International Journal of Human Research and Social Science Studies

ISSN(p): 3050-547X, ISSN(e): 3050-5488

Volume 02 Issue 11 November, 2025

DOI: https://doi.org/10.55677/ijhrsss/22-2025-Vol02I11

Page No : 952-963

Resonant Body Communication for Neurodivergent Contexts: A Multimodal, Temporally Elastic Blueprint for Inclusive Biometric Systems

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ABSTRACT: Prevailing emotion-sensing systems privilege a facial-and-gaze paradigm that encodes neurotypical tempo, channel priority, and expression classes, thereby mischaracterizing or erasing neurodivergent communication. This article advances a design-oriented framework for biometric sensing that centers resonant body communication: temporally extended, multimodal, and environmentally situated patterns of posture, gesture, rhythm, and interoception that carry affective meaning. Through an integrative methodology that synthesizes cognitive neuroscience, embodied arts practices, and human–computer interaction, the study formalizes a theoretical model with four pillars: temporal elasticity, multimodal sensory hierarchies, resonant gestures and rhythmic entrainment, and environmental attunement. Building on this model, the article specifies technical requirements for next-generation systems, including whole-body pose capture, wearable inertial and physiological sensing, ambient context instrumentation, and cross-channel fusion pipelines aligned to individual baselines. Temporal analytics—windowed sequence modeling, rhythm extraction, and state trajectory inference—are proposed to recover slow affective dynamics that escape frame-level classifiers. Illustrative design patterns are presented for clinical diagnostics, affective interfaces, extended reality environments, and learning technologies, emphasizing participatory co-design and neurodiversity-affirming outcomes. A parallel ethics program addresses consent, privacy, representational harm, and the risk of normative enforcement, recommending local control, transparent inference, and disability-led governance for deployment settings. The contribution is twofold: a unifying vocabulary for neurodivergent affect as embodied resonance, and a concrete technical blueprint for inclusive biometric architectures. By rebalancing attention from faces toward bodies in context, affective technology can move from narrow detection toward attuned interpretation, improving accuracy, dignity, and usefulness for a broader range of minds. Future work outlines validation protocols and cross-domain deployment benchmarks.

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KEYWORDS:
Neurodiversity, Biometrics, Embodiment, Interoception, Inclusivity

INTRODUCTION

The contemporary landscape of affective computing is shaped by a persistent face and gaze centric paradigm that systematically underrepresents neurodivergent modes of affective signaling, particularly those grounded in atypical tempo, sensory hierarchies, and expressive repertoires. Recent critiques in philosophy of mind and AI ethics have questioned the scientific validity of inferring discrete emotional states directly from facial configurations, arguing that such systems often generate what might be called “synthetic emotions” that reflect model assumptions more than lived experience (Rad, 2025). At the same time, interdisciplinary scholarship has highlighted the affective harms that arise when emotion recognition technologies are deployed in high stakes contexts such as workplaces and education without regard for neurodiversity, leading to misclassification and stigma for autistic and otherwise neurodivergent individuals (Goffin, 2025). Empirical work on autism and emotion recognition technologies further documents that tools trained on neurotypical facial and vocal data often misread neurodivergent expressions as neutral, incongruent, or deceptive, thereby encoding ableist norms into biometric infrastructures (Katirai, 2025). These converging lines of critique establish a clear problem space in which dominant affect-sensing architectures marginalize neurodivergent signaling and motivate the search for alternative design horizons that move beyond the face and toward bodies in context, which this article conceptualizes as resonant body communication.

Within this problem space, the purpose and scope of the present article are to define resonant body communication as a design horizon for inclusive biometrics by foregrounding temporally extended, multimodal, and environmentally situated forms of affective expression that are particularly salient in neurodivergent lifeworlds. Contemporary clinical and cognitive neuroscience has illuminated the centrality of interoception and atypical sensory integration in autism spectrum conditions, indicating that internal bodily cues and non visual modalities frequently organize emotional experience and expression for autistic individuals (Klein et al., 2025). Complementary work in arts based and developmental research on rhythmic relating shows that autistic communication often unfolds through patterned movement, shared tempo, and bodily entrainment rather than through neurotypical expectations of eye contact and facial mimicry (Daniel et al., 2024). Parallel developments in digital phenotyping demonstrate the feasibility of capturing continuous, real time indices of posture, movement, and bodily representation in autistic adults, suggesting that the sensing infrastructure needed to operationalize resonant body communication is already emerging (Mourad et al., 2024). Taken together, these lines of evidence justify reframing biometric design around neurodivergent embodied practices and lead directly to the formulation of research questions about how to synthesize theory, architecture, and deployment strategies in a coherent framework. The central research questions guiding this article therefore ask how a social science informed model of resonant body communication can (a) theorize neurodivergent affect as an embodied, temporally elastic, and environmentally attuned process, (b) specify a technical blueprint for multimodal sensing and analysis that honors this process, and (c) anticipate the implications of such systems for inclusive deployment in clinical, educational, and interactional contexts. Recent work in embodied cognition reinforces the view that cognition and emotion are jointly grounded in bodily movement, sensory experience, and continuous engagement with environments, providing a conceptual bridge between neuroscience and design oriented inquiry (Zheng, 2025). Experimental studies on mind body practices and interoceptive training further demonstrate that posture, breathing, and muscular activation can be leveraged to regulate and clarify emotional states, thereby underscoring the bidirectional coupling of body and affect that any serious biometric model must accommodate (Lazzarelli et al., 2024). In parallel, participatory and inclusive design research in autism contexts has articulated methodological frameworks for involving neurodivergent children and adults in the co creation of technologies, offering governance and epistemic guidelines for how resonant biometric systems should be specified and evaluated in practice (Ferreira & Castro, 2024). These interdisciplinary resources position the present contribution at the intersection of neuroscience, embodied arts, and human–computer interaction, setting the stage for a literature review that interrogates existing affective computing paradigms and opens conceptual space for resonant body communication as a next generation design framework.

LITERATURE REVIEW

The limits of microexpression and gaze paradigms in emotion inference have become increasingly apparent as empirical and critical work has scrutinized the reliability of automated facial coding under real world conditions. Large scale evaluations of commercial facial emotion recognition systems show that performance metrics reported in laboratory style benchmarks fail to translate into stable accuracy in unconstrained settings, leading some authors to characterize current microexpression driven approaches as technically unreliable for practical decision making (Cabitza et al., 2022). Recent survey work on facial microexpression detection further notes that these signals are extremely brief, low amplitude, and highly sensitive to noise, which magnifies annotation uncertainty and model brittleness even before such systems encounter atypical or neurodivergent expression patterns (Shuai et al., 2025). Complementary eye tracking studies using virtual reality environments demonstrate that autistic adults often deploy gaze in ways that prioritize sensory regulation over direct social signaling, which means that gaze based engagement metrics systematically misinterpret neurodivergent visual behavior when they assume a singular normative pattern of eye contact and face fixation (Jeppesen et al., 2025). Taken together, these findings indicate that microexpression and gaze paradigms rest on fragile technical and conceptual assumptions and therefore motivate an expansion of affect inference beyond isolated facial units toward temporally extended and multimodal indices.

Evidence for temporal expansion and multisensory weighting in neurodivergent affect further destabilizes emotion models that rely on momentary facial snapshots or visual dominance. Behavioral work on autistic children's sensory processing of time and space reveals consistently slower reaction times and broader temporal windows across visual, auditory, and visuospatial tasks, suggesting that information is integrated over longer intervals and that temporal structure itself is a distinctive feature of autistic experience (Coelho et al., 2025). Neuroimaging research examining anxiety, temporal processing, and sensory hyperresponsiveness in autistic adults shows that emotion cued enhancements of temporal resolution observed in neurotypical participants are disrupted in autism, implicating altered timing networks and affective modulation that reshape how emotional information unfolds over time (Atsumi et al., 2025). A recent systematic review of multisensory integration in autism concludes that autistic individuals exhibit consistent differences in combining information across modalities and links these atypical multisensory profiles to core social communication features, arguing that future research must attend more closely to the diversity of sensory channels and their temporal binding characteristics (Vassall et al., 2025). Collectively, these lines of work suggest that neurodivergent affect is best characterized as a temporally expanded and multisensory phenomenon, which in turn implies that biometric systems must be reoriented toward continuous, whole body sensing that respects these dynamics.

Dataset composition, construct validity, and generalization concerns in emotion AI further underscore the inadequacy of face and microexpression centered models for neurodivergent populations. A comprehensive systematic review of emotion recognition techniques from the current decade reports that many studies still rely on narrowly scoped datasets with posed, exaggerated expressions and limited demographic diversity, raising doubts about ecological validity and the robustness of constructs used to label emotional categories (Khare et al., 2024). A recent review and critical analysis of multimodal datasets for emotional AI finds that existing corpora overwhelmingly privilege visual facial data and underrepresent modalities such as body posture, movement, and physiological signals, while also documenting significant gaps in transparency about recording contexts and participant characteristics that affect downstream generalization (Al-Azani & El-Alfy, 2025). Empirical and legal scholarship on emotion AI governance additionally shows that users and regulators are increasingly concerned about bias that arises when models trained on such unbalanced datasets are deployed across gender, racial, and disability groups, highlighting the need to reconceptualize emotion datasets to include neurodivergent communicative repertoires and to define validity in relation to lived experience rather than laboratory caricatures (Ingber, 2025). These critiques together indicate that any serious attempt to design inclusive biometric systems must begin by restructuring datasets and constructs around multimodal, neurodiversity aware representations of affect.

Clinical assessment emphasis on facial and verbal cues generates ecological blind spots that reinforce the same biases embedded in affective computing, especially with regard to autism diagnosis and support **(Table 1)**. Contemporary reviews of diagnostic practice in autism note that standardized instruments and clinical observation protocols still foreground deficits in eye contact, facial expressivity, and conventional verbal reciprocity, which risks pathologizing divergence from neurotypical norms while overlooking alternative embodied channels through which autistic people communicate affect and intent (Qin et al., 2024). Central An overview of the latest clinical frontiers in autism diagnostics describes how emerging tools attempt to augment these traditional practices, yet also acknowledges that many remain focused on facial and gaze cues rather than systematically incorporating body movement, sensory behaviors, or interaction with environments as primary data sources (Cortese et al., 2025). In contrast, a recent scoping review of AI based approaches for detecting autism traits synthesizes work across eight behavioral modalities including voice biomarkers, conversational dynamics, movement analysis, activity recognition, and eye gaze, and argues that observable traits such as motor patterns and head movements offer powerful complementary signals for early identification and characterization (Rakotomanana et al., 2025). These converging arguments highlight a growing recognition that clinically meaningful affective information extends far beyond face and speech, thereby providing a bridge to theoretical frameworks that treat resonant body communication as the central construct for inclusive biometric design.

Table 1. Comparative paradigms in affective computing

Paradigm	Primary modalities	Temporal assumption	Dominant datasets	Neurodivergent fit	Key limitations
Facial microexpression and gaze centred emotion AI	High-resolution facial video; eye gaze; facial action units	Momentary, frame-level snapshots; millisecond-scale microevents	Posed or semi-posed facial expression corpora; lab-based gaze-tracking datasets	Low; atypical facial displays and gaze modulation often misclassified or labelled neutral	Overreliance on facial universality assumptions; poor ecological validity; bias against atypical expression
Unimodal physiological or vocal systems	Heart rate, skin conductance, EEG, vocal prosody	Short windows or isolated segments; quasi-stationary states	Small to medium-sized sensor or speech datasets collected under constrained tasks	Moderate; captures internal arousal but often ignores idiosyncratic meaning and sensory context	Limited interpretability without behavioural context; vulnerable to confounds; weak mapping to everyday affect
Classical multimodal face and voice systems	Facial video, speech acoustics, sometimes text	Short episodes; turn-level or clip-level temporal structure	Benchmark audiovisual corpora with scripted or acted emotions	Low to moderate; still anchored in neurotypical display rules and conversational norms	Fusion dominated by facial cues; underrepresentation of atypical bodies and voices; datasets rarely neurodiversity-aware

Resonant body communication model	Full-body pose and movement, inertial wearables, interoceptive and physiological signals, ambient context	Extended trajectories; rhythms and transitions across seconds to minutes	Emerging multimodal, naturalistic corpora emphasising movement, physiology, and environment; prospective longitudinal datasets	High by design; centres diverse temporal, sensory, and embodied signalling repertoires	Technically complex sensing and modeling; higher privacy stakes; requires participatory design and robust governance

Theoretical Framework: Resonant Body Communication

The concept of temporal elasticity posits that affective meaning does not always arise from discrete moments but unfolds across extended windows and trajectories, which is particularly pertinent in neurodivergent communication contexts. Cognitive neuroscience increasingly demonstrates that timing and duration are foundational to emotional appraisal and regulation—evidence from developmental studies reveals that individuals with atypical sensory processing often rely on prolonged integration rather than instantaneous cues (Buzi et al., 2024). Further, research in second-person neuroscience emphasizes that brain-to-brain synchrony and interpersonal coupling develop over dynamic temporal scales rather than single snapshots, suggesting that affective attunement is inherently processual (Schilbach, 2025). A systematic review of interoceptive and affective processing notes that disruptions in timing networks (such as insular–anterior cingulate connectivity) manifest in altered emotional trajectories rather than static affective deficits (Feldman, 2024). Therefore, embedding temporal elasticity in the design of biometric systems requires analytic models that track rhythmic change, gradual shifts, and latency rather than only instantaneous markers **(Figure 1)**.

The second pillar, multimodal sensory hierarchies, asserts that the body's internal and peripheral sensory channels—interoception, proprioception, tactile, auditory—may serve as primary carriers of affective meaning, especially among neurodivergent individuals whose sensory prioritization often diverges from dominant visual-centric models. The neurobiology of interoception highlights that affective experience arises from representations of bodily states and homeostatic regulation, thus the sensing of heartbeat, muscle tension, and visceral feelings cannot be marginalised in affect recognition (Feldman, 2024). Experimental work with rhythm-based interventions in autism indicates that auditory–motor coupling and tactile feedback often supersede visual cues in emotional regulation and expression among autistic children (Ruiz et al., 2025). Additionally, multisensory research shows that neurodivergent populations frequently exhibit atypical weighting of sensory channels, which suggests that design frameworks must allow for flexible hierarchies of modalities rather than fixed visual primacy (Vassall et al., 2025). Accordingly, biometric architectures should integrate sensors for internal bodily feedback, motion, touch, and sound as first-class inputs to capture the full spectrum of embodied affect.

Resonant gestures and rhythmic entrainment constitute the third pillar of the theoretical framework, emphasizing that patterned posture, movement, and synchronization act as affective signatures that resonate within individuals and across social partners. Research on joint music-making demonstrates that rhythmic entrainment facilitates emotional sharing and behavioral synchrony through coordinated motor and auditory frameworks (Abalde et al., 2024). Clinical studies of autistic populations highlight that rhythm and movement—rather than facial microexpressions—may serve as primary communicative modalities, with interventions showing improved affect regulation when rhythmic entrainment is harnessed (Navarro et al., 2025). Furthermore, work on gesture and speech coordination in autism finds distinct maturational trajectories of synchrony, reinforcing the view that temporal coordination and movement patterns are central to affective expression rather than incidental to it (Eigsti, 2024). From this perspective, biometric systems should attend not merely to pose snapshots but to temporal motion patterns, rhythmic repetition, coupling of agents, and their resonance in social or artefactual environments.

Environmental attunement forms the fourth pillar, advancing the notion that affective expression is not confined to internal or bodily states but is embedded in space, objects, ambient conditions, and the interplay between agent and milieu. Post-cognitivist neurodiversity frameworks argue that the body, artefacts, and environment jointly constitute the communicative system, thereby challenging isolated sensor models (Videla, 2025). Empirical research on behavioural synchrony and shared intentionality shows that people coordinate not just with each other but with rhythmic patterns in the environment, suggesting that space and ambience are affective co-regulators (Schilbach, 2025). Furthermore, multimodal fusion investigations in HCI report that ambient context (lighting, sound, movement of objects) significantly improves affect recognition when incorporated alongside bodily and physiological channels, demonstrating that environment is a salient input rather than noise (Mohamed et al., 2024). As a result, resonant body communication demands sensor networks and analytic models that reflect agent-environment coupling, enabling recognition of affective states as distributed across person and place.

The integrative schema linking neural, behavioral, and contextual layers synthesizes the four pillars into a coherent model of resonant body communication, wherein affect emerges through the interaction of internal bodily states, embodied motion and rhythm, and environmental embedding, all evolving over time. Neuroscience research on temporal structure and synchrony situates neural oscillations and coupling (internal) as foundational to behavioral trajectories (motion and posture) and interpersonal resonance (Schilbach, 2025). Concurrently, embodied arts and movement science emphasise that gesture and rhythm translate internal affect into external behaviour that other agents and systems can track (Abalde et al., 2024). Meanwhile, context-aware computing and affective AI research demonstrate that environmental variables provide critical framing for interpreting bodily signals and calibrating models to actual user states (Mohamed et al., 2024). Thus, the schema proposes a layered architecture: interoceptive and proprioceptive sensing → gesture/rhythm dynamics → environmental context mapping, all feeding into temporal analytic pipelines that detect resonant trajectories rather than discrete frames. This unified model opens the path to technical blueprint design and system architecture that will be detailed subsequently.

Design Principles and Technical Architecture

A multimodal sensing suite constitutes the first design principle because contemporary evidence shows that emotion recognition performance improves substantially when systems integrate visual, physiological, and contextual channels rather than relying on any single modality. Recent comprehensive reviews of multimodal emotion recognition document that state-of-the-art systems draw simultaneously on facial, vocal, and textual data, and argue that future architectures must expand toward richer sensor combinations in order to capture subtle affective cues in real-world settings (Pan et al., 2023; Wu et al., 2025). Systematic surveys of multimodal physiological signals confirm that wearable devices can provide robust streams of heart rate, electrodermal activity, and related measures that are highly informative for affective computing when combined with other channels (Li & Zhang, 2025). Parallel work on skeleton and body-based emotion recognition demonstrates that full-body motion and posture, captured through 3D pose estimation or skeleton tracking, are viable primary modalities for decoding emotion and may be more privacy-preserving than face images in some contexts (Lu et al., 2025). Taken together, these studies justify a sensing suite that integrates full-body pose, inertial wearables, physiological signals, and ambient context as co-equal inputs, which in turn necessitates temporal models capable of handling long sequences.

Temporal modeling constitutes the second principle because affective meaning in natural interaction is carried by how signals evolve across time rather than by single frames or static measurements. Work on temporal modelling in emotion recognition shows that incorporating explicit time-domain structure into model architectures yields significant gains in classification accuracy relative to temporally naïve baselines, particularly in dynamic environments where cues unfold gradually (Chandrasekharan et al., 2024). A complementary time-aware framework proposes an emotion recognition model with temporal attention that selectively weights past emotional states, demonstrating that performance improves when the system learns which segments of a sequence are most informative for prediction (Mahajan, 2025). Outside of classical emotion datasets, deep learning approaches to temporal modeling of social media for depression forecasting likewise illustrate that tracking trajectories across long textual histories captures clinically relevant affective shifts that would be invisible in snapshot analyses (Shen & Paik, 2025). These convergent results indicate that resonant biometric systems should employ windowed sequences, rhythm extraction, and state-trajectory inference to represent affect as a process, paving the way for cross channel fusion strategies.

Cross channel fusion and uncertainty quantification define the third principle by addressing the problem of how heterogeneous modalities can be combined and evaluated in affective inference. A major review of multimodal emotion recognition highlights that feature-level and decision-level fusion strategies consistently outperform unimodal baselines, yet also warns that poorly designed fusion pipelines can introduce redundancy or noise if intermodal correlations are not modeled carefully (Pan et al., 2023). Survey work on deep learning based multimodal emotion recognition emphasizes the need for architectures that learn both shared and modality specific representations and identifies attention mechanisms as particularly effective for weighting channels according to their informativeness in context (Lian et al., 2023). At the same time, research on uncertainty quantification metrics for deep regression stresses that any deployment in sensitive domains should accompany predictions with calibrated estimates of confidence, since deep models are prone to overconfidence and miscalibration without explicit uncertainty modeling (Lind et al., 2024). These insights together suggest that resonant systems require fusion architectures that support sensor synchronization and multimodal attention, paired with principled uncertainty metrics, so that downstream users can interpret affect estimates cautiously and in light of model confidence, which directly links to the need for personalization.

Personalization and adaptation comprise the fourth principle because empirical comparisons between generalized and individualized models indicate that affect recognition performance is strongly user specific. A machine learning study that contrasts personalized and generalized approaches to emotion recognition with consumer wearables finds that subject specific models trained on the same physiological features achieve substantially higher accuracy for stress and amusement classification than aggregated models, underscoring the practical value of individual baselines (Li et al., 2024). In a complementary domain, transfer-learning based personalized facial emotion recognition shows that reusing features learned on large multisubject corpora and fine tuning them with a limited amount of personal data produces subject specific models that outperform both global and purely local alternatives (Rescigno et al., 2020). A systematic evaluation of personalized deep learning models for affect recognition across multiple open datasets further demonstrates that a range of personalization strategies, including user level fine tuning and multi task learning, consistently improve detection of individual affective responses relative to nonpersonalized baselines (Han et al., 2024). Collectively, these studies support design choices that treat personalization as a core architectural feature, incorporating mechanisms for individual baseline estimation, transfer learning, and active correction interfaces, which then interact with environmental sensing to complete the resonant picture.

Environment as signal and actuator provides the fifth principle by recognizing that affect is shaped not only by internal and bodily states but also by contextual conditions that can be sensed and dynamically modulated. A recent survey of context based emotion recognition argues that contextual information, including situational cues and environmental features, is critical for accurate inference and synthesizes methods that incorporate context alongside body language, voice, and facial cues (Abbas et al., 2025). A transformer based multimodal fusion framework for context aware affective state recognition further demonstrates that including textual and task context with thermal and optical facial data improves emotion recognition in human robot interaction, exemplifying how context can be encoded explicitly within fusion architectures (Mohamed et al., 2024). Beyond purely informational roles, a study on daily emotion recognition that integrates environmental data with wearable physiological signals illustrates how ambient features such as temperature and noise can both help interpret physiological arousal and serve as levers for intervention when coupled to actuators such as adaptive lighting or soundscapes (Qu et al., 2024). These lines of work suggest that resonant biometric systems should log environmental variables as standard inputs and be designed to trigger context sensitive adjustments, such as modifying lighting or reducing auditory load, thereby closing the loop between sensing and environmental regulation, which feeds into an end to end pipeline perspective.

An end to end pipeline for resonant body communication must therefore integrate acquisition, preprocessing, feature learning, inference, feedback, and governance into a coherent architectural flow that operationalizes the design principles outlined above. Comprehensive surveys of multimodal emotion recognition and related affective computing systems emphasize that careful data preprocessing, synchronization across modalities, and systematic feature learning are prerequisites for robust performance and replicability in realistic settings (Khare et al., 2024; Pan et al., 2023). A recent review of affective computing methods for multimodal embodied AI proposes a three stage process that moves from multimodal emotion recognition through evolutionary learning of user specific emotional classifications to behavioral feedback in embodied interfaces, effectively sketching a pipeline in which sensing and modeling are tightly coupled to interactive response (Song et al., 2025). Finally, empirical work on emotion AI governance in the United States argues that public perceptions favor strong regulation of emotion data, including bans in some contexts, and recommends regulatory frameworks that recognize the distinct risks of emotion AI relative to nonaffective analytics, implying that privacy by design, consent mechanisms, and transparency about model limitations must be embedded into the pipeline from the outset (Ingber, 2025). Taken together, these contributions support an architectural view in which multimodal acquisition and temporal modeling feed fused and personalized inference, which in turn drives user facing feedback and environmental adaptation under explicit privacy and governance constraints, setting the stage for validation and deployment work in subsequent sections.

Applications and Design Patterns

Clinical diagnostics and therapeutic monitoring represent a primary application domain for resonant body communication, since continuous, ecologically valid sensing can complement traditional, episodic assessments in autism care. Recent systematic work on wearable physiological sensing for autistic populations shows that multimodal wearables capturing heart rate variability, electrodermal activity, respiration, and movement can detect stress and anticipate challenging behavior, thereby supplying clinicians with embodied markers that are difficult to obtain through observation alone (Cano et al., 2024). Parallel advances in tablet- and smartphone-based digital phenotyping demonstrate that computer vision and touch interaction features can quantify social attention, head and facial movements, and visual–motor coordination in autistic children, with strong correlations to gold-standard adaptive behavior scales, which positions such tools as scalable adjuncts for outcome tracking rather than replacements for clinical judgment (Aikat et al., 2025). Complementing these approaches, perspective work on virtual environments in autism argues that immersive, controllable simulations can function as high-ecological validity contexts for both neurodiagnosis and neurotherapy, enabling the systematic study of social behavior, sensory tolerance, and emotional regulation under repeatable conditions (Sokołowska et al., 2025). Taken together, these strands suggest a design pattern in which wearable and app-based digital phenotyping provides continuous embodied markers, while virtual environments create structured probes, and both feed into longitudinal therapeutic monitoring that supports alliance, shared decision making, and iterative treatment adjustment.

Affective interfaces and assistive tools constitute a second application area, with resonant sensing used to support self-regulation, communication, and workplace accommodations for neurodivergent users. A broad review of assistive wearables for mental well-being highlights that devices combining heart rate variability, electroencephalography, and electrodermal activity can detect stress in situ and deliver adaptive feedback or prompts, proposing wearables as front-line assistive technologies when they are designed with comfort, stigma, and usability constraints in mind (Alhejaili et al., 2023). Within explicitly neurodiversity-oriented research, a design study on emotion regulation through wearable technology distills caregiver perspectives on triggers, behavioral cues, and coping strategies for neurodivergent adults, and then implements a smartwatch-based application that recognizes precursor patterns and delivers personalized interventions, framing wearables as socio-technical partners in self-regulation rather than surveillance devices (Kalantari et al., 2021). In the autism-specific domain, a systematic review of stress-monitoring wearables emphasizes that real-time physiological alerts can give autistic individuals and caregivers early warning of escalating arousal and, when paired with tailored interaction schemes, can be integrated into day-to-day routines as subtle self-regulation aids rather than crisis-only tools (Cano et al., 2024). Collectively, these findings articulate a design pattern in which resonant sensing underpins assistive systems that detect stress early, scaffold context-aware coping strategies, and provide data that can be selectively shared with educators, clinicians, or employers to support neurodivergent autonomy and reasonable accommodations.

Extended reality environments form a third application arena, where resonant body communication informs adaptive sensory worlds, body-language avatars, and co-designed training scenarios for autistic and otherwise neurodivergent users. Perspective work on virtual environments in autism argues that immersive systems provide flexible, controllable settings for assessment and intervention, offering opportunities to tune social and sensory parameters and to measure behavioral and physiological responses that would be difficult to observe in conventional clinics (Sokołowska et al., 2025). A co-design framework for autism-focused virtual reality experiential training systems demonstrates how autistic youth, caregivers, and clinicians can collaboratively define scenarios, sensory parameters, and evaluation metrics, thereby aligning VR-based life-skills training with real-world adaptation goals and validating experiential modules through iterative stakeholder feedback (Soccini & Clocchiatti, 2025). In the workplace context, a neurodiversity-affirming perspective on VR highlights strengths-based training experiences in which autistic employees rehearse interviews, disclosure, and sensory coping strategies in low-pressure simulations while neurotypical colleagues engage with perspective-taking modules, positioning VR as a mutual adaptation tool for inclusive organizational cultures (Tatom & Newbutt, 2025). Integrating these strands yields a design pattern in which XR systems use resonant sensing to modulate sensory load, animate avatars with meaningful body-language cues, and dynamically adapt scenario pacing, thereby supporting neurodivergent users in skill building and self-advocacy while also educating non-neurodivergent partners.

Learning technologies constitute a fourth application domain, where resonant data streams enable inclusive engagement detection, multimodal participation metrics, and biofeedback-supported self-awareness in classrooms and online learning environments. A comprehensive review of multimodal analysis in education documents that integrating visual, auditory, and physiological signals yields richer models of engagement, cognitive load, and collaboration than unimodal analytics, and recommends that learning technologies leverage these signals to support personalized and equitable instruction (Guerrero-Sosa et al., 2025). In K–12 settings, empirical work on multimodal learning analytics dashboards shows that combining sensor-based indicators such as facial expressions and heart rate with task traces can give teachers real-time insight into students' affective and behavioral states, although the authors caution that interpretability, workload, and privacy must be carefully addressed when bringing such tools into everyday classrooms (Possaghi et al., 2025). Complementing these system-level dashboards, a multimodal deep learning framework for student engagement assessment demonstrates that fusing video, text, and interaction logs improves the detection of engagement trajectories over time and can be extended to include physiological data, thereby offering a template for resonant engagement analytics that capture diverse forms of participation, including those more characteristic of neurodivergent learners (Yan et al., 2025). These converging lines of work suggest a design pattern in which learning technologies sense engagement through multiple bodily and contextual channels, surface interpretable indicators to teachers and learners, and incorporate biofeedback loops that help students recognize and regulate their own arousal and attention in ways that respect neurodiverse learning rhythms.

DISCUSSION

The synthesis of the theoretical framework of resonant body communication with the proposed technical architecture suggests a significant reframing of affective computing and human–computer interaction, shifting the analytic center of gravity from faces to bodies in context. Recent work on multimodal embodied AI design argues that affective computing should be understood as a three-stage process that moves from emotion recognition to evolutionary learning of user-specific emotional classifications and finally to behavioral feedback in interaction, a sequence that aligns closely with the end-to-end pipeline articulated here (Song et al., 2025). Critical reviews of multimodal emotion recognition in big data similarly identify temporal dynamics, cross-modal dependency modeling, and real-world robustness as the core theoretical gaps that next-generation systems must address, reinforcing the importance of temporal elasticity and multimodal fusion in the present framework (Wafa, 2025). Within HCI, discussions about the future of emotion research emphasize that moving beyond facial metrics toward socially situated, embodied, and ethically aware models is essential if emotion technology is to contribute positively to human experience rather than narrowing it (Wadley et al., 2022). Taken together, these perspectives suggest that resonant body communication can function as a bridging construct between affect science and design practice, providing a conceptual vocabulary and technical blueprint that supports embodied, neurodiversity-affirming interaction while also foregrounding the broader implications for HCI scholarship, which subsequently raises questions about limitations and risks.

Despite these advances, the resonant framework faces limitations, boundary conditions, and risks that must be addressed explicitly if it is to be deployed responsibly in clinical, educational, or workplace contexts. Regulatory developments such as the European Union's Artificial Intelligence Act classify emotion recognition systems as a distinct category and place stringent restrictions, including outright bans in certain employment and educational settings, underscoring the potential for harm when biometric affect inference is misused or poorly governed (Regulation (EU) 2024/1689, 2024). EUR-Lex Legal and policy analyses of Emotional AI further highlight privacy, manipulation, and bias concerns, warning that systems that infer internal states from biometric signals can be used to influence behavior covertly or entrench discrimination if deployed without safeguards or user agency (Bagdasarova, 2024). Commentary from human–computer interaction and information studies scholars likewise argues that Emotion AI in workplaces is unlikely to solve structural problems and may instead burden already marginalized groups, especially when deployed as an evaluative surveillance tool rather than as a voluntary support, thereby pointing to the importance of neurodiversity-affirming objectives and participatory governance (Wadley et al., 2022). These limitations indicate that resonant biometric systems must be constrained by context-specific prohibitions, explicit consent regimes, transparency about uncertainty, and strong community oversight if unintended consequences are to be mitigated, which in turn motivates a careful strategy for translation and interoperability across domains.

A translation strategy for cross-domain adoption and interoperability must recognize that resonant body communication systems will operate within heterogeneous technical and institutional ecosystems that demand shared standards for multimodal data and inclusive design. Work on multimodal data curation via interoperability in medical imaging demonstrates that intentional interoperability frameworks can link previously siloed datasets, enabling more representative and ethically auditable AI models, which suggests that similar strategies are needed for affective and behavioral data to avoid fragmented, non-comparable systems (Chen et al., 2025). An AI-first framework for multimodal data in Alzheimer's and related dementias proposes treating data systems as infrastructures for longitudinal, cross-setting care, indicating that affective sensing for neurodivergent communication will likewise require interoperable pipelines that can support continuity between clinics, homes, schools, and workplaces without duplicating effort or magnifying risk (Jasodanand et al., 2025). Concurrently, design research on AI-supported user interfaces for neurodiverse-friendly IT systems shows that inclusive pattern libraries, participatory data collection, and configuration options can enable interfaces that work for both neurodivergent and neurotypical users, thereby offering a template for cross-domain reusability grounded in neurodiversity-informed design (Keil, 2024). These converging lines of evidence imply that translating the resonant framework into practice will require interoperable multimodal data standards, co-designed interface conventions that foreground neurodivergent needs, and institutional partnerships that span health, education, and work, thereby setting the stage for concluding reflections on the broader significance and future directions of this research.

CONCLUSION

Reframing affect from faces toward bodies in context consolidates a conceptual and technical shift that promises both greater accuracy in inference and greater dignity for neurodivergent communicators. Five-year reviews of automatic facial emotion recognition underscore persistent reliability concerns in real-world use, particularly where spontaneous, ambiguous, or atypical expressions are involved, thereby limiting face-centric systems as comprehensive affect sensors (Carvalho & Mendes, 2025; Kim et al., 2025). Embodied cognition research, by contrast, demonstrates that social understanding and emotional appraisal are deeply rooted in whole-body movement, bodily representations, and situated interaction, providing a theoretical basis for treating posture, gesture, and environmental coupling as primary data rather than incidental noise (Canino et al., 2022; Castro-Alonso et al., 2024). Emerging HCI work on designing with neurodivergent communities similarly argues that accessible systems must be co-created around diverse sensory, temporal, and communicative preferences, extending the notion of inclusion from interface layout to the very signals that systems treat as legitimate forms of expression (Tcherdakoff et al., 2025; Choi, 2025). Taken together, this body of scholarship supports a conclusion that resonant body communication is not merely an alternative sensing strategy but a corrective to longstanding biases in affective computing, enabling technologies that can recognize a broader range of affective lives while reducing pressure on neurodivergent individuals to mask or conform, which directly motivates a realistic roadmap for piloting and infrastructure building.

A roadmap for near-term pilots and long-term infrastructure building must therefore balance ambitious multimodal experimentation with robust governance, interoperability, and neurodiversity-centered design practices. Near-term pilots can focus on bounded, high-value contexts such as autism clinics, specialized classrooms, or voluntary workplace accommodations, where multimodal sensing suites and temporal models are evaluated not only on prediction accuracy but also on user trust, therapeutic value, and perceived respectfulness (Pan et al., 2023; Yu et al., 2025). At the infrastructural level, scholars in AI and health informatics advocate AI-first multimodal data frameworks and interoperability layers that support longitudinal care and cross-setting analysis, offering templates for building shared, ethically curated repositories of motion, physiology, and context data that respect privacy while enabling replication and benchmarking (Jasodanand et al., 2025; Chen et al., 2025). In parallel, critical diversity and design research in HCI emphasizes that the scaling of such infrastructure must be guided by universal design and neurodiversity-informed standards, ensuring that affective computing growth does not simply expand facial recognition markets but rather institutionalizes participatory, embodied, and context-aware approaches across domains (Schelenz, 2025; Zolyomi et al., 2025). Under these conditions, resonant body communication can mature from a theoretical proposal into a practical scaffold for human-centered, neurodiversity-affirming affective technologies that are as attentive to structural justice and lived experience as they are to computational sophistication.

Data Availability
Data available upon request.
Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper.
Funding Statement
NA

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