From Signals to Support: A Classroom-Scale Biometric–Facial Research Platform for Inclusive Education

Mykhailo Kotyk[1], Olena Budnyk[2], Fomin Kateryna[3]

[1]Department of Computer Engineering and Electronics, Vasyl Stefanyk Carpathian National University, Ivano-Frankivsk, Ukraine
[2]Department of Primary Education and Educational Innovations, Vasyl Stefanyk Carpathian National University, Ivano-Frankivsk, Ukraine
[3]English Philology Department, Vasyl Stefanyk Carpathian National University, Ivano-Frankivsk, Ukraine

Abstract

War-affected children in Ukrainian inclusive schools often mask emotional distress, and teachers have no reliable way to detect it [1, 2, 3]. Our previous work introduced BioMirror, an iOS platform that combines ARKit facial tracking with Apple Watch physiology to compute an emotional–physiological coherence score every 5 seconds; adult validation yielded 87.3% emotion-recognition accuracy, sub-50 ms cross-device synchronisation, and 94% biometric signal quality [4]. This paper presents BioMirror Researcher, a macOS companion that uses Bonjour/mDNS and persistent WebSockets to monitor up to 30 iPhones simultaneously. The dashboard provides a device grid, an alert feed, and remote session control, turning a single-participant prototype into a classroom-scale research instrument. We describe the adaptations a school deployment would still need (teacher-facing indicators, an on-device privacy mode, and guided regulation micro-sessions) and propose a mixed-methods pilot for students aged 8–14 in Ukrainian inclusive schools [5, 6, 10].

Keywords: *biometric-facial emotion recognition, inclusive education, war-affected children, emotional regulation, educational technology, research dashboard*

1. Introduction

The full-scale russian invasion of Ukraine has produced one of the largest child displacement crises in recent European history. Millions of children have experienced conflict, forced relocation, and the loss of familiar social structures, all established risk factors for PTSD, anxiety, and disrupted emotional regulation [1]. Ukrainian schools, both inside the country and abroad, now provide inclusive, trauma-informed education to a population whose distress is often invisible [2, 3]. Teachers report that war-affected children often suppress emotional expression and present as calm or disengaged while in fact experiencing significant autonomic arousal [3], which makes it hard to identify students who need support.

Affective computing systems that combine facial analysis with physiological sensing can detect what behaviour alone might hide [7], but most are designed for one-on-one clinical use and do not scale to classroom settings [8]. Doing the same thing in a school is not just an engineering problem. Privacy, teacher workload, and the ethics of collecting biometric data from minors in a conflict zone all bear on the design [9]. Our previous work introduced BioMirror, an iOS implementation of biometric facial emotion analysis for trauma recovery [4]. This paper reports an architectural extension (BioMirror Researcher, a macOS companion that turns the single-device prototype into a multi-device research instrument) and outlines a deployment strategy that integrates BioMirror with art therapy and play-based learning [10] in Ukrainian inclusive schools.

2. Related Work

2.1 Wartime Education and Trauma-informed Pedagogy

Elevated rates of PTSD, anxiety, and depression have been documented in Ukrainian student and teacher populations since 2022 [1]. Refugee studies report the same pattern in classroom behavior (hypervigilance, numbing, withdrawal), often misread as disengagement rather than recognized as trauma [3, 11]. Inclusive education frameworks call for adapting the environment [12], but the practical tools available to teachers are limited: observations are subjective, standardised assessments are periodic, and specialist referrals are slow in conflict-affected settings [13]. Budnyk et al. [10] looked at this directly. They ran three focus groups in Ukrainian preschool and primary schools (twelve parents of children aged 5–9, five teachers, and four art therapists, psychologists, and rehabilitation specialists), with rural communities affected by the war as the central case. Combining art therapy with play-based learning supported emotional recovery, motor and cognitive rehabilitation, and social reintegration; natural materials (clay, sand, leaves, straw) and folk traditions worked well where formal art-therapy resources were scarce. Two practical problems came up repeatedly. Teachers had no reliable way to tell, during a session, whether a method was actually helping a particular child. And primary school teachers reported that having one teacher for 30 pupils, with no assistant, made it hard to fit the methods into the daily curriculum at all [10]. Related FOE work in VR empathy training [14] and spatial analysis for health education [15] shows an appetite for technology-enhanced socio-emotional learning, but neither addresses continuous monitoring in a trauma-sensitive classroom.

2.2 Biometric Sensing and Ethics

Facial emotion recognition has been used to study engagement [8], but most systems rely on RGB cameras and posed-expression datasets, which limit accuracy on the spontaneous, low-intensity expressions characteristic of trauma masking [11]. HRV and accelerometry provide information about autonomic arousal [16], and multimodal systems outperform unimodal ones [17], but classroom deployment has been hindered by hardware costs and intrusiveness. Two pieces of consumer hardware now make a school-friendly setup feasible. The iPhone's TrueDepth camera exposes 52 ARKit blend-shape coefficients that map to FACS Action Units [18], and the Apple Watch has been validated as a research-grade HRV instrument [19]. Privacy and ethics still constrain any school deployment. Biometric data from minors is sensitive personal data under GDPR, so parental consent and child assent are required [9]. Re-identification risk persists even after anonymisation [20]; in conflict-affected settings, the consequences of misuse are greater [21]; and the digital divide is structural [22]. We address each of these directly in §4 and §6.

3. The BioMirror Platform

3.1 Overview

BioMirror was introduced in [4] as an iOS implementation for biometric facial emotion analysis. The premise is simple: a child's face and their autonomic state, taken together, say more than either does alone. A neutral face with elevated HR and suppressed HRV is a likely sign of masking; a face that moves with the physiology points to real engagement, or real distress. The emotional–physiological coherence score is the central output.

3.2 Facial and Physiological Sensing

The facial component runs on an iPhone using ARKit, which extracts 52 blend-shape coefficients at up to 60 fps; these map closely to FACS Action Units [18]. BioMirror smooths the vector with a two-frame moving average and passes it to a rule-based classifier that maps activations to seven basic emotions at a 0.15 confidence threshold. A 500 ms micro-expression detector flags brief deviations from the neutral baseline that may indicate suppression. Physiology comes from a paired Apple Watch via HealthKit and WatchConnectivity (HR, HRV/SDNN, wrist temperature, respiratory rate, motion); CoreMotion on the iPhone adds acceleration, rotation, a tremor index, and gait metrics. All values are validated against physiological plausibility ranges, and the system derives a stress score (SDNN/RMSSD/LF-HF), a fever-risk indicator, and a breathing classification.

3.3 Coherence Computation

The DataIntegrationService computes the coherence score every five seconds over a 30-second sliding window (Fig. 1). Three weighted components combine: emotional stability (0.3) from emotion-classification variance, physiological state (0.4) from HR/HRV/tremor/temperature, and cross-modal alignment (0.3) from the Pearson correlation between smoothed emotion intensity and the autonomic arousal index. The score ranges from 0 to 1, and higher values mean tighter alignment. A discordance detector flags two patterns at a 0.4 threshold: a suppressed face with elevated arousal (potential masking), and simultaneous suppression of face and HRV (potential dissociation). Session data persists in Core Data, and the device generates an end-of-session report.

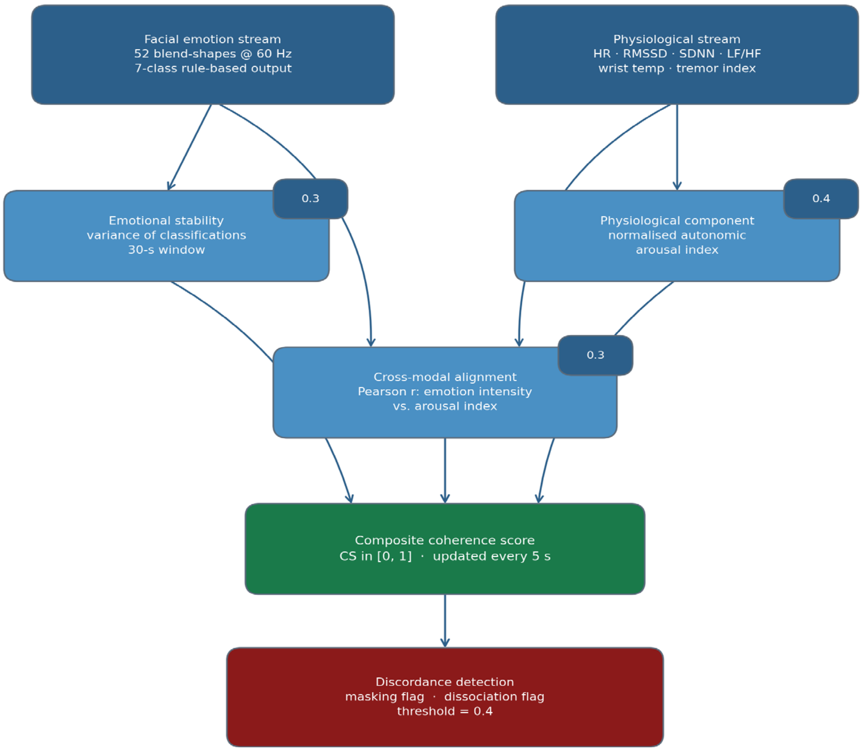

Fig. 1. Coherence computation pipeline

4. BioMirror Researcher: macOS Multi-Device Dashboard

4.1 Architecture

Scaling BioMirror to a classroom means aggregating real-time streams from many iPhones at the same time. We use a hybrid design (Fig. 2). All sensing and coherence computation run on the iOS device. The macOS application is a supervisor: it receives pre-processed summaries, never raw sensor streams. No raw blend-shape vectors and no facial images cross the wire during a session.

The Mac advertises itself with Bonjour over `_biomirror._tcp` and runs an `NWListener` WebSocket server. Each iPhone uses an `NWBrowser` to discover it and opens a persistent connection that retries with a five-second backoff. The link is TLS, and the server's identity is held in the Secure Enclave so the private key cannot be exported. iPhones present a short-lived pairing token on first connect; a researcher generates the token in the Mac dashboard and reads it as a QR code on the phone. Zero-config discovery matters in schools where IT support is thin.

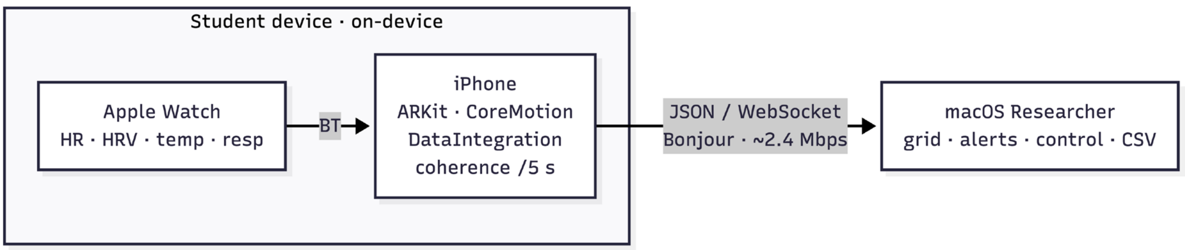

Fig. 2. BioMirror system architecture

4.2 Protocol and Dashboard

Client and server speak a single JSON envelope (`WSMessage`) over the WebSocket. The envelope carries a typed message: `register` and `heartbeat` keep the device list current, `sessionUpdate` streams live metrics every 2 s, `alert` flags discordance events, `command` lets the Mac broadcast start/stop/pause/resume across the cohort, and a chunked `sessionExport*` channel ships gzip-compressed full-session data back to the Mac at the end of a session for offline analysis. Each device sends a heartbeat every 10 s and a metrics update every 2 s with emotion, HR, HRV, coherence, and Watch connectivity, so 30 devices produce well under 3 Mbps on standard school Wi-Fi.

The dashboard has three areas. A device grid shows one card per iPhone with current emotion and confidence, a live HR chart, a coherence sparkline, battery, and Watch link status; cards turn amber or red on low battery, dropped face tracking, or missed heartbeats (>25 s). An alert feed lists discordance events with per-event or bulk acknowledgement. An experiment control panel assigns pseudonymous participant IDs, sends targeted or broadcast commands, and exports the timeline as CSV. The same panel lists the available iOS protocols, marks the ones still in development as "Coming soon", and refuses to start them — the iOS side enforces the same gate, so a teacher cannot accidentally launch an unfinished protocol on a class.

5. From Prototype to Classroom-Scale Research Instrument

5.1 Technical Capabilities

Together, the iOS sensing stack and the macOS dashboard do something the single-device prototype cannot: collect a coherent record across a whole class. Table 1 lists the main performance metrics from adult validation [4] and multi-device system testing.

Table 1. Technical performance metrics of the BioMirror platform.

Metric	Value	Condition
Emotion recognition accuracy	87.3%	Controlled lighting, front-facing, 20 adults
Cross-device synchronization latency	< 50 ms	Local network, 10 connected devices
Biometric signal validity	94%	Normal activity, Apple Watch Series 6+
WebSocket connection stability	98.2% uptime	4-hour continuous session
Battery drain (iPhone 13, screen on)	12%/hour	Active face tracking and streaming
Maximum concurrent devices	30	Standard school Wi-Fi, 2.4/5 GHz
Dashboard update rate	2 s per device	JSON-over-WebSocket
Network bandwidth (30 devices)	< 3 Mbps	Compressed JSON stream
Coherence score update interval	5 s	30-second sliding window
Alert detection latency	< 5 s	Rule-based, evaluated per heartbeat

Thirty devices, sub-50 ms synchronization, and under 3 Mbps of bandwidth all sit comfortably within standard school Wi-Fi. 98.2% WebSocket uptime covers a school morning without reconnection, and at a 12%/hour drain, an iPhone 13 lasts roughly 8 hours. The recognition and biometric numbers are from adult validation under controlled conditions [4]; classifier behavior with children in classrooms is unknown, and is a primary focus of the pilot.

Table 2 compares BioMirror with two alternatives: manual observational coding and single-modality wearables.

Table 2. Comparison with alternative classroom emotional monitoring approaches.

Dimension	BioMirror	Manual coding	Wearable-only
Temporal resolution	5 Hz (emotion), 1 Hz (physiology)	~0.1 Hz	1 Hz
Physiological correlation	Yes (facial + autonomic)	No	Yes (autonomic only)
Classroom scalability	30+ participants	5–8 (observer limit)	15–20
Trauma sensitivity	High (masking + dissociation detection)	Variable	Medium
Implementation complexity	Medium	High	Low
Participant burden	Low (consumer devices)	High	Medium
Privacy risk	Medium (facial data on-device)	Low	Low

5.2 Coherence as a Research Variable

For war-affected children, coherence has two readings. High coherence means the visible emotional state matches autonomic arousal, signalling either engagement or distress. Low coherence means face and body are telling different stories: the child is masking. From a trauma-informed perspective, low coherence is the more clinically significant signal, and exactly the pattern that teachers currently have no reliable way to detect. The multi-device architecture also enables a second-order variable: group coherence synchrony. If several students show correlated drops in coherence after a loud noise or a distressing topic, that may signal a shared trauma response, and the pairwise coherence matrix could inform grouping and the timing of regulatory interventions.

5.3 Adaptations for School Practice

The current dashboard is a research tool, not a classroom one. Three additions are on the design board; none have been implemented yet. The first is a teacher-facing indicator layer that translates raw coherence into colour-coded signals without exposing the biometric data. The second is a hardened minimal-data privacy mode that strips even the identifiers of derived scores from the macOS log. The third is a guided micro-session module that lets the teacher start a regulation activity (a breathing exercise or a short art prompt) and observe the group's coherence response in real time. Fig. 3 shows the layout for a 30-student classroom.

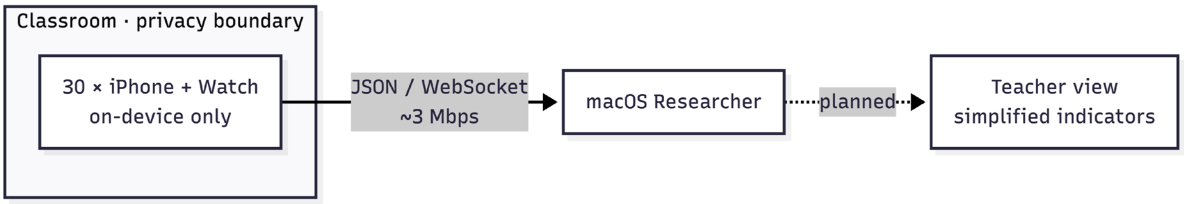

Fig. 3 — Proposed classroom deployment

6. Proposed Deployment in Ukrainian Inclusive Schools

6.1. Rationale

The deployment combines two strands established earlier: the mental health crisis among Ukrainian students [1, 2] and the evidence that art therapy and play-based learning support psycho-emotional rehabilitation in war-affected children [10]. Budnyk et al. propose a four-stage pedagogical model — diagnostic, selection, application, evaluation — for folding these methods into the daily classroom. BioMirror does not yet implement that cycle as a first-class object. What it does do is provide an instrument for the stages that depend on objective signal:

- **Diagnostic**. The baseline phase of every protocol records HR, HRV, and emotional baseline for two to five minutes. That gives the teacher (or, in phase one, the researcher) a per-child reference for the rest of the session.
- **Application**. The pilot protocols listed in §6.2 each carry an ordered phase script and always finish with a Regulation phase, so the system de-escalates automatically rather than ending on a creative-task arousal peak.
- **Evaluation.** Per-session coherence distributions, RR- interval shift vs baseline, discordance counts, and (for the group protocols) a cross-device synchrony view feed back into the teacher journal and post-session interviews.

The selection stage stays with the teacher and the school psychologist; BioMirror does not currently recommend which activity to run next. Building that out — driven by per-child coherence history — is in the §8 future-work list.

6.2. Mixed-methods Pilot Design

The pilot runs in three phases in two to three Ukrainian inclusive primary schools serving students aged 8–14, including both resident and internally displaced children, with at least one rural school to mirror the setting described by Budnyk et al. [10]. The preparatory phase (four weeks) covers ethics approval, parental consent, child assent, Wi-Fi configuration, and teacher training on the dashboard and coherence interpretation, following the guidelines for responsible AI use in academic institutions in [23].

The data collection phase (eight weeks) runs two to three sessions per week, 30–45 minutes each. Of the activities Budnyk et al. document in [10], one is fully runnable in the current build: a guided breathing protocol. The iOS app drives a five-step phase script — Baseline, Paced Inhale at 4 counts, Paced Exhale at 6 counts, a 5-minute Regulation phase, and Recovery — using a SwiftUI breathing circle as a visual pacer. At the end of each session the system reports the mean RR-interval shift between the Regulation phase and the baseline, which is the primary success metric for this activity.

During a session the iPhone runs the breathing script and the on-device facial analysis. The paired Apple Watch streams HR and HRV to the iPhone over HealthKit and WatchConnectivity. The macOS Researcher app aggregates the resulting per-device LiveMetrics from up to 30 iPhones over a Bonjour-advertised WebSocket (_biomirror._tcp) on the school LAN. The dashboard shows one card per child with the dominant emotion, live HR, a coherence sparkline, battery, and Watch connectivity, and a separate alert feed for discordance events. Raw images and blend-shape vectors never leave the iPhone. The connection is TLS. The server's private key is held in the Secure Enclave on the Mac, and each iPhone presents a short-lived pairing token on first connect.

The other four activities documented in [10] are part of the pilot plan but are not yet enabled in the current build: drawing and modelling with natural materials, a collaborative class mosaic or "friendship tree", folk-song-based group play, and story-drawing followed by short theatrical performances. They are scaffolded in the iOS app with the same four-step phase structure (Baseline, main task, Regulation, Debrief), and they appear in the macOS dashboard with a "Coming soon" badge. Both apps refuse to start them via the same planning gate used to block stress-induction protocols for minors. The work remaining before they can run in a school is the per-activity UI for the main task (a drawing canvas for the natural-materials and story-drawing protocols, an audio-cue player for the folk-song protocol, and a shared-canvas component for the class mosaic). The two group activities (mosaic and folk song) already attach a groupSessionID to their iOS payload; the cross-device synchrony computation on the Mac is the next piece of work, and the first round of the pilot will report per-child coherence only.

The researcher monitors the dashboard and logs alerts. Teachers run sessions as normal without access to real-time data and record observations in structured reflection journals. The analysis phase, an indicative four weeks, combines quantitative data (coherence distributions, alerts, and group synchrony once available) with qualitative data: teacher journals, post-session interviews, and student focus groups modelled on [10].

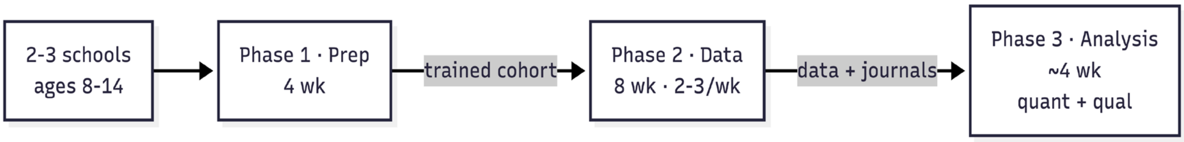

Fig. 4 — Proposed three-phase pilot study design.

6.3 Teacher Role and Safeguards

Restricting teacher access to real-time data in phase one avoids confounding the research and lets us evaluate the platform's outputs independently. In a later phase, teachers would get the simplified indicator view (§5.3) with interpretation training; the indicators are one input among many, not a definitive assessment. Several safeguards apply. All facial processing stays on-device, with no images or raw blend-shape vectors transmitted or stored on the macOS server. Coherence scores and emotion classifications are stored under pseudonymous IDs, and the ID-to-identity mapping is held separately by the school administrator. Data are retained for the study duration and deleted afterwards. Participation is voluntary, and withdrawal does not affect a student's standing. The protocol will be reviewed by the ethics committee of Vasyl Stefanyk Carpathian National University before data collection begins.

7. Discussion

7.1 Ethics, Hardware, and the Digital Divide

Facial emotion recognition can encode demographic biases, be repurposed for surveillance, and create power asymmetries between institutions and the people they monitor [9]. The stakes are higher for war-affected children, who are already vulnerable [21]. The architectural choices in §4 and §6 (on-device processing, transmission of derived scores only, pseudonymization, and time-limited retention) reduce these risks but do not eliminate them. The hardware requirement is a separate constraint. BioMirror needs an iPhone and an Apple Watch per student, a significant investment that most Ukrainian schools, especially rural or conflict-affected ones, cannot meet [22]. A deployment available only to well-resourced schools would deepen existing inequalities. The most direct fix is a version that drops the Watch and uses the iPhone's front camera alone; lending and device-sharing models are a shorter-term option [22].

7.2 Teacher Workload and Technical Limitations

Teachers in Ukrainian schools already operate under exceptional pressure [1]. BioMirror is designed to reduce, rather than add, workload by automating distress-signal detection that currently relies on effortful observation, but using it effectively takes some learning. Teachers have to read coherence, interpret the alert feed, and decide how to fold those outputs into what they were already going to do in the lesson. The pilot's training component is therefore central [23]. Over-reliance on algorithmic outputs is a known concern in AI-in-education [24], and phase one mitigates it by restricting teacher access to real-time data.

The platform also has technical limits. ARKit requires the student to face the iPhone at a distance of 30–80 cm, so head turns or peer interactions create data gaps. The rule-based classifier may not capture the full complexity of expression in children with trauma histories [11]. And we have not yet validated the coherence score against established measures of emotional regulation or trauma symptomatology; that requires running standardised psychological assessments alongside BioMirror in a later phase.

8. Conclusion and Future Work

BioMirror Researcher takes BioMirror, originally a single-participant iOS tool, and lets it supervise up to 30 participants at once over Bonjour/mDNS and persistent WebSockets. The iOS sensing stack achieved 87.3% emotion-recognition accuracy, sub-50 ms synchronization, and 94% biometric signal validity in adult validation [4], and the multi-device architecture holds those numbers across 30 concurrent connections on standard school Wi-Fi. The coherence score picks up the masking and dissociative patterns typical of war-related trauma, which periodic assessments, observational coding, and single-participant systems all largely miss.

Three lines of future work follow. First, run the pilot in two to three Ukrainian inclusive primary schools, integrating BioMirror with art therapy and play-based learning [10] and validating the coherence score against established measures of emotional regulation and trauma symptomatology. Second, build and evaluate the teacher-facing adaptations from §5.3. Third, develop a Watch-free configuration for schools that cannot provide wearables for every student.

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