1. Qualitative analysis of one CANDOR conversation

Using one CANDOR conversation as a motivating case, I theorize that validation is a structural "buffer" that licenses deeper, forward-moving responses to self-disclosure. I hypothesize that responses combining validation with forward-moving actions (questions, guidance, co-disclosure) will foster stronger perceived partner responsiveness and connection than validation alone or forward moves alone, a claim I outline two experiments to test.

Literature Review

Individuals often take interpersonal risks through self-disclosure, revealing difficult or stigmatized aspects of themselves. Whether these risks pay off in the form of deeper connection depends not only on disclosure itself, but also how the partner responds. Recent work identifies the interplay between listening and perceived partner responsiveness as the central engine of interpersonal connection (Itzchakov & Reis, 2023). However, a gap remains in understanding the specific behavioral mechanisms that drive this engine. **While we know responsiveness matters, we lack clarity on the strategic sequence of behaviors required to maximize connection.**

Validation is often conceptualized as the primary vehicle for responsiveness. According to Politeness Theory, validation functions as a "Positive Politeness" strategy that regulates social distance by affirming the speaker's value and creating immediate harmony (Brown & Levinson, 1987). However, drawing on Conversation Analysis, I argue that validation creates a structural paradox. Preferred, affiliative responses, like agreement ("totally") and sympathy (i.e., "that sounds really hard") often function as sequence-closing third turns (Schegloff, 2007). In other words, **while validation displays receipt and alignment while implicitly suggesting that the current link of talk is completely or can be safely dropped.** Thus, I propose that validation serves a specific strategic buffer, or moderator, for building up social connections.

To operationalize these subsequent moves, I draw on functional taxonomies of social support (House, 1981; Cutrona & Suhr, 1992; Nick et al., 2018) and reciprocal disclosure literature (Sprecher et al., 2013). I distinguish three distinct types of forward-moving responses that extend the interaction beyond baseline validation. The first type is personal focused elaboration that explore the discloser's internal landscape, including their experiences, feelings, or goals. The second type of question is problem-focused guidance that provide instrumental support, such as information, warnings, or suggestions for handling the practical issue at stake. Finally, the last type is co-disclosure, where the listener takes similar risk to share their related experience or vulnerability.

Hypothesis

We hypothesize that an explicit validating move (emotional/esteem support) will significantly moderate the relationship between the listener's forward-moving response (person-focused elaboration, guidance, or co-disclosure) and connection. Specifically, the positive effect of the forward-moving response on connection will be significantly when it is immediately preceded by an explicit validating move than when validation is absent or minimal.

Method

To test the hypothesis, I propose two complementary experiments. In **Study 1**, we can recruit approximately 500 participants from Prolific and then provide them a series of video vignettes. The series incorporates scenarios to manipulate the listener's response (validation only, forward-moving, combination) to self-disclosure. Participants, instructed to imagine themselves as the discloser, would rate the felt connection. This vignette study would provide a high-control causal test of whether validation-plus-forward sequences are experienced as more connecting than either validation or forward moves alone.

Study 2 would move to a more interactive setting using an LLM-assisted chat platform as the "listener." Participants would be asked to describe real, but comfortable-to-share current struggle, and would then engage in a short text conversation with an AI agent (being told another person on the other side of the screen,) constrained to follow one of several response policies (validation-only, forward-only, combination.) We would collect both subjective reports (perceived connection) and behavioral indices (word counts, duration of conversation, turn counts).

Converging evidence from these two studies would support the claim that connection after self-disclosure depends not simply on how much validation or advice is present, but on how validation is sequenced with forward-moving actions.

2. Small computational pipeline to extract features from a conversation

See Code: https://github.com/xpan4869/TalkLab/tree/main/scripts/feature-extraction

Step 1: Speech recognition was performed using *WhisperX*, which combines OpenAI's *Whisper* model with forced alignment for sub-second timestamping and a *pyannote*-based diarization module for speaker identification. *WhisperX* was selected because it provides state-of-the-art transcription and alignment capabilities in an open and local environment, without the metered billing associated with commercial services such as *AWS Transcribe*. The output of this stage was a speaker-attributed transcript with precise onset and offset times, which served as the foundation for turn segmentation. Some diarization errors were observed, especially in cases of overlapping speech or similar vocal timbres. Future work can try out different models to find the most suitable one. The other problem observed in hallucination. In the last part of video, one speaker was talking to himself. While the voice is so ambiguous or low, it was transcribed as something totally irrelevant. It is necessary to acknowledge the limitation of technology and manual check should be applied if needed.

Step 2: Automatic speech recognition systems typically fragment speech into short segments separated by silences or listener responses, which do not correspond to turns in the sense used in conversation analysis. Turn segmentation in this study therefore followed the NaturalTurn methodology proposed by Cooney and Reece (2025). Consecutive utterances produced by the same speaker were merged whenever the inter-utterance pause was shorter than 1.5 seconds, reflecting the observation that brief pauses are often cognitive rather than turn-yielding. In addition, backchannels such as "mm-hm" or "yeah," which function as acknowledgements rather than attempts to take the floor, were detected using curated lexical lists and did not terminate an ongoing turn. This procedure reduces artificial fragmentation and produces conversational units that are more psychologically meaningful, retaining the continuity of floor-holding. Although my choice is based on past literature, the decision of the threshold and dictionary is still arbitrary. Before applying those rules, we should tailor those metrics based on context.

Step 3: The final component enriched each identified turn with **text- and audio-based features intended to capture affective dynamics**. The first features are the **sentiment scores** estimated using *VADER* sentiment analyzer. *VADER* is a state-of-art dictionary-based tool. Admittedly, we can use *roBERTa*-base with greater contextual accuracy. However, *VADER* are faster and proven quite useful in informal speech. Each turn received a compound sentiment score between −1 and +1.

A complementary measure of affective states was the **pitch variability** (F0 standard deviation). That was computed over voiced segments using the PYIN algorithm in librosa. This measure indexes vocal expressiveness while controlling for baseline differences across speakers. While PYIN is effective, it is computationally intensive and can struggle with breathy voice quality; future large-scale implementations should mitigate this by migrating the pipeline to a GPU environment and parallelizing processing.

Together, the valence and arousal features provide a multimodal description of how affect is expressed during interaction.

3. Analysis of hand-coded conversation sequence data

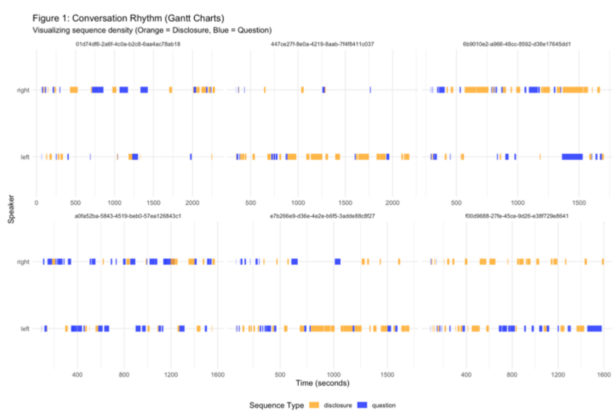
Code:

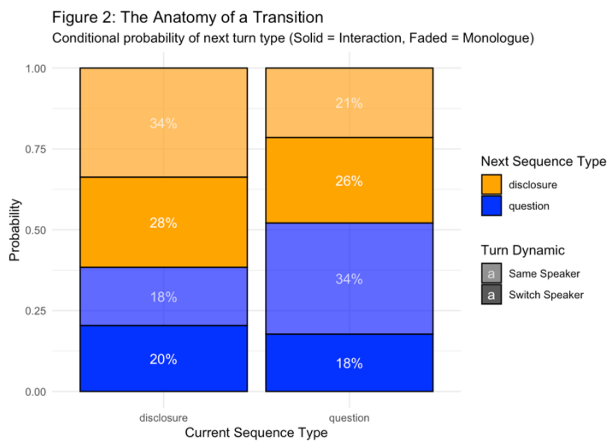
https://github.com/xpan4869/TalkLab/blob/main/scripts/convo-sequence_analysis/sequence-analysis.R

I first examined the basic descriptive structure of the conversations, focusing on the relative prevalence of questions and disclosures. On average, conversations contained slightly more disclosures than questions. The mean number of disclosures was about 32 per interaction, compared with about 26 questions. Variability was higher for questions (SD ≈ 16) than for disclosures (SD ≈ 9), indicating that some conversations were highly question-heavy while others had relatively few. Disclosures, by contrast, were more consistently present across conversations. I run an additional correlation between the number of disclosures and question and no significant results found, indicating a more nuanced approach for sequence turns.

To establish a baseline understanding of conversational flow, I visualize the sequence duration and type for a random sample of dyads. **Figure 1 reveals distinct interaction styles**, ranging from rapid, short exchanges to extended blocks of sustained disclosure. Some dyads are predominantly question-driven, others are disclosure-heavy, and still others maintain a more balanced pattern. In some cases, the interaction even resembles an interview, with one partner actively eliciting information from the other. This variance suggests that the rhythm of interaction, rather than content alone, may be a distinguishing feature of conversation quality.

I then looked into the structural patterns within conversations by analyzing adjacency pairs. Here, I distinguished transitions that involved a speaker switch from those where the same speaker continued. **Figure 2 shows that when a question is followed by another question, this transition most often occurs within the same speaker**. Surprisingly, more than 65% of all Question → Question sequences are self-generated rather than produced by the partner. This indicates that questions are frequently used to continue speaking, often through multi-part or elaborating inquiries, rather than immediately handing over the floor. In contrast, disclosures demonstrated clear momentum. **Once a disclosure occurred, the most likely subsequent turn was also a disclosure,** regardless of whether the speaker switched or stayed the same. The transition from Disclosure → Disclosure therefore operates as a stable conversational state, supporting continuity, **reciprocity**, and an unfolding rhythm of shared vulnerability.





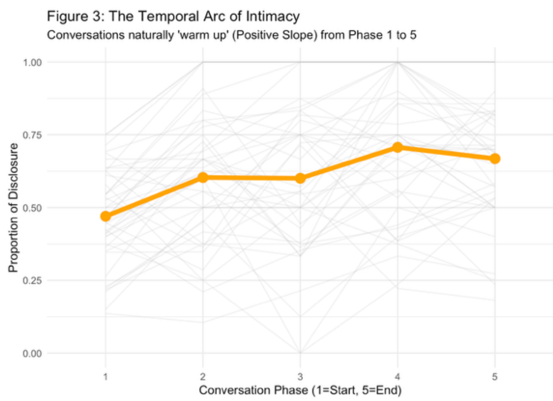
To understand how conversations evolve, I normalized interaction time (0-100%) and divided each conversation into 5 phases. This resolution captures the "warm-up" trajectory while smoothing sequence-level noise.

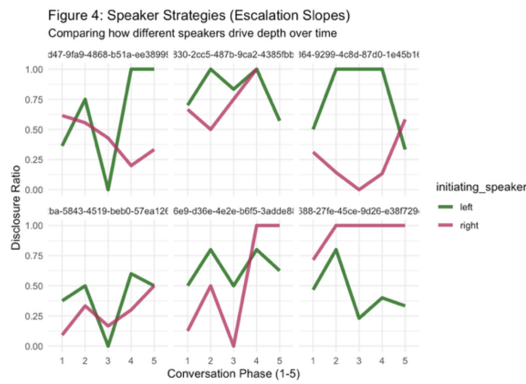
Figure 3 shows how the proportion of disclosure changes across five equal segments of each conversation. The average line (in orange) rises from about 0.48 in Phase 1 to a peak of roughly 0.70 in Phase 4, followed by a slight decline in Phase 5. Most individual conversations (gray lines) show some upward movement from early to later phases, even though trajectories vary. The dominant pattern is a positive slope from the beginning of the interaction into the middle phases. Disclosure gradually becomes more frequent as conversations unfold. The last segment shows a small drop, but remains higher than the starting level.

This suggests that conversations naturally "warm up." Early stages appear to involve less personal sharing, whereas middle and later phases tend to sustain longer or more frequent disclosures. The slight decline at the end may reflect wrap-up or time constraints, rather than a drop in intimacy per se.

To link temporal dynamics to "Good Conversationalist", I disaggregate the analysis by speaker. I calculate an Escalation Slope for each participant, representing the rate at which they deepen the conversation over time. **Figure 4 demonstrates that escalation strategies often differ within**

dyads. Future work could classify trajectory shapes (e.g., rising, convex, plateauing) and test whether alignment or synchrony predicts relational outcomes.





Based on the structural finding that $D \rightarrow D$ represents a stable and reciprocate state, and the temporal finding that conversations follow a distinct escalation arc, I propose two hypotheses to predict Good Conversationalist ratings.

While answering questions ($Q \rightarrow D$) satisfies baseline politeness norms, it can establish an asymmetric "Interview" dynamic. True connection is defined by the symmetric exchange of vulnerability ($D \rightarrow D$). Therefore, the ability to sustain a reciprocity loop represents a higher-order social skill than basic responsiveness. Accordingly, the **first hypothesis** goes: An individual's **Reciprocity Score**, the probability of meeting a partner's disclosure with a reciprocal disclosure, will be a **significantly stronger predictor of partner ratings than their Responsiveness Score**, the probability of self-disclosure after a partner's question.

To evaluate this hypothesis, we could fit a linear regression model in which the reciprocity and responsiveness scores of each participant served as predictors of their partner's perceived good convsersationist rating.

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