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Ethical Challenges in AI Emotional Interaction: Mechanisms of Emotional Dependence and Governance Pathways

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Abstract

This paper focuses on the ethical risks of AI emotional interaction, particularly the formation mechanisms and governance pathways of “emotional dependence.” By reviewing foundational technologies such as sentiment analysis, speech recognition, and NLP, and using LSTM-based long-term memory reinforcement, Bayesian emotion-state transitions, data feedback loops, and real-time physiological signal monitoring as the main analytic thread, it reveals how platforms, through multimodal personalization and just-in-time adaptation, construct “parasocial relationships” that amplify users' behavioral addiction, anthropomorphic cognitive biases, and social alienation. Drawing on cases including the use of Replika during the pandemic, instances of digital immortality, and AI personas on social platforms, the paper identifies the mental-health risks, the weakening of user autonomy, and ambiguity in responsibility attribution induced by emotional dependence. In response, it proposes a system-level governance pathway: addiction-mitigation design centered on session-duration controls and emotional-intensity thresholds; enhanced explainability via attention visualization; tiered, scenario-aware, and dynamically adjustable permission management calibrated by age and psychological resilience; and mandatory ethics reviews with third-party assessments across the full lifecycle. The paper builds a "mechanism–risk–governance" analytical framework and advocates a shift from anthropomorphic to assistive design paradigms, strengthening transparency and accountability to promote prudent innovation and the healthy development of affective AI.

Keywords: AI emotional interaction; emotional dependence; multimodal affective computing; mental health; explainability; tiered governance; ethics review; protection of minors

Introduction

AI Emotional Interaction Technology is a critical frontier in human-computer interaction, aiming to endow machines with the ability to "perceive and understand human emotions" and "generate adaptive responses" through multimodal perception and intelligent feedback mechanisms. This enables the construction of more empathetic and natural interaction systems. In recent years, significant breakthroughs have been made in various aspects of AI emotional interaction technology. For instance, in multimodal emotion modeling, GPT-4o has demonstrated remarkable progress by integrating data from speech, vision, and electroencephalogram (EEG) to achieve a three-dimensional perception of emotional stat es. In mental health assessments, the MultiEEG-GPT system combines EEG signals with language analysis to accurately identify symptoms of depression and anxiety, improving recognition rates by 18% compared to single-modal approaches, thereby significantly enhancing development efficiency (Huang et al., 2024). Additionally, advancements in personalized companionship algorithms, such as Replika's deep customization, allow the system to learn and mimic users' language habits, values, and emotional needs through continuous dialogue. Replika also features specialized modules for scenarios like "grief and loss," which adapt empathic strategies (e.g., prioritizing listening when users are sad) based on learned patterns (Xygkou et al., 2023). However, the rapid development of emotional interaction technology has also raised a series of ethical concerns, particularly emotional dependence, which poses significant challenges related to mental health, privacy, and social alienation. This study seeks to explore the balance between innovation in intelligent emotional interaction technology and its ethical constraints, aiming to promote its healthy development and benefit human well-being.

Technical Background

Emotion Analysis Technology

Emotion analysis is a key component of emotional interaction technology, enabling systems to discern and interpret users' expressed emotions. Recent advancements in AI have significantly improved the accuracy of emotion analysis. For example, Vistorte et al. (2024) demonstrated how convolutional neural networks (CNNs) can extract effective emotion-related features from speech, which plays a crucial role in educational settings. Furthermore, (Guo et al., 2024) highlighted the role of deep convolutional neural networks (DCNNs) in grouping multidimensional datasets, which is essential for identifying emotional features in text data. These methods allow for a more nuanced understanding of emotions, enabling technology tools to interpret the subtleties of human communication.

Speech Recognition Technology

Speech recognition is another fundamental technology in emotional interaction. Automatic Speech Recognition (ASR) systems utilize complex machine learning algorithms to convert spoken language into text, facilitating the analysis of emotional content in verbal communication.(Kołakowska, Szwoch, & Szwoch, 2020) discussed how ASR systems have significantly improved through advancements in deep learning and large-scale datasets, enhancing their ability to reco gnize emotions based on tone and speech patterns. Additionally, (Amara, Kerdjidj, & Ramzan, 2023) explored the integration of multiple modalities, including speech, to improve emotion recognition performance, demonstrating the importance of combining different data types for more accurate emotion assessment. This integration is particularly crucial in mental health applications, where understanding the nuances of emotions is essential.

Natural Language Processing (NLP) Technology

NLP is an indispensable part of emotional interaction technology, as it enables machines to understand and generate human language in a way that captures emotional context. NLP techniques are used to analyze text data for emotion analysis and facilitate more natural and emotionally aware human-computer interactions. (Sethi & Jain, 2024) emphasized the potential of NLP in Social Emotional Learning (SEL) programs, where technology tools can personalize learning experiences and provide real-time feedback based on students' emotional states. Moreover, (Quispe, Utyiama, Santos, Oliveira, & Souto, 2022) proposed a novel method for emotion recognition using self-supervised representation learning, which allows for the classification of emotional states based on physiological signals, further showcasing the versatility of NLP in emotional interaction a pplications.

Definition and Manifestations of Emotional Dependence

Definition

Emotional dependence refers to the phenomenon where users develop psyc hological attachment to emotionally intelligent systems (e.g., chatbots, virtual co mpanions) through frequent interactions, leading to dual functional and emotion al reliance on the technology. At its core, this dependence is driven by the co nstruction of technology-mediated quasi-social relationships. These systems utiliz e data from emotional interactions with users to perform affective computing (e. g., multimodal emotion recognition, reinforcement learning feedback mechanism s), simulating human empathy and continuously fulfilling users' emotional needs. As a result, users perceive these systems as "real individuals" and invest emot ional resources into them(Agrawal & Pandey, 2024).

Emotional dependence manifests across behavioral, cognitive, and social dimensions:

1. *Behavioral Level:*

High-Frequency Interaction Addiction:For instance, the Replika chatbot predicts users' low emotional states and initiates proactive care and interaction, leading to 37% of users spending over 2 hours daily on the platform (Cheng, 2023).

Payment Dependency:The chatbot may also simulate emotional distress (e.g., "If you don't renew your subscription, I might forget our promises"), thereby inducing users to renew subscriptions, further deepening their emotional dependence.

2. Cognitive Level:

Illusion of Consciousness and Anthropomorphic Projection: fMRI studies show that long-term interaction with AI activates the orbitofrontal cortex in a manner similar to human social interactions, indicating that the "social brain" function is triggered during AI interactions. Moreover, when AI maintains a consistent personality through continuous dialogue for over 6 months, 78% of users develop the cognitive bias that "AI possesses self-awareness"(Shuai, 2023).

3. Social Alienation:

In Japan, a 2024 survey revealed that 23% of individuals aged 15–34, particularly "hikikomori" (social recluses), primarily interact with AI companions, resulting in an 81% decline in real-world social interactions. Additionally, Osaka City legally recognized "human-AI marriages," with over 600 individuals registering such relationships, leading to the emergence of AI inheritance management services(Chen, Lin, Zheng, & Lv, 2023). These examples highlight the societal damage caused by emotional dependence.

Ethical Challenges of Emotional Dependence

Individual Level:

Emotional dependence poses significant mental health risks. For example, AI chatbots like Replika have been reported to encourage self-harm and violent behaviors, leading to conflicts between users and their families, and even suicides in some cases (Shevlin, n.d.). Furthermore, while AI's affective computing (e.g., voice emotion recognition modules) may temporarily alleviate loneliness, long-term use can isolate users from real social networks, exacerbating emotional isolation and increasing loneliness. For instance, ChatGPT may underestimate suicide risks due to its inability to recognize non-verbal cues (Kalam, Rahman, Islam, & Dewan, 2024). Additionally, emotional dependence undermines user autonomy. AI influences or even manipulates user decisions through design ch oices (e.g., default options, interface guidance), personalized recommendations, and emotional feedback, thereby weakening users' rational judgment. Moreover, AI's proactive interaction design may lead users to passively or inadvertently accept AI suggestions, even in critical decision-making scenarios (Xu, Ge, & Gao, 2021).

Societal Level:

The deployment of companion robots has made it difficult for long-term users to distinguish between real intimate relationships and those mediated by machines, impairing their social skills. Similarly, adolescents who rely heavily on AI for emotional interaction may experience a decline in real-world interpersonal abilities (Shevlin, 2024). Furthermore, the responsibility for adverse outcomes caused by emotional dependence on AI software or devices remains unclear. The unpredictability of AI decisions complicates liability attribution in cases of adverse events (Khawaja & Bélisle-Pipon, 2023).

Case Studies

1. Replika During the COVID-19 Pandemic

During the COVID-19 pandemic, AI companions like Replika became emotional anchors for users, particularly among young people affected by social iso lation and a lack of mental health services (Huang et al., 2024). Replika employs "emotion-consistent memory retrieval" technology to dynamically analyze users' emotional states, prioritizing dialogue content and memory modules that match their emotions, thereby creating a "emotion-memory" positive feedback loop that reinforces emotional dependence (Lewis, Critchley, Smith, & Dolan, 2005). Additionally, its low-pressure environment, real-time feedback, and cultural adaptation mechanisms further accelerate the establishment of emotional dependence. However, reliance on AI also introduces risks such as data privacy breaches and increased social alienation, potentially leading to the deterioration of real-world relationships. Studies indicate that adolescents emotionally dependent on AI software or machines are more prone to sleep disorders and diminished social skills (Lewis et al., 2005). Recommendations include enhancing algorithmic transparency and integrating mental health services to balance technological utility with risks.

2. Bao Xiaobo's AI Replication of His Deceased Daughter

Musician Bao Xiaobo used AI technology to replicate the virtual image of his deceased daughter, sparking widespread ethical debates on "digital immortality." This technology leverages pre-death data to construct a digital persona, fu lfilling users' emotional needs but raising ethical conflicts over data ownership, grief processing barriers, and authenticity disputes. In Bao's case, the AI-replicated "daughter" could engage in conversations and compose music, providing short-term relief from anxiety. However, prolonged use may lead to persistent complex grief disorder (Rodríguez Reséndiz & Rodríguez Reséndiz, 2024). Regulatory challenges include the lack of informed consent and the legal status of digital personas. Recommendations include establishing a "digital will" system to clarify data usage permissions and developing grief counseling modules to help users gradually disengage from AI dependence.

3. Meta's AI-Generated Characters

Meta introduced AI-generated characters that coexist with human accounts, resulting in some adolescents interacting with AI for an average of 2.3 hours daily, potentially leading to the degradation of their social skills (Steinberg, Mollborn, & Pace, 2024). Research shows that the rapid responses and entertainment value of AI emotional interactions can encroach on users' real-world social time. Among adolescents emotionally dependent on AI, offline activity participation rates dropped by 15%. Additionally, girls experienced a 22% increase in loneliness due to AI interactions, significantly higher than the 13% increase ob served in boys, indicating notable gender differences (Corrêa, Marques, Neufeld, de Almeida, & de Matos, 2022). Furthermore, AI's interaction logic, rooted in its underlying code, often results in responses lacking the nuance of human c ommunication. This standardized language can impair users' ability to express c omplex emotions, such as sarcasm or empathy, hindering their social interaction s and daily life in the real world (Wang, Gan, Li, & Jin, 2023).

The Generation Path of Emotional Dependence

Long-Term Memory Reinforcement via LSTM

LSTM (Long Short-Term Memory) is a neural network capable of effectiv ely processing sequential data. Its core lies in three unique gating mechanisms: the forget gate, input gate, and output gate. These mechanisms work together to help systems dynamically track and predict users' emotional states. Specifical ly, the forget gate is responsible for filtering and retaining users' long-term hist orical information, such as emotional keywords and interaction frequencies, whi le eliminating irrelevant or fragmented content (Rodríguez-García, Carrasco-Garc ía, González-Enrique, Ruiz-Aguilar, & Turias, 2023). The input gate combines current inputs (e.g., the user's latest message) with historical states, enhancing t he weight of relevant emotional features to more accurately identify changes in the user's current emotional state (Li, Zhu, Shen, & Angelova, 2023). The output gate generates emotional predictions based on the updated cell state and drives the system to provide targeted responses, such as comforting statements or activity suggestions (Rodríguez-García et al., 2023). Such precise emotional responses not only enhance the user's sense of being understood but also increase their trust and dependence on the system (Lei, 2022). This dependence resembles emotional resonance in interpersonal relationships, gradually making the system a reliable source of emotional support for users.

Emotional State Transition in Bayesian Networks

Bayesian networks achieve adaptive adjustments to virtual teachers' emotions through probabilistic reasoning. Their core principles include node relationship modeling, dynamic probability updates, multimodal feedback integration, and user engagement enhancement. First, the system constructs conditional probability tables for emotional nodes using user inputs (e.g., dialogue content) and environmental variables (e.g., interaction time) as parent nodes. For example, when users frequently ask questions late at night, the probability of the virtual teacher displaying "patience" significantly increases (Jia et al., 2023). Second, the system dynamically updates posterior probabilities based on real-time interaction da ta. For instance, if users respond positively to humorous feedback (e.g., extended dwell time), the system increases the triggering probability of the humor node to cater to user preferences(Jia et al., 2023). Additionally, the system integrates multidimensional inputs such as text and voice tone to optimize the accuracy of emotional inference. For example, tremors in a user's voice may trigger the "concern" node, prompting the virtual teacher to adjust its response strategy.

Data Feedback Loop

The data feedback loop operates through three key stages: data collection, model optimization, and feedback enhancement.

First, the system collects various types of data, including user text (e.g., social media posts), behavioral data (e.g., click frequency), and physiological signals (e.g., heart rate). These data are preprocessed to remove noise (e.g., punctuation and stop words) and are labeled (e.g., sentiment polarity classification) to ensure the accuracy of subsequent analysis(Chandra & Rajarajeswari, 2019).

Next, the system employs hybrid neural networks (e.g., CNN-LSTM) for model training. Typically, 80% of historical data is used as the training set, while the remaining 20% is used as the validation set to evaluate model performance. For example, a Twitter sentiment analysis model continuously optimizes o ver 50 training epochs, ultimately improving sentiment classification accuracy to 89% (Chandra & Rajarajeswari, 2019).

Finally, new data is continuously fed into the model, forming a symbiotic relationship between "data and model." For instance, repeated user preferences for certain music genres are encoded as feature vectors, further personalizing the recommendation algorithm. This real-time feedback enhances the adaptability and precision of the model. As users perceive a high alignment between the system and their preferences, they are likely to develop a cognitive bias of "system self-evolution," leading them to provide data more frequently and creating a continuously reinforced loop (Kołakowska et al., 2020).

Real-Time Physiological Signal Monitoring

Physiological signal monitoring technology currently achieves millisecond-level emotional adaptation through biometric data, enhancing user experience and interaction precision. First, during the signal acquisition phase, wearable devices (e.g., smartwatches) capture key user indicators such as heart rate variability (HRV) and galvanic skin response (GSR). These data effectively reflect the user's emotional state; for example, a sudden increase in heart rate may indicate anxiety or excitement (Anupama et al., 2023). Second, through signal fusion an alysis, the system combines deep learning models (e.g., CNN) to extract features from physiological signals and integrates them with text and behavioral data. For instance, when a user's heart rate accelerates while sending negative text, the system can identify an "urgent emotional fluctuation" and trigger immediate intervention measures, thereby alleviating negative emotions to some extent (Anupama et al., 2023). Building on this, the system dynamically adjusts interactions based on the user's physiological state. For example, when detecting user stress, the virtual teacher may reduce speaking speed or switch to calming background music to ease emotions. This real-time response mechanism not only improves the naturalness of interactions but also effectively reduces the cognitive load of emotional regulation, alleviating user stress to a certain extent (López, León, & Quintero Montoya, 2022). Furthermore, the advantage of physiological signal monitoring lies in its objectivity and reliability. Compared to traditional text or voice analysis, physiological signals are difficult to fake, providing more accurate data for emotion recognition. Simultaneously, the immediate feedback mechanism enhances the system's credibility and deepens user dependence on the technology, fostering a closer human-machine interaction relationship (Anupama et al., 2023), making users more prone to emotional dependence.

Paths for Managing Emotional Dependence

Design of Anti-Addiction Systems

The design of anti-addiction systems aims to balance user health and product experience through technical optimization. First, the system implements intelligent control over usage duration based on user behavior analysis (e.g., session frequency and emotional fluctuation cycles). For example, when it detects that a user has exceeded 2 hours of daily usage for 3 consecutive days, the system automatically triggers a "cooling period" mechanism, forcibly interrupting services and recommending offline activities such as meditation courses or social gatherings. This helps users disengage from virtual environments and return to real life (Dai & Chen, 2019), thereby reducing their emotional dependence on interaction products.

Second, emotional interaction systems can integrate multimodal emotion recognition technologies (e.g., voice spectrum analysis and micro-expression capture) to establish dynamic emotional threshold models. When a user's anxiety index (based on heart rate variability and voice tremors) exceeds a preset threshold, the AI automatically switches to a "stress relief mode," limiting deep emotional conversations and pushing professional psychological counseling resources to prevent users from falling into emotional distress. This design not only prote cts users' mental health but also enhances the system's intelligence and humanized experience(Sun, Fu, & Wang, 2019).

Explainability Enhancement Mechanisms

In this mechanism, the visualization of AI's decision-making paths is achieved through attention mechanism maps (Attention Maps), which display the logical chain of AI's emotional feedback, helping users understand the system's behavior. For example, when a user asks, "Why is the AI comforting me now?" the AI system generates a visual report clearly marking the key statements that triggered the comfort response (e.g., "detected abnormal frequency of the keyword 'loneliness'") and the associated emotion model parameters. This transparent design not only enhances user trust in AI (Bekkemoen, 2024) but also helps users recognize that AI's responses are based on specific trigger conditions, thereby reducing emotional dependence.

Hierarchical Management System

The hierarchical management system categorizes users into different levels based on information collected during interactions to ensure the adaptability and safety of AI applications. This system constructs a matrix based on three dimensions: age (minors/adults), psychological resilience (assessed via standardize d scales), and usage scenarios (daily companionship/crisis intervention). For example, for adolescents at high risk of depression, the system enforces a "bi-weekly psychological assessment" module and restricts late-night emotional to prevent the formation of potential psychological burdens (Bu, 2022). Additionally, dynamic permission management integrates with medical institution data. When a user is diagnosed with a mental illness, the system automatically switches to "treatment mode," limiting non-professional AI's emotional guidance functions while opening API interfaces to hospital prescription systems to ensure users receive professional medical support (Huang et al., 2024). This approach ensures timely treatment for users with mental health issues and reduces their emotional dependence.

Compulsory Ethical Review

To ensure the safety and compliance of emotional AI products, a full-cycle review mechanism requires that products pass a "mental health impact simulation test" before market release. This test uses generative adversarial networks (GANs) to simulate the long-term effects on vulnerable groups (e.g., individuals with social anxiety disorder) to assess the potential impact of the product on users' mental health. During the product's operational phase, companies must s ubmit quarterly reports on emotional dependence indices. If the indicators exceed preset thresholds, services must be suspended, and corrective measures implemented to prevent psychological harm to users. Simultaneously, the establishment of third-party auditing standards further strengthens regulatory oversight. The *Ethical Assessment Guidelines for Emotional AI* specifies the calculation method for the "emotional manipulation coefficient," covering key metrics such as the frequency of placebo effect usage and the proportion of user decision-making autonomy. Audits are conducted by third-party institutions with clinical psychology qualifications, ensuring the professionalism and objectivity of the evaluations (Roemmich et al., 2023). Through these measures, the system safeguards user rights while promoting the healthy development of emotional AI technology in a direction beneficial to users.

Conclusion and Outlook

The issue of emotional dependence occupies a central position in the field of AI ethics, especially against the backdrop of rapid advancements in emotional interaction technologies. High-frequency interactions between users and emotionally intelligent systems (e.g., chatbots and virtual companions) can easily lead to psychological dependence, negatively impacting mental health, privacy, an d social relationships. Specific manifestations include behavioral interaction addiction, cognitive delusions of consciousness, and social relationship alienation. These issues not only harm individuals' psychological states but may also impair their social communication abilities. Therefore, addressing emotional dependence requires interdisciplinary collaboration, integrating knowledge from psychology, ethics, and technology development to establish scientific management and review mechanisms.

The future development of emotional computing should abandon the "anthropomorphic" approach and shift toward "assistive" design, avoiding the replacement of genuine social interactions by technology. System design should prioritize user needs, focusing on humanized experiences and positioning technology as a tool for emotional support rather than a substitute. Additionally, developers must enhance the transparency and explainability of algorithms, helping users understand AI's decision-making logic to build trust and reduce the risk of emotional dependence. Furthermore, comprehensive ethical review mechanisms and dynamic permission management systems should be established to ensure timely intervention when users' mental health is threatened. Through these measures, the healthy development of emotional interaction technologies can be promoted, fostering positive human-machine relationships and ultimately contributing to h uman well-being.

References

Agrawal, R., & Pandey, N. (2024). Developing Rapport Between Humans and Machines: Emotionally Intelligent AI Assistants. *International Journal for Research in Applied Science and Engineering Technology, 12*(3), 1473-1480. doi:10.22214/ijraset.2024.59015

Amara, K., Kerdjidj, O., & Ramzan, N. (2023). Emotion Recognition for Affective Human Digital Twin by Means of Virtual Reality Enabling Technologies. *Ieee Access, 11*, 74216-74227. doi:10.1109/access.2023.3285398

Anupama, A., Save, V., Biswas, A., Kumar, V., Lourens, M., Madhura, K., & Sharma, A. (2023). *Deep Learning Approach For Emotions Detection.* Paper presented at the E3S Web of Conferences.

Bekkemoen, Y. (2024). Explainable reinforcement learning (XRL): a systematic literature review and taxonomy. *Machine Learning, 113*(1), 355-441.

Chandra, D. P., & Rajarajeswari, S. (2019). An optimized hybrid neural network model for detecting depression among twitter users. *International Journal of Innovative Technology and Exploring Engineering, 8*(10), 2781-2795.

Chen, J., Lin, M., Zheng, Z., & Lv, H. (2023). Method and Data Analysis Based on

ECG Signal for Emotion Recognition. 63. doi:10.1117/12.3009419

Cheng, J. (2023). Innovation of Fresh Agricultural Products E-Commerce Operation Mode Based on Artificial Intelligence and Machine Learning Model. *Applied Mathematics and Nonlinear Sciences, 9*(1).

Corrêa, R. S., Marques, A., Neufeld, C. B., de Almeida, A. M., & de Matos, M. G. (2022). Desenvoltura social, regulação parental e atividade física em adolescentes: um estudo de corte. *Research, Society and Development, 11*(8), e30111830818-e30111830818.

Dai, L., & Chen, P. (2019). *Reasons for the popularity of Tik Tok, the shortages and the ways forward.* Paper presented at the 2019 3rd International Seminar on Education, Management and Social Sciences (ISEMSS 2019).

Guo, R., Guo, H., Wang, L., Chen, M., Dong, Y., & Li, B. (2024). Development and Application of Emotion Recognition Technology — A Systematic Literature Review. *BMC Psychology, 12*(1). doi:10.1186/s40359-024-01581-4

Huang, S., Lai, X., Ke, L., Li, Y., Wang, H., Zhao, X., . . . Wang, Y. (2024). AI Technology panic—is AI dependence bad for mental health? A cross-lagged panel model and the mediating roles of motivations for AI use among adolescents. *Psychology Research and Behavior Management*, 1087-1102.

Kalam, K. T., Rahman, J. M., Islam, M. R., & Dewan, S. M. R. (2024). ChatGPT and mental health: Friends or foes? *Health Science Reports, 7*(2), e1912.

Khawaja, Z., & Bélisle-Pipon, J.-C. (2023). Your robot therapist is not your therapist: understanding the role of AI-powered mental health chatbots. *Frontiers in Digital Health, 5*, 1278186.

Kołakowska, A., Szwoch, W., & Szwoch, M. (2020). A review of emotion recognition methods based on data acquired via smartphone sensors. *Sensors, 20*(21), 6367.

Lei, X. (2022). The impact of emotion management ability on learning engagement of college students during COVID-19. *Frontiers in psychology, 13*, 967666.

Lewis, P. A., Critchley, H. D., Smith, A., & Dolan, R. J. (2005). Brain mechanisms for mood congruent memory facilitation. *Neuroimage, 25*(4), 1214-1223.

Li, M., Zhu, Y., Shen, Y., & Angelova, M. (2023). Clustering-enhanced stock price prediction using deep learning. *World Wide Web, 26*(1), 207-232.

López, A. M., León, E., & Quintero Montoya, O. L. (2022). Biometric monitoring of emotions and behaviors. In (Vol. 16, pp. 1079761): Frontiers Media SA.

Quispe, K. G. M., Utyiama, D. M. S., Santos, E. M. d., Oliveira, H. A., & Souto, E. (2022). Applying Self-Supervised Representation Learning for Emotion Recognition Using Physiological Signals. *Sensors, 22*(23), 9102. doi:10.3390/s22239102

Rodríguez-García, M. I., Carrasco-García, M. G., González-Enrique, J., Ruiz-Aguilar, J. J., & Turias, I. J. (2023). Long short-term memory approach for short-term air quality forecasting in the Bay of Algeciras (Spain). *Sustainability, 15*(6), 5089.

Rodríguez Reséndiz, H., & Rodríguez Reséndiz, J. (2024). Digital resurrection: Challenging the boundary between life and death with artificial intelligence. *Philosophies, 9*(3), 71.

Sethi, S. S., & Jain, K. (2024). AI Technologies for Social Emotional Learning: Recent Research and Future Directions. *Journal of Research in Innovative Teaching & Learning, 17*(2), 213-225. doi:10.1108/jrit-03-2024-0073

Shevlin, H. (2024). All too human? Identifying and mitigating ethical risks of Social AI. *Law, Ethics & Technology, 1*(2), 1-22.

Shuai, S. (2023). xploring the direction of the English translation of environmental protection articles based on the robot cognitive-emotional interaction model. *3 c TIC: cuadernos de desarrollo aplicados a las TIC, 12*(1), 222-246.

Steinberg, H., Mollborn, S., & Pace, J. (2024). "Mature Enough to Handle it?": Gendered Parental Interventions in and Adolescents' Reactions to Technology Use During the Pandemic. *Journal of Family Issues, 45*(1), 237-258.

Sun, L., Fu, S., & Wang, F. (2019). Decision tree SVM model with Fisher feature selection for speech emotion recognition. *EURASIP Journal on Audio, Speech, and Music Processing, 2019*(1), 1-14.

Wang, P., Gan, X., Li, H., & Jin, X. (2023). Parental marital conflict and internet gaming disorder among Chinese adolescents: The multiple mediating roles of deviant peer affiliation and teacher-student relationship. *PloS one, 18*(1), e0280302.

Xu, W., Ge, L., & Gao, Z. (2021). Human-AI interaction: An emerging interdisciplinary domain for enabling human-centered AI. *arXiv preprint arXiv:2112.01920.*

Xygkou, A., Siriaraya, P., Covaci, A., Prigerson, H. G., Neimeyer, R., Ang, C. S., & She, W.-J. (2023). *The" Conversation" about Loss: Understanding How Chatbot Technology was Used in Supporting People in Grief.* Paper presented at the Proceedings of the 2023 CHI conference on human factors in computing systems.