Expression2Emoji: Designing Non-verbal Communication Support Tool for Group Video Meetings

Leave blank for blind peer review Author’s Last Name, Author’s First Name*[a]; Second Author’s Last Name, Second Author’s First Name[b]; Third Author’s Last Name, Third Author’s First Name[b] (Authors: Calibri 10pt)

[a] Leave blank for blind peer review Affiliation Organisation Name, City, Country (Affiliation: Calibri 9pt)
[b] Leave blank for blind peer review Affiliation Organisation Name, City, Country
* Leave blank for blind peer review The corresponding author e-mail address

Remote video meetings obscure non-verbal cues critical for turn-taking, emotional synchrony, and rapid consensus in creative groups. To mitigate this loss we propose Expression2Emoji, a user-configured expression-to-emoji channel that reintroduces lightweight feedback during distributed brainstorming. Two participatory design workshops (N = 18) surfaced 15 recurrent communication moments and distilled 13 corresponding gestures and emojis, informing a prototype. We evaluated the user experience in an exploratory between-subjects study (N = 20) during a one-hour superhero ideation task, triangulating gesture logs, Likert-scale ratings, and post-session interviews. Participants experienced richer social feedback, improved affect, smoother turn-taking, and faster convergence, while occasional misrecognitions only briefly diverted attention. We found that embedding a playful yet intentional non-verbal layer promotes mutual awareness and expressive latitude. Our work contributes (1) empirical evidence that user-defined non-verbal channels enrich remote collaboration, (2) a replicable participatory pipeline for gesture augmentation, and (3) design implications regarding user control, context sensitivity, and group-level feedback scalability.

Keywords: human-centered AI; nonverbal communication; remote video meetings; gesture recognition;

1 Introduction

Video conferencing platforms fundamentally constrain the subtle nonverbal communication essential for effective group ideation and creative collaboration, forcing participants to consciously compensate for missing social cues (Fauville et al., 2023) that naturally facilitate turn-taking, consensus building, and emotional connection in face-to-face interactions. The COVID-19 pandemic transformed video conferencing from a peripheral tool into an essential medium for collaborative work (Karl et al., 2021; Yang et al., 2022), exposing limitations in how these platforms support nuanced human communication (Dragomir et al., 2021). Unlike in-person meetings where participants effortlessly read nods, frowns, raised eyebrows, or spontaneous hand gestures across the room, video conferencing severely constrains both the visibility and interpretability of crucial social signals through small video windows, limited camera angles, and compressed video quality (Hills et al., 2021; Walther, 1993). This technological constraint becomes particularly acute in group ideation contexts, where creative collaboration depends heavily on reading subtle reactions (Brucks & Levav, 2022; Lin et al., 2023), building energy, and maintaining engagement through rich nonverbal exchanges that are difficult to capture or interpret in current video meeting formats (Knapp et al., 2013).

While recent research has explored various approaches to restore nonverbal communication in video meetings, existing solutions suffer from limitations that inadequately address the complex communicative needs of group ideation and creative collaboration contexts. Most current systems implement predetermined solutions by introducing either hand gestures or basic emoji reactions as single communication channels, rather than developing comprehensive approaches grounded in authentic user needs. Hills et al. demonstrated that natural hand signals significantly improve meeting experiences compared to GUI-based emoji buttons, yet their approach used fixed signal sets without exploring user-defined expressions for specific contexts (Hills et al., 2021). Koh et al. developed real-time hand gesture recognition for impromptu polling, but focused primarily on predetermined voting gestures for decision-making rather than the diverse emotional and social signals crucial for creative collaboration (Koh et al., 2019, 2022). Similarly, systems like EmojiCam have explored automatic facial expression detection for emoji overlays, but these approaches relatively hard to address group ideation contexts where complex, nuanced nonverbal signals beyond simple reactions prove essential for maintaining creative momentum and collaborative engagement (Babutsidze et al., 2021; Namikawa et al., 2021).

This research gap reveals insufficient integration of gestural and facial expression recognition with user-centered design approaches that could ground technical development in genuine communicative needs for creative group collaboration. How can we design gesture-based emoji systems that support users' nonverbal communication needs in online collaboration contexts? And how this system can be helpful for user experience? To address this question, we conducted a participatory design process to develop a gesture and facial expression recognition system that overlays contextually appropriate emojis in real-time video feeds during group ideation sessions (Qi & Yu, 2025). Our approach began with two design workshops with diverse participants to elicit authentic gesture and expression repertoires along with corresponding emoji vocabularies that reflect genuine communicative needs. Building on these insights, we implemented an interactive system using a machine learning algorithm that recognizes users' gestures and facial expressions, displaying relevant emojis as overlays in participants' video feeds, and evaluated its impact through comparative group ideation tasks.

This research contributes to human-centered design by demonstrating how participatory methods can ground technical innovation in authentic user needs, bridging laboratory prototypes and actual collaborative usage contexts. Our findings reveal both benefits, such as enhanced expressiveness and improved awareness of others' reactions, as well as limitations, including technical constraints and potential distractions, that provide valuable insights for future development. By foregrounding participatory design and empirical evaluation in real group ideation contexts, this work offers actionable insights for developing remote collaboration tools that support the rich, contextual nonverbal communication essential for effective creative work, highlighting the necessity of understanding user contexts and requirements throughout system implementation and evaluation.

2 Related Work

2.1 Nonverbal Communication and Remote Collaboration

Nonverbal communication, including gestures, facial expressions, and posture, is central to effective group collaboration and creative ideation (Ekman, 1964; Knapp et al., 2013). These signals help facilitate turn-taking, convey agreement or dissent, and support emotional connection among participants (Fussell et al., 2000). In face-to-face meetings, nonverbal cues are readily available and are essential for building rapport and maintaining group awareness. However, in remote settings, such as video conferencing or synchronous online classrooms, these signals become much harder to detect and interpret (Walther & Tidwell, 1995). Recent research has shown that when participants have discretion over their cameras and microphones, most choose not to share their video or participate verbally (Castelli & Sarvary, 2021; Yarmand et al., 2021). This makes it difficult for instructors and group leaders to read the room, reducing their ability to foster community and interpret group dynamics (Ma et al., 2022; Wang et al., 2022). Students in such settings report a weaker sense of connection compared to in-person contexts, further highlighting the challenges of online collaboration where nonverbal cues are limited or absent (Babutsidze et al., 2021; Yarmand et al., 2021).

The limitations of current video conferencing platforms exacerbate these challenges. Small video windows, poor camera angles, and inconsistent video quality often obscure or distort the subtle gestures and facial expressions that are central to productive group work (Namikawa et al., 2021; Olson et al., 1995). Participants are frequently required to exaggerate their expressions or rely on explicit verbal feedback, increasing cognitive load and disrupting the natural flow of conversation (Fauville et al., 2021). These constraints make it difficult to perceive spontaneous reactions and informal signals, ultimately weakening group cohesion, impeding creative momentum, and reducing overall engagement. As remote collaboration becomes more prevalent, the inability to recognize and interpret nonverbal expressions in online environments presents a significant barrier to effective group communication. Recognizing these limitations is critical for understanding the need to better support nonverbal communication in remote creative collaboration.

2.2 Design Approaches for Enhancing Nonverbal Expression in Video Meeting

Existing research approaches show certain limitations in fully addressing the comprehensive communicative needs of group ideation contexts. Current studies tend to implement solutions by introducing either predetermined hand gestures or limited emoji reactions as single communication channels, with relatively less emphasis on developing comprehensive approaches grounded in authentic user requirements. Early work by Koh et al. pioneered the mapping of symbolic hand gestures to analogous emojis through user-defined gesture sets, demonstrating the potential for more intuitive gesture-based communication in computer-mediated contexts (Koh et al., 2019). Building on this foundation, subsequent research has explored real-time hand gesture recognition systems for specific meeting functions, with Koh et al. developing automatic detection of voting gestures like thumbs-up signals and numbered finger displays for impromptu polling during virtual meetings (Koh et al., 2022). However, these approaches have tended to focus primarily on simple decision-making scenarios such as polling and opinion expression, with gesture recognition generally concentrated on predefined sets for basic meeting functions while less extensively exploring the diverse emotional and social signals that may be essential for creative collaboration. Similarly, customized icon sets have been developed through co-design processes with mixed groups of participants (Axelsson et al., 2021) to address specific accessibility needs (Nakao, 2025), though these solutions have remained largely focused on particular communication contexts with limited attention to broader communicative requirements in group ideation scenarios. Systems that automatically detect facial expressions and overlay corresponding emojis in real-time have shown potential for amplifying emotional cues, yet these approaches have provided relatively limited contextual adaptation for different collaborative scenarios (Namikawa et al., 2021).

Beyond individual signal recognition, recent advances in audience feedback systems have explored more sophisticated approaches to nonverbal communication support. Automated systems have been developed to analyze participants' facial expressions and head gestures in real-time, automatically spotlighting video feeds of the most expressive audience members to help presenters gauge reactions more effectively (Murali et al., 2021). Other innovative approaches have introduced collective behavior-driven avatars that monitor group engagement levels and encourage participation through visual animations and movements, demonstrating improvements in self-disclosure and participation equality (Armstrong et al., 2024). However, these systems have primarily focused on presentation contexts or general meeting facilitation with less attention to the complex communicative dynamics of group ideation sessions. Furthermore, existing studies have provided relatively limited design and evaluation approaches specifically tailored to group ideation and collective creativity situations. Previous research has tended to concentrate on general meeting contexts, lectures, or presentations with less investigation into which nonverbal signals prove crucial in group brainstorming sessions and how these signals should be extracted and visualized to enhance creativity, engagement, and collaborative momentum. While gesture-to-emoji mapping has been demonstrated for individual communication enhancement, the specific gestural vocabularies and emoji representations that support collaborative creative processes remain relatively unexplored (Li et al., 2024). This research gap suggests opportunities for more user-centered system design that could ground technical development in genuine communicative needs through participatory approaches (Sanders, 2002; Zhang et al., 2024), potentially enabling gesture-based emoji systems that more authentically support collaborative creative work by integrating both individual expression recognition and group-level communication facilitation.

3 Design Workshops for Nonverbal Expressions in Remote Video-based Group Ideation

Current video conferencing platforms like Zoom offer basic gesture recognition for emoji reactions, and prior research has examined gesture-based polling systems (Koh et al., 2022). However, these approaches lack user-centered design for group ideation's specific communication needs, focusing instead on general meetings or simple decision-making with fixed signals rather than identifying essential nonverbal expressions for creative collaboration. This research fills this gap through design workshops that identify user-defined nonverbal expressions for remote video-based group ideation, focusing on facial expressions, poses, and hand gestures. These modalities can be effectively captured by standard webcams and translated into emoji representations. The two-phase workshop process first identifies critical moments when participants need nonverbal communication support during group ideation, then elicits specific gestures and expressions participants would naturally use in those moments (Figure 1). Researchers then developed emoji mappings to effectively represent and amplify these nonverbal expressions in video meeting interfaces.

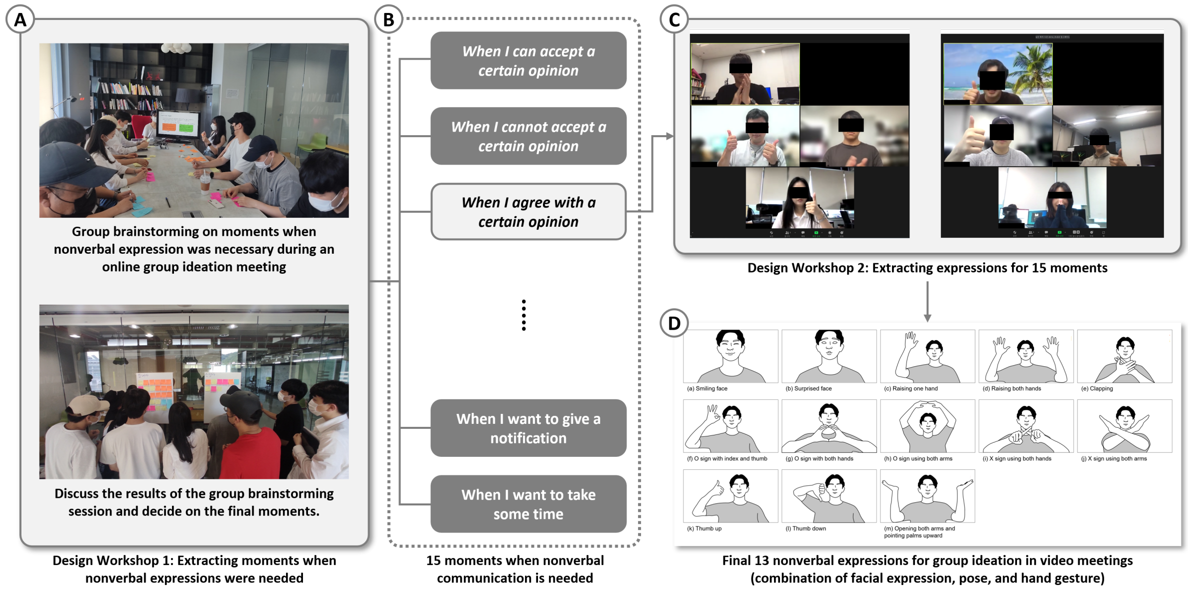


Figure 1. Participatory design process for identifying nonverbal expressions in video-based group ideation.(A) Workshop 1: Participants identified and refined moments requiring nonverbal communication. (B) Fifteen representative moments were derived from group discussions.(C) Workshop 2: Participants generated expressions for each moment while simulating video meeting settings. (D) Thirteen expressions combining facial expressions, postures, and gestures were selected for implementation.

3.1 Design Workshop 1: Identifying Nonverbal Communication Moments in Remote Video-based Group Ideation

3.1.1 Procedure

The first workshop aimed to identify specific moments during remote group ideation sessions when participants need nonverbal communication support. Ten design students with experience in both offline and online meetings participated in this one-hour workshop (7 male, 3 female; average age 26.8 years, SD: 4.42). Participants received 10,000 KRW as compensation to encourage active engagement.

The workshop consisted of three structured sessions. During the introduction and ice-breaking phase (15 minutes), participants introduced themselves and shared uncomfortable experiences from online meetings to establish rapport and context. The second session (15 minutes) focused on recalling nonverbal communication moments from offline meetings, where participants discussed their roles, specific moments requiring nonverbal expression, expression methods, and underlying reasons. This session served to activate participants' awareness of nonverbal communication patterns before addressing online contexts. The final session (30 minutes) concentrated on identifying moments when nonverbal expressions were needed or would be beneficial during online group ideation meetings. Participants considered meeting roles, specific situations, potential expression methods, and rationales for needing nonverbal communication in video conferencing contexts.

3.1.2 Results

Workshop participants identified moments requiring nonverbal expressions, which researchers clustered when similar situations emerged. This process yielded 17 initial moments, from which researchers excluded two items deemed inappropriate for professional meeting contexts: expressing negative emotions and indicating temporary absence. The exclusions occurred because these moments could appear unprofessional or prove difficult to represent through nonverbal expressions effectively. The remaining 15 moments formed the foundation for identifying nonverbal communication needs specific to remote video-based group ideation sessions, providing essential input for the second workshop's expression elicitation process (Table 1).

Table 1. Fifteen moments requiring nonverbal communication in remote group ideation.

1	when I can accept a certain opinion	**2**	when I cannot accept a certain opinion
3	when I agree with a certain opinion	**4**	when I disagree with a certain opinion
5	when I am neutral to a certain opinion	**6**	when I want to say something
7	when I say hi in a friendly way	**8**	when I say hello formally
9	when I want to avoid answering	**10**	when I want to give a notification
11	when I am curious about the other person's reaction	**12**	when I want to take some time
13	when I want to let them know that I am currently focusing on the meeting		
14	when I want to express positive emotions through facial expressions		
15	when I want to express positive emotions through body postures and gestures		

3.2 Design Workshop 2: Eliciting Expressions for Remote Video-based Group Ideation

3.2.1 **Procedure**

The second workshop focused on eliciting specific nonverbal expressions suitable for the 15 moments identified in the first workshop. Eight design students with extensive online meeting experience participated (6 male, 2 female; average age 27.5 years, SD: 4.75). To simulate authentic video meeting conditions, the workshop was conducted in two one-hour sessions with four participants each, where participants used their laptops and observed themselves through webcam screens to replicate the online meeting experience.

For each of the 15 identified moments, participants had one minute to consider appropriate nonverbal expressions, including facial expressions, body postures, and hand gestures. Following this reflection period, participants spent two minutes sketching visual aids that could accompany their expressions in video meeting interfaces. After completing each ideation phase, participants engaged in brief discussions explaining their expression choices and visual aid concepts. This structured approach ensured systematic exploration of nonverbal communication possibilities while maintaining focus on practical implementation considerations for video conferencing contexts.

3.2.2 **Results**

Eight participants generated 46 nonverbal expressions across all identified moments, which researchers grouped and analyzed for practical implementation. Using selection criteria focused on clear expressibility, frequent usage in actual online meetings, and potential to enhance participant interaction, researchers selected 13 expressions for system development (Figure 1-D). To better understand the distribution and salience of expressions across different moments, we visualized the results using a heatmap (Figure 2). The final expression set included two facial expressions and 11 body postures and gestures that met these practical requirements.

While gesture agreement scores were initially considered following established protocols, participant discussions revealed that frequently presented expressions often represented individual habitual behaviors rather than universally meaningful communication signals. Additionally, subtle expressions such as slight head tilts were excluded to prevent unintended gesture recognition that could disrupt meeting flow. This filtering process ensured the final expression set contained deliberate, recognizable nonverbal signals suitable for automated detection and emoji representation in group ideation contexts.

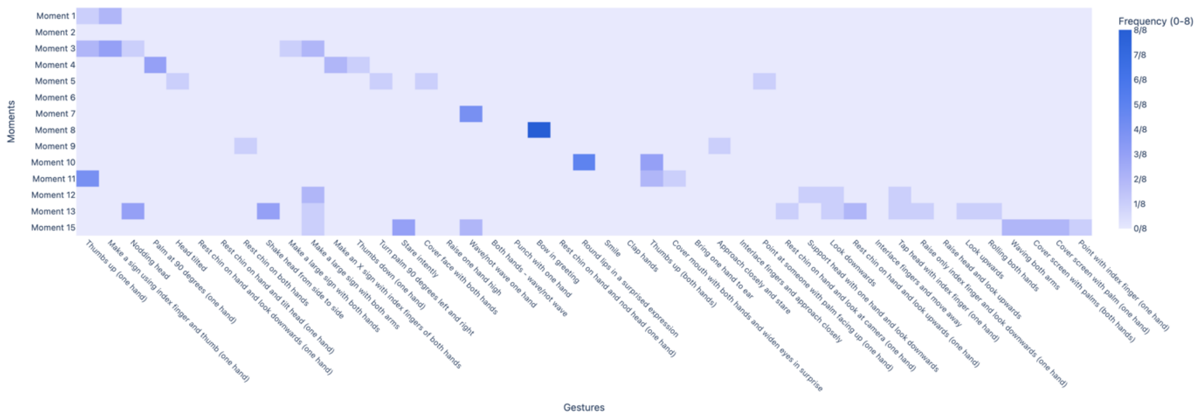


Figure 2. Distribution of proposed 46 nonverbal expressions across 15 identified moments.

3.3 Final Nonverbal Expression & Emoji Set

The final expression set consists of 13 nonverbal expressions comprising two facial expressions and 11 body postures and gestures selected through the workshop process. Based on participant feedback indicating current emoji usage for conveying nonverbal meanings in online meetings, researchers chose emojis as visual representations for recognized expressions using Twemoji, an open-source emoji library from Twitter (Figure 3). The emoji mapping strategy prioritizes conveying the literal nonverbal expression rather than specific contextual meanings, recognizing that identical expressions can serve multiple communicative purposes in group ideation contexts. For example, raising one hand can indicate wanting to speak, greeting others, or requesting attention, so the corresponding emoji represents the hand-raising gesture itself rather than a specific intention. This approach allows meeting participants to interpret emoji meanings according to situational context while maintaining expression authenticity. For expressions sharing identical meanings, researchers mapped the same emoji to maintain consistency and provide users flexibility in expressing similar nonverbal signals during group ideation sessions.

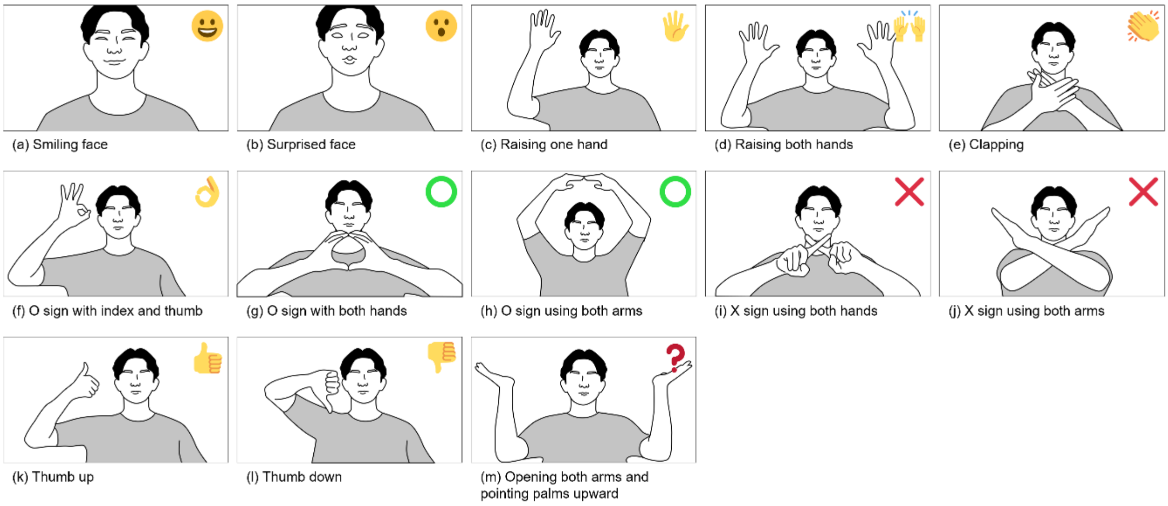


Figure 3. Final set of 13 nonverbal expressions and corresponding emojis for group video meetings.

4 Expression2Emoji System

To implement the gesture and expression vocabularies from our design workshops, we developed the Expression2Emoji system that recognizes nonverbal expressions and displays corresponding emojis as real-time video overlays. The system requires training machine learning models to classify the specific gestures and facial expressions participants identified as meaningful for group ideation, necessitating data collection from multiple users and algorithm optimization for real-time video conferencing performance.

4.1 Machine Learning Model for Nonverbal Expression Recognition

We collected training data from 10 participants to prevent overfitting and ensure robust recognition across diverse users. Participants performed each workshop-identified gesture and facial expression for approximately 10 seconds while being recorded through webcams, naturally varying their body positions and hand locations to ensure data diversity without additional augmentation techniques. We used Google MediaPipe to extract facial and body landmark coordinates, with hand gestures labeled independently for left and right hands. This process yielded approximately 4,500 facial and body landmark data pairs per expression category. We employed 5-fold cross-validation to select optimal classification algorithms, revealing that Logistic Regression achieved highest accuracy for facial expressions while Ridge Classifier performed best for hand gestures, providing the optimal balance between accuracy and computational efficiency for real-time processing (Table 2).

Table 2. Classification accuracy of machine learning models for facial expressions and body gestures.

	Accuracy	
	Facial Expressions	*Body Posture and Gestures*
Logistic Regression	0.811	0.973
Ridge Classifier	0.704	0.980
Random Forest	0.788	0.962
Gradient Boosting Classifier	0.771	0.942
Support Vector Machine (RBF)	0.784	0.975

4.2 System Implementation

We developed Expression2Emoji in Python 3.7.9 and integrated it with video conferencing platforms through Open Broadcasting System (OBS) overlay functionality. The system captures webcam data through OpenCV and transmits processed video feeds to OBS virtual camera using PyVirtualCam, enabling seamless integration with existing video conferencing tools. Google MediaPipe recognizes body, hand, and face landmarks in real-time, feeding coordinate data to our trained classification models for expression recognition (Figure 4).

The system prioritizes gesture recognition over facial expressions for more explicit communication during group ideation sessions, displaying emoji overlays only when both hands are detected to prevent unintended recognition. Classification predictions require exceeding confidence thresholds to trigger emoji displays, and the system averages input data over 2-second intervals to optimize performance and maintain stable frame rates. Body gesture and facial expression models alternate predictions at 1-second intervals to balance computational load. When expressions are recognized, corresponding emojis appear in the upper right corner of the HD resolution (1280x720) video feed, designed to minimize interference with normal video conferencing experiences while providing clear nonverbal communication feedback (Figure 5).

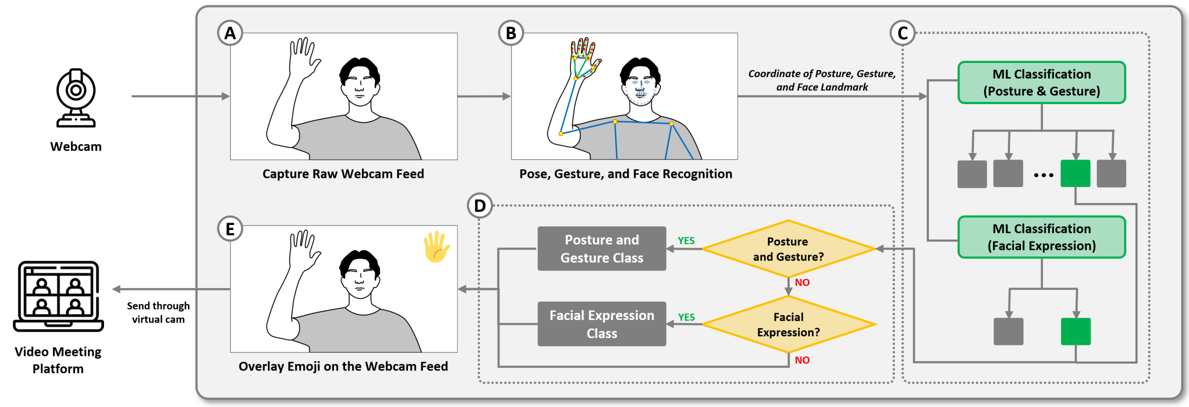


Figure 4. System architecture of the Expression2Emoji platform for real-time emoji overlay. (A–B) The system captures webcam input and extracts body, hand, and facial landmarks using MediaPipe.(C) Landmark data are processed by machine learning classifiers trained separately for gestures and facial expressions.(D) Detected expression classes are filtered based on recognition confidence and modality type.(E) The corresponding emoji is overlaid on the video feed and transmitted via a virtual webcam to the meeting platform.

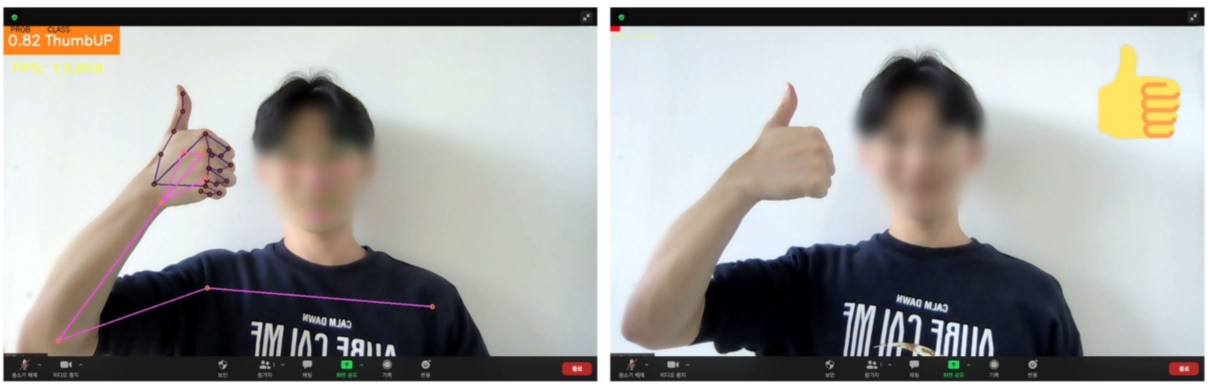


Figure 5. Example of real-time gesture recognition and emoji overlay in the Expression2Emoji system.

5 Exploratory Group Study

To evaluate the Expression2Emoji system's effectiveness in supporting nonverbal communication during remote collaborative ideation, we conducted a comparative group study examining user experiences and system performance across control and experimental conditions. The study employed a between-subjects design where control groups participated in standard video conferencing sessions while experimental groups used the Expression2Emoji system during identical collaborative tasks. All participants engaged in a structured design ideation workshop involving superhero concept development, allowing us to observe nonverbal communication behaviors in authentic creative collaboration contexts. We measured system performance through recognition accuracy logs, assessed user experiences through standardized questionnaires covering collaboration quality and social presence, and gathered qualitative insights through focus group interviews to understand how gesture-based emoji overlays influenced participants' remote collaboration experiences.

5.1 Participants

Twenty participants (13M/7F) were recruited, with ten assigned to each control and experimental group. Participants averaged 25.6 years old (SD: 1.70) and consisted primarily of graduate and undergraduate students from the Department of Design. Each workshop session included five participants, resulting in two control groups and two experimental groups.

Participants' backgrounds were assessed across offline meeting experience, online meeting experience, meeting activities, nonverbal expression experience, and emoji usage in online meetings using 7-point Likert scales. Given the sample size of ten per group, we performed Wilcoxon rank-sum tests to compare control and experimental groups, as normality assumptions were difficult to satisfy. Results showed no significant differences between groups except for one item: "importance of nonverbal cues(offline)" ($p<0.05$). The control group rated this importance higher than the experimental group (average score: 6.8 vs 6.2). Overall, both groups demonstrated similar offline and online meeting experience backgrounds, indicating that participant characteristics would not significantly impact experimental results (Table 3).

Table 3. Background characteristics of participants in control and experimental groups: Mean (Standard Deviation)

Item	Control	Experimental	Item	Control	Experimental
Offline meeting experience	5.8 (1.33)	6.3 (0.78)	*Online meeting experience*	6.1 (0.70)	5.8 (1.40)
Proactiveness in offline meetings	6.3 (0.78)	5.8 (1.25)	*Proactiveness in online meetings*	5.2 (1.40)	4.9 (1.81)
Importance of nonverbal cues (offline)	6.8 (0.40)	6.2 (0.60)	*Importance of nonverbal cues (online)*	5.4 (1.56)	5.4 (1.36)
Frequency of nonverbal cues (offline)	6.5 (0.67)	6.2 (0.75)	*Frequency of nonverbal cues (online)*	5.2 (1.72)	4.1 (1.70)
Usefulness of nonverbal cues (offline)	6.8 (0.40)	6.3 (1.00)	*Usefulness of nonverbal cues (online)*	5.6 (1.36)	5.5 (1.69)

Importance of emoji use in online meetings	4.1 (1.92)	4.5 (1.36)	*Frequency of emoji use in online meetings*	2.7 (1.49)	3.1 (1.70)
Usefulness of emoji use in online meetings	4.6 (1.74)	5.0 (1.55)	—	—	—

5.2 Experimental Task

The experimental task employed the double diamond design process to develop a new Marvel superhero concept, selected for its creative engagement requirements, domain familiarity across participants, and complexity sufficient to generate meaningful nonverbal communication during group discussions. The task progressed through four phases: Discover (exploring impressive movie superheroes and brainstorming novel abilities), Define (selecting the most attractive abilities for development), Develop (creating appearances and names aligned with chosen abilities), and Deliver (reaching consensus on final superhero concept, appearance, and name). Participants completed all phases within one hour, with groups flexibly determining time allocation for each phase. This progression from divergent to convergent thinking mirrors typical design ideation processes while providing multiple opportunities for participants to engage in rich nonverbal communication behaviors that our system aimed to support and enhance.

5.3 Experimental Procedure

The experimental procedure was designed around the experimental group using the Expression2Emoji System, with the control group following an identical process but without the practice session, resulting in a 90-minute duration instead of 120 minutes. All sessions were conducted online through Zoom, with participants receiving compensation (15,000 KRW for control group, 20,000 KRW for experimental group) to encourage participation.

- **Introduction & Practice Session (30 minutes):** Participants received briefings about each other and the workshop objectives without revealing the experimental design specifics. Since this was not a long-term field study, participants learned about Expression2Emoji System usage scenarios and completed a practice session to familiarize themselves with all nonverbal expressions. During practice, participants received guidance on technical requirements for optimal Google MediaPipe recognition: maintaining appropriate distance from laptops, avoiding clothing colors similar to backgrounds, wearing dark outer layers over bright clothes that create shadows, ensuring no background movement, and maintaining adequate lighting similar to general office conditions.

- **Ideation Workshop (60 minutes):** Participants engaged in the superhero design task using the double diamond process as described previously. Experimental group participants were encouraged to actively use Expression2Emoji System's nonverbal expressions throughout the ideation process, exploring how the system could support both divergent and convergent thinking phases. Experimenters maintained minimal involvement to preserve natural online collaboration behaviors.

- **Exit Interview & Questionnaire (30 minutes):** Both quantitative questionnaires and qualitative focus group interviews evaluated online meeting experiences and, for the experimental group, Expression2Emoji System usability. These sessions were conducted offline to facilitate richer participant interactions and deeper insights.

5.4 Measurement

To address our research questions about gesture-based emoji systems supporting nonverbal communication in online collaboration and their user experience impact, we used measurements across system performance, user experience, and qualitative insights. This evaluation framework examined both technical functionality and user-centered design effectiveness during remote collaborative ideation tasks.

- **System Performance Log Data:** We tracked Expression2Emoji System recognition accuracy by logging each participant's posture, gesture, and facial expression attempts alongside system responses. For each nonverbal expression type, we measured hit rates (correct recognition), false alarms (incorrect recognition of unintended actions), and misses (failed recognition of intended expressions). This data revealed individual gesture usage patterns and system reliability across different expression modalities.
- **Self-reported Measures:** Participants completed 7-point Likert scale questionnaires evaluating four key dimensions (Table 4). To explore how the system influenced collaborative dynamics, we measured overall user experience through positivity, efficiency, participation levels, and focus compared to typical online meetings. Meeting satisfaction items assessed participants' contentment with collaborative outcomes and processes. Social presence evaluation examined participants' sense of connection and mutual engagement during remote collaboration. For the experimental group, novelty items assessed perceived innovation in visual communication approaches, while system evaluation items measured recognition performance, usability, and user frustration.
- **Focus Group Interviews:** Focus group interviews provided qualitative explanations for quantitative findings. Both groups discussed online meeting experiences, social presence, and general meeting satisfaction. The experimental group received additional questions about overall system usage experiences, dissatisfying aspects requiring improvement, and new collaborative experiences enabled by the system. These discussions illuminated how participants experienced and adapted to gesture-based nonverbal communication during collaborative ideation.

Self-reported measures were analyzed using Wilcoxon rank-sum tests due to non-parametric data characteristics with small sample sizes. Interview data were transcribed using a commercial Speech-to-Text service (Naver Clovanote) and analyzed through thematic analysis to identify recurring themes and patterns across participant experiences.

Table 4. Self-reported Measurement used to evaluate user experience and system perception

Overall User Experience	
Positive experience	*I think I had a more positive experience than usual online meetings.*
Progress speed	*It seems to have proceeded faster than usual online meetings.*
Activeness in meeting	*I feel like I participated in the meeting more than usual. (I think I gave more opinions to the meeting than usual.)*
Concentration in meeting	*I think I focused more on the meeting than usual. I gave more opinions at the meeting.*
Meeting Satisfaction	
Satisfaction with outcome	*I am happy with the results of today’s meeting.*

Satisfaction with process	*I feel satisfied with the way in which today's meeting was conducted.*
Perceived net goal attainment	*The value I received from today's meeting justifies my efforts.*
Social Presence	
Social presence	*Compared to usual online meetings, I felt that I was participating in meetings with other people.*
Other people's feedback	*I felt that others responded more to my remarks than usual.*
Feedback to other people	*It seems to have responded more to other people's remarks than usual.*
Novelty	
Novelty of system	*I think this system is fresh compared to existing online meeting tools.*
Novelty of body posture and gestures	*The way I sent visual aid through body posture and gestures was new and fresh.*
Novelty of facial expressions	*The way I sent visual aid through facial expression was new and fresh.*
System Evaluation	
Immediacy	*The system quickly recognized my behavior.*
Accuracy	*The system recognized my behavior accurately.*
Learnability	*I was able to adapt quickly to the system.*
Frustration	*I was frustrated that the system did not recognize my behavior properly.*

6 Results

6.1 Quantitative Results

6.1.1 System Performance Log

Ten participants(P1~P10) in the experimental group used the Expression2Emoji system across two ideation sessions, generating usage data for gesture and facial expression recognition. As shown in Figure 7, thumb-up gestures demonstrated the highest successful recognition (39 hits) and usage attempts, followed by OK-sign gestures (24 hits). Complex gestures like clapping and hand-raising showed lower recognition accuracy, with clapping producing the most false alarms. Negative expressions such as thumb-down and X-sign received minimal usage, indicating participants' preference for positive nonverbal communication during collaborative ideation. Figure 6 illustrates system performance across participants and time. Facial expressions, particularly smiling, triggered continuously throughout sessions as natural emotional responses rather than intentional communication signals. Due to excessive triggering frequency, we excluded detailed hit-miss analysis for facial expressions. The timeline visualization reveals concentrated usage patterns during active discussion periods. However, participants P6-P10 experienced system errors during the first 15 minutes of their session, resulting in incomplete log data that was excluded from the analysis.

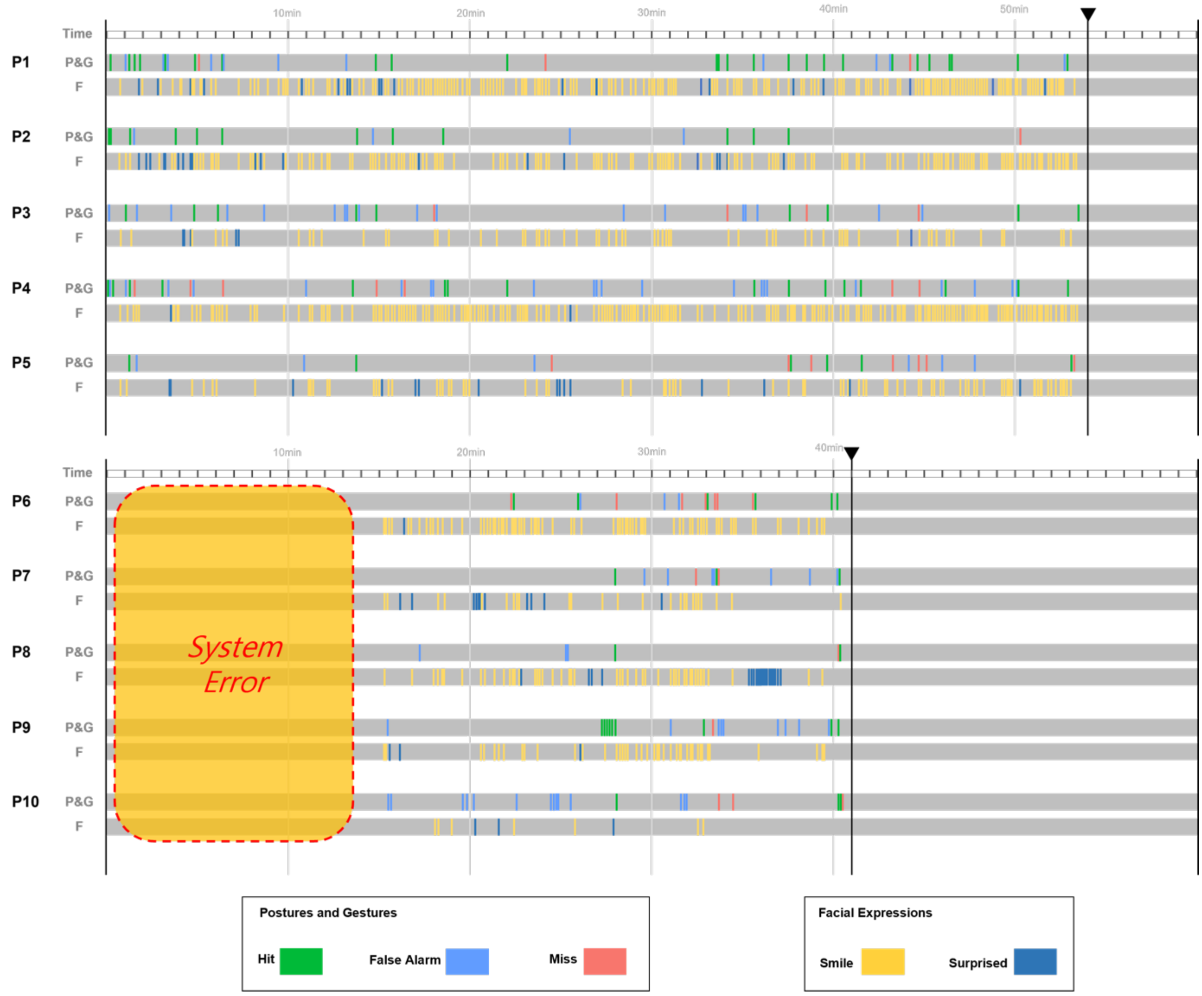


Figure 6. Timeline of recognized nonverbal expressions during the group ideation sessions.

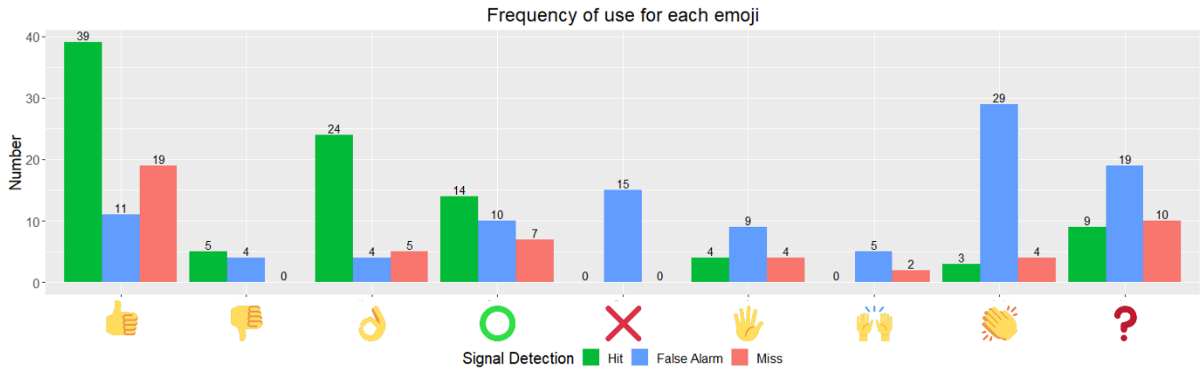


Figure 7. Detection outcomes for each emoji during remote group ideation.

6.1.2 **Self-reported Measurements**

Wilcoxon rank-sum test analysis revealed significant differences between control and experimental groups in two key dimensions. As illustrated in Figure 8, participants using the Expression2Emoji system reported significantly more positive meeting experiences and provided more feedback to others' ideas ($p<0.05$). Three central aspects contributed to enhanced user experience: easier creation of positive atmosphere, improved decision-making processes, and more active responses to other participants' contributions. However, the experimental group showed concerning trends in meeting effectiveness measures. Perceived goal achievement, progress speed, and concentration levels scored lower than the control group, though these differences were not statistically significant. Meeting concentration exhibited particularly high variability in the experimental group, suggesting the emoji system enhanced experience for some participants while creating distractions for others. Figure 9 presents the experimental group's evaluation of the system concept and implementation. Participants rated the novelty of the overall system, body gesture recognition, and facial expression recognition positively (median scores above 6). However, recognition immediacy and accuracy received lower ratings, with median scores around 3-4, indicating technical limitations that affected user experience. System learnability and prevention of frustration showed moderate ratings, suggesting mixed reactions to the system's usability and reliability during collaborative sessions.

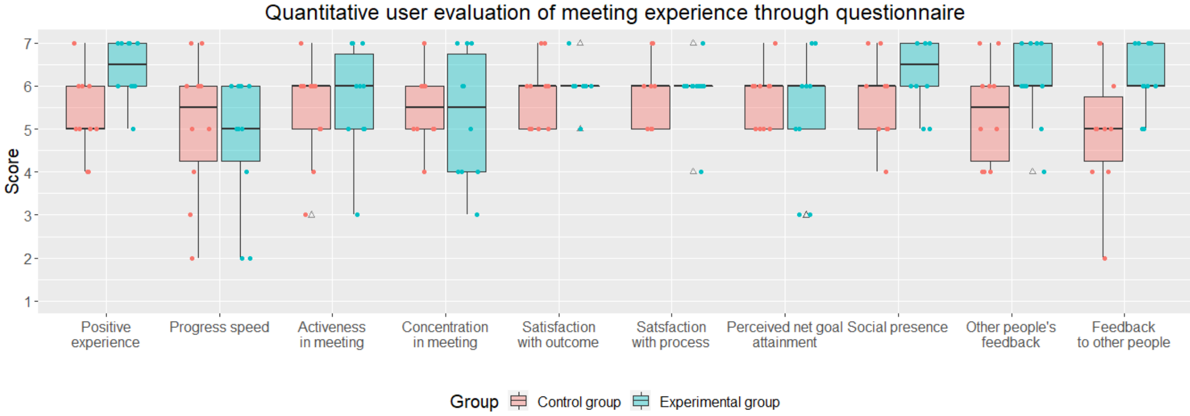


Figure 8. Comparison of meeting experience ratings between control and experimental groups.

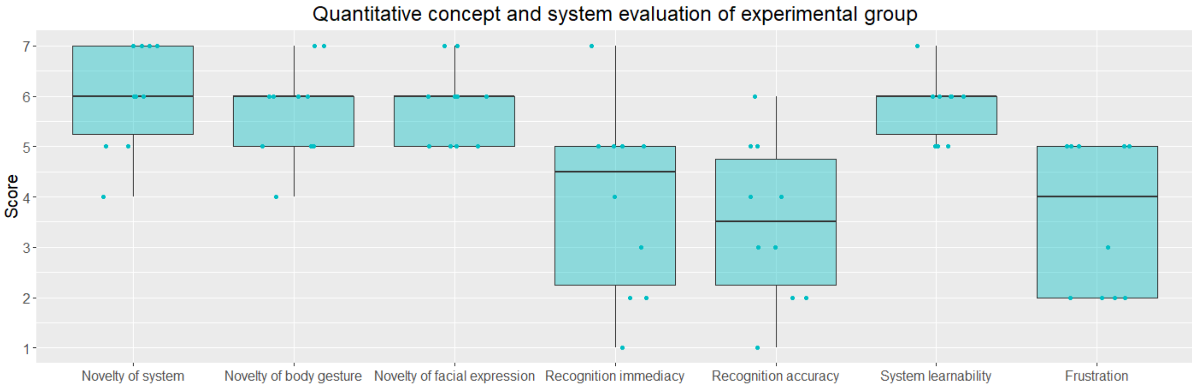


Figure 9. Evaluation of system concept and performance by the experimental group

6.2 Qualitative Results

Exit interviews revealed distinct patterns in nonverbal communication experiences between control and experimental groups. Control group participants highlighted fundamental limitations of traditional video conferencing, reporting passive attitudes toward emoji usage and reliance on minimal nonverbal cues like head nodding. They described barriers to emoji usage, noting awkwardness between actual expressions and digital representations, and expressed anxiety when unable to see others' reactions during presentations. These findings confirm the constrained nonverbal communication environment that motivated our system development.

Experimental group participants provided rich insights into how the Expression2Emoji system transformed their collaborative experience. Thematic analysis identified six major themes illustrating the system's impact on remote group ideation.

6.2.1 **Enhanced Nonverbal Expression and Amplification**

The Expression2Emoji system addressed limitations of online meetings by encouraging more active nonverbal communication. Visual emoji feedback provided confidence that expressions would reach other participants, increasing both frequency and intentionality of gestural communication.

"Just nodding your head, unless you do it like this, people really don't notice. But with this system, I can express my intentions more actively, so the frequency seems to increase too." (P4)

"This tool became a channel for expression." (P4)

The system motivated deliberate gestural expression and clearer communication:

"Rather than expressing myself ambiguously, I can actively communicate to others through these emojis, so it feels like it was conveyed much better." (P5)

6.2.2 **Increased Meeting Engagement and Social Connection**

Visual emoji reactions strengthened participants' sense of involvement and collaborative presence. The system enhanced mutual responsiveness and contributed to emotional bonding among team members (Figure 10-c).

"People responded more and I responded more, so naturally I felt more like I was participating in the meeting." (P1)

"It didn't improve meeting efficiency, but it seemed to help enhance emotional connection." (P2)

The system facilitated ice-breaking effects with unfamiliar colleagues:

"Even though we didn't know each other... when my smiling was recognized and they said 'oh, you're smiling,' it became an ice-breaker." (P6, P9)

6.2.3 **Meeting Efficiency Through Rapid Opinion Convergence**

The system demonstrated particular effectiveness during convergent ideation phases, enabling simultaneous opinion expression that accelerated consensus-building and decision-making processes (Figure 10-b).

"For example, when gathering opinions on whether something is okay, normally everyone has to say 'yes, good, good, good' one by one. But with this, everyone can go 'ding ding ding ding' at the same time, so that time was greatly reduced." (P9)

"When we needed to make decisions quickly, instead of everyone answering verbally, everyone made the OK sign with thumb and index finger to proceed. That was particularly effective." (P1)

6.2.4 **Fun and Novel Communication Experience**

Participants described the system as fresh and enjoyable, with unexpected errors and visual effects creating shared moments of amusement that energized collaborative sessions (Figure 10-a).

"It felt like a new common language was created for online meetings, which was fun." (P3)

"When everyone laughed together, all the laughing face emojis appeared at once. It looked like the effects on Happy Together, which was nice." (P6, P10)

6.2.5 Technical Limitations and Usability Challenges

Recognition accuracy problems and concerns about unintended expressions created significant barriers to seamless adoption. The system sometimes diverted attention from meeting content.

"There were many errors, so it was somewhat inconvenient. I can't say it was smooth, but if this had worked well, it would have been really great." (P1)

"In official, formal, or presentation settings, if something unintended appeared, it could be quite problematic." (P1)

Participants noted attention diversion effects:

"When I was speaking and some emoji appeared, my attention would go there. In that sense, there were side effects." (P9)

6.2.6 Contextual Adaptation and Feature Enhancement Needs

Participants recognized that system effectiveness varied based on meeting context, formality level, and group size. They provided specific suggestions for customization features and system improvements.

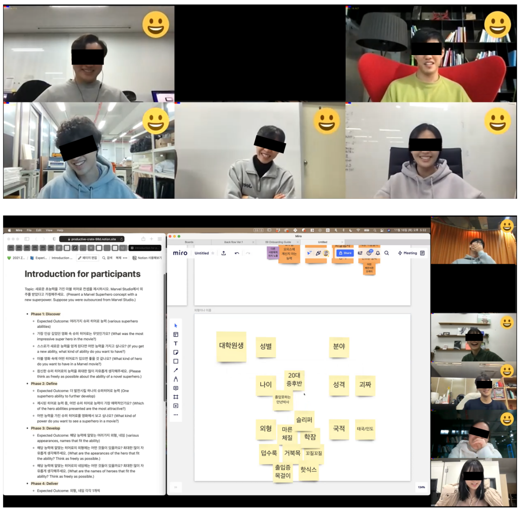
"Because it was ideation, it seemed more effective." (P6)

"Instead of 5 people, if there were about 15 people, it would have been very efficient." (P1)

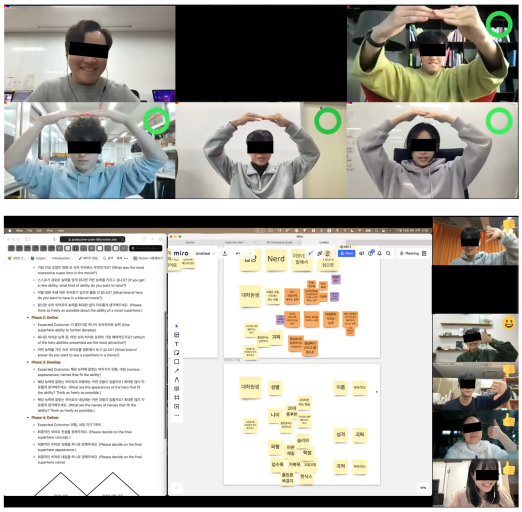
Enhancement requests included categorized expressions, automatic aggregation features, and manual control options:

"Since there are gestures related to opinions and expressions related to my emotions, maybe we could have different expression methods by category." (P4)

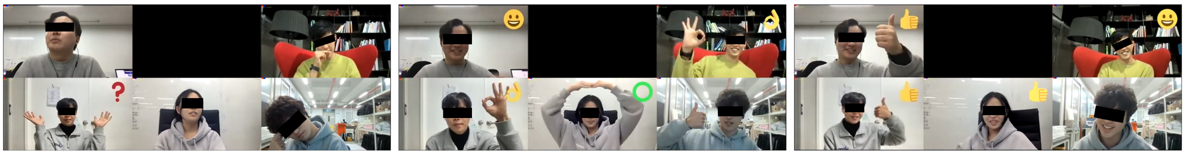
"To prevent unintended expressions from being recognized, a manual trigger would be good." (P5)



(a) Positive Mood



(b) Decision-making



(c) Feedback & Interaction Each Other

Figure 10. Examples of system-supported interactions during remote group ideation. (a) Emoji overlays contributed to a positive and playful group atmosphere. (b) Nonverbal signals such as the "O" sign enabled quick consensus during decision-making phases. (c) The system supported mutual feedback and acknowledgment through gesture-based expressions, enhancing interactivity and social presence.

7 Discussion

7.1 Comprehensive Interpretation of Human-centered Approach

Our findings demonstrate the substantial benefits of grounding gesture-based communication systems in authentic user needs through participatory design, contrasting sharply with existing predetermined solution approaches. Unlike Hills et al. and Koh et al., who implemented fixed gesture sets for specific functions like polling or basic reactions, our user-centered workshops revealed that effective nonverbal communication in collaborative contexts requires contextually adaptive expressions that emerge from genuine communicative needs (Hills et al., 2021; Koh et al., 2022). The Expression2Emoji system's usage patterns validate this approach: participants naturally gravitated toward positive expressions (thumb-up: 39 hits, OK-sign: 24 hits) while avoiding negative gestures, demonstrating authentic usage preferences that predetermined systems would likely miss. This preference for positive communication aligns with the collaborative nature of ideation sessions, where maintaining momentum and encouraging participation proves more valuable than providing comprehensive emotional ranges. The integration of quantitative performance data with qualitative user experiences reveals both the promise and complexity of user-defined expression systems. While technical limitations affected recognition accuracy, particularly for complex gestures like clapping, participants consistently reported enhanced expressiveness and social connection. The significant improvements in positive meeting experiences and feedback provision ($p<0.05$) occurred despite concerning trends in concentration and goal achievement measures, indicating that gesture-based systems create multifaceted effects that simple predetermined approaches cannot anticipate (Fussell et al., 2000). Participants' descriptions of the system as creating "a new common language for online meetings" (P3) and serving as "a channel for expression" (P4) suggest that user-defined gestures enable forms of communication that transcend basic emoji reactions or voting mechanisms (Kwon et al., 2024).

Our findings reveal the performative nature of gesture-based communication in video conferencing contexts, where participants consciously adapted their expressions to ensure system recognition. Rather than relying on subtle, natural gestures, users deliberately amplified their movements and expressions, creating what one participant described as "acting more exaggerated" to communicate effectively through the system. This performative adaptation represents users' willingness to modify their behavior for enhanced communication, suggesting that gesture-based systems create new modes of interaction that blend natural expression with conscious performance (Hills et al., 2021). The system also functioned as a social permission mechanism, encouraging participants who typically remained quiet to contribute through nonverbal channels. This effect proved particularly valuable for ice-breaking with unfamiliar colleagues, as shared moments of system-recognized expressions created opportunities for connection and engagement that might not occur in traditional video meetings. The willingness to "perform" for the system indicates that users can adapt to technological constraints when the benefits of enhanced expressiveness outweigh the effort required for deliberate gesture production (Dagan & Isbister, 2021).

The contextual effectiveness of our system reinforces the importance of participatory design in understanding genuine user needs across different collaborative scenarios. Recognition errors that created shared amusement and positive energy during informal ideation sessions would become significant concerns in more structured or professional contexts, demonstrating that social context determines system acceptability rather than pure technical performance. Participants intuitively understood these contextual boundaries, immediately identifying situations where the system would enhance versus hinder their communication goals. The collective expression effects, where one participant's emoji triggered similar responses from others, mirror natural social dynamics and suggest that gesture-based systems can facilitate group coherence and shared emotional experiences. These emergent usage patterns, from positive expression bias to collective responding behaviors, demonstrate how participatory design captures authentic social dynamics that inform more effective system development beyond the functional specifications that guide predetermined solution approaches.

7.2 Design Implications for Gesture-based Communication System

Our findings highlight the need for gesture-based communication systems that prioritize user control over automated recognition, particularly regarding intentional versus unintentional expressions. The most significant design challenge involves distinguishing between deliberate communicative gestures and incidental movements or natural behaviors (Koh et al., 2022). Participants expressed concerns about unintended expressions appearing during inappropriate moments, suggesting that systems should provide users with selective control over which expressions can be recognized (Hills et al., 2021). This could involve manual activation settings where users can disable specific gesture categories or individual expressions based on their current context or comfort level. Additionally, categorized expression modes could separate opinion-based gestures from emotional expressions, allowing users to choose their communicative intent and selectively enable only relevant expression types for specific meeting phases. This user control mechanism addresses the fundamental tension between automated convenience and social appropriateness, ensuring that participants maintain agency over their nonverbal communication rather than becoming subjects of algorithmic interpretation (Pereira & Hone, 2021).

Context-aware interface design emerges as a critical requirement for gesture-based systems that must function across diverse collaborative scenarios. Our findings reveal that recognition errors carry different social costs depending on meeting formality and purpose, necessitating adaptive system behavior based on contextual cues (Lim, 2024). Systems should provide preset configurations for different meeting types, with brainstorming modes allowing more experimental and playful interactions while structured discussion modes focus on clear, unambiguous signals. Professional contexts would benefit from disabling automatic facial expression recognition while maintaining deliberate gesture recognition for functions like hand-raising or opinion polling. This contextual adaptation could extend to sensitivity adjustments, where informal sessions permit more liberal recognition thresholds while structured meetings require more precise gesture execution. The key insight involves designing systems that understand and respond to social context rather than applying uniform recognition standards across all collaborative situations.

Scalability considerations reveal opportunities for gesture-based systems to transform large group dynamics through aggregated feedback visualization and asymmetric interface design. Participants noted that the system's potential would be fully realized in larger meetings where individual emoji displays become less meaningful than collective response patterns. Future systems should incorporate real-time aggregation features that convert individual gestures into group sentiment indicators, displaying voting results as bar charts or emotional climate as color-coded visualizations (Samrose et al., 2021). Asymmetric interface design should differentiate between presenter and participant needs, providing speakers with aggregated audience feedback dashboards while maintaining individual expression capabilities for attendees. This approach addresses the scaling challenge where individual reactions become noise rather than signal in large groups. Additionally, systems should capture expression nuance through gesture intensity recognition, where small versus large gestures trigger different emoji sizes or visual effects, allowing users to convey subtle gradations of meaning that current binary recognition systems cannot accommodate.

7.3 Limitations & Future Work

This research presents several methodological and technical limitations that constrain the generalizability of our findings. Our study involved a small, homogeneous sample of design students (N=20) from a single institution, potentially limiting the diversity of nonverbal expression preferences and collaborative behaviors observed across broader populations. The experimental design focused exclusively on ideation contexts using creative tasks, which may not reflect the full spectrum of collaborative activities where nonverbal communication proves essential. Technical limitations include recognition accuracy gaps between laboratory training conditions and real-world usage, particularly for complex gestures like clapping and hand-raising that demonstrated lower hit rates compared to simpler expressions. While machine learning models achieved high accuracy for body gestures (98.0%), real-world performance revealed challenges with environmental factors like lighting conditions, background movement, and clothing colors. The fundamental tension between automated recognition and user control emerged as a critical design challenge, as participants valued spontaneous recognition while expressing concerns about unintended expressions appearing during inappropriate moments.

Future research should address these limitations through larger, more diverse participant samples across multiple organizational contexts, investigating how cultural differences, professional backgrounds, and technological familiarity influence system adoption patterns. Longitudinal field studies examining sustained usage patterns over extended periods would reveal whether initial novelty effects give way to sustained behavioral changes that enhance remote collaboration. Technical development should focus on more robust recognition algorithms that accommodate natural gesture variations and context-aware systems that distinguish between intentional communicative gestures and incidental movements. Scalability investigations represent particularly promising directions, as participants noted system benefits would amplify in larger meetings where individual reactions become difficult to perceive. Future work should explore how gesture-based systems can provide presenters with real-time audience sentiment analysis through aggregated visualization while maintaining individual expression capabilities for attendees, potentially transforming large group dynamics through collective behavior patterns and enhanced collaborative effectiveness.

8 Conclusion

This research demonstrates how participatory design can effectively ground gesture-based communication systems in authentic user needs for remote creative collaboration. Through user-centered workshops, we identified 13 nonverbal expressions and developed the Expression2Emoji system that recognizes gestures and facial expressions, displaying emoji overlays in real-time video feeds. Our evaluation revealed significant improvements in positive meeting experiences and feedback provision, with participants reporting enhanced expressiveness, social connection, and decision-making efficiency. However, the system also created attention diversion effects and recognition accuracy challenges that affected concentration for some participants. These mixed results reveal that gesture-based systems create new performative modes of interaction where users consciously adapt their expressions for technological mediation, with participants naturally preferring positive expressions over negative gestures. This work contributes to human-centered design by showing how participatory methods can capture authentic social dynamics, providing actionable insights for creating remote collaboration tools that support rich nonverbal communication while maintaining user agency over expressive choices.

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