REVIEW OF ARTIFICIAL INTELLIGENCE IN EDUCATION

DOI: https://doi.org/10.37497/rev.artif.intell.educ.v6ii.47

ARTICLE

GLOSSARY OF GENERATIVE ARTIFICIAL INTELLIGENCE FOR EDUCATION: A CONCEPTUAL AND PEDAGOGICAL FRAMEWORK

Glosario de Inteligencia Artificial Generativa para Educación: Marco Conceptual y Pedagógico

Glossário de Inteligência Artificial Generativa para a Educação: Um Marco Conceitual e Pedagógico

Jairo Alberto Galindo-Cuesta
La Salle University (Colombia).
E-mail: jairoalberto.galindo@gmail.com

ABSTRACT | Purpose: This glossary serves as a comprehensive terminological resource to understand generative artificial intelligence (AI) in educational contexts. It aims to bridge the gap between technical AI concepts and pedagogical practices, fostering an informed dialogue among educators, researchers, policymakers, and students. **Design/Methodology/Approach:** The glossary was developed through a mixed-methods approach combining a systematic literature review (following PRISMA guidelines), natural language processing techniques (e.g., term frequency analysis, semantic clustering), and a Delphi validation process with multidisciplinary experts. Terms were selected based on pedagogical relevance, conceptual clarity, and frequency of use in educational AI discourse. **Findings:** The resulting glossary offers operational definitions of key terms associated with generative AI—especially large language models (LLMs)—from the perspective of digital pedagogy, computational semantics, and cognitive sciences. It includes evolving concepts, application examples, and cross-referenced terms to support integration in teacher education and curriculum design. **Practical Implications:** This glossary provides a foundational vocabulary for designing educational programs, professional development initiatives, and policy guidelines. It also supports AI literacy by enhancing educators' critical understanding and ethical application of emerging technologies in teaching and learning environments. **Originality/Value:** By aligning technical AI terminology with pedagogical frameworks, this glossary promotes the responsible and effective integration of generative AI in education. It addresses the urgent need for accessible, validated resources to empower educators and institutions in navigating the fast-evolving landscape of AI-enhanced education.

Keywords | Generative artificial intelligence, Large language models, Educational technology, Pedagogical integration, Computational semantics, Teacher training

Qualis B1 CAPES 2021-2024

Indexed in ANPAD SPELL ANPAD

Received: 11 June 2025
Revised: 12 June 2025
Accepted: 13 June 2025
e-ISSN: 2965-4688

Corresponding Author: Jairo Alberto Galindo-Cuesta – E-mail: jairoalberto.galindo@gmail.com

How to cite this article: Galindo-Cuesta, J. A. (2025). Glossary of Generative Artificial Intelligence for Education: A Conceptual and Pedagogical Framework. *Review of Artificial Intelligence in Education*, *6*(i), e047. https://doi.org/10.37497/rev.artif.intell.educ.v6ii.47

RESUMEN | Propósito: Este glosario funciona como un recurso terminológico integral para comprender la inteligencia artificial (IA) generativa en contextos educativos. Su objetivo es conectar los conceptos técnicos de la IA con la práctica pedagógica, facilitando el diálogo informado entre educadores, investigadores, responsables de políticas y estudiantes. **Metodología:** La construcción del glosario siguió un enfoque metodológico mixto que incluyó una revisión sistemática de la literatura (PRISMA), técnicas de procesamiento de lenguaje natural (análisis de frecuencia, agrupamiento semántico) y validación por expertos mediante rondas Delphi. La selección de términos se basó en su relevancia pedagógica, claridad conceptual y frecuencia de uso en entornos educativos. **Resultados:** El glosario presenta definiciones operacionales de conceptos clave relacionados con la IA generativa —especialmente modelos de lenguaje de gran escala (LLM)— integrando perspectivas de pedagogía digital, semántica computacional y ciencias cognitivas. Incluye conceptos en evolución, aplicaciones prácticas y referencias cruzadas que facilitan su implementación en la formación docente y el diseño curricular. **Implicaciones Prácticas:** El glosario ofrece un vocabulario fundamental para cursos universitarios, programas de desarrollo profesional docente y formulación de políticas educativas. Asimismo, contribuye a la alfabetización en IA mediante la promoción de una comprensión crítica y un uso ético de estas tecnologías emergentes en la educación. **Originalidad/Valor:** Al articular la terminología técnica de la IA con marcos pedagógicos, este glosario fomenta una integración reflexiva y efectiva de la IA generativa en la práctica educativa. Representa una herramienta clave para instituciones y docentes comprometidos con la innovación y la equidad en la era digital.

Palabras clave | Inteligencia artificial generativa, Modelos de lenguaje, Tecnología educativa, Integración pedagógica, Semántica computacional, Formación docente

RESUMO | Objetivo: Este glossário atua como um recurso terminológico abrangente para compreender a inteligência artificial (IA) generativa em contextos educacionais. Seu propósito é conectar os conceitos técnicos da IA às práticas pedagógicas, promovendo um diálogo informado entre educadores, pesquisadores, formuladores de políticas e estudantes. **Metodologia:** O desenvolvimento do glossário seguiu uma abordagem metodológica mista, incluindo revisão sistemática da literatura (modelo PRISMA), técnicas de processamento de linguagem natural (análise de frequência, *clustering* semântico) e validação com especialistas por meio do método Delphi. A seleção dos termos considerou critérios como relevância pedagógica, clareza conceitual e frequência de uso em contextos educacionais com IA. **Resultados:** O glossário apresenta definições operacionais de termos-chave relacionados à IA generativa — especialmente modelos de linguagem de grande escala (LLMs) — integrando contribuições da pedagogia digital, semântica computacional e ciências cognitivas. Inclui conceitos em evolução, exemplos de aplicação e referências cruzadas para facilitar sua adoção em programas de formação docente e desenho curricular. **Implicações Práticas:** A proposta fornece uma base terminológica sólida para cursos universitários, programas de formação docente e desenvolvimento de políticas educacionais. Além disso, contribui para a alfabetização em IA por meio do fortalecimento da compreensão crítica e do uso ético das tecnologias emergentes na educação. **Originalidade/Valor:** Ao alinhar a terminologia técnica da IA com estruturas pedagógicas, este glossário promove uma integração mais responsável e eficaz da IA generativa na educação. Representa uma contribuição inovadora para educadores e instituições que buscam navegar com segurança o cenário dinâmico da educação mediada por IA.

Palavras-chave | Inteligência artificial generativa, Modelos de linguagem, Tecnologia educacional, Integração pedagógica, Semântica computacional, Formação docente

INTRODUCTORY NOTE

Purpose and Scope

This glossary serves as a comprehensive terminological resource for understanding generative artificial intelligence (AI) within educational contexts. It addresses the critical need for a common vocabulary that bridges technical AI concepts with pedagogical practice, facilitating informed dialogue among educators, researchers, policymakers, and students.

Target Audience

This work is primarily designed for:

- **Teacher educators** developing AI literacy curricula
- **Pre-service and in-service teachers** seeking to understand and integrate AI tools
- **Educational researchers** investigating AI's impact on learning and instruction
- **Policymakers** formulating guidelines for AI use in educational settings
- **Graduate students** in education, educational technology, or AI fields
- **Administrators** making decisions about AI implementation in schools

Context and Rationale

The rapid emergence of generative AI technologies, particularly large language models, has created both opportunities and challenges for educational practice. This glossary emerges from the recognition that effective integration of these technologies requires not merely technical understanding, but pedagogically informed comprehension that considers learning theories, ethical implications, and practical applications.

How to Use This Glossary

- **Terms marked with *(!)*** indicate concepts that are actively evolving or under scholarly debate
- **Terms marked with** *(&)* include additional reading recommendations
- **Cross-references** are indicated in italics to encourage exploration of related concepts
- **Practical applications** are highlighted to demonstrate educational relevance

1 INTRODUCTION

1.1 Context and Justification

The emergence of generative artificial intelligence in educational settings has created the need to establish a common terminological framework that facilitates understanding, adoption, and critical use of these technologies (Russell & Norvig, 2021). Large language models, particularly those based on transformer architectures, have demonstrated emergent capabilities that transcend simple text generation, becoming cognitive tools that can amplify and mediate learning processes (Brown et al., 2020).

From a curricular perspective, the integration of generative AI in teacher education requires technical vocabulary that enables informed professional dialogue between practicing and pre-service educators. Undergraduate education programs and continuous professional development processes need to incorporate digital competencies that include critical understanding of these emerging technologies.

This terminological compilation arises from the identified need in teacher education contexts to have precise, accessible, and contextually relevant definitions that facilitate the incorporation of specialized vocabulary into everyday pedagogical discourse. This glossary seeks to bridge technical knowledge and educational practice, recognizing that technological appropriation in education requires linguistic mediation that respects both conceptual rigor and pedagogical accessibility.

From a pedagogical perspective, understanding these systems requires a multidisciplinary approach that integrates concepts from computer science, computational linguistics, and cognitive sciences (Mitchell, 2019), always mediated by pedagogical principles that guide their use toward improving teaching-learning processes.

1.2 Theoretical Framework

1.2.1 Pedagogical Perspective

From Vygotsky's social constructivism, cultural tools mediate higher mental activity (Vygotsky, 1978). Generative AI systems can be conceptualized as cognitive artifacts that extend human information processing capabilities, acting as intellectual scaffolding in knowledge construction processes (Salomon, 1993).

Sweller's cognitive load theory (1988) provides a framework for understanding how these systems can optimize information processing by reducing extraneous cognitive load, allowing learners to concentrate their cognitive resources on essential content processing.

The TPACK (Technological Pedagogical Content Knowledge) model by Mishra and Koehler (2006) offers a conceptual framework for integrating AI in teacher education. This model suggests that effective use of educational technology requires the intersection of technological, pedagogical, and disciplinary knowledge. In the context of generative AI, teachers must develop competencies that include not only technical mastery of these tools, but also understanding of their pedagogical implications and their contextualized application in different knowledge areas.

Engeström's activity theory (1987) provides a framework for understanding how AI can transform educational activity systems. AI systems are not simply tools, but mediators that can alter relationships between subjects (teachers/students), objects (learning content), and community (educational community), generating productive contradictions that drive pedagogical innovation.

1.2.2 Semantic and Linguistic Foundations

Distributional semantics, the fundamental principle of vector embeddings, holds that word meanings derive from their usage contexts (Harris, 1954). This perspective has been operationalized in language models through dense vector representations that capture complex semantic relationships in high-dimensional spaces (Mikolov et al., 2013).

Austin's (1962) and Searle's (1969) linguistic pragmatics regarding speech acts gains special relevance in the context of educational AI. Prompts are not simply information requests, but performative acts that configure specific interaction contexts. Pragmatic competence in prompt engineering requires understanding how communicative intentions materialize in linguistic structure.

Bakhtin's theory of discourse genres (1982) offers valuable perspectives for understanding how LLMs can generate different types of educational text. Each genre (explanation, exercise, evaluation) has specific conventions that AI must master to be effective in differentiated pedagogical contexts.

Damasio's somatic marker hypothesis (1994) suggests that human comprehension involves emotional and bodily correlates. Although LLMs lack these experiential dimensions, their capacity to map complex linguistic patterns allows them to simulate aspects of human semantic comprehension, raising fundamental questions about the nature of understanding and meaning.

1.2.3 Cognitive and Neuroeducational Dimension

Attention models, central to transformer architectures, can be understood as computational implementations of selective attentional processes described in cognitive psychology (Vaswani et al., 2017). These mechanisms enable parallel processing of long sequences, overcoming limitations of previous sequential models.

The emergence of capabilities not explicitly trained in these models suggests phenomena analogous to human cognitive generalization, where specific knowledge transfers to related domains (Wei et al., 2022). This transfer capacity has significant implications for designing learning experiences that leverage AI's emergent capabilities.

Gardner's theory of multiple intelligences (1983) provides a framework for understanding how different AI modalities (text, image, audio) can address different types of intelligence, suggesting possibilities for educational personalization based on diverse cognitive profiles.

Neuroeducation principles (Immordino-Yang & Damasio, 2007) highlight the importance of emotion in learning. Although LLMs lack genuine emotional experience, they can generate content that evokes emotional responses in students, raising questions about emotional authenticity in AI-mediated educational interactions.

1.2.4 Learning Theories and AI

Siemens' connectivism (2005) offers a particularly relevant theoretical perspective for the AI era. This theory posits that learning occurs through distributed knowledge networks, where the capacity to form connections is more important than specific knowledge. LLMs can be conceptualized as manifestations of connectivist networks, where knowledge emerges from connection patterns in large datasets.

Lave and Wenger's situated learning theory (1991) emphasizes that learning occurs in specific social contexts. AI personalization for particular educational contexts reflects situated learning principles, where knowledge is constructed in relation to specific communities of practice.

Zimmerman's self-regulated learning framework (2002) provides perspectives on how students can use AI as metacognitive tools. AI systems can act as external scaffolds that support processes of planning, monitoring, and evaluating one's own learning.

1.3 Methodology

The construction of this glossary followed a mixed methodological process that integrated quantitative and qualitative approaches to ensure academic rigor and practical relevance in teacher education contexts.

1.3.1 Systematic Review Phase

A systematic literature review was conducted following PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) criteria. The search included academic databases (ERIC, IEEE Xplore, ACM Digital Library, Google Scholar) using controlled descriptors and keywords related to "artificial intelligence," "natural language processing," "educational technology," "teacher training," and "large language models."

Inclusion criteria prioritized:

- Publications in indexed journals (2020-2025)
- Official technical documentation of prominent models (GPT, BERT, T5, LLaMA)
- Research reports from recognized organizations (OpenAI, Google Research, Meta AI)
- Literature in English and Spanish with educational relevance

1.3.2 Terminological Frequency Analysis

A terminological frequency analysis was implemented using natural language processing techniques to identify terms with high frequency of appearance in educational contexts. More than 500 academic and technical documents were processed, applying techniques of:

- Named entity recognition (NER)
- Terminological co-occurrence analysis
- Semantic clustering of related concepts
- Centrality analysis in conceptual networks

1.3.3 Expert Validation

A multidisciplinary expert panel was constituted comprising:

- 5 researchers in AI and education
- 8 teacher educators with experience in educational technology
- 12 practicing teachers from different educational levels
- 3 computational linguists

The validation process included three Delphi-type rounds to:

1. Evaluate the pertinence of included terms
2. Validate clarity and precision of definitions
3. Determine pedagogical relevance of each concept

1.3.4 Inclusion and Exclusion Criteria

Inclusion criteria:

- Minimum frequency of appearance in educational corpus (>10 mentions)
- Direct relevance for understanding LLMs in education
- Potential application in teacher education
- Expert consensus on pedagogical importance (>70%)

Exclusion criteria:

- Excessively technical terms without direct educational application
- Obsolete or disused concepts
- Definitions with significant conceptual overlap
- Terms with expert consensus below 50%

1.3.5 Definition Construction Process

Each definition was constructed following a structured protocol:

1. **Etymological and conceptual analysis**: Review of term origin and evolution
2. **Educational contextualization**: Adaptation of concept to pedagogical realm
3. **Pedagogical analogies**: Incorporation of familiar comparisons for teachers
4. **Linguistic validation**: Review of clarity and terminological precision
5. **Teacher piloting**: Comprehensibility testing with focus groups

1.3.6 Methodological Considerations

The adopted methodology recognizes inherent limitations to the rapid evolution of the AI field. A continuous updating protocol was established that includes:

- Semiannual monitoring of new technological developments
- Incorporation of feedback from glossary users
- Definition updates based on emerging empirical evidence
- Review of pedagogical analogies according to reported effectiveness

1.3.7 Ethical Aspects

Glossary construction followed educational research ethical principles:

- Informed consent from validation participants
- Transparency in sources and methodology
- Recognition of limitations and potential biases
- Commitment to open access and knowledge democratization

2 GLOSSARY OF TERMS

A

Algorithm: An ordered and precise set of steps followed to solve a problem, similar to a cooking recipe that indicates what to do first, second, and so on. In AI education, algorithms are the "instructions" that tell the computer how to process the information we give it and how to generate useful responses for learning.
(&) Further reading: Cormen et al. (2009) "Introduction to Algorithms"

Artificial Intelligence (AI) ***(!)*****:** Artificial intelligence is the design and study of systems that mimic intelligent behaviors. An interdisciplinary field that combines computer science, mathematics,

philosophy, and cognitive sciences. Note: The definition of AI continues to evolve as capabilities expand and philosophical debates about machine intelligence persist.
(&) Further reading: Russell & Norvig (2021) "Artificial Intelligence: A Modern Approach"

Attention Architecture: Computational mechanism that allows models to weight the relative importance of different elements in an input sequence. Inspired by cognitive attentional processes, it facilitates processing of long-range dependencies in text.

Autoregression: Generation method where each produced token depends on previous tokens in the sequence. It constitutes the fundamental principle of generation in models like GPT, enabling coherent production of extensive text.

B

BERT (Bidirectional Encoder Representations from Transformers): Bidirectional language model that processes both preceding and following context for each token. Especially effective in text comprehension and semantic classification tasks.

Benchmark: Standardized set of tasks and metrics used to evaluate AI model performance. In education, includes evaluations of reading comprehension, explanation generation, and reasoning capabilities.

Bias *(!)*: The tendency of AI to favor certain perspectives or groups over others, reflecting prejudices present in texts used for training. In education, it is fundamental to recognize and mitigate these biases to promote equity and inclusion in the classroom. Note: This remains an active area of research with ongoing debates about measurement, mitigation, and fairness.
(&) Further reading: Barocas et al. (2019) "Fairness and Machine Learning"

C

Chain-of-thought Prompting: Technique that asks the model to make explicit its reasoning process step by step. Significantly improves performance on tasks requiring complex reasoning, facilitating response verifiability.

Computational Cost: Resources required to train and operate a large language model, including computation, storage, and energy consumption. Critical factor for democratizing access to these technologies in educational contexts.

Conversational Interface: System that allows users to interact with AI through natural language, simulating human conversation. Facilitates AI adoption in education by reducing technical barriers to use.

Corpus: Giant digital library of texts (books, articles, web pages) used to "feed" and train AI, similar to how a student needs to read many texts to develop comprehension and writing skills. The quality of this "library" determines how well the AI can function.

D

Dataset: Structured collection of data used to train and evaluate AI models. In educational applications, may include academic text corpora, class transcriptions, and pedagogical materials.

Decoding: Process by which a language model converts internal representations into readable text. Different strategies (greedy, beam search, sampling) produce variations in coherence and creativity of generated text.

Deep Learning: Method that mimics how the human brain processes information, using multiple layers of analysis like when we read a text: first we recognize letters, then words, then phrases, until we understand the complete meaning. In education, it allows AI to understand and generate increasingly sophisticated content.
(&) Further reading: Goodfellow et al. (2016) "Deep Learning"

Distributional Semantics: Hypothesis that word meanings derive from their usage contexts. Fundamental principle underlying vector embeddings in language models.
(&) Further reading: Lenci (2018) "Distributional Models of Word Meaning"

E

Embeddings: Numerical representations that allow the computer to "understand" word meanings, similar to how we associate concepts in our mind. For example, AI can understand that "teacher" and "professor" are related, or that "happy" is closer to "joyful" than to "sad."

Emergent Capabilities *(!)*: Abilities that arise in large language models without being explicitly trained, typically observed when certain scale thresholds are exceeded. Include logical reasoning, mathematical comprehension, and programming capabilities. Note: The nature and predictability of emergence remains an active research question.
(&) Further reading: Wei et al. (2022) "Emergent Abilities of Large Language Models"

Encoder-Decoder: Architecture that separates comprehension (encoder) from generation (decoder) in language models. Especially effective in automatic translation and text synthesis tasks.

Entropy: Measure of uncertainty or randomness in model predictions. In text generation, controls the balance between coherence and creativity in produced responses.

Ethics of AI *(!)*: Set of principles and practices designed to ensure AI systems are developed and used responsibly and beneficially. In education, includes considerations about privacy, equity, and transparency. Note: This is a rapidly evolving field with ongoing debates about governance, accountability, and values alignment.
(&) Further reading: Jobin et al. (2019) "The global landscape of AI ethics guidelines"

Explainability *(!)*: Capacity to understand and explain how an AI model reaches its conclusions or makes decisions. Fundamental for trust and adoption of AI in educational contexts where transparency is critical. Note: Trade-offs between model performance and explainability remain an active research challenge.

(&) Further reading: Ribeiro et al. (2016) "Why Should I Trust You? Explaining the Predictions of Any Classifier"

F

Few-shot Learning: Model's capacity to perform tasks with very few training examples. LLMs demonstrate notable few-shot capacity, quickly adapting to new tasks through examples in the prompt.

Fine-tuning: Process of specializing a general AI for specific tasks, like when a teacher adapts their teaching method for a particular group of students. Allows AI tools to better adjust to specific educational contexts, such as mathematics or science teaching.

Function Loss: Metric that quantifies the difference between model predictions and target values during training. Guides the parameter optimization process toward better performance.

G

Generative AI: Artificial intelligence systems capable of creating new content such as text, images, music, or video. They represent a paradigmatic shift toward creative and generative systems versus merely discriminative ones.

GPT (Generative Pre-trained Transformer): Type of AI that can generate coherent and natural text, like a very advanced writing assistant that can help create explanations, examples, or educational exercises. It is the technology behind tools like ChatGPT.

Gradient Descent: Optimization algorithm used to adjust model parameters by minimizing the loss function. Fundamental in training deep neural networks.

H

Human-in-the-loop: Paradigm that integrates human supervision in AI systems to improve performance and alignment with human values. Especially relevant in educational applications where pedagogical judgment is irreplaceable.

Hyperparameters: Configurations that control the training process but are not learned automatically. Include learning rate, batch size, and network architecture, requiring manual adjustment for optimization.

I

In-context Learning: LLM capacity to learn new tasks solely through examples provided in the prompt, without parameter updates. Demonstrates cognitive flexibility analogous to rapid human learning.

Inference: Process of using a trained model to generate predictions or responses to new inputs. In educational applications, corresponds to practical use of the model to assist in pedagogical tasks.

Instruction Following: Model's ability to follow explicit directions or commands provided in natural language. Critical capability for educational applications requiring specific pedagogical responses.

J

Jailbreaking: Techniques to evade security restrictions in AI models through specifically designed prompts. Represents a security challenge requiring special consideration in educational contexts.

K

Knowledge Distillation: Technique to transfer knowledge from a large model (teacher) to a smaller one (student), maintaining similar performance with lower computational cost. Facilitates AI implementation on resource-limited devices.

L

Latency: Time required for a model to generate a response after receiving an input. Critical factor for user experience in interactive educational applications.

LLM (Large Language Model): AI specialized in understanding and generating human text naturally and coherently, functioning like a very educated conversation partner that has "read" millions of texts. In education, it can act as tutor, content generator, or teaching assistant.

LoRA (Low-Rank Adaptation): Efficient technique for fine-tuning that updates only a subset of model parameters. Significantly reduces computational requirements for model specialization.

M

Machine Learning: Computer capacity to learn patterns and improve performance without a programmer teaching them each specific step, similar to how students learn to recognize patterns in reading through repeated practice. It is the basis on which AI tools used in education function. *(&)* Further reading: Mitchell (1997) "Machine Learning"

Metacognition: Knowledge and regulation of one's own cognitive processes. Some LLMs demonstrate rudimentary metacognitive capabilities by reflecting on their own reasoning.

Multimodality *(!)*: AI systems' capacity to process and generate different types of data (text, images, audio) in an integrated manner. Expands educational possibilities toward richer and more diverse experiences. Note: Integration of multiple modalities presents ongoing challenges in alignment and coherence.

(&) Further reading: Baltrusaitis et al. (2019) "Multimodal Machine Learning: A Survey and Taxonomy"

N

Neural Networks: Computer systems inspired by biological neural networks of the human brain, designed to recognize patterns. They constitute the fundamental computational architecture of modern language models.

Neural Scaling Laws: Empirical principles describing how model performance improves with increases in size, training data, and computation. Guide decisions about investment in educational AI development.

O

Optimization: Process of adjusting model parameters to minimize errors and maximize performance. Involves sophisticated mathematical techniques to navigate high-dimensional spaces.

Overfitting: Phenomenon where a model memorizes training data but fails to generalize to new data. Particularly relevant in educational applications where generalization is crucial.

P

Parameters: Internal "knowledge" of AI, similar to neurons in our brain that store information and experiences. More parameters generally mean that AI can handle more complex tasks, like a teacher with more experience can address more diverse pedagogical situations.

Personalization *(!)*: Adaptation of AI models to satisfy specific user needs or particular contexts. In education, enables learning experiences adapted to individual styles and rhythms. Note: Balancing personalization with privacy and avoiding filter bubbles remains an ongoing challenge.
(&) Further reading: Xie et al. (2019) "Personalized Education: A Machine Learning Perspective"

Pre-training: Initial phase where the model learns general language representations using large text corpora. Establishes the knowledge base that is later specialized for specific tasks.

Procedural Knowledge: Type of knowledge related to skills and procedures for performing specific tasks. LLMs demonstrate coding and problem-solving capabilities suggesting forms of procedural representation.

Prompt: Instruction or question we give to AI to obtain a specific response, similar to how we formulate clear questions to our students to get the answers we seek. The quality of the prompt determines the usefulness of AI's response.

Prompt Engineering *(!)*: Art of formulating effective instructions for AI, similar to how teachers develop skills to ask questions that generate meaningful learning. It is a crucial competency that educators need to develop to use AI effectively. Note: Best practices continue to evolve as models advance.

(&) Further reading: Liu et al. (2023) "Pre-train, Prompt, and Predict: A Systematic Survey of Prompting Methods"

Prompt Injection: Technique where a user attempts to manipulate or evade an AI system's restrictions through specific instructions. Represents an attack vector requiring security considerations.

Q

Quantization: Technique to reduce numerical precision of model parameters, decreasing memory and computation requirements. Facilitates AI implementation on resource-limited devices.

R

RAG (Retrieval-Augmented Generation): Technique that combines information retrieval from knowledge bases with text generation to produce more accurate responses. Particularly useful for specialized and updated content.

Reasoning: Capacity to apply logic and prior knowledge to solve complex problems. LLMs demonstrate emergent forms of reasoning, though with limitations in logical consistency.

Regularization: Techniques to prevent overfitting and improve model generalization. Include methods like dropout, weight decay, and data augmentation.

Reinforcement Learning from Human Feedback (RLHF): Technique that uses human evaluations to train models through reinforcement learning. Fundamental for aligning AI behavior with human preferences and values.

S

Scaling: Process of increasing model size, training data, or computation to improve performance. Scaling laws guide investments in educational AI development.

Self-attention: Mechanism that allows each position in a sequence to attend to all other positions. Fundamental in transformer architectures, facilitates processing of complex dependencies.

Semantic Security: Measures implemented to prevent AI systems from generating harmful, offensive, or inappropriate content. Critical in educational applications where student protection is priority.

Supervised Fine-Tuning (SFT): Process of adjusting a pre-trained model using labeled data for specific tasks. First phase in training conversational models after pre-training.

T

Temperature: Control that determines how “creative” or “conservative” AI will be in its responses, similar to adjusting the level of freedom we give students in a creative activity. Low temperatures generate more predictable responses, high temperatures produce more original but less precise responses.

Tokenization: Process of dividing text into basic units (tokens) that the model can process. Different tokenization strategies affect model efficiency and capabilities.

Tokens: Basic pieces of text that AI processes, similar to how we divide sentences into words to understand them better. Understanding tokens helps educators optimize their interactions with AI tools and control usage costs.

Top-k Sampling: Generation technique that selects the next token from among the k most probable. Balances determinism and creativity in text generation.

Top-p Sampling (Nucleus Sampling): Generation method that selects tokens from a subset whose cumulative probability reaches a threshold p. Produces more natural distributions than fixed top-k.

Transfer Learning: Paradigm where knowledge learned in one task applies to related tasks. Fundamental in modern NLP, enables efficient reuse of pre-trained models.

Transformers: Neural network architecture that revolutionized natural language processing through attention mechanisms. Base of all contemporary large language models.
(&) Further reading: Vaswani et al. (2017) “Attention is All You Need”

U

Underfitting: Situation where a model is too simple to capture underlying patterns in data. Results in poor performance in both training and evaluation.

V

Validation: Process of evaluating models using data not seen during training. Critical for estimating real performance in educational applications.

Vectorization: Conversion of text into numerical representations (vectors) that models can process. Fundamental for all modern NLP operations.

W

Weight Decay: Regularization technique that penalizes large parameters to prevent overfitting. Helps maintain generalization in complex language models.

Z

Zero-shot Learning: AI's capacity to perform tasks without previous specific examples, relying only on its general knowledge, similar to how an experienced teacher can adapt their methods to new situations without specific prior preparation.

3 EDUCATIONAL AND PEDAGOGICAL IMPLICATIONS

3.1 Transformation of Pedagogical Roles

Integration of generative AI in education requires reconceptualization of traditional roles. Educators evolve toward facilitators of AI-mediated learning experiences, requiring new competencies in prompt engineering, critical evaluation of generated content, and design of hybrid (human-AI) learning experiences.

3.2 Personalization and Adaptation

LLMs enable content personalization at previously unattainable scales. The capacity to generate explanations adapted to different learning styles, prior knowledge levels, and cultural contexts represents a significant opportunity to democratize access to quality education.

3.3 Critical Thinking Development

The prevalence of hallucinations in language models requires development of verification and critical thinking skills in students. This presents a pedagogical opportunity to strengthen competencies in source evaluation, fact-checking, and critical analysis of information.

3.4 Ethical Considerations

Implementation of AI in education must address concerns about privacy, algorithmic bias, and technological dependence. It is fundamental to develop ethical frameworks that guide responsible use of these technologies, prioritizing student welfare and educational equity.

4 CONCLUSIONS

This glossary represents an effort to systematize terminological knowledge necessary for understanding and critical adoption of generative AI in educational contexts. The rapid evolution of the field requires continuous updating of this conceptual framework, maintaining a balance between technical precision and pedagogical accessibility.

The intersection of AI and education presents unprecedented opportunities to transform teaching-learning processes, but also significant challenges requiring multidisciplinary approaches. Mastery of this technical vocabulary constitutes a first step toward reflective and effective integration of these emerging technologies.

The inclusion of evolving concepts (marked with ***(!)***) reflects the dynamic nature of this field and encourages users to engage with ongoing debates rather than accept definitions as fixed. This approach promotes critical thinking and adaptability—essential skills for navigating the rapidly changing landscape of AI in education.

Future iterations of this glossary must incorporate emerging developments in areas such as multimodal models, autonomous agents, and AI systems more specialized in specific educational domains, always maintaining pedagogical perspective as the main organizing criterion.

5 PRACTICAL APPLICATIONS AND IMPLEMENTATION GUIDE

5.1 For Undergraduate AI Courses

Introductory Courses (AI 101)

- Begin with foundational terms: Algorithm, Machine Learning, Artificial Intelligence
- Use analogical definitions to build intuitive understanding
- Focus on educational applications rather than technical implementation
- Encourage critical discussion of Bias and Ethics of AI

Intermediate Courses (Educational Technology)

- Emphasize TPACK framework integration with AI concepts
- Practice Prompt Engineering through hands-on exercises
- Explore Personalization possibilities and limitations
- Analyze case studies of AI implementation in various educational contexts

Advanced Courses (AI in Education)

- Deep dive into Emergent Capabilities and their educational implications
- Examine Explainability requirements for educational AI systems
- Design AI-enhanced curricula considering Multimodality
- Conduct original research on AI's impact on learning outcomes

5.2 For Teacher Professional Development

Awareness Level (2-4 hours)

- Introduction to Generative AI and LLMs

- Hands-on experience with educational AI tools
- Discussion of Bias and ethical considerations
- Basic Prompt Engineering skills

Proficiency Level (8-12 hours)

- Advanced Prompt Engineering techniques
- Integration strategies using TPACK framework
- Assessment of AI-generated content quality
- Development of AI-enhanced lesson plans

Leadership Level (20+ hours)

- Policy development for AI use in schools
- Training design for colleagues
- Research methodologies for evaluating AI impact
- Strategic planning for institutional AI adoption

5.3 For Educational Policy Development

Institutional Guidelines

- Use Ethics of AI principles to develop usage policies
- Address Bias mitigation in AI tool selection
- Establish Explainability requirements for high-stakes applications
- Create frameworks for evaluating AI tool effectiveness

Curriculum Integration

- Map AI literacy competencies across grade levels
- Identify subject-specific AI applications
- Develop assessment criteria for AI-enhanced learning
- Plan teacher training and support systems

Research and Evaluation

- Design studies using key terminology for consistency
- Establish metrics for measuring AI impact on learning
- Create protocols for ongoing monitoring of AI implementations
- Develop frameworks for sharing best practices

5.4 Critical Reflection Questions

For Educators:

1. How does understanding Distributional Semantics change your perspective on AI's language understanding?
2. What are the implications of Emergent Capabilities for curriculum design?
3. How can you balance Personalization benefits with privacy concerns?
4. What role should Explainability play in educational AI tools?

For Policymakers:

1. How do evolving definitions of AI impact regulatory approaches?
2. What frameworks are needed to address Bias systematically?
3. How can institutions prepare for unpredictable Emergent Capabilities?
4. What governance structures support responsible AI implementation?

For Researchers:

1. How do terminological inconsistencies affect research reproducibility?
2. What methodologies best capture AI's educational impact?
3. How can we study Personalization effects while protecting student privacy?
4. What interdisciplinary approaches advance AI education research?

5.5 Implementation Recommendations

Phase 1: Foundation Building (Months 1-3)

- Establish common vocabulary using this glossary
- Conduct needs assessment for AI integration
- Begin basic training with core concepts
- Form interdisciplinary working groups

Phase 2: Pilot Programs (Months 4-9)

- Implement small-scale AI integration projects
- Focus on Prompt Engineering skill development
- Monitor for Bias and ethical issues
- Document lessons learned and best practices

Phase 3: Scaling and Evaluation (Months 10-18)

- Expand successful pilot programs
- Conduct formal evaluation of learning outcomes
- Refine policies based on experience
- Share results with broader educational community

Phase 4: Continuous Improvement (Ongoing)

- Regular review and updating of terminology
- Ongoing professional development
- Research collaboration and knowledge sharing
- Adaptation to emerging AI technologies

5.6 Assessment and Evaluation

Knowledge Assessment

- Pre/post tests using glossary terminology
- Practical application assignments
- Peer teaching exercises
- Reflective essays on AI integration experiences

Competency Evaluation

- Prompt Engineering skill demonstrations
- AI tool evaluation rubrics
- Lesson plan development incorporating AI
- Student learning outcome measurements

Impact Measurement

- Learning analytics from AI-enhanced courses
- Student engagement and motivation metrics
- Teacher confidence and adoption rates
- Long-term academic achievement tracking

REFERENCES

Austin, J. L. (1962). How to do things with words. Oxford University Press.

Bakhtin, M. M. (1982). The dialogic imagination: Four essays. University of Texas Press.

Baltrusaitis, T., Ahuja, C., & Morency, L. P. (2019). Multimodal machine learning: A survey and taxonomy. IEEE transactions on pattern analysis and machine intelligence, 41(2), 423-443.

Barocas, S., Hardt, M., & Narayanan, A. (2019). Fairness and machine learning. fairmlbook.org.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. Advances in neural information processing systems, 33, 1877-1901.

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). Introduction to algorithms. MIT Press.

Damasio, A. R. (1994). Descartes' error: Emotion, reason, and the human brain. Putnam.

Engeström, Y. (1987). Learning by expanding: An activity-theoretical approach to developmental research. Orienta-Konsultit.

Gardner, H. (1983). Frames of mind: The theory of multiple intelligences. Basic Books.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Harris, Z. S. (1954). Distributional structure. Word, 10(2-3), 146-162.

Immordino-Yang, M. H., & Damasio, A. (2007). We feel, therefore we learn: The relevance of affective and social neuroscience to education. Mind, Brain, and Education, 1(1), 3-10.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389-399.

Lave, J., & Wenger, E. (1991). Situated learning: Legitimate peripheral participation. Cambridge University Press.

Lenci, A. (2018). Distributional models of word meaning. Annual Review of Linguistics, 4, 151-171.

Liu, P., Yuan, W., Fu, J., Jiang, Z., Hayashi, H., & Neubig, G. (2023). Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. ACM Computing Surveys, 55(9), 1-35.

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017-1054.

Mitchell, M. (2019). Artificial intelligence: A guide for thinking humans. Farrar, Straus and Giroux.

Mitchell, T. M. (1997). Machine learning. McGraw-Hill.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 1135-1144.

Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.

Salomon, G. (1993). Distributed cognitions: Psychological and educational considerations. Cambridge University Press.

Searle, J. R. (1969). Speech acts: An essay in the philosophy of language. Cambridge University Press.

Siemens, G. (2005). Connectivism: A learning theory for the digital age. International Journal of Instructional Technology and Distance Learning, 2(1), 3-10.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive science, 12(2), 257-285.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. Advances in neural information processing systems, 30.

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.

Wei, J., Tay, Y., Bommasani, R., Raffel, C., Zoph, B., Borgeaud, S., ... & Fedus, W. (2022). Emergent abilities of large language models. arXiv preprint arXiv:2206.07682.

Xie, H., Chu, H. C., Hwang, G. J., & Wang, C. C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. Computers & Education, 140, 103599.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory Into Practice, 41(2), 64-70.