

# Exploring the Evolution of Reading Literacy Guided by TALPer: A Case Study Based on Ordered Network Analysis (ONA)

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**Abstract:** This study employs Learning Analytics to investigate the dynamic development of Reading Literacy within the Taiwan Adaptive Learning Platform (TALP), specifically focusing on interactions guided by the AI companion, TALPer. Utilizing Ordered Network Analysis (ONA), we analyze the dialogue records of 19 students to map behavioral transitions based on the Progress in International Reading Literacy Study (PIRLS) framework. Unlike traditional frequency-based analysis, ONA provides insights into the directed connections and temporal order between AI scaffolding (E-codes) and student cognitive responses (S-codes). The results reveal a significant structural shift along the X-axis (MR1) between the early phase (First 3 Days) and the late phase (Last 3 Days) ( $p = 0.04$ , Cohen's  $d = 4.91$ ). The comparison plot highlights the specific shifts in response strength. The transition from diverse scaffolding interactions (e.g., E\_L1~E\_L4, E\_COR) and meaningful response (S\_MEA) toward a highly focused pattern of test initiation and surface response confirms that student engagement evolved from exploratory reading guidance to convergent, assessment-oriented interactions. This research highlights the efficacy of ONA in visualizing the temporal evolution of reading competencies in AI-supported digital environments.

**Keywords:** Taiwan Adaptive Learning Platform, Ordered Network Analysis, Reading Literacy, Learning Analytics

## 1. Introduction

The integration of generative AI into Learning Analytics offers precision in tracking the development of Reading Literacy. This study focuses on TALPer, an AI learning companion in the Taiwan Adaptive Learning Platform (TALP). The advancement of generative artificial intelligence (GenAI) has introduced innovative ways to scaffold reading literacy. This study utilizes the TALP, a nationwide web-based platform designed to support personalized learning. Central to this investigation is TALPer, a GenAI-based learning companion integrated within TALP. TALPer employs Socratic dialogue and scaffolding strategies—such as direct extraction and interpretative integration—to guide students through complex texts, functioning as an interactive tutor that fosters self-regulated learning (SRL) behaviors (Kuo et al., 2025). To capture the temporal and directional nature of the dialogue, we employed Ordered Network Analysis (ONA). Unlike traditional unordered models, ONA accounts for the co-temporal order of interactions by producing directed weighted networks (Tan et al., 2023). This approach is particularly suitable for analyzing how a learner responds to specific AI scaffolding levels, as it models not only the co-occurrence of behaviors but also the sequence in which they occur. By aligning interaction codes with the PIRLS cognitive levels, we aim to reveal how students develop coherent and logically structured reading processes through AI-guided feedback loops.

## 2. Methodology

### 2.1 Data Source and Coding

The study analyzed the dialogue logs of 19 students from grades 1 to 12 who interacted with the AI companion for over 10 days. The total dataset comprised 18,589 dialogue entries, where each entry represents an individual response from either a student or the AI companion. This resulted in an average of 978.37 entries per student. To ensure coding reliability, we employed Google Gemini for initial coding, followed by human researcher review for qualitative synthesis. To examine temporal shifts, we focused on two phases: the early phase (first three days) containing 3,047 entries (mean = 160.37 per student) and the late phase (last three days) containing 4,397 entries (mean = 231.42 per student). This high volume of interaction data provides a robust empirical basis for the subsequent ONA. In this study, we applied ONA to our data using the ONA Web Tool (version 1.8.0) (Marquart, Hinojosa, Swiecki, Eagan, & Shaffer, 2021).

The interaction events were coded based on the PIRLS cognitive framework and interaction types. AI scaffolding codes (E-codes) include: Supportive Scaffolding (E\_SUP) for emotional encouragement; Explicit Retrieval (E\_L1) for locating stated info; Direct Inference (E\_L2) for simple logical links; Interpretative Integration (E\_L3) for cross-paragraph synthesis; and Critical Evaluation (E\_L4) for assessing content validity. Additionally, Test Initiation (E\_TST) represents formal assessment prompts, and Corrective Feedback (E\_COR) provides error clarification. Student responses (S-codes) were categorized into Surface (S\_SUR) (e.g., copying text), Meaning (S\_MEA) (e.g., paraphrasing), and Deep (S\_DEP) (e.g., critical insights). This coding scheme allows ONA to map the directional transitions between AI guidance and student cognitive depth.

### 2.2 Ordered Network Analysis (ONA)

Ordered Network Analysis (ONA) is a method for modeling directed connections in data. It extends Epistemic Network Analysis (ENA) by incorporating the order of events, producing directed weighted networks instead of undirected ones (Tan et al., 2023). Like ENA, ONA uses coded data to measure connections among codes and visualizes these structures in a metric space for statistical and visual comparison (Shaffer et al., 2016; Shaffer & Ruis, 2017; Shaffer, 2017). Unlike ENA, ONA accounts for the sequence of codes, enabling analysis where event order matters. For example, Tan et al. (2023) showed that ONA could detect significant differences in team performance that unordered models could not. Compared to Sequential Pattern Mining (SPM), which focuses on micro-level sequences, ONA captures co-temporal interactions between actions and responses.

Therefore, ONA is particularly suitable for ill-structured problem-solving contexts, where interactions are not strictly sequential but order remains important. It models co-occurrences of codes as directed weighted networks and supports simultaneous visual and statistical comparison across multiple networks (Bowman et al., 2021; Tan et al., 2023).

## 3. Results

### 3.1 Model Consistency

The ONA model revealed a significant qualitative shift in interaction patterns along the X-axis (MR1) between the two periods. To examine whether there is an overall structural difference in the network between the "First 3 Days" and "Last 3 Days," a two-sample t-test assuming unequal variance was conducted along the first dimension (X-axis MR1, explaining 8.2% of the variance). Although this percentage represents a small portion of the

total variance, MR1 in ONA is specifically constructed through Means Rotation to maximize the structural contrast between defined groups (early vs. late phases), thereby capturing the most defining qualitative difference. To ensure statistical rigor, the ONA model normalized the networks for all units before dimensional reduction, accounting for varying dialogue lengths across the 19 students. Our model showed excellent goodness-of-fit, with co-registration correlations of 1.0 (Pearson/Spearman) for the first dimension, and 1.0 (Pearson) and 0.75 (Spearman) for the second. The results indicated that the network centroid of the first three days (mean = -0.20, SD = 0.08) was statistically significantly different from that of the last three days (mean = 0.20, SD = 0.08) at the alpha = 0.05 level ( $t(2.00) = -4.91, p = 0.04$ ). Furthermore, Cohen's effect size was 4.91, indicating a massive difference in interaction patterns between the two phases. This mathematically and statistically confirms a substantial shift in the interaction structure over time.

### 3.2 Visual Analysis of Evolutionary Patterns

The network centroid (red square) is located on the left side of the X-axis. Red edges are densely distributed among S\_SUR (Surface Response), S\_MEA (Meaning Response), E\_COR (Corrective Feedback), and E\_L1 to E\_L4 (various levels of PIRLS). This indicates that the early common ground and responses involved extensive text guidance and diverse cognitive interactions. Blue lines represent connections significantly stronger in the "Last 3 Days". The centroid (blue square) shifted clearly to the right side of the X-axis. The most prominent feature is an extremely thick blue edge tightly connecting E\_TST (Test Initiation) and S\_SUR (Surface Response). For example, Student (S\_SUR - Surface Response): "I have finished reading." AI Companion (E\_TST - Test Initiation): "Awesome! Let's talk about this article now!..." (immediately proceeds with specific test questions). According to edge thickness and node role analysis, this reveals that late-stage interactions were highly concentrated on the TALPer proposing multiple-choice tests and students providing simple option-based or confirmatory responses. The robust blue connection between E\_TST and S\_SUR dominated the interaction space. This implies that the learning activity transitioned from "divergent reading guidance" in the early stage to "convergent summative assessment" in the late stage.

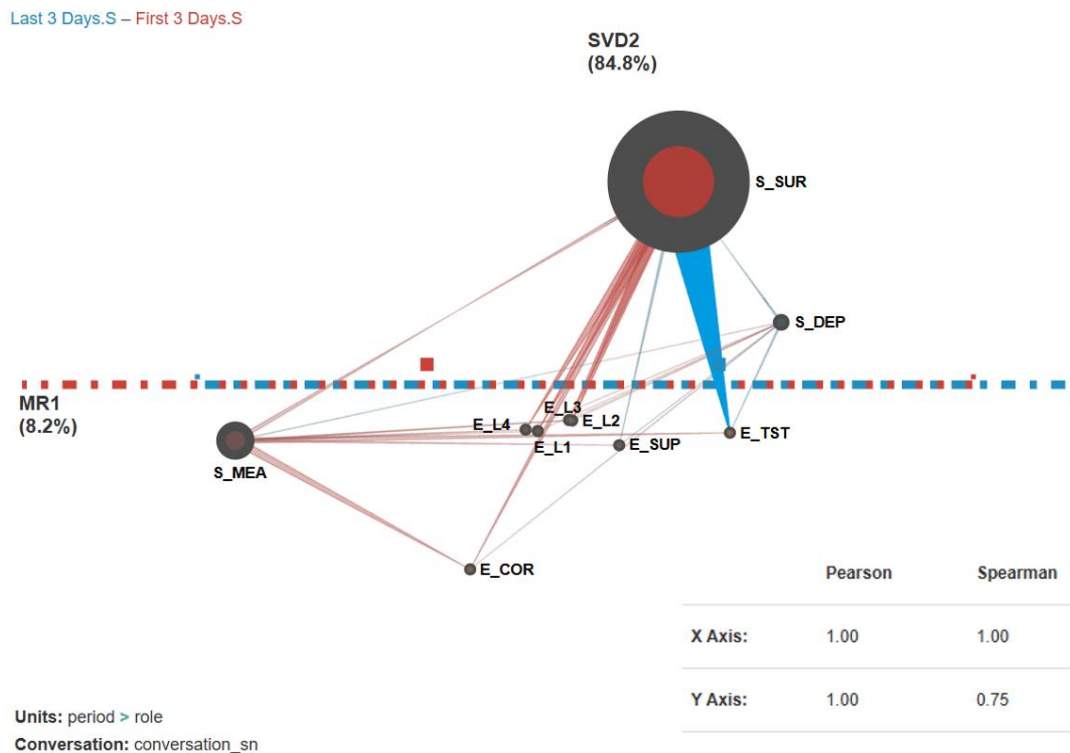


Figure 1. The comparison and difference plot.

## 4. Conclusion

The ONA comparison and difference plots provide a visual and mathematical testament to the net growth in response strength across the 19 students. The distribution of nodes reflects the functional roles of behavioral patterns within different learning strategies. Early interactions were scattered on the left side, involving E\_L1~E\_L4 nodes (Explicit Retrieval, Direct Inference, Interpretative Integration, Critical Evaluation) and students' deep/meaning responses (S\_DEP, S\_MEA). This suggests that during the first three days, the AI companion acted as a "guide and knowledge builder," using multi-level scaffolding questions to help students familiarize themselves with the text, thereby eliciting more diverse thoughtful feedback from students.

The application of ONA within this Learning Analytics study confirms that TALPer effectively scaffolds students through the PIRLS cognitive levels. The findings suggest that the structured feedback loops within TALPer are essential for advancing Reading Literacy from literal comprehension to critical evaluation. Learning is a dynamic process. Based on the temporal dynamic model revealed by ONA, instructional systems should be "time-aware." Future instructional designs can leverage this temporal dynamic model to further optimize adaptive feedback mechanisms.

## References

- Bowman, D., Swiecki, Z., Cai, Z., Wang, Y., Eagan, B., Linderoth, J., & Shaffer, D. W. (2021). The mathematical foundations of epistemic network analysis. In A. Ruis & S. B. Lee (Eds.), *Advances in quantitative ethnography* (pp. 91–105). Springer.
- Marquart, C. L., Hinojosa, C., Swiecki, Z., Eagan, B., & Shaffer, D. W. (2021). *Epistemic network analysis* (Version 1.8.0) [Computer software]. <http://app.epistemicnetwork.org>.
- Kuo, B. C., Bai, Z. E., & Lin, C. H. (2025). Developing an AI learning companion for mathematics problem solving in elementary schools. *Computers & Education*, 105463.
- Shaffer, D. W. (2017). *Quantitative ethnography*. Cathcart Press.
- Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, 3(3), 9–45.
- Shaffer, D. W., & Ruis, A. R. (2017). Epistemic network analysis: A worked example of theory-based learning analytics. In C. Lang, G. Siemens, A. F. Wise, & D. Gašević (Eds.), *Handbook of learning analytics* (pp. 175–187). Society for Learning Analytics Research.
- Tan, Y., Ruis, A. R., Marquart, C., Cai, Z., Knowles, M. A., & Shaffer, D. W. (2023). Ordered Network Analysis. *Communications in Computer and Information Science*, 101-116.