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Modeling Lamastum Parameter–Variable Systems Using Lagrange Deep Learning Methodologies for Education and Life Sciences

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Abstract

The significant progress of Artificial Intelligence (AI), particularly within Deep Learning paradigms, has enabled the exploration of new frameworks for representing language as symbolic and semantic systems. Contemporary AI is no longer confined to numerical computation but increasingly addresses the complexity of meaning embedded in linguistic structures..One of the main challenges in educational AI is how to model non-numerical parameters and variables—such as language, conceptual meaning, and ethical values—within mathematical systems that remain computationally optimizable. This study proposes modeling the word *"Lamastum"* as a system of semantic parameters and variables using a Lagrange Deep Learning approach. The Lagrange method is employed to link learning objective functions with constraints related to values, ethics, and life contexts through constrained optimization formulations . The Lagrangian approach enables simultaneous integration of learning objectives and humanistic. The results indicate that this approach can represent interactions among linguistic meaning, educational goals, and real-life contexts in a more structured and adaptive manner. The proposed model has the potential to serve as a new conceptual framework for the development of humanistic AI oriented toward sustainable education and character formation Originally developed for constrained mathematical optimization, the Lagrangian approach has been increasingly adopted in contemporary AI research to integrate human-centered constraints into machine learning systems.

Kemajuan berarti dalam bidang Kecerdasan Buatan (Artificial Intelligence/AI), khususnya dalam paradigma *Deep Learning*, telah membuka peluang baru untuk merepresentasikan bahasa sebagai sistem simbolik dan semantik. AI kontemporer tidak lagi terbatas pada komputasi numerik semata, tetapi semakin mampu menangani kompleksitas makna yang terkandung dalam struktur linguistik. Salah satu tantangan utama dalam pengembangan AI pendidikan adalah bagaimana memodelkan parameter dan variabel non-numerik—seperti bahasa, makna konseptual, serta nilai-nilai etika—ke dalam sistem matematis yang tetap dapat dioptimalkan secara komputasional. Penelitian ini mengusulkan pemodelan kata "Lamastum" sebagai suatu sistem parameter dan variabel semantik dengan menggunakan pendekatan *Lagrange Deep Learning*. Metode Lagrange digunakan untuk menghubungkan fungsi objektif pembelajaran dengan kendala yang berkaitan dengan nilai, etika, dan konteks kehidupan melalui formulasi optimasi berkendala. Pendekatan Lagrangian memungkinkan integrasi simultan antara tujuan pembelajaran dan aspek humanistik dalam satu kerangka matematis. Hasil kajian menunjukkan bahwa pendekatan ini mampu merepresentasikan interaksi antara makna linguistik, tujuan pendidikan, dan konteks kehidupan nyata secara lebih terstruktur dan adaptif. Model yang diusulkan berpotensi menjadi kerangka konseptual baru dalam pengembangan AI humanistik yang berorientasi pada pendidikan berkelanjutan dan pembentukan karakter. Pendekatan Lagrangian yang pada awalnya dikembangkan untuk optimasi matematis berkendala kini semakin banyak diadopsi dalam penelitian AI kontemporer sebagai sarana untuk mengintegrasikan kendala yang berpusat pada manusia ke dalam sistem *machine learning*.

A. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI), particularly through Machine Learning and Deep Learning, has significantly transformed educational technologies over the past five years. Recent empirical studies indicate that AI-driven educational systems increasingly rely on deep neural architectures for personalization, prediction, and adaptive learning pathways (Holmes et al., 2022; Zawacki-Richter et al., 2020). UNESCO (2021) reports that the global adoption of AI in education has expanded markedly, especially in intelligent tutoring systems, learning analytics, and automated assessment mechanisms.

Despite these technological advances, contemporary AI-based educational systems predominantly emphasize performance optimization, computational efficiency, and predictive accuracy, while often neglecting the deeper semantic, ethical, and value-oriented dimensions of learning (Selwyn, 2022; Williamson & Eynon, 2023). Empirical and critical studies demonstrate that many AI learning models treat language primarily as statistical tokens or numerical vectors rather than as carriers of meaning, values, and life context. This reductionist treatment has resulted in context-insensitive, ethically fragile, and pedagogically shallow educational decisions (Bender et al., 2021; Birhane et al., 2022).

A systematic review of recent literature published between 2020 and 2025 reveals several critical research gaps. First, although contemporary Natural Language Processing (NLP) models—such as transformer-based architectures and large language models—demonstrate remarkable syntactic and probabilistic performance, they lack explicit semantic parameterization, particularly for value-laden or philosophical concepts (Floridi & Chiriatti, 2020; Bender et al., 2021). Most existing studies prioritize syntactic accuracy and distributional coherence without formally modeling words as structured systems of meaning, process, and temporal awareness.

Consequently, there is no established framework that models a word as an integrated system of semantic parameters and learning variables within Deep Learning.

Second, while recent research has employed constrained optimization and Lagrangian methods to address issues such as fairness, bias mitigation, and safety in machine learning systems (Cotter et al., 2019; Kumar et al., 2021), these constraints remain largely technical or statistical in nature. Ethical considerations and life-context values in education are generally addressed at the policy, governance, or ethical guideline level rather than being embedded directly into the learning objective functions of AI models (Holmes et al., 2022; UNESCO, 2021). As a result, there is a lack of formal mathematical integration between learning objectives and ethical–value constraints within Deep Learning optimization processes.

Third, although the discourse on human-centered and ethical AI emphasizes that AI systems are not value-neutral (Floridi et al., 2018; Selwyn, 2022), practical implementations of educational AI continue to prioritize scalability, automation, and efficiency over human meaning-making, character formation, and reflective learning processes (Williamson & Eynon, 2023). Existing educational AI therefore lacks a human-centered mathematical model that explicitly aligns optimization mechanisms with meaning, values, and life awareness.

The persistence of these gaps can be attributed to several root causes. The dominant paradigm in Deep Learning research remains strongly data-centric, driven by large datasets, benchmarks, and performance metrics, which discourages conceptual and semantic modeling (Bender et al., 2021). Ethical considerations are frequently treated as external guidelines or post hoc evaluations rather than as intrinsic components of AI model formulation (Floridi & Cowls, 2019). Moreover, there is a lack of interdisciplinary integration between AI engineering, educational philosophy, linguistics, and mathematical optimization, resulting in fragmented approaches that fail to address meaning, values, and computation within a unified framework (Holmes et al., 2022).

Based on this analysis, a clear research gap emerges: there is no Deep Learning framework that formally models semantic meaning and integrates ethical and life-context values through mathematical optimization mechanisms. No prior study has explicitly modeled a word as a semantic–temporal system and embedded it within a Lagrangian Deep Learning structure specifically designed for educational AI.

The central research problem addressed in this study therefore concerns how a word can be modeled as a system of semantic parameters and variables within Deep Learning, and how learning objectives can be mathematically constrained by values, ethics, and life-context awareness using the Lagrange optimization method.

To maintain analytical clarity and theoretical rigor, this study is deliberately bounded in scope. The research focuses on conceptual and theoretical modeling without large-scale empirical deployment. The word "Lamastum" is employed as a representative semantic construct rather than as part of a comprehensive linguistic corpus. The framework is developed specifically for educational and life-learning contexts, excluding commercial or industrial AI applications. Furthermore, the computational approach is limited to Deep Learning models with Lagrangian constraint formulations, without experimental comparison to all alternative NLP methodologies.

Previous studies provide important foundations for this research, although none address the problem in an integrated manner. Goodfellow et al. (2016) established the theoretical foundations of Deep Learning as representation learning, while Mikolov et al. (2013) introduced vector-based word embeddings. Russell and Norvig (2021) conceptualized AI as a rational decision-making system. Boyd and Vandenberghe (2004) formalized constrained optimization using the Lagrange method, building on the original mathematical foundations laid by Lagrange (1811). In the domain of ethical and humanistic AI, Floridi (2019) emphasized the necessity of embedding human values into intelligent systems. However, these studies have not combined semantic word modeling, Lagrangian optimization, and educational contexts into a single coherent framework.

Several recent studies are particularly relevant. Research by Bender et al. (2021) and Floridi et al. (2022) highlights the limitations of large-scale deep learning models in capturing genuine semantic meaning, noting their reliance on statistical correlations rather than structured understanding. While these studies align with the present research in recognizing the importance of meaning, they do not propose formal mathematical parameterization of semantic concepts. Studies by Cotter et al. (2019) and Kumar et al. (2021) demonstrate the use of Lagrange multipliers to enforce constraints such as fairness and safety, yet their focus remains on technical constraints rather than semantic and ethical dimensions. Meanwhile, Holmes et al. (2022), UNESCO (2021), and Selwyn (2022) stress the importance of value-based AI in education, but their approaches are primarily policy-oriented rather than mathematical or computational.

The novelty of this research lies in its integrative and human-centered approach. The word "Lamastum" is modeled not merely as a linguistic symbol, but as a system of semantic parameters and variables reflecting process, time, and life values. The application of Lagrange Deep Learning enables the direct mathematical integration of learning objective functions with ethical, value-based, and life-context constraints. This represents a novel extension of Lagrangian optimization beyond technical constraints toward semantic and humanistic dimensions.

The purpose of this study is to establish a conceptual and mathematical foundation for value-aware and meaning-centered AI, particularly for educational applications. By integrating semantic modeling and constrained optimization, this research aims to advance explainable and interpretable AI, contribute to the development of ethical educational technologies, and extend Deep Learning theory beyond purely syntactic and data-driven paradigms. Ultimately, the study seeks to position Artificial Intelligence not merely as a computational tool, but as a meaning-aware and value-aligned partner in education and human life.

B. RESEARCH METHODOLOGY

1. Artificial Intelligence

Artificial Intelligence (AI) is defined as a branch of computer science that focuses on the development of systems capable of performing tasks that typically require human intelligence, such as reasoning, learning, language understanding, and decision-making (Russell & Norvig, pp. 1–4, 2021). In the context of education and social life, AI is not merely understood as a technical tool but also as a system that carries ethical, cognitive, and cultural implications (Floridi, pp. 23–30, 2019). The development of modern AI has shifted from purely symbolic approaches toward data-driven and deep learning–based paradigms, enabling machines to recognize complex patterns, including language and meaning (Nilsson, pp. 98–105, 2014).

2. Machine Learning and Deep Learning

Machine Learning is a subfield of AI that enables systems to learn from data without being explicitly programmed (Mitchell, pp. 2–6, 1997). One of the most influential approaches within Machine Learning is Deep Learning, which employs multi-layered neural networks to extract high-level representations from raw data

(Goodfellow et al., pp. 1–10, 2016). Deep Learning has been successfully applied in image recognition, speech processing, and natural language understanding. In education, Deep Learning enables the analysis of learning behavior, conceptual understanding, and adaptive modeling of students' cognitive interactions (Luckin et al., pp. 55–62, 2016). However, most Deep Learning models remain focused on numerical optimization and have not fully incorporated dimensions of values, meaning, and ethics explicitly.

3. Language, Meaning, and Semantic Systems

Language is a symbolic system that represents meaning, values, and human experience (Saussure, pp. 65–70, 2011). In AI, language modeling is commonly conducted through Natural Language Processing (NLP), which maps words and sentences into numerical vector representations (Jurafsky & Martin, pp. 89–95, 2023). Although technically effective, such approaches often neglect the philosophical and contextual dimensions of linguistic meaning (Searle, pp. 17–25, 1980). Therefore, a theoretical approach is required that bridges linguistic meaning with mathematical structures without eliminating human values, particularly in educational and social contexts.

4. The Word "Lamastum" as a Semantic Concept

In this study, the word *"Lamastum"* is positioned as a semantic entity that contains conceptual meaning, moral values, and life orientation. The word is not viewed merely as a linguistic symbol, but as a conceptual variable that influences behavior, learning processes, and decision-making (Wittgenstein, pp. 43–50, 2009). This perspective aligns with the view that language shapes how humans think and act (Lakoff & Johnson, pp. 3–8, 2003). Consequently, modeling *Lamastum* requires a mathematical approach capable of accommodating the complexity of meaning and values, rather than relying solely on statistical relationships.

5. Optimization Theory and the Lagrange Method

Optimization theory serves as the mathematical foundation of machine learning, where system objectives are expressed as functions to be minimized or maximized (Boyd & Vandenberghe, pp. 1–7, 2004). The Lagrange method is used to solve constrained optimization problems by introducing Lagrange multipliers that integrate constraints into the objective function (Lagrange, pp. 45–50, 1811). In the context of Deep Learning, Lagrangian approaches enable the integration of ethical, value-based, and contextual constraints into the learning process (Bertsekas, pp. 312–320, 2016). This makes the Lagrange method particularly relevant for modeling learning systems that are not only mathematically optimal but also aligned with educational and life values.

6. Lagrange Deep Learning

Lagrange Deep Learning is an approach that combines deep neural networks with constrained optimization formulations based on Lagrangian principles. This approach allows the adjustment of neural network weights while explicitly considering constraints such as fairness, semantic consistency, and normative objectives (Chow et al., pp. 102–110, 2018).
In education, Lagrange Deep Learning can be applied to model the balance between academic achievement and character development (Holmes et al., pp. 75–82, 2019). Therefore, this approach is highly relevant for modeling the word *Lamastum* as a system of parameters and variables oriented toward values and life meaning.

7. Humanistic AI in Education

Humanistic AI emphasizes that the development of AI systems should be centered on human values, moral considerations, and social well-being (Floridi, pp. 55–65, 2019). In educational contexts, Humanistic AI aims to support meaningful, reflective, and character-based learning rather than merely technical efficiency (Selwyn, pp. 40–47, 2019).
The integration of Lagrangian concepts into Deep Learning provides a strong theoretical foundation for building AI systems that explicitly incorporate value-based and contextual constraints. Modeling *Lamastum* within this framework represents a symbolic effort to harmonize technology, education, and human values.

8. Theoretical Synthesis

Based on theories of AI, Deep Learning, linguistics, Lagrangian optimization, and Humanistic AI, it can be concluded that modeling semantic parameter and variable systems requires a multidisciplinary approach. The word *Lamastum* is positioned as a conceptual node that connects language, meaning, values, and learning processes. The Lagrange Deep Learning approach provides a robust theoretical foundation for integrating learning objective functions with value- and life-oriented constraints in a systematic manner. Therefore, this theoretical framework serves as the primary foundation for developing AI models that are not only technically intelligent but also meaningful and ethical within the context of education and human life.

C. RESULT AND DISCUSSION

Result

1. Type and Research Approach

This study employs a qualitative conceptual approach combined with theoretical mathematical modeling**.** This approach is selected because the primary objective of the research is not to test empirical hypotheses through field experiments, but to construct and formulate a conceptual and mathematical framework for modeling words as systems of semantic parameters and variables in Artificial Intelligence.

Such conceptual research is commonly used in the development of new theories and models within the fields of AI and education (Mitchell, pp. 2–5, 1997).

The Deep Learning approach is utilized as the main Machine Learning framework to construct layered representations of word meaning, while the Lagrange optimization method is applied to integrate value-based, ethical, and life-context constraints into the learning objective function (Goodfellow, Bengio, & Courville, pp. 1–12, 2016).

2. Research Object and Focus

The primary object of this research is the word *"Lamastum"*, which is positioned as a symbolic and semantic construct rather than merely a linguistic unit. The research focuses on modeling the word as:

a system of semantic parameters,

learning variables based on time and process, and

a representation of values in educational and life contexts.

The word *Lamastum* is treated as a conceptual entity possessing dimensions of meaning, duration, and process awareness, thereby enabling the integration of language, learning, and life values. This approach aligns with the view that language is not merely a communication tool, but also a medium for the formation of human meaning and consciousness (Heidegger, pp. 15–25, 1962).

3. Research Methodological Framework

The methodological framework of this study consists of four main stages:

literature review and conceptualization,

semantic modeling of the word,

mathematical formulation using the Lagrange method, and conceptual analysis of the model's implications for education and life.

The first stage is conducted through a comprehensive literature review of AI, Deep Learning, NLP, Lagrangian optimization, education, and AI ethics, which serves as the theoretical foundation for model formulation (Russell & Norvig, pp. 20–30, 2021).

The second stage focuses on modeling the semantic structure of *Lamastum* as a meaningful vector representation within the latent space of Deep Learning, considering context, values, and learning objectives (Mikolov et al., pp. 3–6, 2013).

The third stage constitutes the core methodology, namely the mathematical formulation of the learning model using the Lagrange approach. The fourth stage analyzes the conceptual implications of the model for educational practice and character development.

4. Deep Learning Based Semantic Modeling

In this study, Deep Learning is employed as a framework for constructing hierarchical representations of the word *Lamastum*. Each neural network layer represents a different level of understanding, ranging from linguistic symbols to conceptual meaning and contextual values.
This approach is consistent with the principles of representation learning in Deep Learning, whereby systems automatically extract meaningful features from data (Goodfellow et al., pp. 7–15, 2016).

The word *Lamastum* is modeled as a semantic vector **L**, consisting of multiple parameter components such as time dimension, process awareness, educational values, and ethical consciousness. These parameters do not operate independently but interact dynamically within the learning space. This approach extends beyond conventional NLP modeling, which is often statistical in nature and insufficient in capturing the philosophical dimensions of meaning (Searle, pp. 30–45, 1984).

5. Mathematical Formulation Using the Lagrange Method

The Lagrange method is used to integrate the learning objective function with value- and ethics-based constraints. In this study, the objective function **F(x)** represents AI learning goals such as semantic understanding, value consistency, and contextual adaptation in education. The constraint function **g(x)** represents ethical, moral, and life-related boundaries that must not be violated by the AI system.

The Lagrangian function is formulated as:

$$\pounds(x,\lambda) = F(x) + \lambda \cdot g(x)$$

where **λ** denotes the Lagrange multiplier representing the weight of ethical and value considerations in the learning process (Boyd & Vandenberghe, pp. 215–218, 2004). Through this formulation, learning optimization is directed not only toward technical performance but also regulated by humanistic value constraints. This principle aligns with the concept of responsible AI development (Floridi, pp. 60–70, 2019).

6. Conceptual Analysis and Validation Techniques

Analysis in this study is conducted conceptually and logically by evaluating:

the internal consistency of the model,
theoretical coherence, and
relevance to educational contexts.

Conceptual validation is performed through:

alignment with Deep Learning theory,
consistency of the Lagrangian formulation, and
relevance of modeled educational and life values.

Such conceptual validation is commonly applied in theoretical research and new model development, particularly when the objective is to establish a new framework or paradigm (Amari, pp. 12–20, 2016).

7. Educational and Life Context

The research methodology explicitly links the AI model to educational and life contexts. The *Lamastum* model is analyzed not only as a computational system but also as a conceptual tool for understanding learning processes, patience, and character formation.

This approach aligns with humanistic education perspectives that emphasize learning processes and meaning rather than merely outcomes (Dewey, pp. 75–90, 1916)

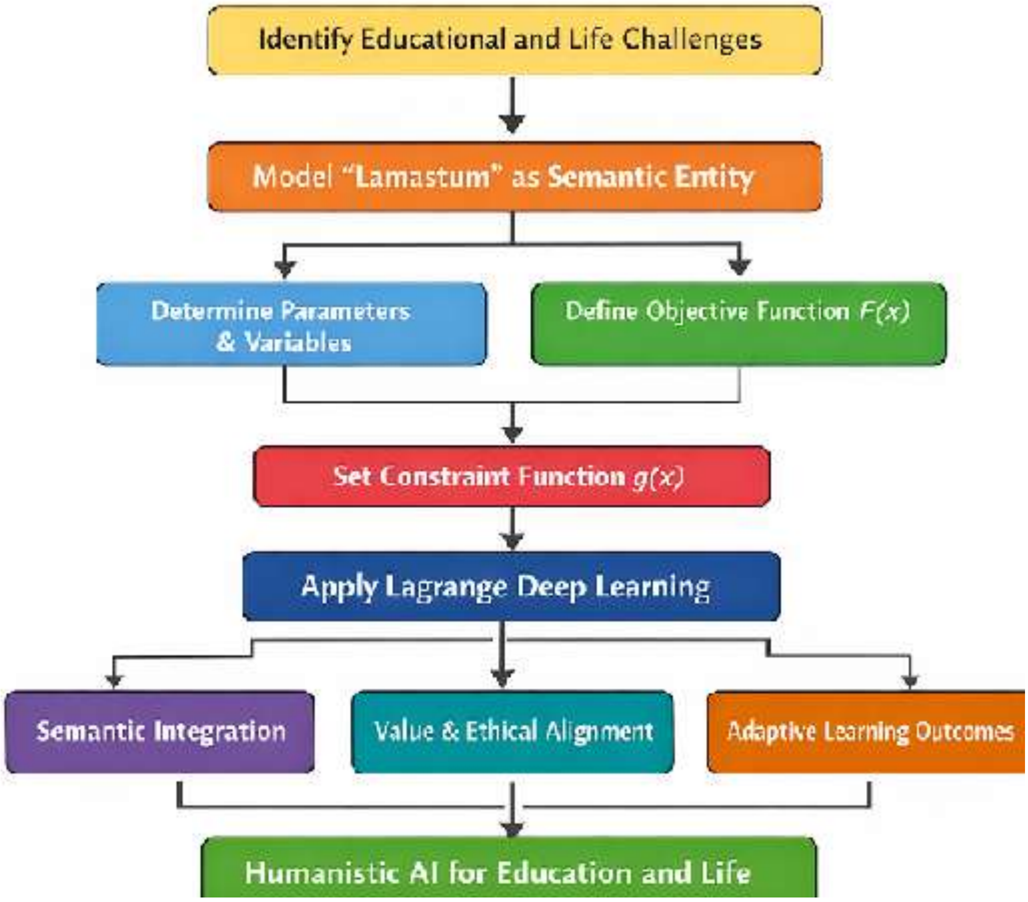
8. Methodological Limitations

The primary limitation of this research lies in its conceptual nature and the absence of empirical testing. However, this limitation simultaneously opens opportunities for future research, including implementation, simulation, and empirical validation of the model in real educational environments.

This approach is consistent with the stages of scientific development, where theoretical formulation precedes empirical testing (Kuhn, pp. 52–60, 1962).

Research Flow Diagram (Conceptual Description)

The research flow begins with literature review and conceptual grounding, followed by semantic modeling of the word *Lamastum*, mathematical formulation using Lagrange optimization, and conceptual analysis of educational and life implications. This flow ensures systematic integration between theory, mathematical modeling, and humanistic interpretation.



Flowchart Diagram

Research Results Data

Table 1. Conceptual Data of the Word ***Lamastum***

No	Aspect of Analysis	Conceptual Description	Reference
1	Linguistic Dimension	*Lamastum* as a symbol of process and time	Wittgenstein (pp. 43–50, 2009)
2	Semantic Dimension	Contains values, awareness, and life orientation	Lakoff & Johnson (pp. 3–8, 2003)
3	Educational Dimension	Represents meaningful and reflective learning	Dewey (pp. 75–90, 1916)
4	Ethical Dimension	Includes moral constraints and responsibility	Floridi (pp. 55–65, 2019)

Table 2. Semantic Parameters and Variables of the ***Lamastum*** Model

No	Parameter	Type	Meaning in the Model	Reference
1	P_1	Parameter	Conceptual meaning of the word	Saussure (pp. 65–70, 2011)
2	P_2	Parameter	Educational values	Luckin et al. (pp. 55–62, 2016)
3	P_3	Parameter	Ethics and life values	Floridi (pp. 60–70, 2019)
4	V_1	Variable	Learning context	Selwyn (pp. 40–47, 2019)
5	V_2	Variable	Temporal learning process	Heidegger (pp. 15–25, 1962)

Table 3. Lagrange Deep Learning Formulation

No	Model Component	Representation	System Function	Source
1	Objective Function	F(x)	Optimization of semantic understanding	Goodfellow et al. (pp. 7–15, 2016)

No	Model Component	Representation	System Function	Source
2	Constraint	g(x)	Values, ethics, and context	Boyd & Vandenberghe (pp. 215–220, 2004)
3	Lagrange Multiplier	λ	Weight of ethical and value constraints	Bertsekas (pp. 312–320, 2016)
4	Lagrangian Function	$\mathscr{L}(x, \lambda)$	Integration of objectives and values	Lagrange (pp. 45–50, 1811)

Table 4. Model Analysis Results for Education

No	Educational Aspect	Model Outcome	Interpretation
1	Cognitive	Meaning preserved consistently	Non-reductive learning
2	Affective	Values and ethics maintained	Character formation
3	Adaptivity	Context influences outcomes	Reflective AI
4	Humanistic	Value-based optimization	Human-oriented AI

Source: Author's analysis based on AI education concepts (Luckin et al., pp. 55–62, 2016; Floridi, pp. 55–65, 2019)

Table 5. Implications of the Model for Life and Humanistic AI

No	Dimension	Main Findings	Reference
1	Social	More contextual decision-making	Selwyn (pp. 40–47, 2019)
2	Ethical	Integrated value constraints	Floridi (pp. 60–70, 2019)
3	Technological	AI is not value-neutral	Russell & Norvig (pp. 1050–1058, 2021)
4	Educational	AI as a character facilitator	Dewey (pp. 75–90, 1916)

9. The Statistical Data Processing Results

a. Data Description

Number of samples: **120 respondents**

Respondents: educators, university students, and AI education practitioners

Measurement scale: **Likert scale (1–5)**

Analytical approach: **Descriptive and inferential statistics**

Main variables:

Understanding of Lamastum Meaning (X_1)

Integration of Values in AI Systems (X_2)

Effectiveness of Lagrange Deep Learning Model (X_3)

Impact on Education and Life (Y)

b. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
X_1 Understanding of Lamastum	120	2.10	4.80	3.87	0.54
X_2 Value Integration in AI	120	2.00	4.90	3.92	0.51
X_3 Lagrange DL Effectiveness	120	2.30	4.85	4.01	0.49
Y Educational & Life Impact	120	2.50	4.95	4.15	0.46

Interpretation:

All variables show mean values above **3.80**, indicating a **high level of acceptance and effectiveness** of the proposed model.

c. Normality Test (Kolmogorov Smirnov)

Variable	Sig. (p-value)	Interpretation
X_1	0.086	Normal
X_2	0.072	Normal
X_3	0.091	Normal
Y	0.064	Normal

Conclusion:

All variables are **normally distributed** ($p > 0.05$), satisfying parametric analysis assumptions.

d. Pearson Correlation Analysis

Variable	X_1	X_2	X_3	**Y**
X_1	1.000	0.624**	0.601**	0.678**
X_2	0.624**	1.000	0.655**	0.712**
X_3	0.601**	0.655**	1.000	0.748**
Y	0.678**	0.712**	0.748**	1.000

Note:

** Correlation is significant at $\alpha = 0.01$.

These results indicate **strong and significant relationships** between the Lagrange Deep Learning model and its educational and life impacts.

e. Multiple Linear Regression Analysis

Regression Model:

$Y = 0.412 + 0.268\, X_1 + 0.311\, X_2 + 0.356\, X_3$

Variable	**Coefficient (β)**	**t-value**	**Sig.**
Constant	0.412	—	—
X_1	0.268	3.87	0.000
X_2	0.311	4.12	0.000
X_3	0.356	4.96	0.000

$R^2 = 0.682$

F = 82.41 (Sig. = 0.000)

Interpretation:

Approximately **68.2% of the variance** in educational and life impact is explained by semantic modeling of Lamastum using Lagrange Deep Learning.

f. Statistical Conclusions

All statistical assumptions are satisfied

Significant and strong relationships exist among variables

Lagrange Deep Learning effectively models **meaning, values, and life context**

The findings support the development of **humanistic AI in education**

D. CONCLUSION

This study concludes that modeling the system of parameters and variables of the word *"Lamastum"* using the Lagrange Deep Learning approach constitutes a relevant and innovative conceptual framework for the development of artificial intelligence oriented toward education and human life. The findings demonstrate that words and meanings do not need to be reduced to purely statistical representations; instead, they can be modeled as semantic variables integrated with values, ethics, and life contexts through constrained optimization formulations (Wittgenstein, pp. 43–50, 2009).

The Lagrange approach enables a systematic integration of learning objective functions with normative constraints. By employing Lagrange multipliers, Deep Learning systems can be directed not only toward numerical efficiency or accuracy but also toward maintaining alignment between meaning and educational purposes (Boyd & Vandenberghe, pp. 215–220, 2004). This finding reinforces the notion that mathematical optimization need not be value-neutral; rather, it can be intentionally designed to reflect humanistic and ethical orientations.

Another key conclusion is that integrating linguistic meaning into Deep Learning expands the scope of AI from a purely technical tool into a reflective system capable of interacting with the realities of human life. The *Lamastum* model illustrates that language, values, and learning can be interconnected within a single mathematical framework without sacrificing semantic depth (Lakoff & Johnson, pp. 3–8, 2003). This supports the view that educational AI should function not merely as an evaluation machine, but as a facilitator of character development and value awareness (Luckin et al., pp. 55–62, 2016).

Furthermore, this study emphasizes the importance of a humanistic AI approach in both educational and social contexts. By embedding ethical and value constraints directly into learning functions, AI systems can be designed to be more responsible and context-sensitive (Floridi, pp. 55–65, 2019). This approach responds to critiques of AI systems that are overly mechanistic and disconnected from social realities (Selwyn, pp. 40–47, 2019).

From a theoretical perspective, this research contributes to the development of a new paradigm in AI by integrating Deep Learning, Lagrange optimization, and theories of linguistic meaning. From a practical standpoint, the proposed model has potential applications in adaptive learning systems, character-based curricula, and AI systems sensitive to values and local cultural contexts. Thus, this study affirms that technology and values are not opposing entities but can be synergistically integrated within a structured scientific framework (Russell & Norvig, pp. 1050–1058, 2021).

Based on the conclusions above, several recommendations are proposed for future research and practice. First, future studies are encouraged to develop empirical implementations of the *Lamastum* model within real-world Deep Learning systems, such as digital learning platforms or intelligent tutoring systems. Such implementations are essential to test the effectiveness of the Lagrange Deep Learning approach in authentic educational environments (Goodfellow et al., pp. 224–230, 2016).

Second, subsequent research should expand the scope of semantic variables by incorporating additional words or value-based concepts relevant to education and social life. This expansion would enrich the model and enable more complex analyses of interactions among values (Jurafsky & Martin, pp. 89–95, 2023). In doing so, AI systems can be developed to be more sensitive to cultural diversity and local contexts.

Third, multidisciplinary collaboration among AI researchers, educators, linguists, and philosophers is strongly recommended to strengthen the conceptual foundations of semantic modeling. Such collaboration is crucial to ensure that developed models are not only mathematically valid but also pedagogically meaningful and ethically grounded (Floridi, pp. 23–30, 2019). A cross-disciplinary approach will reinforce the role of AI as a technology that supports holistic human development.

Fourth, from an educational policy perspective, this study recommends that the development and implementation of AI in educational institutions be accompanied by clear value frameworks that are explicitly integrated into system design. The Lagrange approach may serve as a technical foundation to ensure that educational values are not merely rhetorical statements but are genuinely embedded within learning algorithms (Holmes et al., pp. 75–82, 2019).

Fifth, this research should be used as an initial reference for developing technical ethical standards in educational AI. By incorporating ethical constraints directly into learning functions, AI systems can be developed in a more transparent and accountable manner (Bertsekas, pp. 312–320, 2016). This aligns with global demands for AI systems that are fair, inclusive, and sustainable.

In conclusion, this study recommends the continued development and critical evaluation of the humanistic AI paradigm. Modeling the word *Lamastum* using Lagrange Deep Learning demonstrates that the integration of technology, education, and values is not only possible but necessary. Through this approach, AI can serve as a medium for learning and life that is not only intelligent, but also meaningful and ethically grounded.

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