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DIMS: a no-code dashboard linking multimodal dynamic signals to communication practices

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ABSTRACT

Communication research increasingly relies on multimodal time-series data spanning physiological, behavioral, audiovisual, and transcript-based measures. Yet the phenomena these data are meant to capture, such as social connection or attitude, often unfold in temporally specific ways that are lost when signals are reduced to averages or analyzed in isolation. This article introduces the Dynamic Interaction and Multimodal Signals (DIMS) Dashboard, an open-source tool that aligns multiple time series with synchronized video and transcript, allowing researchers to inspect how statistically identified patterns correspond to communicative events. We present two exploratory case studies. The first examines inter-brain synchrony during interpersonal conversation; using a dynamic dyadic systems lens, we show how synchrony peaks can be read as candidate dyadic events whose meaning depends on interactional context. The second examines coupled facial electromyography during advertisement viewing; using an emotional-flow lens, we show how orbicularis oculi activity that appears positive in isolation can signal a sustained, co-active mixed-emotion state when paired with corrugator activity. Across both cases, DIMS supports an iterative qualitative-quantitative workflow: quantitative signals flag moments worth inspecting, and qualitative interpretation clarifies what they mean. DIMS does not replace statistical or qualitative analysis but creates a shared analytical space for theoretically meaningful observation.

Communication research increasingly relies on multimodal, time-series data (e.g., Han et al., 2025; Solomon et al., 2021, 2023). Whether two partners are building a conversation turn by turn or an audience is responding to a message as it plays, communication outcomes researchers seek to explain (e.g. social connection, engagement, persuasion, attitude change) emerge from dynamic processes that continuously interact with one another. Capturing these processes usually means recording physiological, behavioral, audiovisual, and transcript-based measures within a single session, each sampled densely across the entire experimental protocol. Yet the analytic conventions applied to such data often work against their temporal grain. When each signal is modeled in isolation and reduced to an average over a condition or a participant, the moment-to-moment relationships among signals (or the very structure in which the phenomenon lives) are flattened out of view (Han et al., 2025). The problem is both practical and statistical: researchers typically inspect their signals in separate tools and separate windows, scrolling a video in one place, a physiological trace in another, and a transcript in

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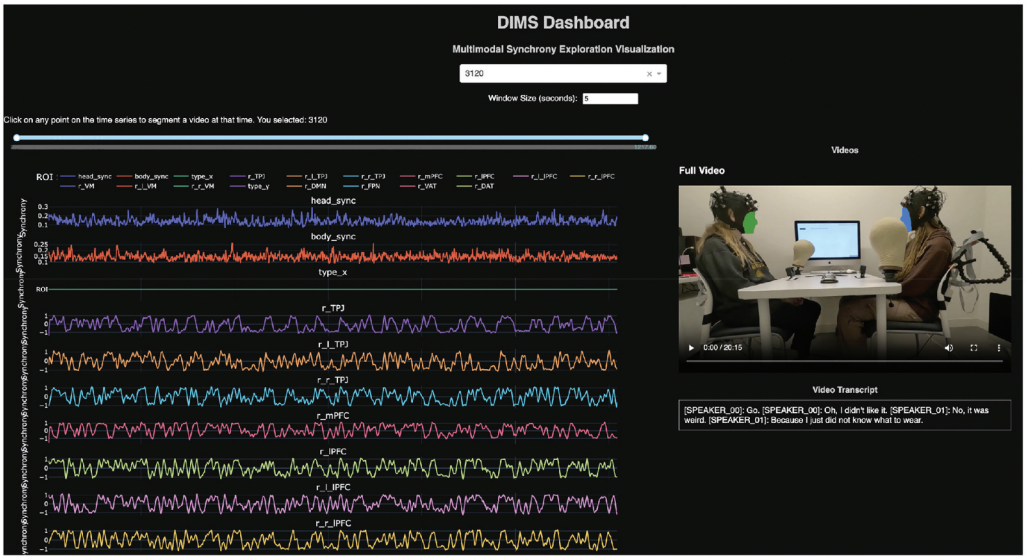


Figure 1. DIMS dashboard visualization of inter-brain synchrony during get-to-know-you conversation.

a third. As a result, patterns spanning modalities are easily overlooked, simply because no single view holds them together.

This points to a methodological challenge that is easy to detect but hard to resolve: once a statistical pattern has been found in multimodal data, how does a researcher return to the raw record (e.g. the video, the transcript, the co-occurring signals) to interpret what actually produced it? The stakes here are not merely procedural, but theoretical. Many of the dynamics that distinguish one communicative process from another are latent beneath the surface of the observable data pattern, yet it is precisely these dynamics that adjudicate between competing theoretical accounts and reveal where existing theory needs development (Solomon et al., 2023). Advancing communication theory therefore depends on being able to see these dynamics. Many pipelines can preprocess raw data and compute summary statistics or dynamical measures, but far fewer help researchers inspect how those derived measures relate to the events from which they arise. Annotation environments such as ELAN (Wittenburg et al., 2006) support careful coding and segmentation, yet they are not built for flexible, side-by-side exploration of multiple researcher-generated time series alongside synchronized video. What is missing is an interpretability aid: a way to ask, of any moment in any derived measure, "what was actually happening here?"

In this Teacher's Corner, we introduce the Dynamic Interaction and Multimodal Signals (DIMS) Dashboard, an open-source tool built to close this gap between computed signals and the interaction that produced it. DIMS synchronizes a video recording with an unlimited number of user-supplied time series and a transcript through an interactive, point-and-click interface: clicking on a moment in any time series cues a short video segment and transcript centered on that moment, so an analyst can move fluidly between a peak in the data and the event on screen (Figure 1). DIMS is deliberately not a preprocessing pipeline: it does not clean signals, estimate synchrony, or align clocks. It assumes that researchers have already generated time-aligned modalities, and provides a single space in which the temporal structure of communication can be interrogated against the record of the interaction itself. In this sense, DIMS is intended not only as visualization convenience but also as an instrument for communication theory development: by making latent temporal dynamics inspectable, it helps researchers test whether a computed pattern reflects the communicative process a theory posits, and refine that theory when it does not. The dashboard is publicly available at https://github.com/dims-network/dims, with a demo, a source-code version researchers can adapt to their own data, and a no-

code point-and-click version. Some built-in quantitative analyses (including recurrence quantification, wavelet analysis, and plotting) are also available for users.

DIMS in interpersonal and mass communication

The reason both interpersonal communication (e.g. Solomon et al., 2021, 2023) and mass communication (e.g., Han et al., 2025) research increasingly relies on multimodal, time-series data lies in their common foundational element: interaction. Interaction is where communication happens, whether between two people in conversation or between an audience and a mediated message. The study of interpersonal communication rests on the premise that partners in dialogue encode thoughts into symbols, draw inferences from one another's behavior, and take on personal and relational consequences from their exchanges, so that conversations become the place where stressors are amplified or attenuated, conflicts entrenched or resolved, and goals advanced or thwarted (Solomon et al., 2021, 2023). Mass communication is interactional in its own right: media messages such as advertisements are constructed to engage audiences, audiences respond to them dynamically as they unfold, and those responses in turn shape attitudes, memory, and ultimately public opinion (Han et al., 2025; Lang et al., 2009). In both cases interaction is where messages acquire their force. That shared structure is why one workflow can serve both. We therefore develop a case study from each subfield to show how DIMS keeps those interactional dynamics in view.

In interpersonal communication, the unit of interest is typically a dyad or small group interacting in real time, and the data streams reflect that: prosodic and turn-level features from speech, head and body movement from video-based motion tracking, peripheral physiology such as heart rate or skin conductance, and even inter-brain neural synchrony from portable neuroimaging, all time-aligned to a recording of the conversation. Theoretically, as the dynamic dyadic systems perspective suggests, this is the terrain of approaches that treat conversation as a dynamic system unfolding turn by turn, in which the meaning of any moment depends on what preceded it (Solomon et al., 2021, 2023). The questions these approaches raise are about temporal structure beyond conversation-level averages: when partners align, how a shared state is sustained or repaired, and how a dyad moves from one conversational mode to another. DIMS helps by letting a researcher take a candidate event in one of these streams, such as a peak in inter-brain synchrony, and return it to the conversational moment that produced it, so that a computed dynamic can be recognized as a communicative practice and be differentiated from an artifact. Our first case study demonstrates the capacity of DIMS for this in detail.

In mass communication, the unit of interest is oftentimes an individual responding to a mediated message. This human-media interaction produces multimodal data, including neurological, physiological, cognitive, emotional, behavioral, experiential, and outcome measures. Outcome variables typically reflect the media effects of interest and by examining the process-related signals, researchers try to understand how detected media-effect pattern arise from those multimodal dynamic signals (Han et al., 2025; Lang, 2017). Here too the theoretically decisive pattern is, beyond averaged signals, temporal and within-individual: for example, how a viewer's emotional responses arise, blend, and resolve across the message. DIMS helps by aligning the physiological streams with the unfolding advertisement and the viewer's reported attitude, so that a configuration such as coupled facial response signals can be read against the exact moment of the message that produced it. Our second case study demonstrates this in detail.

Beyond these two demonstrations, we provide a practical guide for applying the DIMS approach to a reader's own data, including the no-code workflow for building a dashboard without programming, and we situate DIMS within the broader landscape of multimodal-data tools. For researchers who work in a dynamical-systems idiom, the point-and-click version also builds in analyses such as recurrence quantification and cross-wavelet plotting; but these are conveniences layered on the tool's central purpose, which is to keep the temporal structure of communication visible long enough

for researchers to identify patterns that can explain statistical findings and thus facilitate theoretical testing.

Our aims in this article are threefold. First, we demonstrate DIMS with two case studies chosen to span the communication subfields: an interpersonal communication case, in which neurological signals recorded during dyadic conversations are examined through the lens of the dynamic dyadic systems framework (Solomon et al., 2021, 2023), and a mass communication case, in which multimodal physiological responses recorded during advertisement viewing are examined in relation to psychological outcomes such as attitudes and memory (Han et al., 2025). Second, we discuss how communication scholars could apply the DIMS approach to their own datasets. Third, we situate DIMS within the broader landscape of multimodal data tools and communication research, and discuss how it supports the complete circle of scientific inquiry (Babbie, 2017) by bridging qualitative and quantitative analysis.

Case study 1: inter-brain synchrony during bonding conversation

Our first case study focuses on interpersonal conversation and uses DIMS to examine moments when two strangers' neural signals become more synchronized while they get to know each other. The theoretical starting point is that conversation is not only a linguistic exchange, but a process where neurocognitive resources are employed while gaining mutual understanding. Specifically, we focus on the default mode network (DMN), a collection of distributed, interconnected brain regions that are typically suppressed when a person is focused on external stimuli, but that become active in the absence of such demands, "defaulting" to internally oriented thought such as self-reflection, recall of personal experiences, mind-wandering, and envisioning the future (Andrews-Hanna et al., 2014; Buckner & Carroll, 2007; Menon, 2023). Although the DMN was first characterized by what it does at rest, subsequent work has recast it as an active sense-making system: it integrates incoming information with stored knowledge to build and continuously update coherent models of narratives, events, and social situations (Fedorenko et al., 2024; Yeshurun et al., 2021). Understanding a conversation is not only a matter of decoding words: each partner must hold context, infer the other's intentions, connect incoming utterances to prior knowledge, and keep updating an internal model of what kind of interaction is unfolding. These integrative, internally oriented processes are supported by and reflected in the DMN network in the human brain.

In conversation, these processes also become interpersonal. Inter-brain synchrony within the DMN (i.e. the co-fluctuation of DMN activity between the interlocutors) can therefore be understood as a candidate marker of shared sense-making, not simply because two brains are "doing the same thing," but because two people may be aligning in how they interpret the unfolding interaction (Lieberman, 2022; Stephens et al., 2010; Yeshurun et al., 2021). In the present case study, we focus on inter-brain synchrony in the right temporoparietal junction (rTPJ), a key DMN subregion and the strongest single-region predictor of interpersonal connection within the network in Miao et al. (2026), making it a useful target for inspecting DMN-based dyadic sense-making in the dashboard.

The dynamic dyadic systems (DDS) framework treats conversation as a coupled system in which two partners act and react to one another as they jointly construct the interaction (Solomon et al., 2021). Rather than characterizing a conversation by an overall score, DDS uses dyadic time series to examine how partners' back-and-forth contributions are organized in time: identifying individual moves, the dyadic states those moves create, recurrent conversational units, and how those units evolve within a conversation and differ across dyads (Solomon et al., 2021, 2023). For the present case study, the value of DDS is that it specifies what a peak or transition in a dyadic signal might mean. When we compute inter-brain synchrony from two conversing brains, a rise in synchrony can be treated as a candidate dyadic-system event: a moment in which the partners' states became more coupled. Whether that moment corresponds to mutual engagement, a task transition, a recognizable communicative practice, or an artifact can only be adjudicated by returning the signal to its interactional context.

We apply this logic to the conversation data displayed in the DIMS Dashboard. The data come from ConvoConnect, a dataset of 70 stranger dyads completing 20-minute get-to-know-you conversations while wearing portable neuroimaging equipment, with synchronized audiovisual recordings and transcripts (Miao et al., 2025, 2026). The dashboard displays time series of neural synchrony, head synchrony, and body synchrony, and video and transcript in the same interface, and allows the analyst to click on a point in the time series to preview the corresponding video segment (Miao et al., 2025). Visual inspection showed that rTPJ synchrony fluctuated over the conversation, with the two brains dynamically aligning and diverging. To examine what these fluctuations corresponded to interactionally, we selected ten 10-second windows centered on sharp rises in rTPJ synchrony and used the dashboard's point-and-click video preview to inspect what was happening at each moment (Miao et al., 2025).

The inspection was revealing in two ways. In eight of the ten segments, a sharp rise in rTPJ synchrony coincided with visibly high engagement: verbal moves such as agreement, supporting examples, repetition of each other's exact words, overlapping speech during storytelling, rhetorical questions, and shared laughter, along with nonverbal moves such as frequent head nods and partners moving their bodies at a similar frequency (Miao et al., 2025). These moments offer a face-validity check on the social-neuroscience claim that rTPJ synchrony can track mutual social engagement. The remaining two segments showed the same synchrony signature but a different interactional event: a prompt transition, in which one partner was finishing the previous prompt while the other began reading the next one (Miao et al., 2025). These two readings do different theoretical jobs. The 80% case supports the interpretation of rTPJ synchrony as a marker of shared engagement; the 20% case flags a confound that is also theoretically useful, suggesting that sharp rTPJ rises may need to be subtyped into engagement-driven versus task-transition-driven synchrony.

Crucially, the qualitative pass also seeds a quantitative test. If engagement-driven synchrony is carried by shared bodily behavior, then sharp rises in rTPJ synchrony should be associated with concurrent movement synchrony. To test this, Miao et al. (2025) identified sharp rises as peaks in the first time-derivative of rTPJ synchrony and regressed the magnitude of those rises against concurrent head- and body-motion synchrony across the sample conversations. Head-motion synchrony was reliably associated with the size of rTPJ rises, whereas whole-body synchrony was not (Miao et al., 2025). This quantitatively echoes the qualitative observation that these coupled moments are multimodal and, more specifically, head-anchored.

The analytic point is that rTPJ synchrony, even when theoretically grounded in the DMN, is not a single psychological object. A rise in synchrony can index different dyadic processes depending on what the partners are doing at that moment. In a static plot, the peaks may look equivalent. In DIMS, they become inspectable. The analyst can ask: What was being said? Who was speaking? Was one partner elaborating while the other acknowledged? Did the partners laugh, nod, repeat each other's language, or move together? Was the dyad deepening a topic, repairing the interaction, or transitioning into a new prompt? These questions move the interpretation from "inter-brain synchrony increased" to "what kind of dyadic event did this increase correspond to?"

Case study 2: emotional flow during advertisement viewing

Our second case study's focus shifts to advertisement viewing. While traditional mass communication research has primarily focused on media effects, understanding the psychological processes that unfold during media use is essential to fully understand those outcomes that arise from the processes (Han & Lang, 2019). One common approach to understand media processes is to use psychophysiological measures that are meant to capture the dynamic changes in users' cognitive and emotional processing during media exposure (Potter & Bolls, 2012), however, the statistical methods used to analyze those data often summarize this process through averages, which can obscure important temporal patterns, such as when a typical response occurred, what other signals it co-occurred with,

and how the viewer moved into or out of that state (Han et al., 2025). Here, we use DIMS to make that temporal structure visible.

The case study is a secondary analysis of the multimodal advertisement-viewing dataset reported by Han et al. (2025). The focal psychological outcome is attitude toward the advertisement, and the focal physiological signals are facial electromyography over orbicularis oculi (OO) and corrugator supercilii (CORR). Specifically, OO measures the activation of the orbicularis oculi muscles located beneath the lower eyelid. Because these muscles are activated during smiling, OO activity is commonly interpreted as an index of positive emotion. In contrast, CORR measures the activation of the corrugator supercilii muscles located above the eyebrow, which are associated with frowning, and is therefore commonly interpreted as an index of negative emotion (Potter & Bolls, 2012). In the original analysis, Han et al. (2025) argued that attitude is better understood through the coupling of these signals over time than through either channel alone. The theoretically interesting object is therefore not simply whether a viewer "smiled more" or "frowned more," but how audiences respond emotionally to the ad at specific moments and how positive and negative emotional responses jointly shape their attitude toward the ad and the brand.

This case study is organized around the concept of emotional flow, which focuses on the way emotional experience changes within a viewer during exposure (Nabi, 2015; Nabi & Green, 2015; Shen & Li, 2023). Shen and Li (2023) argued that this temporal dimension has often been undermeasured: rather than directly modeling emotional flow, many studies infer it from message conditions or from shifts between dominant emotions. Their proposed solution is a longitudinal, within-individual approach in which emotional flow is quantified as the shape and amount of change in one or more discrete emotions over time (Shen & Li, 2023), and this approach has been shown to reveal nuanced relationships between fear appeal and persuasion (Shen, 2017). For the purpose of this demonstration, we borrow this analytic stance: the object of analysis is not only "how much emotion" a viewer shows, but the temporal form that emotion takes while the message unfolds (Shen, 2017; Shen & Li, 2023).

We extend this stance to coupled facial electromyography in ad viewing. Emotional flow in this case is the unfolding configuration of positive and negative emotional responses during advertisement exposure (Han et al., 2025). Notably, while a rise in OO alone could be read as positive engagement, the same trace points to a different emotional flow when it co-occurs with sustained CORR: a co-active, mixed, or tense response rather than straightforward liking (Han et al., 2025). Read this way, Han et al.'s central finding on attitudes is fundamentally a finding about trajectory. Viewers who passed through a less stable co-active state with moments when OO and CORR were both high, but not sustained as a stable pattern, reported more favorable attitudes and purchase intentions, whereas viewers who showed a more stable, sustained co-active state reported less favorable attitudes (Han et al., 2025). In emotional-flow terms, a brief moment of mixed activation that resolves is not the same process as sustained mixed tension, even when average levels of OO and CORR look similar (Shen & Li, 2023).

To make this pattern inspectable in DIMS, we load each advertisement as its own session and display viewers with the two lowest and two highest self-reported attitudes toward the same ad. The clearest example is the elevator advertisement (Figure 2). At the level of visible content, the ad is tense and suspenseful: the viewer is placed in front of an elevator, with the narrative tension depending on what will happen next as a woman walks toward her car. At the level of physiology, this creates a useful case for showing why single-channel interpretation is risky.

The dashboard displays time-aligned facial electromyography responses from four viewers watching the same 30-second elevator ad from the Han et al. (2025) advertisement-viewing dataset. The top four traces show orbicularis oculi (OO) activity and the bottom four traces show corrugator supercilii (CORR) activity. Viewers are selected to contrast the two lowest-attitude participants for this ad (LowAttitudeSub141, LowAttitudeSub142) with the two highest-attitude participants (HighAttitudeSub125, HighAttitudeSub176). The video panel on the right links the physiological traces to the full advertisement and to the currently selected segment, allowing the analyst to inspect what was occurring in the ad at moments of physiological

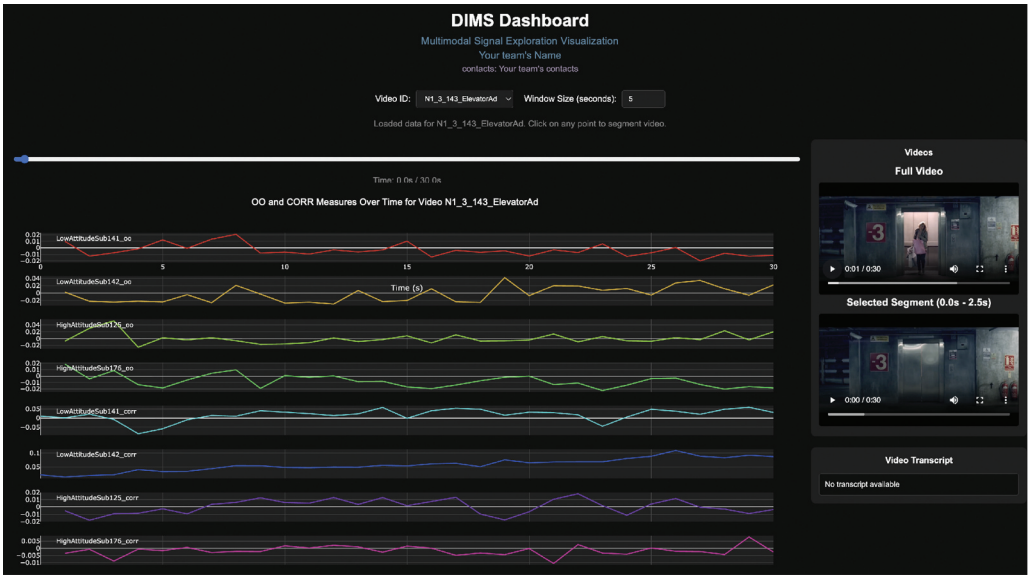


Figure 2. DIMS dashboard visualization of emotional flow during the elevator advertisement.

change. This example illustrates why single-channel interpretation is limited: apparent OO activation can be read differently depending on whether it co-occurs with sustained CORR, indicating a more co-active or mixed emotional state rather than straightforward positive engagement.

One low-attitude viewer (Subject142) shows noticeable OO activation in the second half of the clip. Read alone, that trace could be mistaken for positive engagement: the viewer's OO is rising, so perhaps the ad makes this viewer feel positive and thus builds a positive attitude toward the ad and the brand. But the paired CORR trace tells a different story. During the same window, CORR is also high and sustained. The viewer is not simply showing positive facial activation; they are in a sustained co-active state, where signals associated with both emotional valence are moving together. In other words, the viewer's emotional response looks tense and mixed rather than cleanly favorable.

The high-attitude viewers do not show the same sustained CORR pattern. Their OO responses are not necessarily larger in a global sense, but when OO rises, it is less consistently paired with strong sustained CORR and sometimes with even suppressed CORR. This is the key analytic point: stronger OO activation does not necessarily correspond to positive attitudes. A strong physiological response can mean that the ad is engaging the viewer, but engagement can take different emotional forms (Han et al., 2025). For a low-attitude viewer, the ad may produce arousal or tension without resolving that tension into a favorable response. For a high-attitude viewer, the emotional flow may include moments of tension, but those moments appear less stable and less locked into sustained OO-CORR co-activation.

This is where DIMS adds something beyond either the statistical model or an average pattern. The dashboard allows the analyst to move between three levels of evidence: the raw physiological traces, the coupled emotional state, and the exact moment in the advertisement that coincides with a peak or transition. Instead of saying "OO went up," the analyst can ask: OO went up with what? At what moment in the ad? Did CORR rise with it? Did the state persist, or did the viewer move out of it? These questions turn physiological time series into interpretable media-process data, and in turn, motivate researchers to use or develop analytical methods that better capture such dynamics.

Applying DIMS to your own data

The two case studies above use different modalities and theoretical frames, but they follow the same basic workflow. In this section, we reconstruct Case Study 2 as a step-by-step example of how a researcher can build a DIMS dashboard from their own files.

Preparing the data

Researchers begin by organizing the data streams they want to display in the dashboard. In DIMS, each recording session is organized around a single video. For an interpersonal dataset, one session can be one dyadic conversation that comes with a recording video of their interactions. For an advertisement-viewing dataset, one session can be a single viewing period for one audiovisual advertisement. Each session can include a video file, an optional transcript, and one or more time-series CSV files.

Each CSV file is visualized as one time-series curve. The CSV format should contain one column for time and one column for value (see examples in Figure 3). The time column could be integers or numbers with decimals, but should be in seconds, using the same clock as the video. The value column can contain raw or preprocessed signals, such as the OO and CORR indices used in Case Study 2, or derived measures, such as the inter-brain synchrony scores used in Case Study 1. DIMS can also import .eaf files from ELAN, allowing researchers who already use ELAN for qualitative annotation to bring those annotations into the same dashboard environment.

Correct temporal alignment is the most important requirement. The time axis of each signal must map directly onto the video clock. In other words, the 0-second of video should match with 0-second of CSV time, and the time-series duration should match the duration of the video for that session. If the files are misaligned, the dashboard will still display them, but the interpretation will be wrong. To help researchers handle this step during setup, the builder includes options for trimming video stimuli or adding zeros before or after a signal, but we highly recommend aligning timestamps across data sources at the preparation phase.

DIMS uses file names to help match time-series files to the correct video. The naming strategy for each CSV file is, thus, to begin each with the full name of the corresponding video, followed by a label

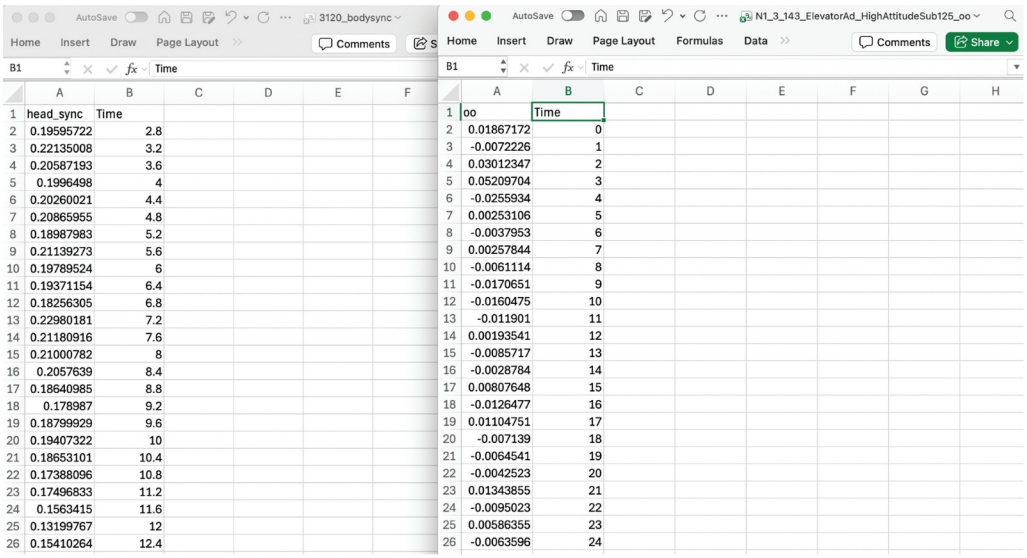


Figure 3. Preparing files: example data files in DIMS dashboard. Note: Each CSV file has two columns: value and time (in seconds). The names of the CSV files have two parts: the first part should be the exact same as the video file names, and the second part is what you'd like to display on the dashboard right next to the timeseries.

for the specific signal, to allow DIMS to automatically detect same-session data using the video name. For example, the video named N1_3_143_ElevatorAd.mp4 (Figure 2) in the dashboard will be paired with CSV file N1_3_143_ElevatorAd_LowAttitudeSub142_oo.csv (Figure 3 right); and the video named 3120 (Figure 1) will be paired with CSV file 3120_bodysync (Figure 3 left). In this case, the shared file stem tells the builder that the video and the physiological files belong to the same session, while the final label tells the dashboard what curve to display.

Building the no-code DIMS dashboard

The no-code workflow is designed for researchers who want to create a dashboard in a point-and-click way. After downloading the DIMS folder from GitHub (https://github.com/dims-network/dims) (Figure 4), users open the builder folder and run the file that corresponds to their operating system: run.bat for Windows, run.command for macOS, or run.sh for Linux (Figure 4). On macOS, users may see a security warning because the file was downloaded from the internet. In that case, they can open System Settings, go to Privacy & Security, and choose "Open Anyway" for the blocked run.command file (Figure 4).

Once the builder opens in the browser, Step 1 asks for basic study information. As shown in Figure 5, the user specifies whether they are starting a new study or opening a previous one, chooses the folder where the dashboard should be created, and enters the title, subtitle, authors, contact information, and playback window.

The playback window determines how long the video is displayed when the analyst clicks on a point in the time series. This is not a fixed property of DIMS, but should be chosen based on the timescale of the phenomenon being studied. For a conversation in Case Study 1, a 10-second window may be useful because it captures several turns or a short sequence of social action. However, for a 30-second advertisement in Case Study 2, a time window should be chosen based on the response pattern of a specific physiological signal. For example, electrodermal activity responds on a timescale of seconds while startle responses occur on a millisecond basis.

Step 2 imports the files (Figure 6). Users can drag files into the builder or browse for them manually. The builder identifies whether each file is a video, transcript, ELAN file, or time-series CSV, and it assigns each file to a session based on the file name. The user can then check and edit the session name and data label before proceeding. This step is important because it gives the researcher a chance to catch mistakes before the dashboard is built: a file assigned to the wrong session, a mislabeled signal, or a time series whose name is too vague to interpret later.

After the files are imported, users proceed through the remaining builder steps: align the data, choose tabs and analyses, build the dashboard, and open the finished version. The alignment step is an optional convenience for adjusting the temporal correspondence between a time series and the video within DIMS. Because accurate alignment is essential for interpretation, we include this feature as a simple way to diagnose or make small adjustments when needed. However, we generally recommend correcting the timestamps directly in the source CSV files before import, as this provides a more accurate, reproducible, and sustainable solution across analyses and future uses of the data. Users can also optionally add built-in analyses, including CRQA, wavelet coherence, and effector analyses, depending on their research questions; these analysis options will be described in greater detail in a separate paper. Once the dashboard is built, it displays the video, the selected segment, the transcript if available, and all time series associated with the session. Researchers can click any point in a time series to cue the corresponding segment of the video. An interactive demo DIMS Dashboard is available at: https://dims-network.github.io/case-demo/.

For readers who feel comfortable with the command-line, we provide a separate tutorial in the released DIMS v1.5 documentation: https://dims-network.github.io/dims/1.5/getting-started/. This alternative path is more flexible: the same setup can be repeated automatically across many studies instead of redone by hand each time. For researchers who would like to contribute technically by adding new tabs, analyses, or features, the contributor-facing documentation is available here: https://dims-network.github.io/dims/1.5/extending/.

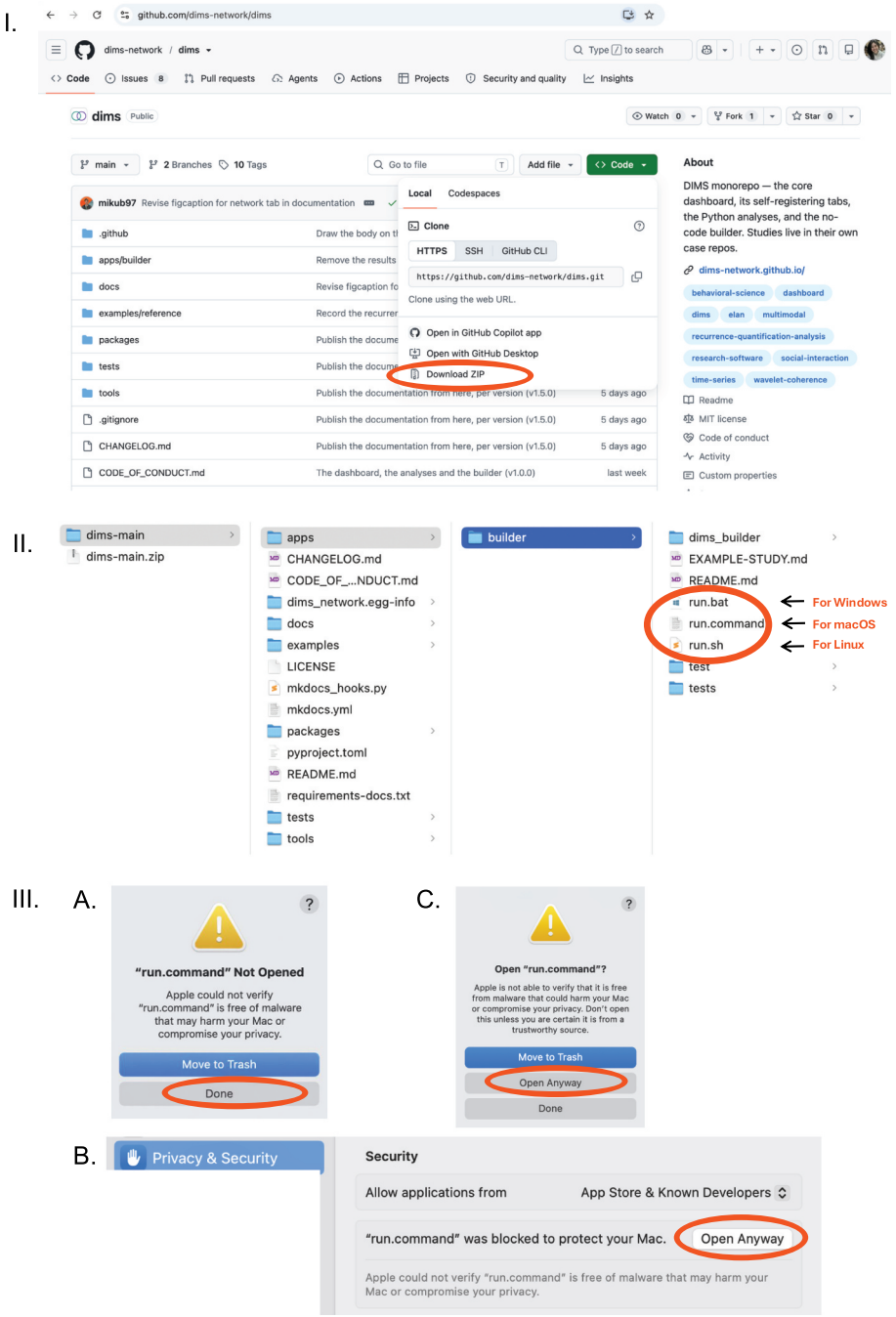


Figure 4. Launching the builder: download ZIP, open the OS-specific run file, and handle the macOS security warning. Note: Red circles and fonts indicate what users should follow from this figure.

Interpreting the dashboard

DIMS does not decide what a signal means. The researcher brings the theory, the research question, and the interpretation. What the dashboard provides is a way to move from a temporal pattern to the moment that produced it. In the elevator ad example (Case Study 2), the analyst can click on a rise in

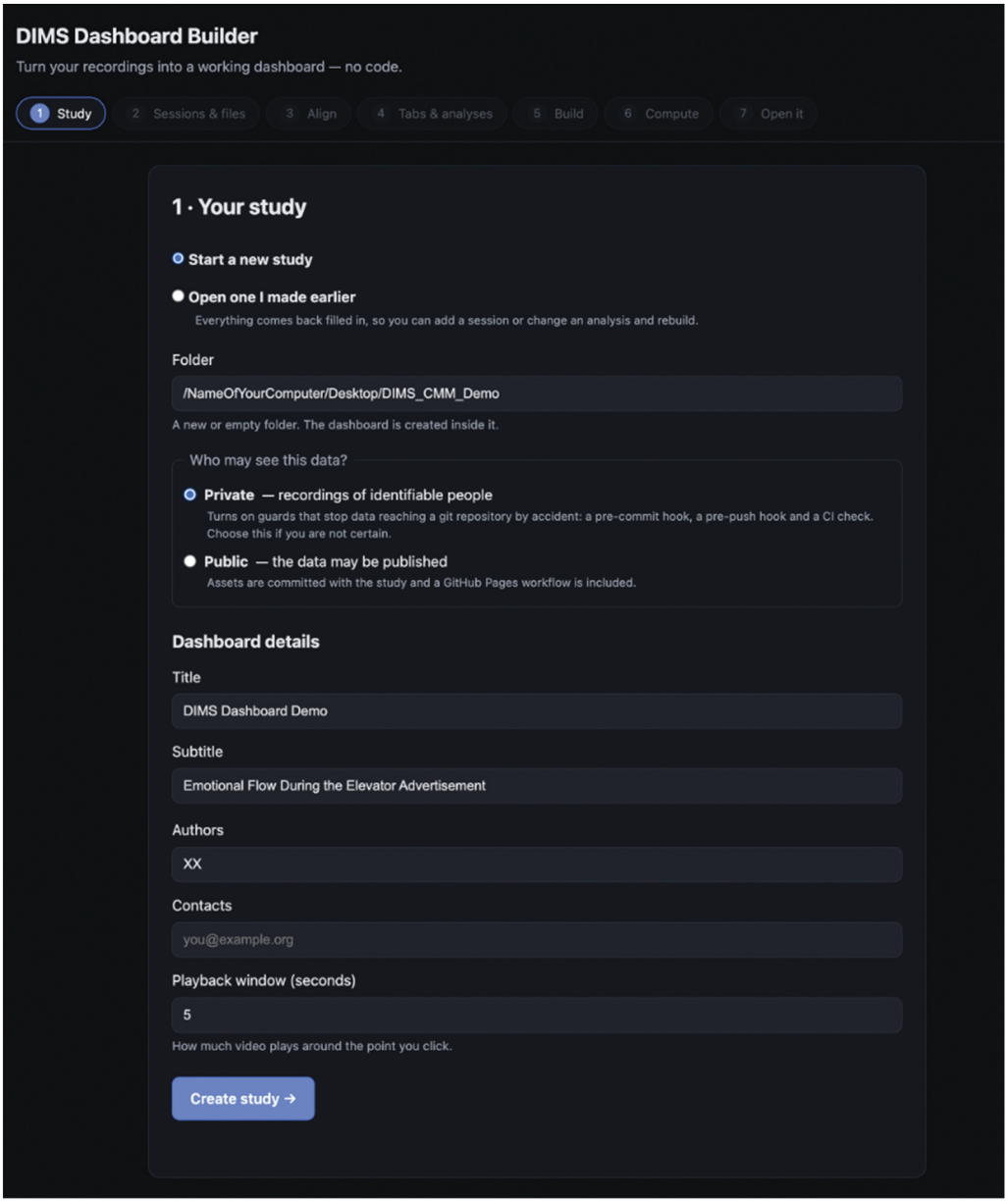


Figure 5. Builder step 1: study metadata, private/public setting, playback window.

OO and inspect the corresponding segment of the advertisement. The important question is not simply whether OO increased, but what it increased with. If OO rises while CORR remains low or decreases, the pattern can be interpreted differently from a moment when OO and CORR rise together. This is how the dashboard turns a physiological trace into an interpretable media-process question: What was happening in the ad at this moment, and what emotional configuration did the viewer appear to occupy?

The same logic applies to interpersonal data (Case Study 1). A peak in inter-brain synchrony can be clicked and inspected against the transcript, video, and head-motion synchrony. The analyst can then ask whether the peak corresponded to shared laughter,

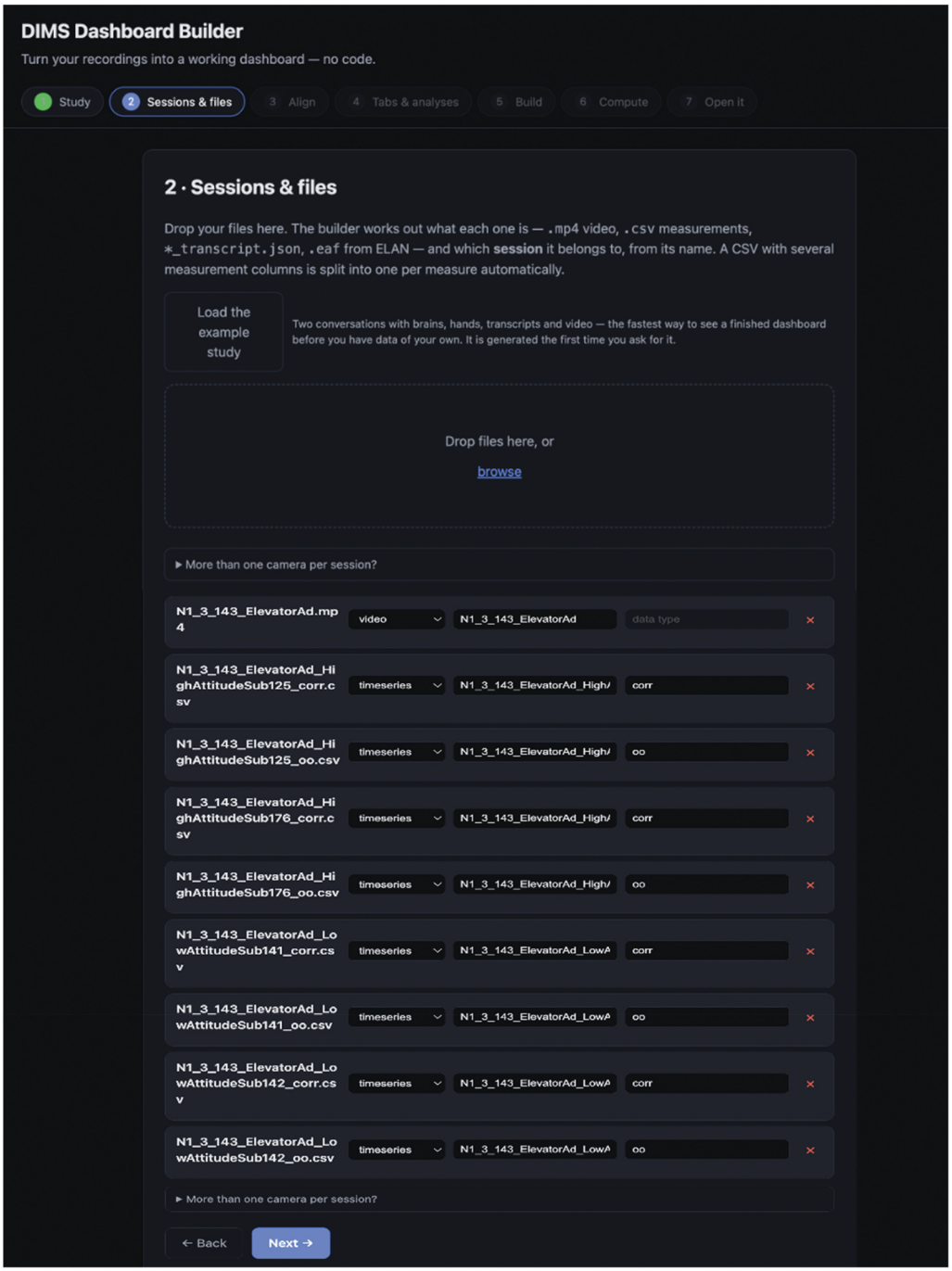


Figure 6. Builder step 2: importing appropriate files.

agreement, a topic transition, a repair sequence, or a tracking artifact. Across domains, the workflow is the same: use the time series to locate a moment, inspect the observable record, refine the interpretation, and then use that interpretation to generate better quantitative features or follow-up hypotheses.

When is DIMS appropriate? Why choose DIMS?

DIMS is most useful when a researcher has time-aligned data streams and wants to understand how a quantitative signal relates to observable communication. It is especially appropriate for studies where the research question concerns temporal process: how partners move into and out of synchrony, how a viewer's emotional response changes across a message, how a behavioral signal coincides with a conversational transition, or how different modalities converge around the same moment.

As outlined in Table 1, DIMS is less appropriate when the data do not have a meaningful time axis, when there is no video or transcript to return to, or when the goal is preprocessing rather than interpretation. The dashboard does not produce the time series, clean the data, estimate synchrony, or automatically validate a measure. It assumes that researchers have already generated the signals they want to inspect. In this sense, DIMS is not a replacement for signal-processing pipelines, statistical models, or qualitative coding software. It is a local interpretability tool: a way to bring already-prepared signals back into contact with the communication event from which they came.

As shown in Table 2, the advantages of DIMS over other software tools with similar goals are apparent: first, DIMS is fully open source, allowing users to freely access, modify, and extend the code to suit their own research needs; second, DIMS is data-agnostic. It can integrate and synchronize any type of time-series or event-based data, whereas many existing commercial platforms are designed for specific data types. For example, BIOPAC's Multi-Subject Monitoring Systems (BIOPAC Systems, Inc [BIOPAC], n.d.) only supports the integration of physiological raw data with videos recording participants' behavior, and ELAN (Wittenburg et al., 2006), though excellent for time-aligned annotation, is optimized for categorical event tiers rather than for exploring many continuous, researcher-generated time series side by side. By being open-sourced and modality-independent, DIMS provides a more general infrastructure for multimodal communication research.

Table 1. When is DIMS appropriate?

DIMS is appropriate when …	DIMS is inappropriate when …
The study has video/audio and one or more time-series signals	The study has static or survey-only variables
The research question concerns temporal process	The research question only concerns aggregate group differences
Qualitative inspection can refine quantitative hypotheses by inspecting what happened behaviorally during signal signatures (e.g. peaks, dips, or transitions)	The signal doesn't concern behavioral signatures that could be inspected in video/audio formats
Signals are already preprocessed and time-aligned	The goal is signal cleaning, tracking, or synchrony estimation

Table 2. Why choose DIMS?

Tool	Primary use	Strength	Limitation for Communication Research
DIMS Dashboard	Aligning timeseries with video/transcript for inspection	Open-source, no-code builder, modality-agnostic, supports many researcher-generated signals, including ELAN files	Does not preprocess signals or validate alignment automatically
ELAN	For researchers to generate (edit and search) annotation/coding of audio/video	Strong for time-aligned qualitative annotation and coding	Not designed primarily for side-by-side exploration of many continuous researcher-generated time series
BIOPAC Multi-Subject Monitoring Systems	Physiological acquisition, synchronization, and analysis	Strong hardware-software ecosystem for collecting physiological data with synchronized multi-camera video, useful when data are acquired directly through BIOPAC systems	More specialized around BIOPAC-style acquisition and physiology workflows than arbitrary post-processed multimodal research signals, such as researcher-generated synchrony estimates, motion-tracking outputs, transcript-derived measures, or mixed signals from multiple pipelines; purchase is required.

Discussion

This article introduces the DIMS Dashboard as a methodological tool that addresses a key challenge in communication research: once a statistical pattern is detected, how can researchers go back to the raw data especially the ones with multimodal signals, to interpret, understand, and theorize the processes that give rise to that pattern? Across both interpersonal and mass communication settings, communication unfolds in time, but many common analytic workflows compress that unfolding into averaged scores across time. The two case studies show how DIMS keeps the temporal structure of communication visible by allowing researchers to move between time series, video, and transcript within the same screen window, thus helping the understanding of their findings and facilitating theoretical building.

The first case study extends the dynamic dyadic systems (DDS) approach into multimodal social neuroscience. Solomon and colleagues argued that conversational theories cannot be adequately tested if turn-to-turn behavior remains inside a black box; without temporal order, researchers are left with only the frequency of conversational behaviors and their association with outcomes (Solomon et al., 2021, 2023). DIMS applies the same logic to neural and behavioral time series. An rTPJ synchrony score is not treated as an endpoint, but as a pointer back into the conversation. By aligning inter-brain synchrony with head motion, video, and transcript, the dashboard allows researchers to ask whether a computationally identified dyadic event corresponds to a recognizable interactional practice, a phase shift in the conversation, a task transition, or an artifact. The takeaway is not that rTPJ synchrony always means mutual engagement, even though rTPJ is a theoretically important DMN subregion and a strong predictor within the network (Miao et al., 2026). The more useful claim is that DIMS makes it possible to separate candidate subtypes of DMN-based inter-brain synchrony. Some synchrony peaks may reflect shared social engagement; others may reflect coordinated task transitions; still others may correspond to different pragmatic modes that require further qualitative and quantitative analysis. In this case, the dashboard turns rTPJ synchrony from an abstract time-series measure into an interactionally grounded object of analysis: a moment in which two people may be jointly making sense of the conversation, but whose meaning has to be read in context.

The second case study makes a parallel point in the context of advertisement viewing. The takeaway from the elevator ad is not that this specific advertisement causes a specific attitude pattern. Rather, this case is to show how DIMS can turn a post-exposure outcome difference (i.e. attitude toward the ad) into a temporally inspectable process. Instead of simply asking which viewers liked the ad more, the dashboard allows us to ask what processes were involved during ad viewing that ultimately led the viewer to form a low or high level of attitude. In this example, high-attitude viewers did not simply "react more." Rather, low- and high-attitude viewers appeared to occupy different emotional flows. One low-attitude viewer's response was embedded in sustained mixed tension, while the higher-attitude viewers' responses were less dominated by stable OO-CORR co-activation. This is the kind of process that disappears when physiology is reduced to single-channel averages, but becomes visible when multimodal signals are aligned with the unfolding media object (Han et al., 2025; Shen, 2017; Shen & Li, 2023).

Across the two cases, DIMS supports four recurring workflows. First, it helps researchers move from a time-series pattern to an inspectable moment. Instead of treating a peak, dip, or transition as meaningful on its own, the analyst can click into the corresponding video segment and ask what was happening in the interaction or media object at that time. Second, it supports quality checking and anomaly inspection: the analyst can check whether an apparent event reflects a genuine communicative dynamic, a preprocessing error, a tracking failure, or temporal misalignment. This is especially important when the phenomenon of interest is subtle and latent, because noise can easily be mistakenly understood as meaningful dynamics and genuine dynamics can just as easily be treated as noise. Third, it supports cross-modality triangulation: researchers can ask whether independent signals point to the same interpretation of a moment. In Case Study 1, rTPJ synchrony can be

inspected alongside head motion, transcript, and visible interactional behavior. In Case Study 2, the OO-CORR pairing turns a "smile-like" signal into an interpretable emotional-flow pattern. Lastly, it supports an iterative qualitative-quantitative workflow. Quantitative signals can direct the analyst to moments that deserve closer inspection, while qualitative inspection can suggest better features, labels, or hypotheses for later quantitative testing. In doing so, DIMS encourages researchers to traverse the full cycle of scientific inquiry within one single study, from hypothesis testing to interpretation and observation and to hypothesis refinement and ultimately to theory development, as described by Babbie (2017).

DIMS contributes to theory development by keeping the moment-to-moment process visible so that different frameworks can be examined on the temporal terms each specifies. For a dynamic dyadic systems analysis, DIMS makes candidate dyadic events inspectable and supports the move from a noticed temporal pattern to a testable cross-modal hypothesis (Solomon et al., 2021, 2023). For an emotional-flow analysis, DIMS keeps the within-individual trajectory in view, rather than reducing it to an average, and allows researchers to distinguish trajectories that a single averaged score would conflate (Nabi, 2015; Shen, 2017; Shen & Li, 2023). In both cases, DIMS does not do the theorizing, but reduces the friction that often prevents researchers from checking what their temporal measures are actually capturing.

DIMS should be understood as an environment designed to improve the interpretability of study findings. Reliability and validity therefore enter at several points in the workflow. First, the time-series measures displayed in DIMS inherit the reliability and validity of the upstream pipeline that produced them, whether that pipeline involves fNIRS preprocessing, motion tracking, facial EMG processing, or synchrony estimation. Second, temporal alignment should be checked directly, because even a valid signal becomes misleading if it is offset from the video. Researchers can perform simple alignment checks by clicking known events (such as the speech onset, a visible movement, or a stimulus transition) and confirming that the corresponding signal appears at the expected time. Third, interpretations generated through DIMS can be made more reliable by treating inspected windows as codable observations: researchers can define coding categories, have multiple analysts annotate the same selected segments, report agreement, and then test whether the resulting labels predict or explain quantitative patterns in a larger sample. In this way, DIMS supports validation not by certifying a measure automatically, but by making the link between a computed signal and an observable communicative event inspectable, repeatable, and open to disagreement.

Finally, DIMS does not automate preprocessing, cleaning, or temporal synchronization. It depends on the quality of upstream work: noisy or misaligned inputs will be displayed faithfully as noise and misalignment. Nor does the dashboard, by itself, establish the validity of a derived measure. Instead, it provides an environment for inspecting how candidate measures relate to observable events. Interpretations generated from single cases should therefore be treated as candidate hypotheses, not established findings. This caution applies with particular force to the small, exploratory case studies reported here, which should be followed by independent validation, larger-sample tests, or pre-registered analyses when the goal is confirmatory inference (Wagenmakers et al., 2012). We see this limitation as part of the point. DIMS is not meant to replace qualitative interpretation or quantitative modeling, but to create a shared workspace where both can iteratively build into a Quali-Quanti workflow and inform theoretical development.

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Data availability statement

The DIMS Dashboard, including its source code, no-code builder, and tutorials, is openly available at https://dims-network.github.io/. The datasets analyzed in the two case studies were obtained from prior studies (Han et al., 2025; Miao et al., 2025, 2026) and are subject to those studies' data-sharing terms.

References

Andrews-Hanna, J. R., Smallwood, J., & Spreng, R. N. (2014). The default network and self-generated thought: Component processes, dynamic control, and clinical relevance. *Annals of the New York Academy of Sciences*, *1316* (1), 29–52. https://doi.org/10.1111/nyas.12360

Babbie, E. R. (2017). *The basics of social research* (7th ed.). Cengage Learning.

BIOPAC Systems, Inc. (n.d.). *Multi-subject video systems sync with data*. https://www.biopac.com/multi-subject-video-systems-sync-with-data/

Buckner, R. L., & Carroll, D. C. (2007). Self-projection and the brain. *Trends in Cognitive Sciences*, *11*(2), 49–57. https://doi.org/10.1016/j.tics.2006.11.004

Fedorenko, E., Ivanova, A. A., & Regev, T. I. (2024). The language network as a natural kind within the broader landscape of the human brain. *Nature Reviews Neuroscience*, *25*(5), 289–312. https://doi.org/10.1038/s41583-024-00802-4

Han, J., & Lang, A. (2019). It's a journey: From media effects to dynamic systems. *Media Psychology*, *23*(3), 415–435. https://doi.org/10.1080/15213269.2019.1604236

Han, J., Ni, Y., Amon, M. J., Necaise, A., Han, M., & Lee, M. (2025). Multimodal physiological responses predict advertisement effectiveness. *Journal of Advertising*, *54*(5), 693–712. https://doi.org/10.1080/00913367.2025.2524185

Lang, A. (2017). Limited capacity model of motivated mediated message processing (LC4MP). In P. Rössler, C. A. Hoffner, & L. van Zoonen (Eds.), *The international encyclopedia of media effects* (pp. 1–9). Wiley.

Lang, A., Potter, R. F., & Bolls, P. (2009). Where psychophysiology meets the media: Taking the effects out of mass communication research. In K. Floyd & R. Weber (Eds.), *Media effects* (pp. 201–222). Routledge.

Lieberman, M. D. (2022). Seeing minds, matter, and meaning: The CEEing model of pre-reflective subjective construal. *Psychological Review*, *129*(4), 830. https://doi.org/10.1037/rev0000362

Menon, V. (2023). 20 years of the default mode network: A review and synthesis. *Neuron*, *111*(16), 2469–2487. https://doi.org/10.1016/j.neuron.2023.04.023

Miao, G. Q., Lieberman, I., Binnquist, A., Pluta, A., Goldstein, B. M., Dale, R., & Lieberman, M. D. (2026). Making new connections: An fNIRS machine learning classification study of inter-brain synchrony in the default mode network. *Social Cognitive and Affective Neuroscience*, *21*(1), nsag044. https://doi.org/10.1093/scan/nsag044

Miao, G. Q., Trujillo, J., Bulls, L. S., Thornton, M. A., Dale, R., & Pouw, W. (2025). DIMS dashboard for exploring dynamic interactions and multimodal signals. In A. Ruggeri, D. Barner, C. Walker, & N. Bramley (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society* (pp. 1023–1030). Cognitive Science Society, San Francisco, CA.

Nabi, R. L. (2015). Emotional flow in persuasive health messages. *Health Communication*, *30*(2), 114–124. https://doi.org/10.1080/10410236.2014.974129

Nabi, R. L., & Green, M. C. (2015). The role of a narrative's emotional flow in promoting persuasive outcomes. *Media Psychology*, *18*(2), 137–162. https://doi.org/10.1080/15213269.2014.912585

Potter, R. F., & Bolls, P. (2012). *Psychophysiological measurement and meaning: Cognitive and emotional processing of media*. Routledge.

Shen, L. (2017). Putting the fear back again (and within individuals): Revisiting the role of fear in persuasion. *Health Communication*, *32*(11), 1331–1341. https://doi.org/10.1080/10410236.2016.1220043

Shen, L., & Li, S. S. (2023). Quantifying emotional flow: Testing the emotional flow hypothesis from a longitudinal latent growth curve (LGC) modeling approach. *Media Psychology*, *26*(4), 436–459. https://doi.org/10.1080/15213269.2022.2156886

Solomon, D. H., Brinberg, M., Bodie, G. D., Jones, S., & Ram, N. (2021). A dynamic dyadic systems approach to interpersonal communication. *Journal of Communication*, *71*(6), 1001–1026. https://doi.org/10.1093/joc/jqab035

Solomon, D. H., Brinberg, M., Bodie, G., Jones, S., & Ram, N. (2023). A dynamic dyadic systems perspective on interpersonal conversation. *Communication Methods and Measures*, *17*(4), 273–292. https://doi.org/10.1080/19312458.2023.2237404

Stephens, G. J., Silbert, L. J., & Hasson, U. (2010). Speaker-listener neural coupling underlies successful communication. *Proceedings of the National Academy of Sciences*, *107*(32), 14425–14430. https://doi.org/10.1073/pnas.1008662107

Wagenmakers, E.-J., Wetzels, R., Borsboom, D., van der Maas, H. L. J., & Kievit, R. A. (2012). An agenda for purely confirmatory research. *Perspectives on Psychological Science*, *7*(6), 632–638. https://doi.org/10.1177/1745691612463078

Wittenburg, P., Brugman, H., Russel, A., Klassmann, A., & Sloetjes, H. (2006). Elan: A professional framework for multimodality research. In Calzolari N. Choukri K. Gangemi A. Maegaard B. Mariani J. Odijk J. Tapias D., (Eds.), *5th international conference on language resources and evaluation (LREC 2006)*, European Language Resources Association (ELRA) (pp. 1556–1559).

Yeshurun, Y., Nguyen, M., & Hasson, U. (2021). The default mode network: Where the idiosyncratic self meets the shared social world. *Nature Reviews Neuroscience*, *22*(3), 181–192. https://doi.org/10.1038/s41583-020-00420-w