 | Airway | Action | Prepare airway equipment. | IntManage |
| 6 | Defib | Action | Continue chest compressions. | IntManage |
| 7 | Nurse | Action | Prepare epinephrine syringe. | IntManage |
| 8 | Team Leader | Dialogue | "Any rhythm change?" | JointInfo-Processing |
| 9 | Airway | Dialogue | "No pulse. Two minutes have elapsed." | JointInfo-Processing |
| 10 | Team Leader | Dialogue | "Administer the next dose." | Coordination |
| **11** | **Nurse** | **Action** | **Inject EPI one milligram.** | **IntInject** |

Table 1 presents a sequence of communication and action events from a collaborative medical resuscitation simulation in which a healthcare team manages a patient experiencing cardiac arrest. In this example, the team identifies pulseless ventricular tachycardia, performs and coordinates ongoing resuscitation

activities, monitors the timing of epinephrine administration, and ultimately administers the next dose. The anchor event, highlighted in bold, is the administration of epinephrine (Event 11). This example illustrates two key ideas. **First, varied window lengths can produce different interpretations and induced network representations of the same event. Second, each unique modalities may require a specific temporal window because prior events contribute to interpretation over different durations.**

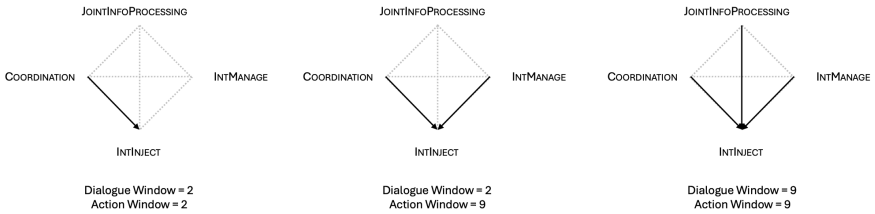



**Fig. 1.** Different temporal window assumptions produce different induced network representations of the same anchor event.

Figure 1 shows three induced networks generated from the event sequence under different window configurations. In the first configuration, both dialogue and action events receive short windows (Dialogue = 2, Action = 2). Only the most recent communication events remain connected to the anchor, producing a network that emphasizes relationships from JointInfo-Processing to Coordination and from Coordination to IntInject. Under this representation, the administration of epinephrine appears to be a direct response to a recent verbal directive.

In the second configuration, dialogue remains short while action receives a longer window (Dialogue = 2, Action = 9). Earlier intervention-management activities, such as chest compressions and medication preparation, remain connected to the anchor. The resulting network introduces additional relationships involving IntManage, representing the intervention as the culmination of an ongoing treatment process rather than a simple response to a command.

In the third configuration, both dialogue and action receive long windows (Dialogue = 9, Action = 9). Nearly all prior events remain connected to the anchor, producing a substantially denser network. Additional relationships emerge among JointInfo-Processing, Coordination, IntManage, and IntInject, including connections generated by events that are only loosely related to the medication administration. As a result, the representation becomes increasingly difficult to interpret.

Together, these induced networks demonstrate that temporal windows are not merely technical parameters. Different window assumptions produce different contextual representations of the same event. More importantly, the example

suggests that communication and action may require different temporal windows because they contribute to interpretation over different timescales.

### 2.3 Existing Approaches to Window Selection

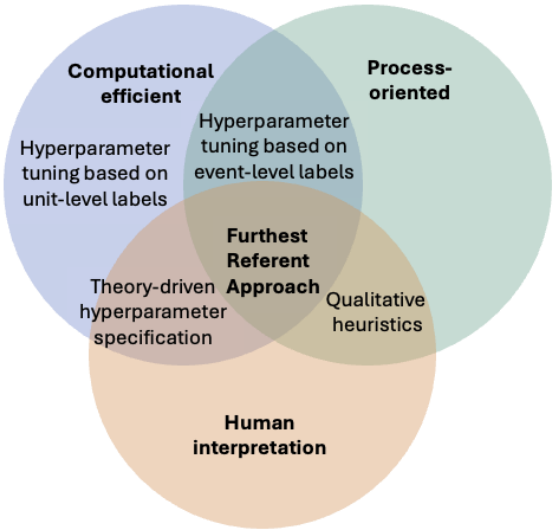



**Fig. 2.** Comparison of existing approaches to temporal window selection across three methodological goals.

Although the recent temporal context is central to state-dependent modeling, operationalizing it remains a persistent challenge. A common solution is to represent contexts using a sliding window. Events occurring within the window are treated as contextually relevant, whereas events outside the window are excluded. The length of windows, therefore, determines how far back prior events remain relevant and directly shapes the resulting representation of a process. Despite the importance of this decision, the derivation of window lengths has remained difficult across many process-oriented modeling approaches. Figure 2 summarizes the existing approaches with their affordances and limitations.

One family of approaches treats window length as a computational hyperparameter. Researchers evaluate alternative window lengths and select the one that best predicts an external target, such as learning gains, performance outcomes, group membership, or event labels. Because optimization can be automated and applied systematically across large datasets, these approaches are computationally efficient and scalable. However, the resulting window is selected because it predicts an outcome well rather than because it accurately represents the process

being modeled. As a result, window derivation becomes disconnected from the local and grounded interpretations that state-dependent models are intended to represent.

To address this limitation, researchers often rely on theory to guide window selection. For example, social and interactional processes operate across different timescales: turn-taking may unfold over milliseconds, mirroring over minutes, and empathy over hours or even days. Such theories provide valuable guidance regarding the temporal dynamics of human activity and help justify why some processes require longer or shorter contextual spans. However, theories rarely specify precise values that can be directly operationalized in computational models. Consequently, theory-driven approaches preserve interpretability but often offer limited guidance on selecting specific parameter values in a given context.

Alternatively, researchers may derive windows through direct qualitative interpretation of activity. By examining interactions closely, researchers can estimate how far context extends for understanding an anchor event. These approaches preserve strong connections between parameter selection and the process being modeled, but they are often difficult to translate into precise and reproducible window lengths.

The Furthest Referent Approach (FRA) proposed by Ruis and colleagues represents perhaps the closest attempt to balance computational efficiency, process orientation, and interpretive involvement [3]. FRA asks researchers to identify how far back prior events remain necessary for interpreting an anchor event and subsequently derives a window length from the resulting empirical distribution of referents.

However, FRA becomes increasingly difficult to apply in multimodal settings. Different modalities reveal different dimensions of activity and may operate on distinct temporal scales. Extending FRA, therefore, requires either conducting separate analyses for each modality or making assumptions that modalities share equivalent temporal dynamics. Both options introduce challenges. The first substantially increases human effort, whereas the second risks oversimplifying relationships among modalities. More importantly, modalities often cannot be interpreted in isolation because meaning emerges through relationships among modalities rather than within a single stream of activity.

### 2.4 Opening the Interpretive Loop

To address these challenges, Wang and colleagues introduce Qualitative Parameter Triangulation (QPT), a method to derive multimodal windows from human interpretations of anchor events and their surrounding contexts [10]. QPT is motivated by two principles that have long guided Quantitative Ethnography. First, computational representations should remain aligned with the phenomena they are intended to represent. Second, interpretation should be grounded in local contextual evidence rather than isolated observations. Together, these principles suggest that temporal parameters should emerge from interpretations of activity rather than being selected independently of the process being modeled.

Traditionally, researchers close the interpretive loop after a model has been constructed by comparing computational outputs against qualitative evidence, which is referred as *closing the interpretive loop*. QPT reverses this process. Rather than using interpretation to validate parameters after they have been selected, QPT begins with interpretation itself. Human interpretations are formalized as anchor networks and subsequently translated into temporal parameters through systematic computational search. In doing so, QPT treats interpretation not as a retrospective validation procedure but as a foundational component of parameter derivation. The goal is to develop an approach that remains process-oriented, grounded in human interpretation, and computationally tractable while supporting the increasing complexity of multimodal state-dependent models.

## 3 Qualitative Parameter Triangulation

Qualitative Parameter Triangulation (QPT) derives temporal windows by aligning computational representations with human interpretations of local events. Rather than asking researchers to directly specify or optimize window lengths against external outcomes, QPT begins with interpreting meaningful events in their surrounding contexts. The method consists of three key components: (1) sampling and interpretation toward anchor events, (2) comparison between anchor networks and induced networks, and (3) optimization through a qualitative loss function.

**Sampling and Interpretation toward Anchor Events.** QPT begins by sampling anchor events from a multimodal event stream. For each anchor, researchers review surrounding events and identify which prior events remain relevant for interpreting the focal event. Rather than estimating window lengths directly, researchers make qualitative judgments about concrete examples situated within their natural contexts. These interpretations are grounded in domain knowledge, theoretical assumptions, and contextual evidence. The process can be repeated across multiple anchors until sufficient examples are collected to represent the range of processes in the dataset.

**Anchor Networks and Induced Networks.** Interpretations collected during annotation are represented as anchor networks, which capture the relationships researchers identify as meaningful for understanding an anchor event. QPT then generates induced networks by applying candidate temporal windows to the event stream. Whereas anchor networks represent human interpretation, induced networks represent the temporal assumptions encoded by a particular window configuration. Comparing these two representations creates an explicit bridge between qualitative interpretation and computational modeling.

**Qualitative Loss Function and Optimization.** QPT evaluates the degree of disagreement between anchor networks and induced networks across sampled anchors. Window configurations that reproduce more interpreted relationships yield lower loss values, whereas configurations that omit meaningful relationships or introduce unintended ones yield higher loss values. A computational search identifies the dialogue and action windows that minimize disagreement

between human interpretation and computational representation. The resulting parameters therefore operationalize temporal assumptions directly from process interpretation rather than from external outcome measures.

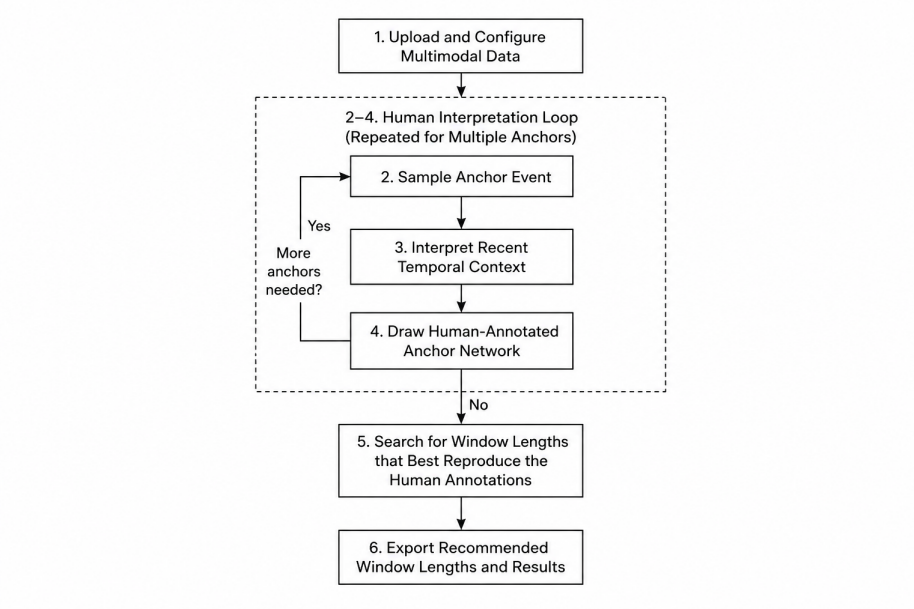



**Fig. 3.** QPT workflow for deriving temporal window parameters.

## 4 Running Example: Collaborative Clinical Simulation

Throughout this section, QPT is illustrated in the context of an immersive multi-user virtual reality (VR) medical emergency simulation [2]. In the simulation, four-person teams consisting of a team leader, airway manager, chest-compression provider, and defibrillator specialist collaborate to manage a patient experiencing cardiac arrest in accordance with Advanced Cardiac Life Support (ACLS) guidelines. As the patient's condition evolves, team members must diagnose changes in the patient's condition, perform clinical interventions, administer medications, and coordinate their activities under time pressure. The resulting multimodal data contain two complementary streams of events: dialogue events that capture processes such as information sharing and coordination, and action events that capture clinical activities such as chest compressions, airway management, and medication administration.

This setting provides a useful example of the temporal-context problem because dialogue and action may operate on different temporal scales. The interpretation of an utterance may depend primarily on a small number of nearby

conversational events, whereas a clinical action may depend on assessments, decisions, and interventions occurring over a longer period. Applying the same temporal assumption to both modalities may therefore include events that are no longer relevant or exclude earlier events that remain important for interpreting the process. QPT addresses this problem by deriving modality-specific temporal windows from researchers' interpretations of local moments in the activity.

To demonstrate this process consistently throughout the section, we use a fictitious sequence constructed to resemble the structure of the clinical simulation data. The example focuses on the administration of epinephrine during cardiac arrest management as the anchor event. Prior to the injection, the team identifies the patient's condition, performs chest compressions and other intervention-management activities, monitors the timing of the previous epinephrine dose, prepares the medication, and coordinates administration of the next dose. The example is designed to make the temporal distinction explicit: recent dialogue may provide the immediate communicative context for the injection, while earlier clinical actions may remain relevant over a longer temporal span.

Figure 3 summarizes how QPT uses such local interpretations to derive temporal parameters. Researchers first upload and configure the multimodal event data. QPT then samples anchor events, which researchers interpret iteratively by examining their surrounding context and constructing anchor networks that represent the relationships they consider meaningful. Once a collection of anchor networks has been constructed, QPT searches for modality-specific temporal windows that produce induced networks most closely aligned with those interpretations.

### 4.1 Upload Data and Configure Analysis

QPT begins by loading a coded event dataset and identifying the variables that define event order, modalities, and coded categories (Figure 4). Researchers specify the modalities for which temporal windows will be derived and the number of anchor events to sample. In the running example, dialogue and action are treated as separate modalities, allowing QPT to estimate a distinct temporal window for each.

### 4.2 Interpret Anchor Events and Construct Anchor Networks

For each sampled anchor event, QPT presents the event together with its surrounding context (Figure 5). Researchers determine which relationships among the surrounding events are necessary for interpreting the anchor and represent those judgments as an anchor network. In the fictitious example, the anchor is the administration of epinephrine (IntInject). The researcher interprets the injection as contextually related to prior Coordination and IntManage events, resulting in connections from Coordination to IntInject and from IntManage to IntInject. The researcher does not specify a numerical window at this

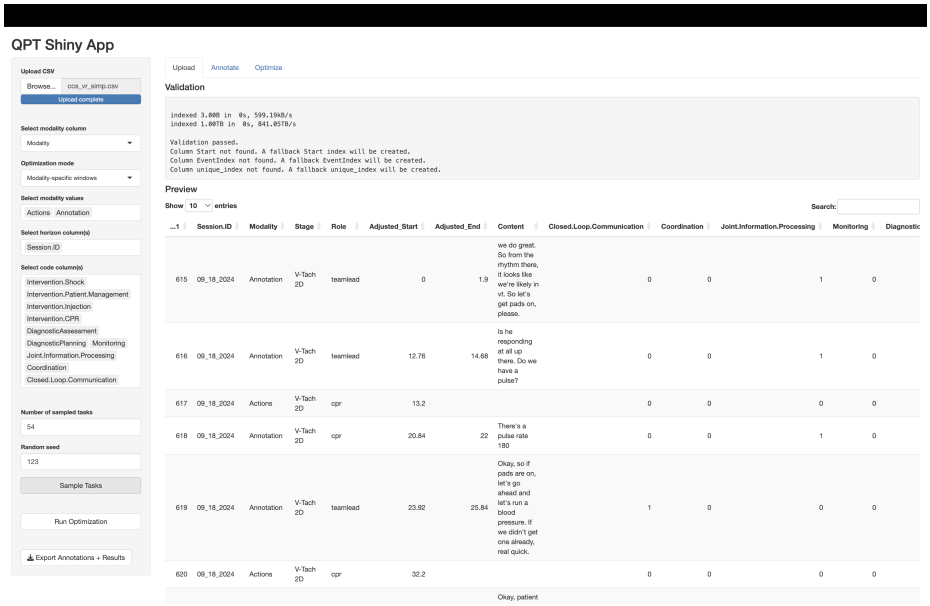



**Fig. 4.** Uploading multimodal event data and configuring QPT analysis settings.

stage. Instead, the annotation records what the relevant context means qualitatively. This procedure is repeated across sampled anchors to construct a set of locally grounded interpretations of the process.

### 4.3 Optimize Temporal Windows

QPT then translates these qualitative interpretations into temporal parameters. For each candidate combination of modality-specific windows, QPT applies the windows to the original event sequences and constructs an induced network for each anchor. The induced networks are compared with their corresponding anchor networks using the qualitative loss function, and the optimization procedure searches for the window configuration that minimizes disagreement across the sampled anchors.

Figure 6 presents the resulting optimization and recommended window lengths. The final parameters therefore do not originate from researchers directly estimating how many seconds an event should remain relevant. Instead, researchers specify meaningful contextual relationships, and QPT identifies the temporal parameters that most closely reproduce those relationships computationally. In this way, QPT translates local qualitative interpretations into explicit, modality-specific assumptions about recent temporal context.

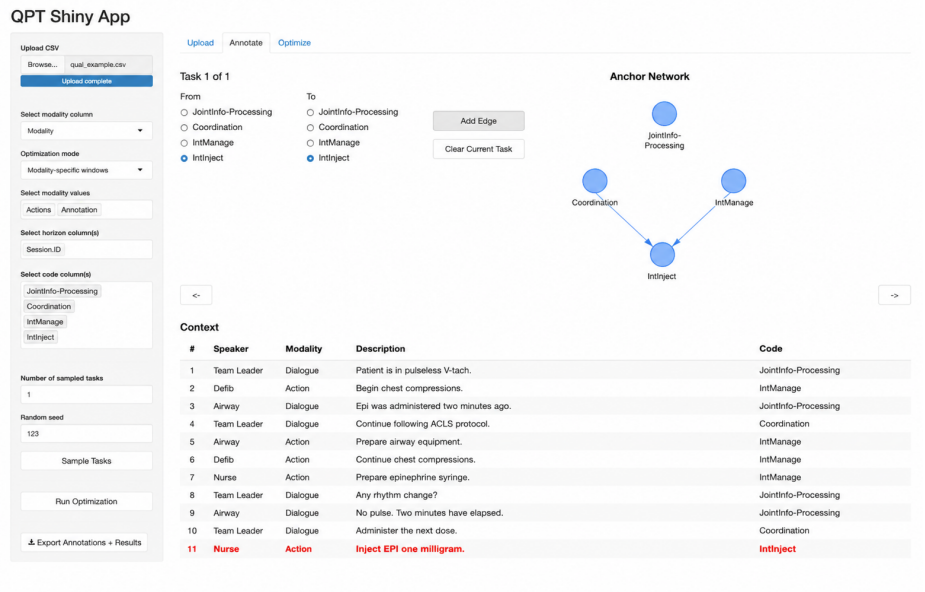



**Fig. 5.** Interpreting the context of a sampled anchor event and constructing an anchor network.

## 5 Discussion and Conclusion

This paper introduced Qualitative Parameter Triangulation (QPT), a method for deriving temporal windows in state-dependent models by aligning computational representations with human interpretation. Rather than treating temporal windows as arbitrary hyperparameters or relying solely on external outcomes for parameter selection, QPT formalizes a process in which researchers interpret local contexts, represent those interpretations as anchor networks, and derive window lengths that best reproduce those interpretations computationally. In doing so, QPT reframes temporal parameterization as both a computational and interpretive problem.

The contribution of QPT extends beyond the derivation of temporal windows. More broadly, it provides a framework for investigating how modeling assumptions shape computational representations of learning. State-dependent models necessarily make assumptions about which prior events remain relevant for interpreting a focal event. These assumptions influence the resulting network structures, patterns, and conclusions produced by an analysis. By making temporal assumptions explicit and subject to systematic evaluation, QPT provides a mechanism for examining how parameter choices affect the representations that researchers ultimately use to reason about learning processes.

The empirical results presented in this paper demonstrate that QPT is a feasible approach for deriving modality-specific windows with tractable compu-

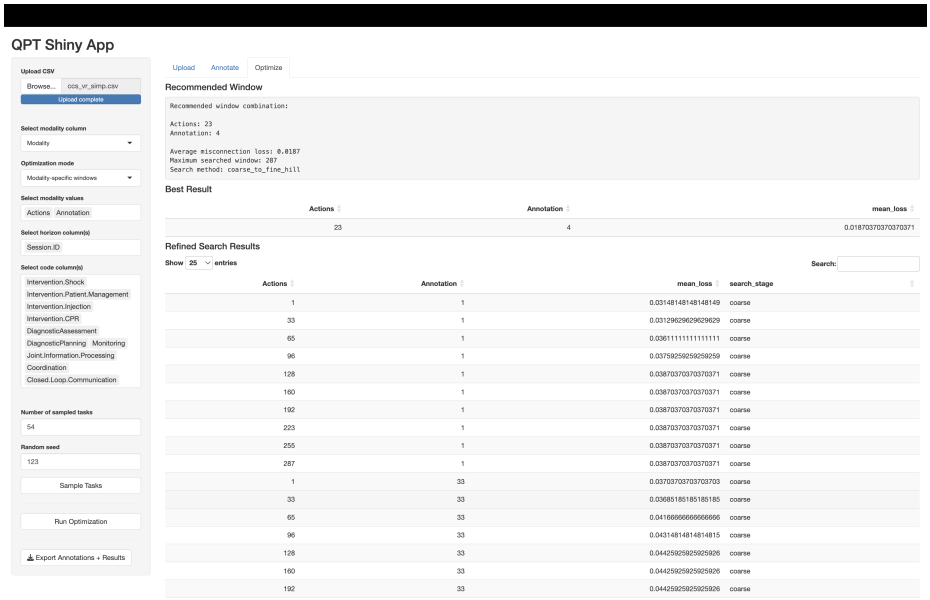



**Fig. 6.** Optimizing modality-specific temporal windows based on the annotated anchor networks.

tational costs. The optimization procedure successfully identified window configurations that reproduced human-annotated interpretations while remaining computationally practical for real-world multimodal datasets. Although the present study focused on collaborative problem solving in a virtual clinical simulation, we have also applied QPT to additional contexts involving different learning environments, coding schemes, and modalities. Across these applications, QPT has consistently produced interpretable and theoretically meaningful parameter estimates, suggesting that the approach may generalize beyond the specific setting examined in this paper.

Several limitations and opportunities for future work remain. First, additional research is needed to understand how human interpretive factors influence the resulting parameter estimates. The current implementation assumes a single analyst's interpretation, but different researchers, practitioners, participants, or communities may construct different yet defensible interpretations of the same anchor event. Future work should therefore investigate interpretive disagreement, multiple coders, and systematic annotation biases, as well as how such differences propagate into temporal parameter estimates. This direction also provides an opportunity to connect QPT with Participatory Quantitative Ethnography, in which members of relevant communities participate in constructing and interpreting computational representations. From this perspective, disagreement need not be treated solely as annotation error; it may reveal meaningful differences in how temporal context is understood across interpretive perspectives.

Second, there are important extensions to the temporal assumptions currently implemented in QPT. The present implementation estimates one fixed window for each modality, assuming a common temporal scale among events within that modality. However, temporal dynamics may also vary substantially within modalities. For example, a brief conversational acknowledgment may depend primarily on immediately preceding dialogue, whereas strategic coordination may depend on a longer interaction history. Future extensions could therefore move from modality-specific windows toward code-specific, event-specific, or adaptive temporal windows. Such extensions would allow temporal context to vary according to both modality and the function of particular events. Future work should also investigate alternative qualitative loss functions and more efficient optimization strategies, particularly as increasingly granular temporal assumptions introduce additional parameters.

Finally, broader adoption of QPT will require additional human-centered supports for scalable interpretation and annotation. Although QPT substantially reduces the amount of qualitative interpretation required compared with fully manual approaches, anchor annotation remains an expert-driven process. Future work should investigate user-centered interface designs, annotation workflows, collaborative interpretation strategies, and AI-assisted supports that make qualitative parameter derivation more efficient while preserving interpretive validity.

Ultimately, QPT is motivated by a simple premise: deriving parameters for state-dependent models should not be separated from the interpretive processes that give those models meaning. By formalizing human interpretation as an explicit component of parameter derivation, QPT provides a transparent and theoretically grounded approach for operationalizing recent temporal context in multimodal learning analytics and other state-dependent modeling frameworks.

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