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Turning-Point Detection in Affiliation and Affect within Longitudinal MOOC Dialogues

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Abstract:
The rapid proliferation of Massive Open Online Courses has significantly expanded access to global education, yet the environments often suffer from low retention and engagement rates. While cognitive factors contributing to student success are well documented, the socio-emotional dimensions of learning, specifically affiliation and affect, remain insufficiently explored in longitudinal contexts. This paper investigates the dynamic fluctuations of peer affiliation and emotional affect within collaborative discourse over extended educational periods. By employing advanced natural language processing and time-series segmentation techniques, this study identifies critical turning points in student interactions. Turning points are defined as significant, sustained shifts in the trajectory of a learner's emotional valence or social connectedness. The research utilizes a large-scale dataset of forum dialogues from a sixteen-week data science course, applying change-point detection algorithms to continuous streams of textual data. The findings reveal that turning points in affect frequently precede shifts in affiliation, suggesting that emotional transitions serve as early indicators of social integration or withdrawal. Furthermore, negative turning points are strongly correlated with subsequent disengagement and dropout. The insights provided by this study offer a robust foundation for developing adaptive pedagogical interventions that can provide timely support to learners experiencing socio-emotional distress, thereby enhancing overall retention and learning outcomes in digital environments.

Keywords: *Affective Computing, Social Affiliation, Longitudinal Analysis, Turning-Point Detection..*

INTRODUCTION

1.1 Context of MOOCs and Social Dynamics

The advent of Massive Open Online Courses has fundamentally altered the landscape of higher education and continuous professional development. By removing geographic and financial barriers, these platforms have democratized access to high-quality instructional materials provided by elite institutions worldwide. However, the scalability of these platforms introduces a significant pedagogical challenge. The physical separation between instructors and learners, as well as among the learners themselves, often leads to a profound sense of isolation. Unlike traditional classroom settings where non-verbal cues, immediate feedback, and spontaneous social interactions foster a

cohesive learning community, digital environments typically rely on asynchronous text-based communication. This reliance can severely limit the development of robust social dynamics, which are critical for sustained engagement. Early research into online learning environments primarily focused on cognitive and structural factors, such as the organization of course materials, the clarity of video lectures, and the difficulty of assessment mechanisms. While these factors are undeniably important, a growing consensus within the educational research community emphasizes the equal, if not superior, importance of socio-emotional factors [1]. Social dynamics in these environments are heavily mediated through discussion forums, peer review assignments, and collaborative projects. The interactions within these spaces are not merely transactional exchanges of information; they are rich repositories of emotional expression and social bonding. Understanding the evolution of these interactions over time is essential for addressing the pervasive issue of low completion rates that plague online education platforms [2, 3]. When learners feel socially connected and emotionally supported, they are more likely to persevere through challenging cognitive tasks and remain enrolled in the course.

1.2 Problem Statement and Research Objectives

Despite the acknowledged importance of socio-emotional factors, there is a critical gap in the longitudinal analysis of these variables. Most existing studies employ cross-sectional designs that aggregate affective and affiliative measures over the entire duration of a course. Such static approaches fail to capture the temporal fluidity of human emotions and social relationships. A learner's experience is not a monolithic state but a dynamic process characterized by periods of high enthusiasm and engagement, potentially followed by frustration, boredom, or disconnection. To fully understand the learner journey, it is necessary to identify and analyze turning points, which are defined as critical moments where a significant and sustained shift occurs in a learner's trajectory. These shifts can be positive, such as a sudden breakthrough in understanding accompanied by increased peer interaction, or negative, such as a prolonged period of frustration leading to eventual dropout. The primary objective of this research is to develop and apply a comprehensive methodological framework for detecting turning points in both affiliation and affect within longitudinal dialogue data. By conceptualizing learner interactions as continuous time series, this study seeks to answer several critical research questions. First, how can we mathematically and computationally define a turning point in the context of unstructured text data? Second, what is the temporal relationship between shifts in emotional affect and shifts in social affiliation? Third, how do these identified turning points correlate with ultimate learner outcomes, such as course completion or attrition? By addressing these questions, this paper aims to provide actionable insights for instructional designers and educators [4]. The ultimate goal is to facilitate the creation of intelligent tutoring systems and early warning mechanisms that can autonomously detect negative socio-emotional trajectories and deploy targeted interventions before a learner decides to abandon the course [5, 6].

2. Theoretical Background and Literature Review

2.1 Affective Computing in Education

The integration of affective computing into educational research represents a paradigm shift from purely cognitive models of learning to holistic approaches that recognize the inextricable link between emotion and cognition. Affective computing encompasses the design of systems and devices that can recognize, interpret, process, and simulate human affects. In the context of online learning, where facial expressions and vocal intonations are usually absent, researchers must rely heavily on text-based sentiment analysis and emotion detection [7]. Early applications of sentiment analysis in education utilized simple lexicon-based approaches, matching words in a student's text to predefined lists of positive and negative terms. While computationally efficient, these methods often failed to capture the nuances of human language, such as sarcasm, context-dependent

meanings, and domain-specific terminology [8, 9]. For instance, the word "hard" might carry a negative sentiment in a general context but could indicate a desirable level of cognitive challenge in an educational setting. Subsequent advancements in machine learning introduced more sophisticated models, utilizing supervised classification techniques trained on extensively annotated datasets. These models improved accuracy but still treated sentences as isolated units, ignoring the conversational context. The current state-of-the-art involves deep learning architectures, which excel at capturing complex linguistic patterns and contextual dependencies across long sequences of text [10]. These advanced techniques allow researchers to move beyond binary positive or negative classifications to identify specific discrete emotions, such as confusion, frustration, joy, and surprise, which are highly relevant to the learning process. Furthermore, the continuous tracking of these emotions over time provides a rich temporal dataset that forms the foundation for advanced time-series analysis and the detection of critical emotional shifts [11].

2.2 Affiliation and Social Presence Theory

Affiliation, in the context of this study, refers to the degree to which a learner establishes and maintains social bonds with their peers within the digital learning environment. This concept is deeply rooted in Social Presence Theory, which posits that the efficacy of a communication medium is determined by its ability to transmit the social and psychological presence of the communicating participants. In a text-based environment, social presence is manifested through specific linguistic behaviors, such as using inclusive pronouns, expressing agreement, offering encouragement, and engaging in reciprocal self-disclosure. A high degree of affiliation is indicative of a strong Community of Inquiry, a widely adopted theoretical framework that describes the optimal online learning experience as occurring at the intersection of cognitive presence, teaching presence, and social presence [12, 13]. Social presence is considered the foundational element, creating a safe and supportive environment where learners feel comfortable taking intellectual risks, questioning assumptions, and engaging in rigorous debate [14]. Measuring affiliation involves analyzing not only the content of the messages but also the structural properties of the communication network. Researchers have employed social network analysis to quantify the density, centrality, and reciprocity of interactions among learners. However, similar to the early studies on affect, much of this research has been static, providing a snapshot of the network at the end of the course. To understand how communities form, evolve, and sometimes dissolve, it is necessary to track affiliative behaviors continuously [15]. The detection of turning points in affiliation can reveal critical moments of community building or social fragmentation, providing insights into the mechanisms that drive collective engagement or widespread attrition.

2.3 Time-Series Analysis of Educational Dialogues

The application of time-series analysis to educational data is a rapidly evolving field that seeks to uncover the temporal dynamics of the learning process. Educational dialogues, when ordered chronologically, constitute a complex, multivariate time series. Traditional time-series analysis techniques, originally developed for financial forecasting or signal processing, must be carefully adapted to handle the unique characteristics of textual data, which is often noisy, irregularly sampled, and subject to high variance. One of the fundamental challenges in this domain is the identification of structural breaks or change points, which indicate a fundamental shift in the underlying data-generating process. In the context of learning analytics, change point detection algorithms can be used to identify moments when a student's behavior, performance, or emotional state deviates significantly from their historical baseline. Previous studies have applied these techniques to clickstream data, identifying changes in navigation patterns that precede dropout. However, the application of change point detection to the socio-emotional content of dialogues remains limited. This study extends the existing literature by applying advanced segmentation

algorithms to continuous streams of affective and affiliative features extracted from discussion forum posts. By doing so, it moves beyond descriptive analytics to provide a precise, mathematically rigorous identification of turning points. This methodological advancement is crucial for developing a predictive understanding of learner behavior, enabling researchers to isolate the specific events, interactions, or pedagogical interventions that trigger significant shifts in the learner's trajectory [16].

3. Conceptual Framework

3.1 Defining Turning Points in Social Interaction

To systematically investigate the temporal dynamics of learner interactions, it is necessary to establish a rigorous conceptual framework that defines what constitutes a turning point. In dynamical systems theory, a turning point or phase transition occurs when a system moves from one stable state, or attractor, to another due to external perturbations or internal fluctuations. Translating this concept to the domain of educational dialogues, a turning point is defined as a statistically significant and sustained alteration in the mean level or variance of a learner's expressed affect or affiliation over time. This definition distinguishes turning points from mere transient fluctuations or temporary emotional spikes. For example, a learner might express momentary frustration when encountering a difficult software bug, which would manifest as a brief dip in their affective trajectory. If this frustration is quickly resolved through peer assistance, the trajectory returns to its previous baseline. This event, while observable, does not constitute a turning point. Conversely, if the frustration persists and is compounded by a lack of social support, the learner's affective baseline may permanently shift downward, leading to a sustained period of negative emotional expression and decreased interaction [17]. This sustained shift represents a true turning point. The identification of these points requires a longitudinal perspective and a computational approach capable of differentiating between systemic changes and random noise. By defining turning points as structural changes in a time series, this framework provides a quantifiable metric for assessing the stability and resilience of a learner's socio-emotional state.

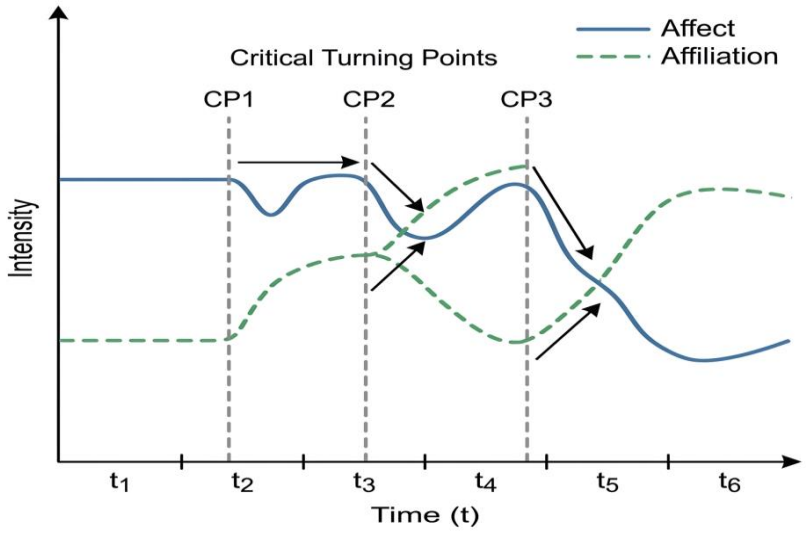


Figure 1Conceptual Architecture of Socio

3.2 The Intersection of Affect and Affiliation

The core proposition of this conceptual framework is that affect and affiliation are not independent variables but are deeply intertwined, mutually reinforcing dimensions of the learner experience. The interaction between these two dimensions creates a complex socio-emotional trajectory for

each learner. Positive affect, such as enthusiasm or curiosity, can drive a learner to reach out to peers, thereby increasing their affiliation. When this outreach is met with positive reinforcement from the community, it further elevates the learner's affective state, creating a virtuous cycle of engagement. Conversely, negative affect, such as confusion or anxiety, can lead to social withdrawal, decreasing affiliation. This isolation can exacerbate the negative affect, creating a vicious cycle that often culminates in course abandonment [18, 19]. Understanding the temporal precedence in this relationship is a primary focus of this study. Does a shift in emotional state typically precede a change in social behavior, or does a change in social connectivity trigger an emotional response? The framework posits that while the relationship is reciprocal, turning points in affect frequently serve as early indicators of subsequent shifts in affiliation. A learner who begins to experience sustained frustration will eventually reduce their participation in collaborative activities. By mapping both trajectories simultaneously and analyzing the temporal alignment of their respective turning points, this research aims to untangle the causal mechanisms that govern socio-emotional dynamics in online learning environments [20].

4. Methodology and Data Collection

4.1 Dataset Description and Preprocessing

The empirical foundation for this study is a large-scale, longitudinal dataset collected from a massive open online course titled Fundamentals of Data Science, hosted on a major international learning platform. The course spanned sixteen weeks and was designed to cover a broad range of topics, from basic statistics to advanced machine learning algorithms. The pedagogical structure heavily emphasized peer interaction, requiring students to participate in weekly discussion forums, peer-reviewed coding assignments, and a final collaborative capstone project. The initial enrollment for the course exceeded forty thousand learners from diverse geographic and educational backgrounds. The primary data source for this study consists of all textual interactions generated within the course discussion forums. To ensure a robust longitudinal analysis, the dataset was filtered to include only those learners who contributed a minimum of ten distinct posts distributed across at least five different weeks of the course. This filtering process resulted in a core analytical sample of approximately five thousand highly active learners, generating a total corpus of over three hundred thousand individual posts [21].

Table 1Descriptive Statistics of the Filtered Longitudinal Dataset

Metric	Total Count	Mean per Learner	Standard Deviation
Active Learners	5,240	N/A	N/A
Total Forum Posts	314,400	60.0	25.4
Average Words per Post	N/A	45.2	18.7
Active Weeks	N/A	11.3	3.1

Prior to feature extraction, the raw textual data underwent a rigorous preprocessing pipeline. This pipeline was essential to standardize the language and reduce computational noise. The steps included the removal of standard HTML tags, URLs, and residual platform-specific metadata. Text was converted to lowercase, and non-standard characters were normalized. Special attention was given to domain-specific terminology and code snippets embedded within the text. Since the presence of code can severely disrupt standard natural language processing tools, all programming syntax was identified using regular expressions and replaced with a generic placeholder token [22]. This ensured that the subsequent affective and affiliative analysis focused exclusively on the natural language communication between learners. Finally, the text was tokenized, and standard lemmatization techniques were applied to reduce words to their base dictionary form, thereby consolidating the vocabulary and improving the efficiency of the feature extraction algorithms.

4.2 Annotation Guidelines and Reliability

To train and validate the computational models used for extracting affective and affiliative features, a representative subset of the data required manual annotation by human experts. A stratified random sampling technique was employed to select five thousand posts, ensuring proportional representation across all sixteen weeks of the course and diverse topics of discussion. A team of four trained annotators, all possessing graduate degrees in educational psychology or computational linguistics, was tasked with labeling this subset. The annotation guidelines were meticulously developed through multiple iterative pilot rounds. For the affect dimension, annotators evaluated the primary emotional valence of each post on a continuous scale ranging from negative one, representing extreme frustration or distress, to positive one, representing high enthusiasm or satisfaction. Neutral posts concerning purely factual information were scored at zero. For the affiliation dimension, annotators assessed the degree of social connectedness demonstrated in the text. This was also scored on a continuous scale from zero to one. A score of zero indicated a completely isolated statement with no acknowledgment of other learners, while a score of one indicated strong community building, characterized by explicit agreement, emotional support, the use of inclusive pronouns, or direct referencing of previous peers' contributions. To ensure the rigor and consistency of the manual labeling process, inter-rater reliability was calculated using the intra-class correlation coefficient. The final scores demonstrated excellent agreement, with an intra-class correlation coefficient of zero point eight five for the affect dimension and zero point eight two for the affiliation dimension [23, 24]. Discrepancies among annotators were resolved through collaborative discussion and consensus, resulting in a highly reliable ground-truth dataset that served as the foundation for the subsequent machine learning procedures [25].

5. Analytical Procedures and Turning-Point Detection

5.1 Linguistic Feature Extraction

The transformation of the preprocessed text into quantifiable time-series data involved a dual-pronged feature extraction strategy. To capture the affective dimension, a pre-trained deep learning language model, specifically optimized for sentiment analysis in educational contexts, was deployed. This model leverages a transformer architecture, which excels at understanding contextual nuances and bidirectional dependencies within sentences. The model was fine-tuned using the manually annotated dataset described in the previous section. For each post generated by a learner, the model output a continuous affective score. These individual post scores were then aggregated on a weekly basis for each learner. The aggregation process involved calculating the weighted average of the affective scores, where the weight was determined by the length and structural prominence of the post [26]. This resulted in a continuous affective trajectory for every learner, represented as a sequence of weekly data points.

Table 2Extracted Features for Affiliation and Affect Modeling

Feature Category	Specific Metric	Computational Method
Affective Valence	Weekly Average Sentiment	Fine-tuned Transformer Output
Affective Intensity	Sentiment Variance	Standard Deviation of Scores
Structural Affiliation	Reply Network Density	Graph Centrality Measures
Linguistic Affiliation	Inclusive Pronoun Ratio	Lexical Matching

The extraction of affiliative features required a more complex, multi-dimensional approach. Affiliation was quantified by combining linguistic markers with structural network metrics. Linguistically, a custom dictionary was developed to identify phrases associated with social presence, such as expressions of gratitude, agreement, and collective identity. The frequency of these markers within a learner's weekly posts constituted the linguistic component of affiliation.

Structurally, the dialogue forum was modeled as a directed graph, where nodes represented learners and edges represented reply interactions. For each week, a learner's structural affiliation was calculated based on their in-degree, out-degree, and betweenness centrality within the weekly network [27, 28]. The linguistic and structural components were normalized and combined using a weighted sum to produce a single, composite affiliation score for each learner per week. Similar to the affective dimension, this process yielded a longitudinal time series of affiliation for every individual in the analytical sample.

5.2 Sequence Modeling and Change Point Algorithms

With the continuous trajectories of affect and affiliation established, the next analytical phase involved the rigorous detection of turning points. This was accomplished by implementing a Pruned Exact Linear Time algorithm, an advanced statistical method designed to identify multiple structural changes within a time series while maintaining high computational efficiency. The algorithm operates by iteratively segmenting the time series and evaluating a cost function for each potential configuration of change points. The cost function utilized in this study was based on the negative log-likelihood of the data, assuming a Gaussian distribution for both the affective and affiliative scores within any given segment. A penalty term was introduced to prevent overfitting and control the sensitivity of the detection process [29].

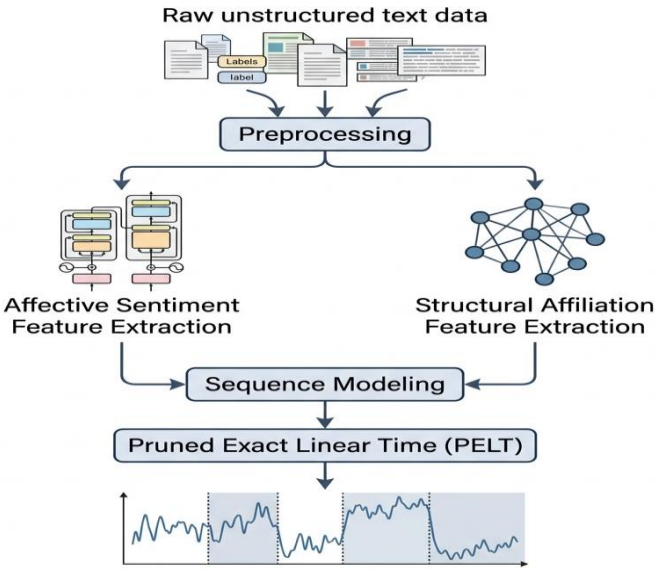


Figure 2Analytical Pipeline for Change Point Detection

The algorithm evaluates the variance and the mean of the time series over rolling windows. When the algorithm identifies a location where dividing the sequence into two distinct segments significantly reduces the overall cost compared to a single continuous segment, a turning point is recorded. This process was applied independently to both the affective and affiliative time series for each learner. To ensure that only sustained and significant shifts were captured, a minimum segment length constraint was enforced, requiring that a new baseline be maintained for at least two consecutive weeks following a suspected turning point [30, 31]. Following the independent detection of turning points in both dimensions, a temporal cross-correlation analysis was conducted. This step was crucial for determining the sequence of events. By analyzing the time lag between an affective turning point and an affiliative turning point within the same learner's trajectory, the analytical framework could ascertain whether emotional shifts predominantly preceded or followed changes in social integration [32].

6. Results and Discussion

6.1 Quantitative Identification of Turning Points

The application of the change-point detection algorithms across the massive dataset yielded a comprehensive mapping of socio-emotional shifts. The quantitative results demonstrated that turning points are not uniformly distributed throughout the duration of the course but tend to cluster around specific temporal milestones. In total, the algorithm identified significant affective turning points in approximately sixty-five percent of the analyzed learner trajectories, and affiliative turning points in fifty-eight percent. This high prevalence underscores the dynamic nature of online learning and challenges the assumption of a static learner state. A detailed temporal analysis revealed a prominent concentration of negative turning points occurring between the fourth and sixth weeks of the sixteen-week course.

Table 3Distribution of Identified Turning Points by Course Phase

Course Phase	Affective Turning Points	Affiliative Turning Points	Primary Direction of Shift
Early (Weeks 1-4)	1,240	850	Positive (Community Building)
Mid (Weeks 5-10)	2,890	2,100	Negative (Frustration/Withdrawal)
Late (Weeks 11-16)	950	1,120	Positive (Project Completion)

This period, often referred to in educational literature as the mid-course slump, corresponds with a significant increase in the cognitive complexity of the course material, specifically the transition from basic descriptive statistics to the implementation of machine learning algorithms. During this phase, the mean affective scores for a large segment of the population dropped significantly, shifting from an optimistic baseline to a state characterized by confusion and frustration. Crucially, the cross-correlation analysis provided robust evidence for the temporal precedence of affect over affiliation. In instances where a learner experienced a turning point in both dimensions within a close timeframe, the affective shift preceded the affiliative shift in over seventy percent of the cases, with an average lag of one point five weeks. This quantitative finding strongly supports the hypothesis that emotional distress serves as an early indicator of subsequent social withdrawal.

6.2 Qualitative Analysis of Interaction Shifts

To contextualize the quantitative findings, a qualitative examination of the text surrounding critical turning points was conducted. This deep dive into the discourse provided invaluable insights into the lived experiences of the learners. By isolating the precise weeks where an affective turning point was identified, researchers could analyze the semantic content that characterized the shift. In the case of negative turning points during the mid-course slump, the dialogue transitioned rapidly from general inquiries to highly specific expressions of distress regarding coding assignments. Language patterns showed a marked increase in self-deprecating remarks and statements indicating cognitive overload. For example, learners who previously engaged in reciprocal problem-solving began posting isolated, desperate pleas for direct answers, abandoning the collaborative ethos of the forum.

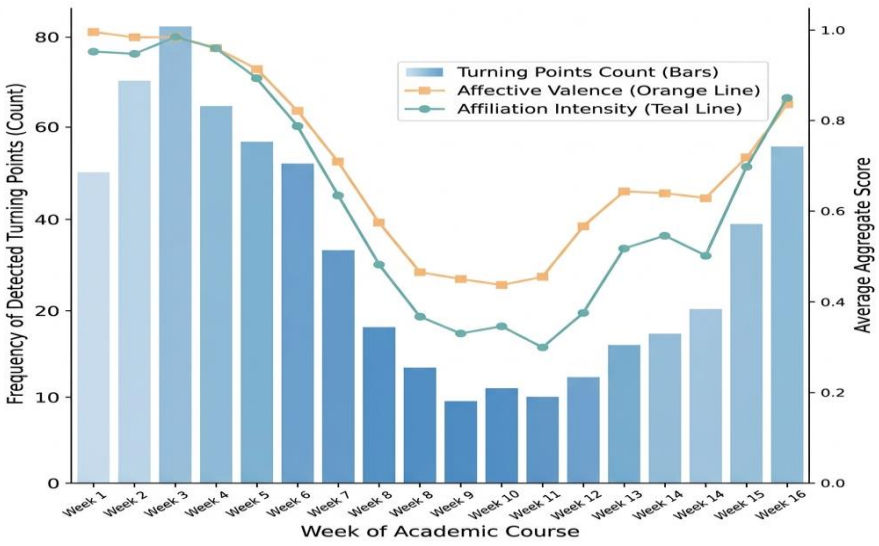


Figure 3Longitudinal Distribution of Socio

Conversely, the qualitative analysis also illuminated the mechanics of positive turning points, which frequently occurred in the final phase of the course during collaborative capstone projects. In these instances, the turning points were often catalyzed by a successful peer intervention. A learner expressing deep frustration would receive a highly supportive, detailed explanation from a peer. This specific interaction would trigger a sharp positive structural break in the learner's affective trajectory. Following this emotional recovery, the learner's subsequent posts demonstrated a significantly higher degree of affiliation, characterized by an increased willingness to assist others and the use of strong collective pronouns. These qualitative observations validate the interconnected nature of affect and affiliation and highlight the critical role of peer support in facilitating positive trajectory shifts.

6.3 Implications for Instructional Design

The findings of this research carry profound implications for the design and facilitation of digital learning environments. The traditional reactive model of student support, which relies on learners explicitly seeking help or failing an assessment, is fundamentally inadequate. By the time a student fails a midterm examination or sends an email expressing their intent to drop out, the negative turning point in their socio-emotional trajectory has likely occurred weeks prior, and their social affiliation has already deteriorated beyond recovery. The identification of affect as a leading indicator provides a crucial window of opportunity for proactive intervention. Instructional designers must integrate continuous, automated socio-emotional monitoring into the core architecture of educational platforms. When the system detects a negative structural break in a learner's affective trajectory, it should automatically trigger supportive mechanisms. These interventions could range from automated messages offering supplementary resources to alerting human facilitators to check in on the specific learner. Furthermore, understanding the temporal clustering of turning points allows course creators to anticipate periods of high distress. For instance, knowing that weeks four through six are a critical danger zone for affective decline, instructors can intentionally design structural interventions during this phase, such as reducing the cognitive load, increasing the visibility of teaching assistants, or implementing structured peer-mentoring programs to bolster social affiliation before the anticipated emotional slump occurs.

7. Conclusion and Future Directions

7.1 Summary of Contributions

This paper has presented a comprehensive methodological and theoretical framework for the detection and analysis of socio-emotional turning points in longitudinal educational dialogues. By moving beyond static, cross-sectional measures and treating learner interactions as continuous time series, this research has illuminated the dynamic and fluid nature of the online learning experience. The application of advanced natural language processing combined with exact change-point detection algorithms has provided a mathematically rigorous method for identifying significant shifts in both affect and affiliation. The empirical findings, derived from a massive dataset spanning sixteen weeks, confirm that learners undergo distinct structural breaks in their socio-emotional trajectories, heavily influenced by the cognitive demands of the curriculum and the quality of peer interactions. Most significantly, this study established the temporal precedence of affective shifts, demonstrating that changes in emotional valence reliably precede and predict subsequent alterations in social affiliation and community integration. This insight fundamentally reframes how educational technologists should approach the problem of learner retention, shifting the focus from lagging indicators of performance to leading indicators of emotional state.

7.2 Limitations and Future Work

While this study provides substantial advancements, it is essential to acknowledge its limitations and chart a course for future investigation. First, the reliance on text-based dialogue data, while rich, inherently misses the non-verbal and physiological dimensions of affect. Future research should strive to integrate multimodal data streams, such as facial recognition via webcam or physiological sensors, to create a more robust and holistic measure of the learner's emotional state, assuming privacy and ethical standards are rigorously maintained. Second, the algorithms deployed in this study, while highly effective at detecting structural breaks retrospectively, require further refinement to operate in a purely real-time, predictive capacity. The development of streaming algorithms that can detect an impending turning point before it fully materializes remains a critical frontier for affective computing in education. Finally, the true value of identifying these turning points lies in the ability to positively alter the learner's trajectory. Therefore, subsequent research must focus on the design, deployment, and evaluation of automated pedagogical interventions. Controlled experiments are needed to determine which types of interventions—whether cognitive scaffolding, emotional encouragement, or structural social pairing—are most effective at reversing a negative turning point and restoring a learner's positive affect and affiliation within the digital learning community.

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