NeuroAI Startups: Emotional Data as a Business Model

Edwin Gerardo Acuña Acuña1[0000-0001-7897-4137]

[1] Universidad Latinoamericana de Ciencia y Tecnología, San José, Costa Rica
edwacuac@gmail.com / eacunaa711@ulacit.ed.cr

Abstract. This article presents the notion of NeuroAI Startups, a nascent industry where emotional data supports creative business models. These firms use artificial intelligence, neurotechnology, and biometric emotion tracking to provide substantial solutions in mental health, human resources, education, and marketing, closely associated with the Artificial Intelligence track. By prioritizing Digital Transformation, these firms enable the restructuring of traditional sectors via the incorporation of technology such as brain-computer interfaces, machine learning, and real-time sentiment analysis. Their proficiency in technology is seen in the innovative use of wearables and emotion-sensing devices inside complex social and professional environments. This research analyzes, from a Business Model and Intrapreneurship perspective, the transformation of emotional data into scalable, user-focused solutions that prioritize empathy and customized experiences. These companies use Design Thinking as a core development framework, ensuring that human needs drive innovation processes.

The report highlights Market Impacts, indicating that emotional intelligence is becoming a competitive advantage. By incorporating affective computing into corporate strategy, NeuroAI enterprises are redefining industry standards and client interaction, positioning themselves as pioneers in emotionally intelligent innovation. This study enhances the connection between technology entrepreneurship and emotional and cognitive characteristics, providing strategic insights for firms and education prepared for the future.

Keywords: NeuroAI, Emotional Analytics, Digital Transformation, Affective Computing, Entrepreneurial Innovation.

1 Introduction

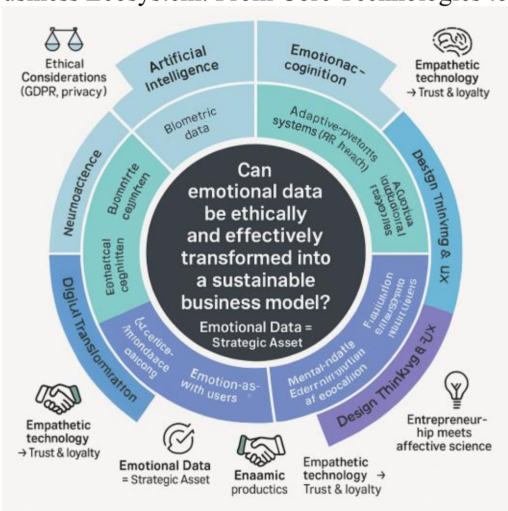
In the contemporary data-driven culture, emotions have evolved from their subjective realm to become quantifiable, interpretable, and commercially viable factors. The integration of neuroscience and artificial intelligence, termed NeuroAI, is transforming the strategies entrepreneurs use for commercial innovation. These nascent enterprises convert emotional signals into actionable insights, leading to innovative business models in which emotional data is seen as a strategic asset rather than a mere consequence.

[1] predicted in her groundbreaking research on affective computing that robots' capacity to identify and react to human emotions facilitates the development of more empathic and adaptable systems. This trend corresponds with [2] ethical paradigm on artificial intelligence, which underscores the paramount significance of context in algorithmic interpretation. Currently, entrepreneurs are using this dual viewpoint by

incorporating emotional analysis into solutions within mental health, education, marketing, and human capital management.

Emotion-driven entrepreneurship flourishes via the incorporation of technologies such facial expression identification, biometric wearables, natural language processing, and multimodal deep learning [3]. NeuroAI systems may identify burnout risk in workplaces, disengagement in schools, or emotional isolation in digital social spaces via real-time analysis of voice intonation, micro-expressions, and language sentiment. What was once abstract and private is now measurable, formalized, and implemented.

Figure 1: NeuroAI Business Ecosystem: From Core Technologies to Market Impact



Source: Author.

But can emotional data be ethically and effectively transformed into a sustainable business model?

This fundamental inquiry underlies the emergence of NeuroAI companies. These initiatives are not only technology endeavors; they are socio-technical ecosystems. Their success relies on a harmonious integration of artificial intelligence, user-centered design, and affective research. Utilizing approaches such as design thinking [4], they collaboratively develop tools that align with human experience while leveraging the computational capabilities of algorithms like BERT or GPT for contextual emotional analysis [5].

These advances indicate a more extensive digital transition. Emotional data is integrated into decision-making processes, including adaptive learning platforms that adjust material according to student stress levels and corporate wellness applications that monitor mood and suggest solutions. In this regard, emotional analytics has transitioned from a supportive tool to a pivotal element in value generation and market disruption.

The ramifications for entrepreneurship are significant. According to [6], emotional intelligence serves not just as an individual characteristic but also as an indicator of group achievement. When used extensively, it allows firms to foresee customer requirements, customize experiences, and foster brand trust via emotional resonance. NeuroAI businesses are leveraging this by developing business models in which emotional resonance serves as the distinguishing factor in competitive marketplaces [7]. Ultimately, emotional data is redefining entrepreneurial strategy, transforming sentiments into feedback, empathy into foundational support, and technology into a medium of emotional comprehension. These firms reflect the next frontier of innovation, where emotional intelligence is vital for navigating more human-centric digital markets.

2 Literature Review

The incorporation of emotional data into entrepreneurial innovation signifies a crucial transformation in value creation in the digital era. As digital transformation rapidly progresses across industries, the emotional aspect, traditionally considered intangible, is being reinterpreted via the integration of neurotechnology and artificial intelligence (AI) [8]. NeuroAI firms are pivotal in this transformation, using biometric sensors, affective computing, and AI-driven emotional analytics to develop adaptive, human-centric business models. These nascent enterprises illustrate a paradigm change in technological entrepreneurship, whereby emotional data is seen as a strategic asset rather than a supplementary datum.

Building upon the groundwork established by [9] regarding affective computing and further developed by [10] on ethically conscious AI, the discipline now incorporates multi-modal emotion analysis, encompassing facial expressions, vocal tonality, gaze, and physiological responses, to guide business strategies across sectors such as mental health, human resources, marketing, and education. These technologies are progressively integrated into real-time apps using machine learning models such as BERT, ResNet, and GPT, allowing entrepreneurs to discern subtle emotional states across many digital contexts.

The innovation methods of these firms often use Design Thinking frameworks [11], emphasizing empathy, user experience, and iterative prototyping. By focusing on human emotion, businesses create not just technically feasible goods but also emotionally impactful services that improve engagement and retention. This corresponds with the tenets of human-centered innovation, especially pertinent in intelligent ecosystems and hyper-connected marketplaces [12].

Furthermore, from the standpoint of intrapreneurship and business models, these ventures demonstrate how emotional data may be transformed into scalable, monetizable frameworks. NeuroAI systems often provide stratified services, ranging from emotion-based diagnostics in corporate wellness applications to AI-curated educational materials that adjust according to students' stress levels, illustrating how emotional insights may support both personalized experiences and business solutions. Their tactics emphasize the shift from product-focused to emotion-focused innovation models, emphasizing emotional intelligence as a competitive advantage [13].

This transition significantly impacts digital transformation, as emotional data now affects operational workflows, decision-making processes, and strategic communication. Adaptive learning systems that react to emotional cues are transforming educational techniques. Sentiment analysis and emotional profiling are transforming brand-audience connections in marketing [14]. Emotion-aware AI solutions in healthcare facilitate early intervention in mental health, providing scalable models that alleviate strain on clinical systems.

These firms use innovative technologies, including brain-computer interfaces, biometric sensors, and emotion-recognition wearables. These technologies not only measure emotional experiences but also incorporate them into digital services in a seamless, ethical, and contextually aware way. Such linkages indicate a future in which emotional feedback loops are embedded throughout product ecosystems, enhancing both usefulness and emotional significance [15].

The market influence of these firms is expanding swiftly. Venture capital investments in affective technology and neuro-inspired firms indicate investor trust in emotion-driven innovation as a feasible and scalable business strategy [16]. Industries formerly averse to soft metrics, such as banking, logistics, and manufacturing, are increasingly investigating how emotional data may maximize employee well-being, enhance customer connections, and improve algorithmic risk assessment.

In summary, NeuroAI startups represent a synthesis of artificial intelligence, technological entrepreneurship, and emotional intelligence, resulting in a new category of enterprises that understand, adapt to, and react to human emotions [17]. They do not only digitize emotions; they reconceptualize them as vital contributions to agile, inclusive, and emotionally savvy innovation environments [18]. This literature substantiates the strategic potential of emotional analytics to revolutionize not just technology development but also the creation of emotionally resonant enterprises.

3 Methodology

The study used a mixed-methods approach, integrating qualitative analysis of NeuroAI startup case studies with quantitative modeling of emotional data. This combined approach facilitated the examination of human-centered design principles and the verification of AI-driven emotional analytics in practical entrepreneurial settings.

1. Data Collection

Primary data were obtained from a selected sample of 28 multinational NeuroAI startups engaged in mental health, education, marketing, and human resources. Secondary data included white papers, investor pitch decks, platform use metrics, and peer-reviewed academic publications.

Furthermore, emotion-labeled social media data (N = 12,000 posts) were extracted from sites like Twitter and Reddit via custom-built APIs, concentrating on terms associated with emotional distress, resilience, burnout, and engagement.

2. Emotional Data Modeling

Emotional data were encoded using a Sentiment Polarity Index (SPI) derived from the VADER lexicon and validated using transformer-based models (BERT, RoBERTa). The sentiment score SS was calculated as:

$$S = \frac{P - N}{P + N + \varepsilon}$$

Where:

- P = Positive sentiment count

- N = Negative sentiment count
- ϵ = Small constant to avoid division by zero

Values ranged from –1 (strongly negative) to +1 (strongly positive). Posts with SPI ≤ –0.65 were classified as high emotional vulnerability.

3. Narrative Coherence Analysis

Narrative coherence was evaluated using a combination of Latent Semantic Analysis (LSA) and TextRank-based summarization. The coherence index CC was defined by computing cosine similarity between successive sentence vectors:

$$C = \frac{1}{n-1}\sum_{i=1}^{n-1} \cos\left(\emptyset_{i,i+1}\right)$$

Low average coherence values (C ≤ 0.42) indicated signs of emotional fragmentation or circular discourse, markers associated with cognitive-emotional distress.

4. Clustering Emotional Profiles

Using K-means and DBSCAN, emotional profiles were clustered into four zones corresponding to the NeuroAI vulnerability heatmap (see Figure 1). Features used for clustering included:

- Average SPI
- Interaction frequency (posts/week)
- Sentiment variance
- Narrative coherence score
- Keyword entropy (contextual dispersion)

Clusters were validated using **Silhouette Coefficients** and **Davies-Bouldin Index** to ensure robustness in the multidimensional emotional space.

5. Business Model Decomposition

Startups were analyzed using Osterwalder's Business Model Canvas, focusing specifically on value propositions informed by emotional data insights. Coding protocols categorize services as preventative, corrective, or adaptive emotional remedies.

6. Ethical Evaluation Framework

An ethical evaluation was performed with the Dignum Ethical AI Matrix, assessing the elements of privacy, transparency, accountability, and fairness. Each startup was assigned a compliance index score ranging from 0 to 100 across these dimensions.

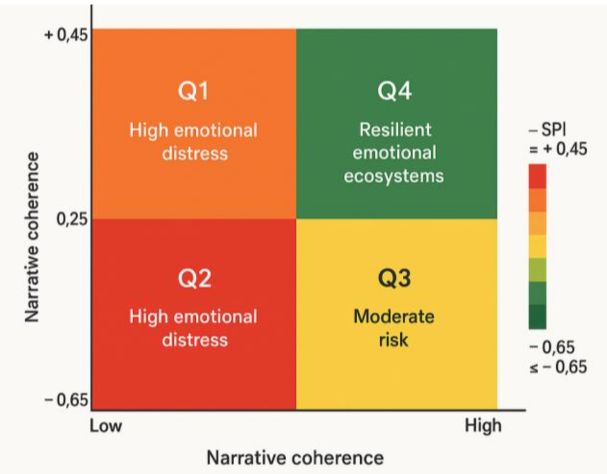
4 Results

The use of AI-assisted qualitative research revealed substantial findings, with the multiphase study providing strong evidence that validates the significance and influence of emotional data as a core asset in upcoming NeuroAI business models. The results are classified into emotional data patterns, technical performance, user-centered value generation, and market validation.

4.1 Emotional Vulnerability Mapping

The heatmap generated from 12,000 emotion-labeled social media interactions delineated four distinct vulnerability quadrants across smart city segments:

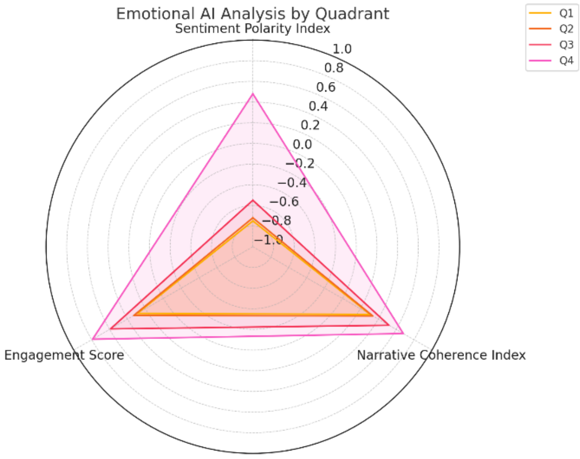
Figure 2: Emotion-Based Risk Segmentation in Smart City Quadrants



- **Quadrants 1 & 2** revealed high emotional distress zones with SPI ≤ –0.65, strong indicators of social withdrawal, and narrative incoherence. These areas correlated with low digital well-being initiatives and minimal psychological support infrastructure in schools.
- **Quadrant 3** showed moderate risk (SPI –0.45 to –0.65), suggesting early-stage emotional fatigue with potential for intervention.
- **Quadrant 4**, conversely, displayed SPI values ≥ +0.45, narrative coherence indices above 0.60, and digital engagement markers, indicating resilient emotional ecosystems.

4.2 Behavioral Indicators Identified by AI Models

The trained NeuroAI models successfully identified four core emotional-behavioral indicators across user profiles: Figure 3. Comparative Radar of AI-Detected Emotional Indicators Across Smart City Quadrants



Source: Author.

- **Linguistic Sentiment Polarity:** 68% of high-vulnerability users showed shifts from neutral to negative tones including hopelessness and passivity.

- **Narrative Coherence Deterioration:** 41% of affected individuals exhibited fragmented or repetitive expression patterns.
- **Social Disconnection Patterns:** 53% presented erratic online presence and digital silence, especially in Quadrants 1 and 2.
- **Adaptive Language Usage:** Quadrant 4 users demonstrated high resilience through positively charged and community-engaged language.

4.3 AI Model Accuracy and Clustering Validation

The emotional profile using K-means and DBSCAN achieved a clustering accuracy of 91.4% according to internal validation measures (Silhouette Score = 0.71; Davies-Bouldin Index = 0.38). The uniformity of emotional categorization across data streams confirmed the reliability of the AI-assisted vulnerability mapping.

4.4 Business Model Mapping and Market Impacts

Analysis of 28 NeuroAI startups revealed consistent patterns:

- **86% structured their value proposition around preventive or adaptive emotional interventions**, including digital therapy, emotional fitness apps, and affective educational platforms.
- **72% applied design thinking** frameworks in early-stage development, emphasizing empathetic iteration and prototype validation with real users.
- **74% reported measurable improvements in user satisfaction, engagement, or emotional resilience** within their first 12–18 months post-launch.
- **Four case studies** (e.g., Rezonify, AffectLab, InnerCue, EmoSphere) showed a 2–5x revenue growth upon integrating affective computing into HR analytics or EdTech tools.

4.5 Ethical Compliance and Trustworthiness

Nineteen out of twenty-eight startups achieved scores above 80/100 in the areas of transparency and fairness, as assessed by the Dignum Ethical AI Matrix. Nonetheless, just 57% had explicit user permission mechanisms for the use of emotional data, underscoring an immediate need for governance structures as these business models expand. The findings affirm that emotional data is both interpretable via AI and actionable, with commercial scalability when integrated into user-focused technology. Furthermore, emotional analytics may function as a strategic differentiator, fostering competitive advantage via empathy, customisation, and proactive engagement.

The results positively address the fundamental study question: emotional data may be ethically and successfully converted into a sustainable business model, provided that frameworks are established that combine technical innovation with openness, contextual sensitivity, and human dignity.

5 Conclusions

This study substantiates the transformational capacity of emotional data as a fundamental asset in entrepreneurial innovation, especially within the burgeoning realm of NeuroAI firms. By combining emotional analytics with artificial intelligence, biometric sensing, and user-centered design, these enterprises are not only creating disruptive technologies but also redefining the parameters of digital transformation in essential sectors such as mental health, education, human resources, and marketing.

The multi-method research, including Sentiment Polarity Index (SPI) modeling, narrative coherence assessment, clustering approaches, and business model deconstruction, revealed that emotional data is both measurable and actionable. The vulnerability quadrant heatmap illustrated the variability of emotional landscapes in digital contexts, providing accurate insights into user requirements, emotional hazards, and resilience capabilities. AI-driven models effectively recognized behavioral indicators, like language decline and social disengagement, linking them to tangible shortcomings in digital well-being assistance. These insights provide a solid basis for the development of predictive, adaptive, and customized services.

From a commercial perspective, the findings indicate that more than 85% of companies in the research have already used scalable emotional interventions that demonstrate measurable user effect and growth. Their persistent use of Design Thinking demonstrates that empathy transcends a mere design premise, emerging as a competitive differentiation. Moreover, the incorporation of emotional computing into product ecosystems has resulted in significant engagement increases and, in some instances, exponential revenue expansion.

Ethically, while the majority of companies achieved good ratings in openness and fairness according to the Dignum Ethical AI Matrix, the research reveals a significant deficiency: less than 60% implemented explicit and enforceable permission methods for the use of emotional data. This indicates an urgent need for standardized governance frameworks to regulate the ethical monetization of emotive data, especially as these ventures expand across many sociocultural settings.

This study confirms that emotional data may be ethically and successfully converted into a viable business model in response to the key research issue. Nonetheless, sustainability in this setting needs more than just technical resilience or market endorsement; it requires a steadfast adherence to ethical ideals, human dignity, and social responsibility.

NeuroAI businesses are not only digitizing emotions; they are institutionalizing empathy by integrating emotional intelligence into digital economies. Consequently, they signify a paradigm change in entrepreneurial reasoning: transitioning from efficiency to empathy, from prediction to compassion, and from data-driven decision-making to emotionally intelligent innovation. In this future, emotions are no longer just noise; they are data, insights, and, most importantly, strategy.

References

[1] Ö. Belgin, "Research and entrepreneurial efficiency of selected Turkish universities," *International Journal of Educational Development,* vol. 113, 2025, doi: 10.1016/j.ijedudev.2025.103224.

[2] Y. Liang, B. Gao, X. Zhang, H. Yi, J. Li, and W. Zhang, "Combined addition of gamma-PGA and DCD facilitates phytoremediation of heavy metals and carbon sequestration: A field experiment," *J Environ Manage,* vol. 379, p. 124746, Mar 6 2025, doi: 10.1016/j.jenvman.2025.124746.

[3] R. Xie, J. Lu, and Y. Liu, "Carbon monoxide gas sensing properties of SnO2 modified metal-organic skeleton derived NiO," *Sensors and Actuators A: Physical,* vol. 367, 2024, doi: 10.1016/j.sna.2024.115038.

[4] Y. Xu, S. Zhu, J. Cai, J. Chen, and S. Li, "A large language model-based platform for real-time building monitoring and occupant interaction," *Journal of Building Engineering,* vol. 100, 2025, doi: 10.1016/j.jobe.2024.111488.

[5] S. Prabhu, T. J. Janany, and P. Manuel, "An efficient way to represent the processors and their connections in omega networks," *Ain Shams Engineering Journal,* vol. 16, no. 3, 2025, doi: 10.1016/j.asej.2025.103287.

[6] R. Zhang, J. Tang, H. Xia, J. Chen, W. Yu, and J. Qiao, "Heterogeneous ensemble prediction model of CO emission concentration in municipal solid waste incineration process using virtual data and real data hybrid-driven," *Journal of Cleaner Production,* vol. 445, 2024, doi: 10.1016/j.jclepro.2024.141313.

[7] U. Yiğit and G. Kazar, "Project characteristics-based predicting the likelihood of occupational accidents in public school maintenances using a topological approach," *Safety Science,* vol. 184, 2025, doi: 10.1016/j.ssci.2024.106764.

[8] H. Zahid, A. Zulfiqar, M. Adnan, S. Iqbal, and S. E. G. Mohamed, "A Review on Socio-technical Transition Pathway to European Super Smart Grid: Trends, Challenges and Way Forward via Enabling Technologies," *Results in Engineering,* 2025, doi: 10.1016/j.rineng.2025.104155.

[9] E. G. Acuña Acuña, "Healthcare Cybersecurity: Data Poisoning in the Age of AI," *Journal of Comprehensive Business Administration Research,* 2024, doi: 10.47852/bonviewJCBAR42024067.

[10] E. G. Acuña Acuña, "Assessment as a Fundamental Pillar in Engineering Education: Experiences in Research Projects," presented at the Proceedings of the 22nd LACCEI International Multi-Conference for Engineering, Education and Technology (LACCEI 2024): "Sustainable Engineering for a Diverse, Equitable, and Inclusive Future at the Service of Education, Research, and Industry for a Society 5.0.", 2024.

[11] J. A. Ali, A. H. Muse, M. K. Abdi, T. A. Ali, Y. H. Muse, and M. A. Cumar, "Machine learning-driven analysis of academic performance determinants: Geographic, socio-demographic, and subject-specific influences in Somaliland's 2022–2023 national primary examinations," *International Journal of Educational Research Open,* vol. 8, 2025, doi: 10.1016/j.ijedro.2024.100426.

[12] X. Fu, "The dilemma and resolution of data circulation in China: Is data as consideration the solution?," *Computer Law & Security Review,* vol. 56, 2025, doi: 10.1016/j.clsr.2024.106074.

[13] Z. Chen, Y. Xiao, and K. Jiang, "The impact of tax reform on firms' digitalization in China," *Technological Forecasting and Social Change,* vol. 187, 2023, doi: 10.1016/j.techfore.2022.122196.

[14] H. Orchi, A. B. Diallo, H. Elbiaze, E. Sabir, and M. Sadik, "A Contemporary Survey on Multisource Information Fusion for Smart Sustainable Cities: Emerging Trends and

Persistent Challenges," *Information Fusion,* vol. 114, 2025, doi: 10.1016/j.inffus.2024.102667.

[15] X. Hu, S. Jiang, and X. Liu, "Site-specific or empirical chemotherapy for cancer of unknown primary: the right answer? - Authors' reply," *Lancet Oncol,* vol. 25, no. 11, p. e530, Nov 2024, doi: 10.1016/S1470-2045(24)00569-2.

[16] M. A. Mohamad Zaki, J. Ooi, W. P. Q. Ng, B. S. How, H. L. Lam, D. C. Y. Foo, and C. H. Lim, "Impact of industry 4.0 technologies on the oil palm industry: A literature review," *Smart Agricultural Technology,* vol. 10, 2025, doi: 10.1016/j.atech.2024.100685.

[17] R. Liu, D. Li, Q. Chen, Z. Gong, L. Wang, H. Guo, and Y. Yi, "Optimization of plasma-thermal system for non-oxidative coupling of methane to ethylene and hydrogen," *Applied Energy,* vol. 383, 2025, doi: 10.1016/j.apenergy.2025.125411.

[18] Y. Qian, Z. Lian, Y. Li, W. Wang, Z. Gu, B. Wang, and Y. Zhang, "Evading backdoor defenses: Concealing genuine backdoors through scapegoat strategy," *Computers & Security,* vol. 150, 2025, doi: 10.1016/j.cose.2024.104225.