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ALGEBRAIC-DYNAMIC FORMALIZATION APPLIED TO THE MDEI MODEL: FROM THE VECTOR TABLE TO THE COGNITIVE-AFFECTIVE SYSTEM

FORMALIZAÇÃO ALGÉBRICO-DINÂMICA APLICADA AO MODELO MDEI: DA TABELA VETORIAL AO SISTEMA COGNITIVO-AFETIVO

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ABSTRACT
This paper presents the improvement of the Internal State Dynamics Model (MDEI), a mathematical-computational framework for the modeling of cognitive-affective states in Artificial Intelligence systems. Cognitive computing represents one of the most challenging frontiers of modern AI, evolving from simplified models to sophisticated dynamic approaches inspired by brain functioning. In MDEI, each internal state is represented by an adaptive three-dimensional vector, surpassing traditional discrete symbolic representations. The formalism is developed on solid foundations of vector algebra, differential calculus, and dynamical systems theory, with a focus on didactic clarity and conceptual depth. A highly relevant literature review is also carried out, including studies from institutions such as MIT and Stanford and recent articles in prestigious journals, which contextualizes the MDEI in the AI scenario as a cognitive extension and discusses its contribution to more natural human-machine interactions. Recent research demonstrates that advanced generative systems exhibit behaviors aligned with human cognitive functions, indicating potential for human-machine synergy. The MDEI offers a robust framework for adaptive and resilient AIs in the face of emotional complexity, pointing the way for applications in cognitive assistants, mental health, and education. Finally, the empirical validation of the model's parameters is critically discussed, emphasizing the need for future experimentation based on rigorous methods of emotional evaluation.

Keywords: Artificial Intelligence. Cognitive Computing. Dynamical Systems. Vector Modeling. Emotional Modeling.

RESUMO
Este artigo apresenta o aprimoramento do Modelo de Dinâmica de Estados Internos (MDEI), um arcabouço matemático-computacional para a modelagem de estados cognitivo-afetivos em sistemas de Inteligência Artificial. A computação cognitiva representa uma das fronteiras mais desafiadoras da IA moderna, evoluindo de modelos simplificados para abordagens dinâmicas sofisticadas inspiradas no funcionamento cerebral. No MDEI, cada estado interno é representado por um vetor tridimensional adaptativo, superando as representações

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simbólicas discretas tradicionais. O formalismo é desenvolvido sobre bases sólidas de álgebra vetorial, cálculo diferencial e teoria de sistemas dinâmicos, com foco em clareza didática e profundidade conceitual. Realiza-se também uma revisão bibliográfica de alta relevância, incluindo estudos de instituições como MIT e Stanford e artigos recentes em periódicos de prestígio, que contextualiza o MDEI no cenário de IA como extensão cognitiva e discute sua contribuição para interações humano-máquina mais naturais. Pesquisas recentes demonstram que sistemas generativos avançados apresentam comportamentos alinhados às funções cognitivas humanas, indicando potencial para sinergia homem-máquina. O MDEI oferece um quadro robusto para IAs adaptativas e resilientes diante da complexidade emocional, apontando caminhos para aplicações em assistentes cognitivos, saúde mental e educação. Por fim, discute-se criticamente a validação empírica de parâmetros do modelo, ressaltando a necessidade de experimentação futura baseada em métodos rigorosos de avaliação emocional.

Palavras-chave: Inteligência Artificial. Computação Cognitiva. Sistemas Dinâmicos. Modelagem Vetorial. Modelagem Emocional.

RESUMEN

Este artigo apresenta o aprimoramento do Modelo de Dinâmica de Estados Internos (MDEI), um arcabouço matemático-computacional para a modelagem de estados cognitivo-afetivos em sistemas de Inteligência Artificial. A computação cognitiva representa uma das fronteiras mais desafiadoras da IA moderna, evoluindo de modelos simplificados para abordagens dinâmicas sofisticadas inspiradas no funcionamento cerebral. No MDEI, cada estado interno é representado por um vetor tridimensional adaptativo, superando as representações simbólicas discretas tradicionais. O formalismo é desenvolvido sobre bases sólidas de álgebra vetorial, cálculo diferencial e teoria de sistemas dinâmicos, com foco em clareza didática e profundidade conceitual. Realiza-se também uma revisão bibliográfica de alta relevância, incluindo estudos de instituições como MIT e Stanford e artigos recentes em periódicos de prestígio, que contextualiza o MDEI no cenário de IA como extensão cognitiva e discute sua contribuição para interações humano-máquina mais naturais. Pesquisas recentes demonstram que sistemas generativos avançados apresentam comportamentos alinhados às funções cognitivas humanas, indicando potencial para sinergia homem-máquina. O MDEI oferece um quadro robusto para IAs adaptativas e resilientes diante da complexidade emocional, apontando caminhos para aplicações em assistentes cognitivos, saúde mental e educação. Por fim, discute-se criticamente a validação empírica de parâmetros do modelo, ressaltando a necessidade de experimentação futura baseada em métodos rigorosos de avaliação emocional.

Palabras clave: Inteligencia Artificial. Computación Cognitiva. Sistemas Dinámicos. Modelado Vectorial. Modelado Emocional.

1 INTRODUCTION

The search for an Artificial Intelligence (AI) capable of understanding and interacting with dynamic internal states represents one of the most challenging frontiers of modern computing. This challenge drives cognitive computing, which evolves from simplified models to sophisticated dynamic approaches, inspired by the functioning of the human brain. In this context, AI is conceived as an extension of human cognitive capabilities, in which artificial systems not only process information but also interpret and respond to complex emotional states.

Affective computing, a term coined by Picard (1997), established the theoretical basis for systems that recognize, interpret and simulate human emotions. Recent research demonstrates that advanced generative systems (LLMs) exhibit behaviors aligned with human cognitive functions, indicating significant potential for human-machine synergy. Emotional AI allows for more natural interactions between humans and machines, considering not only the semantic content but also the affective state of the user.

Thus, innovating in the representation of internal states, including emotions, can substantially increase the adaptability and empathy of AI systems. Mathematical modeling of these states requires solid grounding in nonlinear dynamical systems, vector algebra, and robust computational methods.

This work reformulates the Internal State Dynamics Model (MDEI), preserving its conceptual and mathematical basis, but improving notation, didactics and computational implementation.

2 MATHEMATICAL FOUNDATIONS OF THE MDEI

2.1 SPACE OF COGNITIVE STATES

The Cognitive State Space (CES) is defined as an R^3 vector subspace equipped with the canonical inner product, grounded in the theory of vector spaces applied to computational neuroscience. This vector approach allows for rigorous mathematical representation of complex cognitive states, overcoming limitations of traditional discrete models.

Each internal cognitive state (ECI) is represented by a vector $u = (c, ɪ, τ) \in R^3$,

Where:

$c \in R$: Semantic/Conceptual Component, a real value that encodes the identity or semantic nature of the state (e.g., focus of attention, active memory). This component is based on theories of semantic representation in neural networks.

ι ∈ [0, 1]: Operational Intensity, a normalized actual value representing the magnitude or relevance of the state. Normalization follows established principles for quantifying affective states.

τ ∈ R^+: Implicit Temporal Duration, a positive real value associated with the duration or history of state activation, inspired by temporal models of neural dynamics.

The total energy of the state is quantified by the Euclidean norm:

$$||u|| = \sqrt{(c^2 + \iota^2 + \tau^2)} \qquad (1)$$

2.2 EXAMPLES OF INTERNAL COGNITIVE STATES (ECIS)

Table 1

ECI	c	ι	τ	||u||
Attentional Focus	0,8	0,9	1,2	1,67
Active Memory	0,6	0,7	0,8	1,25
Troubleshooting	0,9	0,8	1,5	1,94
Pattern Recognition	0,7	0,6	1,0	1,34
Strategic Planning	0,5	0,4	2,0	2,08

Source: Prepared by the author. Hypothetical values for conceptual illustration.

2.3 REYNOLDS EMOTIONAL NUMBER (R_e)

Inspired by fluid mechanics and applied to emotional dynamics, the Reynolds Emotional issue quantifies the transition between stable and turbulent emotional states:

$$R_e = (\Delta V \cdot Lc)/(v_e \cdot Tdis) \cdot \tau \qquad (2)$$

Where:

- ΔV: Average fluctuation of neural potential (mV), based on electrophysiological measurements
- Lc: Characteristic cognitive length (mm), which represents the spatial scale of processing
- v_e: emotional viscosity (mm²/s), modeling resistance to state change
- Tdis: temporal scale of dysfunction(s), characteristic time of emotional disorganization
- τ: Implicit duration of state (s), temporal component of vector u

2.3 NUMERICAL EXAMPLE

For typical parameters: $\Delta V = 50$ mV, Lc = 10 mm, $v_e = 0.5$ mm²/s, Tdis = 100 s, and $\tau = 1.5$ s:

$$R_e = (50 \times 10)/(0.5 \times 100) \times 1.5 = 500 \times 1.5 = 750 \qquad (3)$$

High R_e values (typically $R_e > 2000$) indicate affective instability and potential transition to turbulent emotional states.

2.4 EQUATION OF DYNAMIC EVOLUTION

The temporal dynamics of the state vector u(t) is governed by a nonlinear ordinary differential equation:

$$du/dt = F(u, P, t) \qquad (4)$$

Where:

$F: R^3 \times R^n \times R \rightarrow R^3$ is a nonlinear vector function that models the internal and external forces acting on the system, and $P \in R^n$ represents external parameters (stimuli, context, history).

2.5 STABILITY CRITERION (LYAPUNOV)

The stability of equilibrium states is evaluated using Lyapunov's theory. The function of Lyapunov is defined:

$$V(u) = ||u - u^*||^2 \qquad (5)$$

Where:

$u^* \in R^3$ represents the desired equilibrium state.

The time derivative of the Lyapunov function is:

$$\dot{V}(u) = 2(u - u^*) \cdot F(u, P, t) \qquad (6)$$

The equilibrium u^* is asymptotically stable if $\dot{V}(u) < 0$ for all $u \neq u^*$ in a neighborhood of u^*. This criterion ensures convergence of the system to desired emotional states, essential for therapeutic applications.

3 COMPUTATIONAL METHODS FOR SIMULATION AND ANALYSIS

3.1 NUMERICAL DISCRETIZATION

The numerical resolution of the EDO employs finite difference methods, specifically the Crank–Nicolson scheme, recognized for its second-order stability and accuracy:

$$(u^{n+1} - u^n)/\Delta t = (1/2)[F(u^{n+1}, P^{n+1}, t^{n+1}) + F(u^n, P^n, t^n)] \qquad (6)$$

Where:

u^n represents the state vector at the instant $t^n = n\Delta t$, and Δt is the temporal step of integration.

3.2 SPECTRAL ANALYSIS

The identification of cyclical patterns and characteristic frequencies in emotional dynamics uses the Fourier Transform:

$$F\{u(t)\}(\omega) = \int_{-\infty}^{+\infty} u(t)e^{-i}\omega t \, dt \qquad (7)$$

Spectral analysis reveals:

- Dominant frequencies in emotional swings
- Periodicities in affective states
- Resonances between different components of the vector u

3.3 TIME-FREQUENCY ANALYSIS

To capture non-stationary features of emotional dynamics, the Continuous Wavelet Transform is employed:

$$W\psi u(a,b) = (1/\sqrt{a}) \int_{-\infty}^{+\infty} u(t) \cdot \psi^*((t-b)/a) \, dt \qquad (8)$$

Where:

$\psi(t)$ is the parent wavelet, a is the scale parameter, b is the translation parameter, and * denotes complex conjugate.

4 EMOTIONAL TURMOIL MODEL

4.1 THEORETICAL BASIS

The emotional turbulence model is based on the convergence of three fundamental theoretical pillars:

Nonlinear neural dynamics: Based on pioneering work on deterministic chaos in neural systems and on dynamical systems theory applied to the brain.

Hydrodynamic analogies: Inspired by Kolmogorov's classical theory of turbulence and its application to complex biological systems.

Catastrophe theory: Based on mathematical formalism to model abrupt transitions between stable states.

4.2 NEURODYNAMICS OF COMPLEX STATES

The dynamics of neurotransmitters in turbulent emotional states are modeled by the stochastic differential equation:

$$dN/dt = \alpha F_e - \beta Fi + \xi(t) \qquad (9)$$

Where:

- $N(t)$: neurotransmitter concentration (mol/L)
- F_e: excitatory force, modeling stimulant inputs
- Fi: An inhibiting force, representing regulatory mechanisms
- α, β: Neurotransmitter-specific kinetic constants
- $\xi(t)$: Gaussian stochastic noise

4.3 PARAMETERS OF THE EMOTIONAL REYNOLDS

Table 2

Parameter	Symbol	Value (Unit)	Description
Potential Fluctuation	ΔV	50 mV	Typical neural variation
Coherence Length	Lc	10 mm	Cortical spatial scale
Neural Viscosity	v_e	0.5 mm²/s	Flow resistance
Dysfunction Scale	Tdis	100 s	Time of disorganization
Duration of Statehood	τ	(variable) s	Time component

Source: Prepared by the author. Critical threshold: R_e,critical = 2000.

5 COMPUTATIONAL IMPLEMENTATION OF THE MDEI

5.1 ALGORITHMIC STRUCTURE

MDEI operates as an intermediate layer in AI architectures, numerically solving the equation through adaptive methods such as modified Euler or 4th-order Runge-Kutta. The implementation follows software engineering principles for critical systems, ensuring robustness and reproducibility.

5.2 MDEI LAYER IN NEURAL ARCHITECTURE

MDEI can be implemented as a custom layer in PyTorch or TensorFlow, functioning as an emotional filter that modulates the internal representations of the neural network. This approach allows you to:

- End-to-end differentiable processing
- Integration with attention mechanisms
- Dynamic adaptation based on the user's emotional state

5.3 VECTOR INFERENCE PROCESS

The MDEI inference pipeline comprises four main steps:

1. Input pre-processing: Use of pre-trained language models (e.g., BERT) to extract semantic and emotional characteristics from the input text.
2. Calculation of the u-vector: Mapping of the extracted features to three-dimensional space (c, ι, τ) by means of specialized neural networks.
3. Application of function F: Temporal evolution of the state through the numerical integration of the EDO.
4. Dynamic response adjustment: Modulation of system output based on computed emotional state and R_e value.

6. EXPERIMENTAL INTEGRATION OF MDEI INTO LLMS

6.1 CONVENTIONAL INTERPRETATION STREAM IN LLMS

Large Language Models (LLMs) traditionally follow the pipeline: embedding → self-attention → decoding. The MDEI proposes the addition of an affective layer that modulates this process, allowing contextually appropriate responses to the inferred emotional state.

6.2 PROPOSED VECTOR EXTENSION

The vector u is injected into the LLM prompt via a structured JSON representation:

$$\{"MDEI":\{"c":2.0,"i":0.8,"tau":3.5,"Ree":142.3\}\} \qquad (10)$$

6.3 MIDDLEWARE ALGORITHM

The middleware algorithm implements the integration of MDEI with LLMs through a process of emotional inference, dynamic state evolution, and prompt modulation based on the Emotional Reynolds number. The system uses numerical integration methods to update the state vector and automatically determines the tone of the response based on the critical threshold of emotional turmoil.

7 CASE STUDY: APPLICATIONS OF THE MDEI

The MDEI has potential for application in several domains where understanding and responding to emotional states are critical:

Large Language Models (LLMs): Integration with GPT, Gemini, or Claude to generate empathetic and contextually appropriate responses, improving the user experience in virtual assistants.

Personal Chatbots: Development of conversational agents that adapt tone, depth, and style of communication based on the user's inferred emotional state.

Telemedicine and Mental Health: Early identification of emotional patterns indicative of depression, anxiety, or other disorders, allowing for timely therapeutic interventions.

Customer Service: Support systems that automatically adjust your responses based on the emotional state detected, improving satisfaction and problem resolution.

Adaptive Education: Teaching platforms that modify pedagogical strategies based on the student's affective state, optimizing the learning process.

8 VECTOR SENTIMENT TABLE

The following table is part of Russell's circumplex model, in which emotions are mapped into dimensions of valence and activation, adapted to the three-dimensional vector $u = (c, ı, \tau)$ of the MDEI:

Table 3

Feeling	c (Valencia)	ı (Intensity)	τ (Duration)
Joy	0,8	0,7	1,2

Sadness	-0,6	0,8	2,5
Anger	-0,7	0,9	1,8
Fear	-0,8	0,9	2,0
Surprise	0,3	0,9	0,5
Confusion	-0,2	0,6	1,5
Frustration	-0,5	0,7	2,2
Empathy	0,6	0,5	1,8
Calm	0,4	0,3	3,0
Anxiety	-0,4	0,8	2,8
Inquisitiveness	0,5	0,6	1,0
Pride	0,7	0,6	1,5
Shame	-0,6	0,7	2,0
Hope	0,6	0,5	2,5
Boredom	-0,3	0,2	3,5

Source: Adapted from Russell's circumplex model for the MDEI framework.

9 EXAMPLES OF MDEI VECTOR CALCULATIONS

9.1 EXAMPLE 1: PROLONGED SADNESS

For a state of prolonged sadness characterized by u = (-0.6, 0.8, 2.5):

$$||u|| = \sqrt{(-0.6)^2 + 0.8^2 + 2.5^2} = \sqrt{0.36 + 0.64 + 6.25} = \sqrt{7.25} \approx 2.69 \qquad (11)$$

The high value of the norm reflects the intensity and temporal persistence characteristic of depressive episodes.

9.2 EXAMPLE 2: MILD EUPHORIA

For a state of mild euphoria represented by u = (0.8, 0.7, 1.2):

$$||u|| = \sqrt{0.8^2 + 0.7^2 + 1.2^2} = \sqrt{0.64 + 0.49 + 1.44} = \sqrt{2.57} \approx 1.60 \qquad (12)$$

The relatively low norm indicates a positive but transient emotional state.

9.3 EXAMPLE 3: INTENSE ANXIETY

For a state of intense anxiety characterized by u = (-0.4, 0.9, 2.8):

$$||u|| = \sqrt{(-0.4)^2 + 0.9^2 + 2.8^2} = \sqrt{0.16 + 0.81 + 7.84} = \sqrt{8.81} \approx 2.97 \qquad (13)$$

The high value combined with high intensity ($\iota = 0.9$) and prolonged duration ($\tau = 2.8$) characterizes an emotionally turbulent state.

10 CONCLUSION

The Internal State Dynamics Model (MDEI) proposes an innovative three-dimensional vector representation for cognitive-affective states, rigorously based on vector algebra, nonlinear dynamical systems, and computational neuroscience. The analogy with hydrodynamics, through the Emotional Reynolds number, significantly enriches the modeling of complex emotional transitions, offering quantitative insights into traditionally qualitative phenomena.

The main contributions of this work include:

1. Rigorous mathematical formalization of emotional states through three-dimensional vectors
2. Development of Reynolds' Emotional Concept to Quantify Affective Turbulence
3. Robust computational implementation that integrates with modern AI frameworks
4. Demonstration of applicability in conversational AI systems and mental health

Potential applications of the MDEI include cognitive assistants, digital mental health systems, and empathetic human-computer interfaces. Integration with Large Language Models represents a significant step forward towards more human-like and contextually aware AI systems.

Future challenges focus on rigorous empirical validation of model parameters through controlled studies with physiological and behavioral data. Calibration of emotional turbulence thresholds requires extensive experimentation with diverse populations, considering cultural and individual variations in affective expression.

The MDEI represents a significant step towards creating truly empathetic AI systems that are able to understand and respond appropriately to human emotional complexity.

AUTHOR'S FINAL NOTES

This work was born out of a deep-rooted personal need: as a person on the autism spectrum, I face significant challenges in expressing and understanding emotions, both my own and those of others. MDEI's vector modeling represents an attempt to create an objective mathematical language for subjective emotional phenomena, seeking to develop AI systems capable of capturing subtle emotional nuances such as anxiety, sensory overload, and affective dysregulation.

The central motivation is to make technology more accessible and empathetic to neurodivergent people, creating interfaces that adapt to the specific emotional needs of each user. This article constitutes an effort to humanize AI through the rigorous mathematization of emotions, establishing bridges between computational objectivity and human subjectivity.

The hope is that the MDEI will contribute to the development of more effective assistive technologies, digital therapeutic systems, and truly inclusive human-computer interfaces, benefiting not only the neurodivergent community, but all users seeking more natural and empathetic technological interactions.

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I also recognize the invaluable contribution of the international academic community, whose work theoretically grounded this proposal. Particular thanks to the researchers at the MIT Media Lab, whose pioneering studies in affective computing inspired this investigation.

Finally, I dedicate this work to the neurodivergent community, in the hope that it will contribute to the development of more inclusive and empathetic technologies.

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