Qualitative Parameter Triangulation: A Conceptual and Methodological Framework for Event-Based Temporal Models

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Abstract

Learning is a complex process that occurs over *time*. To represent this complex process, interests has been rising in conceptualizing and integrating temporality into model constructions. However, the construction of an event-based temporal model is challenging. Specifically, researchers struggle with translating qualitative heuristics and theoretical hypotheses into quantifiable temporal parameters. Existing methods of parameter derivation also suffer from issues of model transparency and oversimplification of learning contexts. Thus, we proposed a conceptual and methodological framework, Qualitative Parameter Triangulation (QPT), to center human interpretation in model construction. Based on human interpretations, QPT constructs a qualitative loss function and derives temporal parameters using an automatical optimization algorithm. The final step is to check consistency between a global representation with local qualitative evidence given specific learning moments. By presenting a worked example of QPT, we demonstrated the process of maintaining pairwise alignments across interpretation, systematization, and approxi-gation. As a proof of concept, QPT is a feasible framework for determining temporal parameters and constructing event-based temporal models.

Keywords

Temporal Analysis, Interpretivity, Methodology, Event-based Modeling.

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1 Overview

Learning is a dynamic and interactive process that unfolds over time [2]. The goal of learning analytics (LA) is to understand and represent such a complex learning process using computational models. While traditional LA models have been *variable-centred*, Reimann proposed the integration of variable-centred approach with *event-based temporal analysis*, which can better capture and represent complex learning processes [21]. That is, temporal models specify the basic unit of analysis as learning events, instead of factors summarized at an individual- or a group-level. Due to a fine granularity, event-based temporal models incorporates the passage of time and the order of events [17] to represent the interdependence across different learning moments and the dynmanics of learning trajectories. With temporal aspects integrated, these event-based temporal models provide more accurate predictions [23], fairer assessment [6], better accountability and actionability to close the feedback loop [5], enhanced interpretivity of learning models [24].

In spite of affordances, the event-based temporal models demands extra human effort in modeling and interpreting. According to Knight and colleagues, the major challenges of constructing temporal analysis are theorizing temporal relationships across learning constructs and specifying these assumptions with appropriate methods [14]. Specifically, Knight and colleagues discussed the methodological challenges such as complexity in model parameterization due to complicated relationships based on heterogeneous data sources and different theoretical assumptions. For example, they described the dilemma of researchers determing the the analytical time unit of joint attention due to lack of clear theoretical assumptions.

Additionally, the complexity in modeling finally results in challenges of model explainability and interpretability. To enhance model transparency, recent LA research shows a growing interest in the applications of Explainable Artificial Intelligence (XAI). XAI is a tool that penetrates the black box of machine learning algorithms and helps LA researchers to understand the outcome and reasoning of models. For example, existing XAI algorithms, such as SHapley Additive exPlanation (SHAP), are used to explain the importance of predictive features in predicting the final grades using formative assessments and submissions in CS education [13]. However, as highlighted by Mohammed[16], the trade-off lies between complex learning processes and oversimplified interpretations of

AI models. That is, facing educational data with complex structures and diverse contexts, XAI techniques show limited power aiming for transparency for educational researchers and other stakeholders in the system. Through a comprehensive survey on XAI application in interdisciplinary studies, Abdul and colleagues [1] highlight the significance of empowering humans in early model constructions and interpretations. That is, integrating human heuristics before and during model constructions instead of after the model is constructed.

Along the line of interpretation-oriented model construction, we propose to address the complexity in event-based temporal model by (1) involving researchers' interpretation *early* in the modeling stage, (2) automating parameterization based on qualitative human interpretation of *local* learning moments, and (3) verifying the alignment between a *global* quantitative model and the deictic local evidence in the qualitative data. Thus, we will introduce a conceptual and methodological framework called *Qualitative Parameter Triangulation* (QPT) to achieve these three proposals. Conceptually, QPT argues that a temporal parameter is the key to warrant model validity and interpretation alignment across local and global representations, and across qualitative heuristics and quantitative models. Methodologically, QPT can guide researchers to determine the optimized values of temporal parameters based on three steps: *systematizing human interpretation*, *optimizing parameters*, *verifying hermeneutics*. To demonstrate the feasibility of QPT conceptually and methodologically, we will present a worked example for optimizing the values of a temporal parameter for an event-based temporal model, which uncovers the patterns of puzzle solving in a game-based learning environment.

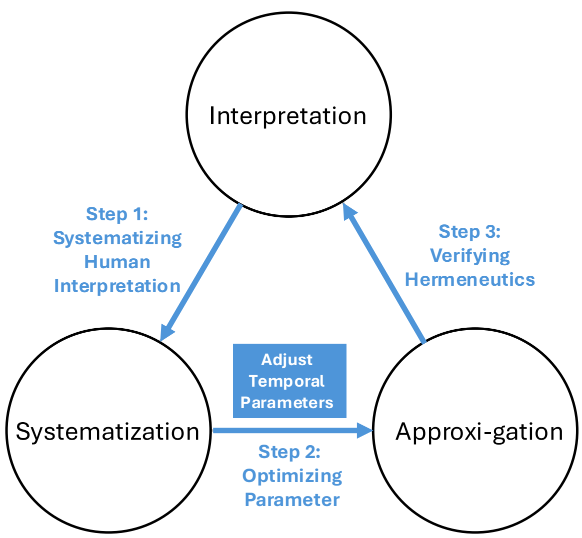


Figure 1: Qualitative parameter triangulation

2 Qualitative Parameter Triangulation

2.1 Three Components in Model Constructions

2.1.1 Interpretation. According to Geertz [10], interpretation focuses on understanding meanings, motivations, and patterns of human actions based on their symbolic system and cultural background. In Geertz's original cited example, two kids "contracting their right eyelids" (a thin description) can be interpreted as "an involuntary twitch or conspiratorial signal to their friend" (thick descriptions). That is, the same captured action can be interpreted from completely different angles based on contexts and individuals. Unfortunately, coming from a big data perspective, early learning analytics or educational data mining models suffer from thin descriptions of learning behaviors. Various LA researchers [8, 9] criticized this problem of focusing on the easily captured behaviors (i.e. click stream data pulled from tutoring system) and oversimplification in labeling learners and learning processes [19]. To solve this issue, LA scholars have attempted to increase model comprehensiveness by including qualitative data [28], and multimodal data [20]). With denser information and thicker description per time unit [20], LA researchers can better understand learning behaviors and processes for educational stakeholders and community members; at the same time, thicker descriptions warrant the model fidelity and validity by provding more contextual information and inferring learning constructs based on data with higher confidence.

2.1.2 Systematization. From a qualitative perspective, interpretation can be captured by grounded *stories*. According to Ricoeur [22], a story is defined as a sequence of actions by human that describes the changes or interactions within a complex system. Such stories can be captured and represented through microgenetic analysis, which refers to short-term development (i.e. minutes, hours, days, etc) of understanding a specific cognitive or social process in knowledge construction. These grounded stories can be represented in various means, such as narratives, charts, storyboards, movies, and other multimedia forms. However, even if capturing nuances and thickness of human activities, qualitative descriptions fail to provide a scalable representation that can be used for quantitative analysis [30].

To *systematize* qualitative descriptions of critical learning processes, researchers condense information and stripe noise from qualitative observations using *coding* or *feature engineering*. Furthermore, these systematized codes or features can describe sophisticated relationships (e.g., co-temporal, ordered, sequential, dependent, causal, etc) across moment-by-moment learning events. The representation of thsee relationships should be determined through theoretical lenses[34]. For example, grounded in the perspective of learning-is-making-connections, networks have been widely used in social sciences to represent one's mental model, knowledge organization, and interaction dynamics (as reviewed by Borgatti and colleagues [3]). Sitting in the middle of a thick qualitative description and a parsimonious quantitative representation, networks not only provide graphical and scientific descriptions but also serve as a tool to elicit a deep understanding of a learning culture. In practice, networks have been used in participatory studies for co-interpretation with researchers and practitioners [29]. Thus, a network as a systematization increases communicational efficiency across different educational stakeholders and promotes research validity, interpretivity, and actionability through a highly iterative process [29].

2.1.3 Approxi-gation. Given specific learning moments, grounded stories can be represented as *local* systematizations; similarly, for a continous learning process, these local systematizations can delineate and construct a *global* representation. For example, Vega and colleagues explored the behavioral patterns of collaborative learning processes using Epistemic Network Analysis (ENA) as a global representation. To ensure the model validity and interpretability, Vega and colleagues developed a tool, *Connect*, to invite learners and teachers to draw connections given learning moments and contrast the local networks against the global network [32]. Here, the hand-drawn networks are local representations while the aggregated ENA is a global represent.

We further term the process of constructing global representations as *approxi-gation*, which involves both *approximation* and *aggregation*. That is, when linking the local representations with a global representation, this process expects the margin of error due to transformation or deduction in information. However, this process can also be viewed as information condensing regarding specific research questions or contexts. Additionally, a computational model assumes that an optimization routine can minimize this margin of error and overcome randomness based on large-scale data [7]. In addition to approximation, various local systematizations are *aggregated* as one holistic global model through different mathematical transformations, depending on the assumption of learning or research questions. For example, ENA is an *accumulated* representation with the assumption that learning is an *accumulative* process that can be represented by meaningful co-occurrences [26]. That is, ENA is constructed based on connections made among codes within a recent temporal context for all learning events and then aggregated at an individual level or a group level. Different from an *accumulated* aggregation, local traces can be *inferred* in a holistic model based on statistical model fitting. For example, a vector autoregression (VAR) is a *latent* representation with the assumption that precedent learning events can *predict* future learning events given any learning moments. That is, VAR model represents the temporal dynamics by predictive weights given code presence within a lag of time or records.

In summary, any learning process model at a global level is an approxi-gation of local systematizations through accumulations, inferences, or other statistical techniques. With the hypothesis specified and model fitted, the margin of error exists but is controlled by statistical metrics to ensure research rigorousness and model validity. Based on the approxi-gated global models, researchers can derive insights about the general patterns for learners or learning processes and provide feedback to educational stakeholders to close the loop [33].

2.2 Methodological Procedures for QPT

In this section, we will describe three steps to derive temporal parameters and construct an event-based temporal model. These three steps maintain pairwise alignments across interpretation, systematization, and approxi-gation, which ensures the validity of temporal models. Specifically, the optimization of temporal parameters plays a critical role in the second step when linking local systematizations with a global approxi-gation.

Step 1: Systematizing Human Interpretation. For an interpretation-oriented model, the first step of model construction is understanding the grounded stories and making meaningful interpretations of learners given a specific learning moment. Although free-form storytelling captures thick descriptions of learning, the qualitative interpretation can be conceptualized as a mixture of useful signals and useless noise. Norman defined that the construction of scientific representations requires striping irrelevant details from the original perceptions and experiences [18]. Thus, this denoising process involves steps as follows: (1) sampling learning moments as *anchors* for interpreting the whole process, (2) making interpretations about the learner's actions or motivations for the *anchor event*, and (3) representing the qualitative interpretations as local systematizations. For a final global representation of networks, for example, the local representation can be specified as *anchor networks*.[1] By repeating the process of interpreting anchor events and drawing anchor networks, researchers can remove extraneous details in the grounded interpretations and represent qualitative interpretations as an abstract quantitative representation for scalability. Based on the definition in the last section, both interpretation and systematization here are defined locally. Thus, the alignment between interpretation and systematization is the key to warrant a fair *local* representation given a learning moment for a learner. To ensure the thoroughness of anchor sampling, this systemizing process of human interpretation is sufficient until reaching *theoretical saturation*. That is, human researchers will continue sampling random anchors to understand the whole learning process until seeing repeated patterns that were observed over and over again previously.

Step 2: Parameter Optimization. Temporal paramters, such as the size of a sliding window, defines a recent temporal context or a common ground within a group of learners. That is, mechanically, by specifying the size of a sliding window, researchers can identify the approximated range of relevant context, in seconds or in lines of data, for a specific learning moment. Within the range of common ground, connections can be constructed based on co-occurences. We term the network based on co-occurences within the same window as a *parameter-induced network*.

With multiple anchor networks, we can set the local systematizations as anchors and triangulate for the best temporal window lengths that capture the most connections. To construct a principled optimization routine for deriving temporal parameters, we propose to construct a *Qualitative Loss Function* (QLF) which conceptually defines the discrepancy between human interpretations and model representations; operationally, a QLF quantifies the average residual between human identified anchor networks and parameter-induced networks. In other words, we construct a complex labeling system that captures the nuanced relationships across critical components in human interpretations using anchor networks. This proposed process is similar to a hyper-parameter tuning routine in educational data mining. However, the differences between parameter optimization with anchor networks and traditional EDM parameter tuning lie in that (1) anchor networks are more sophisticated than single outcome labels, and that (2) optimization based on anchor networks focuses on internal generalization (descriptive)

[1]Similarly, if the global representation is a lag sequential model, the local representations can be specified as *anchor sequences*. That is, a sequence of learning events defines the critical unfolding of this learning process.

while hyper-parameter tuning focuses on external generalization (predictive).

Step 3: Verifying Hermeneutics With a global approxi-gation constructed, the last step of model construction is to ensure model validity by verifying hermeneutics between *parts and the whole*. According to Martin [15], hermeneutics refers to the consistency between parts and the whole in a complex system; the verification of interpretation is not complete until going through a circular interrogation between the local and the global. In the QPT framework, hermeneutics verifications are the last step of linking the global approxi-gation back to specific learning moments to warrant the claims made by a *quantiative* model using *qualitative* deictic evidence. *Closing the interpretive loop* is a methodology widely adopted by *quantitative ethnographers* to evaluate model and enhance model explanability. That is, after deriving quantitative models, researchers will dive back to the qualitative data to evaluate whether the model represents the phenomenon shown in the original qualitative model accurately and fairly. This practice warrants validity by ensuring that (1) important signal in the qualitative data is not eliminated during the process of information reduction by coding and modeling, (2) both quantitative representation and qualitative data, and both local systematization and global approxi-gation corroborate with each other. With the verification, the construction of an event-based temporal model is complete.

2.3 Assumptions for QPT

Constructing an event-based temporal model requires a bridge between the local statics and global dynamics and a linkage between qualitative and quantitative perspectives. To ensure pairwise alignments, the use of QPT framework requires the following 3C assumptions (coherent learner group or process, critical moments, and conjugated representations):

(1) Coherent learner group or processes: By definition, an approxi-gated global model is an optimized and coordinated representation that minimizes the residual between local systematizations and global estimations. Thus, such a long and complex learning process should be segmented and defined with a meaningful unit of analysis to maintain the coherence of learning processes if using only a fixed set of temporal parameters. For example, with strong assumptions of subgroup differences, a global approxi-gation should be constructed within each subgroup to maintain modeling fairness or based on differnet parameter derivations for each subgroup to minimize residual.

(2) Critical moments: The construction of a fair model relies on fair sampling. According to Goodman [11], a fair sample should be a mixture of random draws from a population and the sample size is sufficient to cover patterns that are predominant in the population. Thus, to apply QPT based on a fairly selected sample, selections of anchor events should be randomly selected and cover critical moments in the learning process. Two methods can be applied to select critical moments. Randomly sampled learning events should be sufficient to reach theoretical saturation. Other sampling techniques can be applied to enhance the efficiency of reaching theoretical saturation. For example, based on pedagogical design or theoretical significance, some rare but impactful learning events should be included as local anchors to optimize temporal parameters. However, anchor selections can only be interpolated within the anchor networks identified within theoretical saturation to answer one specific question. When switching research questions, anchor selections and criteria of theoretical saturation may be subjected to change. Whereas, for a model for a coherent learner group or learning process, the estimation of temporal parameters should remain stable and robust to the inclusion or exclusion of a small number of anchors.

(3) Conjugated representations: Due to the structure of local and group representation, the premise of optimizing parameters is forcing these representations to be conjugated. That is, both local systematizations and the global approxi-gation should share the same structure such as networks, sequences, etc. For example, if a qualitative interpretation is represented as a network of epistemic frames [25] for local systematizations, the global model should be constructed by epistemic network analysis which remains the same structure: nodes present codes derived from the epistemic frame while edges represent the co-occurrence of two epistemic beliefs, skills, knowledge at the same time.

3 Methods

3.1 Dataset

Baba Is You is a problem-solving game that allows players to alter predefined rules to accomplish their goals. For example, as shown in the first level of Baba Is You (Figure 2 Left), a player starts as the white bunny (Baba), enclosed by surrounding walls. To win the level, the player needs to use keystrokes to move Baba and ultimately reach the flag icon outside of the surrounding wall. However, due to the presence of the rule WALL-IS-STOP, Baba cannot move across the wall to reach the flag. That is, the player will experience a stop if Baba bumps into the wall. Specifically, this frustrated moment is termed and coded as Deviation. The mechanism to win this level is to manipulate Baba and break the rule so the surrounding wall blocks become ineffective. Level 2 (Figure 2 Right) is a near-transferred problem of level 1. That is, Baba is again blocked by surrounding barriers of flags, instead of surrounding walls. To win level 2, players need to deactivate the rule by pushing any word in the rule WALL-IS-STOP to break the wall barriers and reach the upper area.

Carpenter and colleagues [4] collected log data and gaze data to explore the relationship between human attention and action in puzzle solving. In this study, we continued to explore the patterns of coordination of attention and action before and after students mastered the game mechanism. These multimodal interactions were collected from 10 students with 59 attempts of tried (27 in the first level and 32 in the second level). Log data captured the locations of Baba and the status of the objects, such as rule effectiveness and movements of Baba. Gazing fixation were collected using an Eye Link II eye tracker (SR Research) at 250 HZ. A human researcher defines the area of interest and coded the fixation zone based on the area of interface (Figure 2). By comparing strategies players used at different stages of problem solving, the same domain expert coded the multimodal data traces manually and labeled play sessions *before* or *after* a player discovered the mechanism of winning. According to the mechanism of the game, we hypothesized that players who hadn't discovered the game mechanism would be more *exploratory*. That is, these learners were more likely to bump into the wall and attempt to solve the issue by glancing through the objects on the interface. However, learners who learned the game mechanism would be more *experimental*. That is, these learners spent more time observing obstacles and developing plans for breaking the rule.

To understand the strategy applied in the learning process, two human raters coded learning events to reach perfect agreement. According to Table 4, there are 4 meaningful behaviors captured and coded by log-data while 10 meaningful zones are encoded based on the player's fixation (see specific zones marked in Figure 2 with different colors). To investigate interactivity and interdependency within and across models, an event-based temporal model was constructed to represent the patterns of where learners paid attention to and what learners manipulated [4].

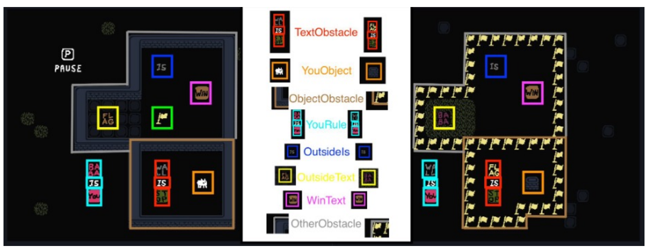


Figure 2: Baba Is You Interface: Level 1 (left) and Level 2 (right)

3.2 Transmodal Ordered Network Analysis and Window Length Parameters

Learning analytics researchers use state-dependent models to depict event-by-event dependency in a learning process [12]. That is, a learning event at any time point is impacted by and can even be predicted by precedent events within a recent temporal context. Thus, such event-based temporal models usually incorporate a sliding window to bound the event-to-event dependency within a short temporal frame. Common event-based temporal models in learning analytics include Epistemic Network Analysis, Ordered Network Analysis (ONA), Process Mining, Vector Autoregression, etc. For example, ONA models the ordered connections among critical actions or views coded in problem-solving, collaboration, and other cognitive and social learning processes [31]. Like other event-based temporal models, to construct an ONA model, researchers need to specify a temporal parameter, the length of the fixed-size window, to approximate the range of contexts given a learning event. However, for multimodal learning analytics, a fixed length window may favor a modality that has a high frequency of data collection or underestimate the impact of infrequent records collected from other modalities. Transmodal Analysis [27] addresses this challenge by augmenting existing state dependent modeling and specifying unique window sizes to represent nuanced recent temporal contexts for different modalities. Thus, we used T/ONA as an appropriate event-based temporal model to model microgenetic changes in this puzzle-solving process with the coordination of attention and actions.

When specifying window length parameters for log data and eye-gaze data, an domain expert in game-based learning started with providing a qualitative heuristic on the characteristics of different modalities: discourse events have a longer recent temporal context due to a gradual construction of conversations and topics, while gazing events only need a short window due to frequent switches of gazing fixation. While qualitative heuristics is simple to elicit, specifying window parameters into certain values is extremely challenging for human researchers. To address this practical challenge, we will focus on optimizing the window length parameters for multimodalities in this study.

4 Worked Example of QPT with Three-Step Procedures

In this section, we will demonstrate the process of determining temporal parameters for an event-based temporal model using a multimodal dataset. Specifically, we will investigate the problem-solving patterns in *Baba Is You* and construct a T/ONA model with unique temporal parameters for log and gaze modalities. We acknowledge that this is a simplified worked example for methodological clarity. However, other temporal parameters within the same or a different event-based temporal model can be determined following a similar procedure.

Following the QPT framework, we will demonstrate the following steps for parameter derivation and model construction: (1) systematizing human interpretations: collecting human qualitative interpretation and manually drawn anchor networks to represent the learner's problem-solving process given one specific learning moment, (2) optimizing parameters: with all anchor networks collected, construct a qualitative loss function and optimize for the window sizes of log and gaze modalities that captures human interpretations, and (3) verifying hermeneutics: verify a T/ONA model with qualitative data to demonstrate the different problem-solving strategies before or after students mastered the game mechanism.

4.1 Tell Qualitative Stories and Construct Anchor Networks

We randomly sampled 100 learning events from the multimodal dataset collected from log traces and gaze fixation during play sessions. Then, we presented these 100 randomly sampled learning events with their contextual events to a researcher who is an expert in game-based learning. For example, Table 2 shows a clip of a multimodal dataset with event descriptions, modalities, timestamps, and a subset of codes, given a specific sampled event (line 13) and its contextual events (line 1 to line 12). At the same time, we provided the human researcher access to the game for them to track the locations of Baba based on the learning events presented. To articulate player's gazing fixation and Baba's location under the player's manipulation, we constructed a *screenshot replay* to visualize the problem-solving process in Figure 3. The orange eye icons indicate gazing events (line 2, 3, 4, 5, 6, 7, 8, 9, 11) while the green mouse icons indicate log events (line 1, 10, 12, 13).

Based on the data clip in Table 2 and multimodal replay on Figure 3, the human researcher interpreted this learning process as an initial exploration and first experience of deviation from the expected movement (stopped by the wall). At the beginning, this

Table 1: Codebook for Learning Events from Log Data and Eye Fixation

	Code	Description
Log	Start-or-Restart	Player enters the level or restarts it from the beginning.
	Deviation	Player can't get YouObject through ObjectObstacle.
	RuleBreak	Player moves a text block away from TextObstacle.
	PassedBoundary	Player moves YouObject passed the ObjectObstacle.
Eye Fixation	Flag	Player looks at the goal for winning this level.
	YouObject	Player looks at Baba.
	YouRule	Player looks at the rule of BABA-IS-YOU.
	TextObstacle	Player looks at the rule of WALL-IS-STOP.
	BrokenStop	Player looks at the broken rule of WALL-IS-STOP.
	OutsideText	Player looks at the character of FLAG.
	WinText	Player looks at the character of WIN.
	IsOutside	Player looks at the character of IS.
	ObjectObstacle	Player looks at the surrounding wall which blocks the player.
	OtherObstacle	Player looks at the upper wall.

Table 2: Example of an Anchor Network Identification.

	Content	Modality	Start	End	Startor Restart	Devia- tion	Flag	You Rule	Text Obstacle	Outside Text	Object Obstacle	...
1	event_start_	log	0	0	1	0	0	0	0	0	0	
2	Flag	eye	4.32567	4.58967	0	0	1	0	0	0	0	
3	WallText	eye	5.51767	6.05767	0	0	0	0	1	0	0	
4	WallText	eye	6.43367	6.82967	0	0	0	0	1	0	0	
5	BabaText	eye	7.35767	7.56567	0	0	0	1	0	0	0	
6	FlagText	eye	8.22967	8.52167	0	0	0	0	0	1	0	
7	IsText-Baba	eye	9.20567	9.38167	0	0	0	1	0	0	0	
8	BabaText	eye	9.40967	9.61767	0	0	0	1	0	0	0	
9	IsText-Baba	eye	9.64167	9.87367	0	0	0	1	0	0	0	
10	input_up_	log	10.01667	10.01667	0	0	0	0	0	0	0	
11	WallBlock1	eye	10.25367	10.74967	0	0	0	0	0	0	1	
12	input_up_	log	10.48334	10.48334	0	0	0	0	0	0	0	
13	input_up_	log	10.81667	10.81667	0	1	0	0	0	0	0	

player started the level (line 1) and then looked at the flag icon as a goal for Baba to reach (line 2). Then, the player noticed a nearby rule "WALL IS STOP" that can be possibly manipulated by Baba (line 3 and line 4). With this rule activated, Baba was expected to be stopped by the wall and could not pass the boundary and reach the goal flag. The player glanced at "BABA" (line 5) and then quickly looked at the text "FLAG" (line 6) which can possibly form another rule after Baba breaks the wall. Without being accessible to a text rule "FLAG", the player pivoted their focus back to the nearby rule "BABA IS YOU" by glancing back and forth between "BABA" and "IS" (line 7 to line 9). Based on the rule "BABA IS YOU", the player recognized that they can manipulate Baba to move across the space. So, the player moved Baba up for one step (line 10). Then, the player might think of the rule "WALL IS STOP" and stare at the upper wall block (line 11) as they may expect a deviation when they reach the wall. As a result, when the player pressed the "up" keystroke twice (line 12 and line 13), Baba was able to move only one step.

With line 13 as a sampled line and being requested to describe the learning process that leads up to the deviation moment in line 13, the human researcher identified that the behavior of Deviation was tightly related to recognizing rule of "WALL IS STOP" (TextObstacle) and "BABA IS YOU" (YouRule) and the corresponding block of upper wall (ObjectObstacle). However, Deviation was not related to the beginning of the level (StartorRestart), the icon flag (Flag) and the un-manipulatable rule related to the flag (OutsideText). Thus, the human researcher drew the anchor network (see Figure 4 Left) with three binarized connections from TextObstacle to Deviation, from YouRule to Deviation, from ObjectObstacle to Deviation. Then, this anchor network was digitalized and transformed into a matrix representation (see Figure 4 Right) for the next step of optimization.

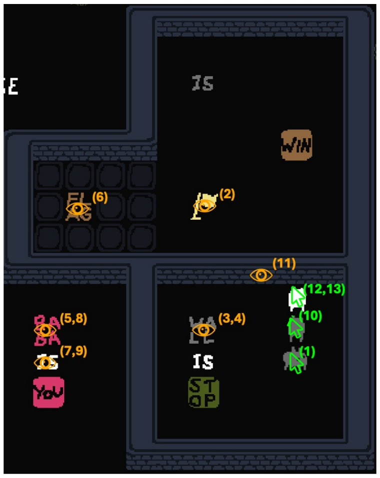
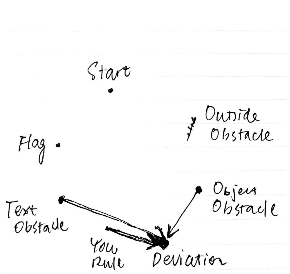


Figure 3: Screenshot Replay of Anchor Network Identification with Eye Fixation (Orange) and Keystroke Manipulations (Green)



	Startor Restart	Devi-ation	Flag	You Rule	Text Obstacle	Outside Text	Object Obstacle	...
Startor Restart	0	0	0	0	0	0	0	...
Devi-ation	0	0	0	0	0	0	0	...
Flag	0	0	0	0	0	0	0	...
You Rule	0	1	0	0	0	0	0	...
Text Obstacle	0	1	0	0	0	0	0	...
Outside Text	0	0	0	0	0	0	0	...
Object Obstacle	0	1	0	0	0	0	0	...
...	...	...	...	...	...	...	...	...

Figure 4: Hand-Drawn Anchor Network (Left) and Digitalized Connection Matrix (Right) Capturing the Qualitative Story in Table 2

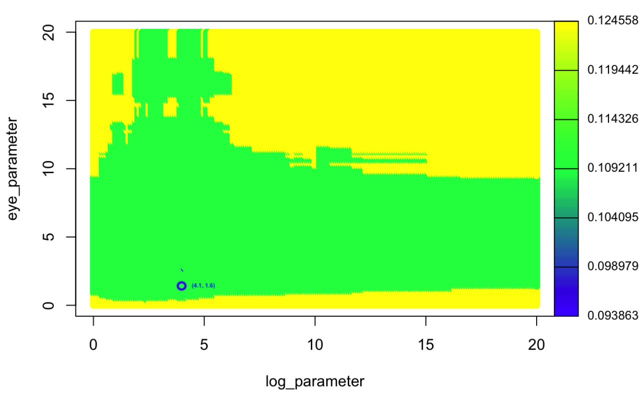


Figure 5: Qualitative Loss Values based on Different Parameters for Log and Gaze Modalities (Global Minimum Circled)

4.2 Optimizing Temporal Parameters for Different Modalities

Following the same procedure of randomly sampling learning events and collecting human-identified anchor networks, the human researcher identified 85 anchor networks and stopped identification due to the reach of theoretical saturation. That is, the human research claimed that these 85 anchor networks are sufficient to represent grounded interpretations about the learning process; even with more anchors shown, the human researcher did not detect new information about the learning process. Using these anchor networks, we constructed *parameter-induced* networks given any temporal parameters for the same grounded stories, defined the *qualitative loss function* (QLF) for all 85 anchors to measure the average of misalignment between all pairs of anchor networks and induced networks, and used an optimization routine to determine the optimized temporal parameters that minimize the qualitative loss value. Due to non-convexity, non-continuity, and no analytical form of QLF, we ran *repeated Nelder-Mead* to approximate the global minimum of loss value with the lowest local minimums of loss values. To obtain the least repetitions needed for this algorithm, we conducted a Monte Carlo study by randomly selecting initial window length parameters (WLPs) for both log data and gaze data and constructing the distributions of optimized WLPs with increasing repetition numbers. As a result, after 50 repetitions of Nelder-Mead with random starts, more than 95% of optimized gaze window lengths and log window lengths converged to 1.6 seconds and 4.1 seconds respectively. To confirm the global minimum, we also brute forced the parameter space for both the window sizes of eye gaze and log data with a step size of 0.1 seconds. According to the visualization (Figure 5), the global minimum of QLF exists when the log parameter is 4.1 seconds and the gaze parameter is 1.6 seconds.

4.3 Explaining the Approxi-gated Model with Qualitative Deictic Evidence

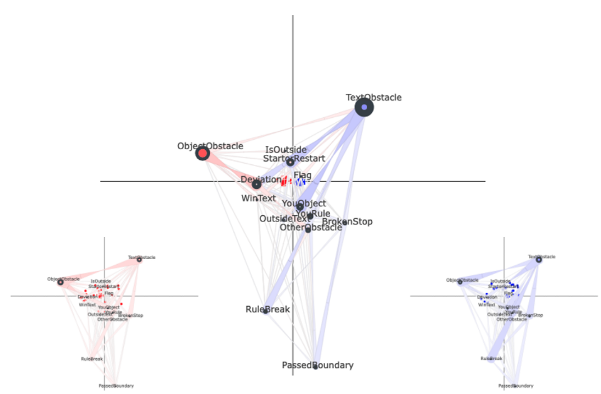


Figure 6: T/ONA Models to Compare Problem-Solving Strategies Before and After a Player Masters the Game Mechanism: primary plot for the model before mastery (left-red), primary plot for the model after mastery (right-blue), and subtracted plot (middle).

With the optimized gaze window lengths as 1.6 seconds and log window lengths as 4.1 seconds, we can construct the T/ONA model to compare the problem-solving patterns before and after mastering the game mechanism (Figure 6). According to the subtracted plot, players who failed to master the mechanism show frequent connections from Deviation to ObjectObstable and strong self-connection within ObjectObstable. That is, students were confused by the Deviation by walls and, thus, stared at the walls for a prolonged time (ObjectObstable), trying to break out from the inside of surrounding walls. However, students who experienced an epiphany understood that the key to the puzzle was breaking the rule of "WALL IS STOP" (TextObstable). Thus, they made frequent connections either from gazing at TextObstable to gazing at other objects (YouObject) or checking on TextObstable before manipulating other gaming factors (e.g., StartorRestart, Deviation, RuleBreak, PassedBoundary). That is, after realizing the key of solving this level, players were pondering about the relationship between at "WALL IS STOP" (TextObstable) and the avatar (YouObject), before making any changes to the game. Some students restarted the level to reboot the location of baba (StartorRestart) after checking on the rule "WALL IS STOP" (TextObstable). Some students gazed at the rule (TextObstable) and then broke the rule (RuleBreak) by moving Baba to push the text rules originally in a vertical line. Some students experimented with the manipulation of Baba and verified whether Baba would go across the wall barrier (PassedBoundary) after looking at "WALL IS STOP" (TextObstable). These different patterns in connection making contributed to statistically significant differences in individual T/ONA scores for students who mastered and failed to master the game mechanisms. According to a Wilcoxon Rank Test, the patterns of connection-making for students who mastered the game mechanism are significantly different from those who didn't master (W = 1094, p < 0.01, Cliff's Delta = 0.3565).

To close the interpretive loop, we dived back into the raw qualitative data to verify insights drawn from the T/ONA model based on optimized temporal parameters for WLPs of log and gaze data. Here are two examples that manifested the patterns of students who mastered and didn't master the game mechanism.

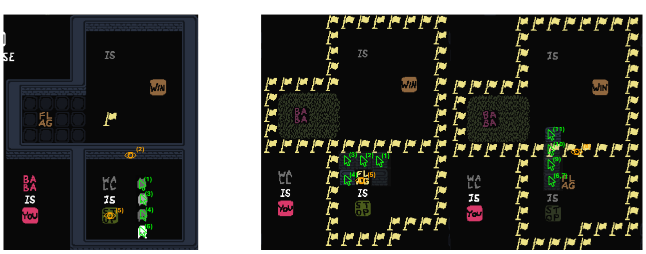


Figure 7: Screenshot Replay of a Student Who Failed to Master the Game Mechanism (Left) and Who Mastered the Game Mechanism (Middle and Right).

Example 1: Failed Explorations
Table 3 and Figure 7 (Left) demonstrated a failed exploration for a confused player who hadn't mastered the game mechanism. Baba started by moving towards the upper wall block (line 1). Then, the player stared at the upper wall (ObjectObstacle) and expected the potential deviation that could result from further moving up (line 2). Instead of moving further up, the player moved Baba down for two steps (line 3 and line 4). Then, the player glanced at the "STOP" text (TextObstacle) in the rule "WALL IS STOP" (line 5) and got confused by whether the bottom wall would also stop Baba. To explore the possibility of passing the bottom wall, the player moved Baba one more step down (line 6) but was stopped by the wall for moving further down (Deviation). This qualitative example shows that players, who hadn't mastered the game mechanism, make more connections with Deviation. Specifically, it shows a strong self transition within ObjectObstacle, a connection from ObjectObstacle to Deviation, and a connection from TextObstacle to Deviation. These three strong connections are matched with the connection patterns for students who failed master the game mechanism in the T/ONA model.

Example 2: learned status Table 4 and Figure 7 (Middle and Right) demonstrated a successful experimental process for a player who broke the rule and passed the boundary. Baba started by moving towards the upper wall block (line 1), then moving towards the left twice (line 2 and line 3), and moving down (line 4). Then, the player stared at the text "FLAG" in the rule "FLAG IS STOP" (TextObstacle) and expected a potential rule break (line 5). The player conducted the experiment by moving Baba right (line 6) and correspondingly broke the rule (line 7). Due to the deactivation of the rule, "FLAG IS STOP" was greyed out (RuleBreak). Meanwhile, the player glanced at the upper barriers made with flags (ObjectObstacle) to observe changes in barriers when the rule was deactivated (line 8). Then, the player moved Baba up with two moves (line 9 and line 10). At the last up movement (line 11), Baba passed the boundary and showed the success of experimentation for breaking the rule (PassedBoundary). This qualitative example shows that players, who realized the game mechanism, make more connections with Deviation. Specifically, it shows a strong consequent self transition within ObjectObstacle, from ObjectObstacle to Deviation, and from TextObstacle to Deviation, which is matched with the connection patterns for students who mastered the game mechanism in the T/ONA model.

5 Discussion

In this paper, we proposed qualitative parameter triangulation (QPT) as a human interpretation oriented framework, to determine temporal parameters for event-based temporal models. Conceptually, QPT highlights three key components in constructing event-based temporal models: interpretation, systematization, and approxi-gation. Methodologically, QPT centers human interpretation and guides model construction by achieving pairwise alignments across the three key components. That is, under the guidance of QPT, an event-based temporal model can (1) systematize qualitative thick descriptions of a learning process using a structural and scalable representation, (2) determine the optimized temporal parameter values to estimate the recent temporal context of a learning moment, and (3) bridge the deictic qualitative interpretations with the global model to ensure model explainability. Practically, this study explored the potential solution to solve a challenge in algorithm explainability by eliciting human interpretations as a

Table 3: Example of a Student Who Failed to Master the Game Mechanism.

	Content	Modality	Start	End	Startor Restart	Rule Break	Deviation	Passed Boundary	Object Obstacle	Text Obstacle	...
1	input_up_	log	17.86667	17.86667	0	0	0	0	0	0	
2	WallBlock2	eye	20.05367	21.35767	0	0	0	0	1	0	
3	input_down_	log	21.31667	21.31667	0	0	0	0	0	0	
4	input_down_	log	21.55	21.55	0	0	0	0	0	0	
5	StopText	eye	21.60567	21.84567	0	0	0	0	0	1	
6	input_down_	log	21.76667	21.76667	0	0	1	0	0	0	

Table 4: Example of a Student Who Mastered the Game Mechanism.

	Content	Modality	Start	End	Startor Restart	Rule Break	Deviation	Passed Boundary	Object Obstacle	Text Obstacle	...
1	input_up_	log	21.6	21.6	0	0	0	0	0	0	
2	input_left_	log	22.73334	22.73334	0	0	0	0	0	0	
3	input_left_	log	22.73334	22.73334	0	0	0	0	0	0	
4	input_down_	log	23.35	23.35	0	0	0	0	0	0	
5	FlagText	eye	23.51334	24.20134	0	0	0	0	0	1	
6	input_right_	log	23.95	23.95	0	0	0	0	0	0	
7	event_rule_remove: flag is stop	log	23.95	23.95	0	1	0	0	0	0	
8	FlagBlock1	eye	24.22534	24.72134	0	0	0	0	1	0	
9	input_up_	log	24.55	24.55	0	0	0	0	0	0	
10	input_up_	log	24.81667	24.81667	0	0	0	0	0	0	
11	input_up_	log	25.03334	25.03334	0	0	0	1	0	0	

first step of model construction and optimizing for the temporal parameters to align quantitative models with qualitative interpretations.

In spite of successful preliminary exploration, QPT as a conceptual and methodological framework needs to be further examined in the following directions. First, we only tested the feasibility of QPT to determine window length parameters for gaze and log modalities in a game-based learning context. But, as a methodological framework, it should be generalizable to determine other parameter values for different event-based temporal models such as lag sequential model, vector auto-regression, etc. Additional exploration is needed to prove the feasibility and generalizability of QPT. Second, hand-drawn networks are error-prone due to human fatigue. Thus, a user-centered interface will support human elicitation and ease the process of identifying anchor networks. Last, the current practice relies on human-identified anchor networks as grounded stories for parameter determination, which demands considerable human effort to reach estimation convergence and qualitative theoretical saturation. Potentially, this parameter derivation and model construction process can be accelerated by integrating a time series analysis technique to automatically fit temporal parameters that predict upcoming learning events.

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References

[1] Ashraf Abdul, Jo Vermeulen, Danding Wang, Brian Y Lim, and Mohan Kankanhalli. 2018. Trends and trajectories for explainable, accountable and intelligible systems: An hci research agenda. In *Proceedings of the 2018 CHI conference on human factors in computing systems*. 1–18.

[2] Patricia A Alexander, Diane L Schallert, and Ralph E Reynolds. 2009. What is learning anyway? A topographical perspective considered. *Educational psychologist* 44, 3 (2009), 176–192.

[3] Stephen P Borgatti, Ajay Mehra, Daniel J Brass, and Giuseppe Labianca. 2009. Network analysis in the social sciences. *science* 323, 5916 (2009), 892–895.

[4] Zack Carpenter, Yeyu Wang, David DeLiema, Panayiota Kendeou, and David Williamson Shaffer. 2023. Using Multi-Modal Network Models to Visualize and Understand How Players Learn a Mechanic in a Problem-Solving Game. In *The 13th International Learning Analytics and Knowledge Conference*. 99–101.

[5] Bodong Chen, Simon Knight, and Alyssa Wise. 2018. Critical issues in designing and implementing temporal analytics. *Journal of Learning Analytics* (2018).

[6] Oscar Blessed Deho, Lin Liu, Jiuyong Li, Jixue Liu, Chen Zhan, and Srecko Joksimovic. 2024. When the past!= the future: Assessing the Impact of Dataset Drift on the Fairness of Learning Analytics Models. *IEEE Transactions on Learning Technologies* (2024).

[7] Susan Dumais, Robin Jeffries, Daniel M Russell, Diane Tang, and Jaime Teevan. 2014. Understanding user behavior through log data and analysis. *Ways of*

Knowing in HCI (2014), 349–372.
[8] Maka Eradze et al. 2020. *Learning Interactions Across Spaces: a Framework for Contextualised Multimodal Observations.* Tallinna Ülikool.
[9] David H Freedman. 2010. Why scientific studies are so often wrong: The streetlight effect. *Discover Magazine* 26 (2010), 1–4.
[10] Clifford Geertz. 2008. Thick description: Toward an interpretive theory of culture. In *The cultural geography reader*. Routledge, 41–51.
[11] Nelson Goodman. 1978. Ways of worldmaking. *Hackett Pub Co Inc* (1978).
[12] Anika Gupta, Deepak Garg, and Parteek Kumar. 2022. Mining sequential learning trajectories with hidden markov models for early prediction of at-risk students in e-learning environments. *IEEE Transactions on Learning Technologies* 15, 6 (2022), 783–797.
[13] Muntasir Hoq, Peter Brusilovsky, and Bita Akram. 2023. Analysis of an Explainable Student Performance Prediction Model in an Introductory Programming Course. *International Educational Data Mining Society* (2023).
[14] Simon Knight, Alyssa Friend Wise, and Bodong Chen. 2017. Time for change: Why learning analytics needs temporal analysis. *Journal of Learning Analytics* 4, 3 (2017), 7–17.
[15] Wallace Martin. 1972. The hermeneutic circle and the art of interpretation. *Comparative Literature* 24, 2 (1972), 97–117.
[16] Belghachi Mohammed. 2024. The Synergy of Explainable AI and Learning Analytics in Shaping Educational Insights. *IAENG International Journal of Computer Science* 51, 9 (2024).
[17] Inge Molenaar and Alyssa Friend Wise. 2022. Temporal aspects of learning analytics-grounding analyses in concepts of time. *The handbook of learning analytics* (2022), 66–76.
[18] Don Norman. 2014. *Things that make us smart: Defending human attributes in the age of the machine.* Diversion Books.
[19] Xavier Ochoa, Charles Lang, George Siemens, Alyssa Wise, Dragan Gasevic, and Agathe Merceron. 2022. Multimodal learning analytics-Rationale, process, examples, and direction. *The handbook of learning analytics* (2022), 54–65.
[20] Sharon Oviatt, Joseph Grafsgaard, Lei Chen, and Xavier Ochoa. 2018. Multimodal learning analytics: Assessing learners' mental state during the process of learning. In *The Handbook of Multimodal-Multisensor Interfaces: Signal Processing, Architectures, and Detection of Emotion and Cognition-Volume 2.* 331–374.
[21] Peter Reimann. 2009. Time is precious: Variable-and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning* 4 (2009), 239–257.
[22] Paul Ricoeur. 1983. Action, story and history: On re-reading The Human Condition. *Salmagundi* (1983), 60–72.
[23] Mohammed Saqr, Jalal Nouri, and Uno Fors. 2019. Time to focus on the temporal dimension of learning: A learning analytics study of the temporal patterns of students' interactions and self-regulation. *International Journal of Technology Enhanced Learning* 11, 4 (2019), 398–412.
[24] Shiva Shabaninejad, Hassan Khosravi, Solmaz Abdi, Marta Indulska, and Shazia Sadiq. 2022. Incorporating explainable learning analytics to assist educators with identifying students in need of attention. In *Proceedings of the Ninth ACM Conference on Learning@ Scale.* 384–388.
[25] David W Shaffer. 2006. Epistemic frames for epistemic games. *Computers & education* 46, 3 (2006), 223–234.
[26] David Williamson Shaffer. 2017. *Quantitative ethnography.* Lulu. com.
[27] David Williamson Shaffer, Yeyu Wang, Andrew R. Ruis, and Zhiqiang Cai. [n. d.]. *Transmodal Analysis.*
[28] Bruce Sherin, Nicole Kersting, and Matthew Berland. 2018. Learning analytics in support of qualitative analysis. In *International Society of the Learning Sciences, Inc.[ISLS].* Springer.
[29] Simon Buckingham Shum, Golnaz Arastoopour Irgens, Hollie Moots, Michael Phillips, Mamta Shah, Hazel Vega, and Abigail Wooldridge. 2021. Participatory Quantitative Ethnography. *Advances in Quantitative Ethnography* (2021), 126–138.
[30] Florence R Sullivan, W Richard Adrion, and P Kevin Keith. 2015. Microgenetic learning analytics: A computational approach to research on student learning. In *Proceedings of the annual meeting of the American Educational Research Association.* 16–20.
[31] Yuanru Tan, Andrew R Ruis, Cody Marquart, Zhiqiang Cai, Mariah A Knowles, and David Williamson Shaffer. 2022. Ordered network analysis. In *International Conference on Quantitative Ethnography.* Springer, 101–116.
[32] Hazel Vega, Golnaz Arastoopour Irgens, Tolulope Famaye, Ibrahim Adisa, and Caitlin Lancaster. 2023. Connect: A Tool for Collaborative Interview Data Analysis. In *Proceedings of the 17th International Conference of the Learning Sciences-ICLS 2023, pp. 2033-2034.* International Society of the Learning Sciences.
[33] Alyssa F Wise, Simon Knight, and Xavier Ochoa. 2021. What makes learning analytics research matter. *Journal of Learning Analytics* 8, 3 (2021), 1–9.
[34] Alyssa Friend Wise and David Williamson Shaffer. 2015. Why theory matters more than ever in the age of big data. *Journal of Learning Analytics* 2, 2 (2015), 5–13.