International Journal of Humanities and Social Science Invention (IJHSSI)
ISSN (Online): 2319 – 7722, ISSN (Print): 2319 – 7714
www.ijhssi.org ||Volume 15 Issue 7 || July 2026 || PP. 22-29

Demystifying mechanical Intelligence: "Autolligence" (A.L.) and the Illusion of Artificial Intelligence (A.I.) in contemporary education

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ABSTRACT:
The text critically examines contemporary Artificial Intelligence as a historical and ideological continuation of the industrial organisation of education, psychometrics, and techno-administrative control. Its central argument is that current algorithmic systems do not possess genuine intelligence, intention, or consciousness, but rather operate as mechanisms of statistical recombination of data; for this reason, the term Autolligence is proposed as a more accurate designation. Using a historico-hermeneutic approach, the paper traces the genealogy of these mechanisms from the factory-school model and teaching machines to learning and assessment systems based on standardisation, quantification, and algorithmic classification. It further argues that the integration of AI into education tends to reduce pedagogical autonomy, intensify surveillance, homogenise creativity, and reproduce inequalities. As an alternative, the paper advances a critical, biocentric pedagogical perspective, termed critical enbiagogy, which seeks to reconnect learning with living, communal, and non-anthropocentric forms of knowledge and practise.

KEYWORDS: *Autolligence, A.I., Critical pedagogy, Historico-hermeneutic approach, Enbiagogy*

Date of Submission: 09-07-2026 Date of acceptance: 20-07-2026

I. INTRODUCTION: Algorithmic rationalism, psychometrics and psychopedagogical principles

Psychometrics has its historical roots in the quest to quantify mental abilities, initiated by Galton, who posited that "mental attributes" could be measured similarly to physical magnitudes. This laid the foundation for the psychometric paradigm and its association with eugenic projects (Michell, 2021). The subsequent contributions of pioneers such as Wundt, Cattell, and Binet were instrumental in the systematic development of educational and psychological assessments. These efforts established fundamental concepts like standardization, reliability, and validity, and led to the creation of scales such as the Binet–Simon and later, Wechsler's WAIS (Wechsler, 1981; Nicolas et al., 2013). A significant aspect of psychometrics is its social and historical application, particularly in the classification of children and the restructuring of educational systems in France and globally, which has had profound implications for the concept of "normality" and educational inequalities (Chang 2024).

Contemporary psychopedagogical discourse increasingly recognizes constructivism, as developed by theorists such as Jean Piaget and Lev Vygotsky, alongside Self-Regulated Learning (SRL), as foundational frameworks for understanding critical pedagogical contexts of the 21st century. SRL is described as an umbrella that integrates cognitive, metacognitive, behavioral, motivational, and emotional aspects of learning, which helps explain why it remains central in educational psychology (Panadero, 2017) .

Cyclical models of Self-Regulated Learning conceptualize learning as an iterative, dynamic process encompassing distinct phases of forethought, performance, and self-reflection, wherein students autonomously establish goals, monitor their cognitive progress, and qualitatively evaluate outcomes. Concurrently, Mayer's Cognitive Theory of Multimedia Learning (CTML) delineates how effective instructional design must account for human cognitive architectures through three core principles: dual-channel processing, limited cognitive capacity, and active processing. Instructional tenets such as coherence, spatial and temporal contiguity, segmenting, and pre-training are explicitly engineered to optimize working memory management within stringent biological constraints (Mayer, 2024).

The integration of modern artificial intelligence into this theoretical landscape introduces a radical paradigm shift. Rather than reinforcing human agency, this emerging technology intertwines the fluid mechanisms of SRL and CTML with a rigid algorithmic rationalism. This rationalism translates holistic, subjective learning processes into quantifiable variables, observable behavioral indicators, and inflexible predictive models designed to inform automated pedagogical interventions. Consequently, the dynamic cycle of SRL is increasingly enveloped by predictive analytics, automated recommendation software, and conversational agents. Rather than cultivating genuine metacognition, these systems standardize self-regulatory processes with automated algorithm guidance, replacing pedagogical judgment (Chang et al., 2023).

II. The ontological boundaries of Artificial Intelligence: Introducing Autolligence

To navigate this technological transformation with philosophical rigor, a precise terminological distinction must be established. We propose the term *Autolligence* (A.L.) to supplant the inherently anthropomorphic and misleading concept of "Artificial Intelligence". Autolligence more accurately describes the evolution of these systems from auxiliary tools into specialized instruments of computation, statistical synthesis, and algorithmic reconstitution, which remain entirely devoid of intrinsic rationale, deep semantic reasoning, or common sense.

The primary philosophical challenge resides in the system's inability to achieve *noesis*—the domain of conscious thought, self-awareness (perception/appraisal), and the active mind (intellect/understanding) that characterizes human judgment. Instead, machines are confined to logos operating at the fundamental level of mechanical execution. These "logo-machines" mimic discrete cognitive faculties and computational functions without possessing unified temporal experience, embodied biological phenomenology, or any genuine grasp of meaning. Human cognition retains conscious supremacy in contextual judgment, flexible attention allocation, and autonomous decision-making, whereas Autolligence provides merely a superficial functional verisimilitude that conceals a total absence of subjective awareness (Mason, 2025; Mogi, 2024).

A secondary ontological deficiency stems from the stark dichotomy between technological determinism and conscious intentional agency. The Large Language Models (LLMs) underpinning Autolligence operate as general-purpose predictive sequence models. Utilizing transformer architectures, they execute highly efficient parallel statistical processing to generate symbol sequences based exclusively on the probabilistic likelihood of subsequent tokens. Recent architectural developments, such as test-time compute and chain-of-thought loops, attempt to extend these capabilities via recursive reasoning pathways; however, these iterations remain fundamentally bound to advanced statistical optimization rather than conscious understanding.

Critiques characterizing LLMs as "stochastic parrots" emphasize that their outputs are entirely contingent upon pre-existing training distributions optimized against a mathematically defined loss function (Bender et al., 2021). Whether employing mean squared error or cross-entropy, neural network training is statistically equivalent to Maximum Likelihood Estimation (MLE) under specific error probability assumptions (Berzal, 2025). This deterministic framework directly invalidates any assertion that machines possess the internal states of belief and desire required for genuine intentionality. Robust free will remains incompatible with such determinism; hence, uniquely human capacities—termed andrographic or anthropic-algorithmic—remain fundamentally non-reproducible by statistical engines (Onyeukaziri, 2025).

Moreover, the activation of subjective experience - the "hard part" of consciousness - remains an insurmountable obstacle to the realization of genuine artificial consciousness. (Chalmers, 1995). Resolving this issue necessitates elucidating distinct anti-functionalist frameworks that are frequently conflated yet remain structurally divergent. According to Integrated Information Theory (IIT), phenomenal experience is strictly determined by the causal architecture of a system rather than its material substrate. Consequently, IIT theoretically permits that a neuromorphic silicon substrate could embody genuine consciousness, provided it achieves a sufficiently high degree of systemic integration. Conversely, type-identity theorists entirely reject this possibility, postulating that phenomenal states are inextricably bound to specific biological physical substrates and are not multiply realizable in silicon (Polák & Marvan, 2018). This architectural constraint is further compounded by the fact that transformer models are predominantly feedforward architectures, lacking the recurrent, recursive neural loops central to prominent neurobiological theories of consciousness.

III. Creativity as statistical synthesis and educational technology

The creative output of Autolligence further exposes its mechanical constraints. Instead of mirroring deliberate command/setting, mechanical creativity is completely combinatory, dependent on rearranging the range of existing patterns derived from collective bodies of learning (Franceschelli & Musolesi, 2024). Even though LLMs match or exceed median human scores on standardized divergent thinking assessments, they lack the authentic intentionality required to execute conceptual leaps or deliberately contest established conventions (Haase et al., 2025). Authentic human creativity remains deeply anchored in lived, subjective experience and an intrinsic drive to transcend structural boundaries.

From a psychological standpoint, authentic human creativity is deeply rooted in lived, subjective experiences and intrinsic motivation. Phenomenological and psychodynamic approaches conceptualize creative acts as mechanisms for articulating and transforming personally meaningful experiences, rather than merely recombining neutral symbols or solving abstract problems (Kozbelt, Beghetto, & Runco, 2010). Concurrently, research in Self-Determination Theory indicates that creativity is closely linked to intrinsic motivation, which arises when individuals experience autonomy, competence, and relatedness. This suggests that genuinely creative activity is driven by an inherent tendency toward exploration and self-expression rather than external control (Ryan & Deci, 2017).

Cognitive psychology complements this understanding by framing creativity as a process of restructuring mental representations, engaging in divergent thinking, and flexibly reframing problems to break away from dominant schemas (Guilford, 1967; Ward, Smith, & Finke, 1999). Studies on creative problem-solving reveal that original solutions typically emerge when individuals transcend well-learned routines, generate multiple alternative perspectives, and reorganize the structure of a problem space, effectively overcoming the cognitive constraints imposed by prior knowledge and conventional task framings. Models of creative cognition further emphasize fluency, flexibility, and originality as core dimensions of creative thought, all of which depend on the individual's capacity to distance themselves from rigid patterns and recombine experiential elements into novel, personally meaningful configurations (Runco & Jaeger, 2012).

Collectively, these research findings substantiate the assertion that genuine human creativity is rooted in both the subjective, affect-laden texture of lived experience and an intrinsic motivation to transcend structural boundaries—whether these pertain to social norms, established representational schemas, or externally imposed task constraints. The uncritical integration of these automation tools into educational workflows introduces severe risks of cognitive dependence and cultural homogenization. Controlled experiments reveal that when individuals rely on LLMs for creative ideation, their collective outputs exhibit compressed semantic diversity and elevated uniformity, despite superficial enhancements in volume or baseline quality (Anderson et al., 2024). Furthermore, while algorithmic assistance augments short-term performance during the assisted phase of a task, it subsequently impairs independent performance, threatening to erode long-term autonomous creative resilience and independent problem-solving skills (Wenger & Kenett, 2025).

IV. Educational technology: critical reflection

At the institutional and political level, algorithmic surveillance operates as a mechanism of governance and control. Algorithmic systems predetermine institutional visibility by tracking specific performance metrics, engagement data, and behavioral profiles, subsequently categorizing human learners into simplistic taxonomies such as "at-risk" or "high-potential" (Zeide, 2017). These classifications significantly impede access to resources and structural support. Because corporate governance of platforms, algorithmic architectures, and data ownership remain largely centralized, pedagogical agency is disenfranchised from both educators and students. This algorithmic bias—manifested across linguistic, gendered, socioeconomic, and geopolitical boundaries—ultimately strengthen existing social stratifications in the name of neutral technical efficiency. (Oguz, 2025).

For years, critical pedagogy has cautioned against a reductionist approach to human learning, advocating instead for structural transformations that enable genuine transformative action (Chourdakis, 2021; Hourdakis, 2020). When implemented without due care, Autolligence automates educational dynamics across three distinct tiers:

Automation of Cognitive Processes: Personalized chatbots simplify the complex, exploratory cycle of goal-setting and metacognition into standardized, scripted interactions. This substitution of deep cognitive engagement with adherence to pre-determined pathways undermines Mayer's active processing principle as outlined in the Cognitive Theory of Multimedia Learning (CTML). Authentic instructional design necessitates that students actively select, organize, and integrate incoming information to construct coherent mental models. However, the rigid framework of conversational agents diminishes the cognitive effort required from students, reducing their role to passive participants within predetermined pathways. Consequently, these systems promote superficial behavioral compliance rather than fostering genuine metacognition and long-term knowledge retention (Guan et al., 2024).

The automation of pedagogical choices in AI-driven systems increasingly relies on the operationalization of instructional frameworks such as Bloom's Taxonomy and, more indirectly, TPACK into machine-readable categories for lesson planning, learning-objective classification, task difficulty calibration, and assessment design (Jin et al., 2022). Originally developed as reflective heuristics for educators, these frameworks were not intended as prescriptive engines for automated sequencing. Their computational translation into algorithmic pipelines risks pre-structuring pedagogical decisions in ways that may narrow critical instructional autonomy, repositioning teachers as managers of system-generated options rather than as authors of context-sensitive educational judgment. This concern is heightened when AL systems are presented as efficient substitutes for pedagogical deliberation, as the automation of instructional choices may obscure the interpretive, relational, and situational dimensions of teaching that cannot be exhaustively formalized through taxonomies or design templates (U.S. Department of Education, 2023). Additionally, students may face significant systemic vulnerabilities when instructional support is mediated by large language models whose fluency can mask substantial epistemic limitations. Recent research indicates that current LLMs often exhibit poor confidence calibration, meaning their expressed certainty does not reliably reflect their actual accuracy, and they can remain highly confident even when their answers are incorrect or incomplete (Steyvers et al., 2025). Related studies argue that such systems do not yet possess reliable, individuated metacognitive capacities necessary for trustworthy self-monitoring, error awareness, and uncertainty reporting in complex reasoning tasks (Griot et al. 2025) . For educational contexts, this means that AI-generated explanations, recommendations, or lesson adaptations may be delivered with an unwarranted tone of authority, thereby increasing the risk that both teachers and students accept erroneous outputs as pedagogically valid simply because they appear coherent, personalised, and confident (U.S. Department of Education, 2023; Steyvers et al., 2025)

The automation of administrative processes in higher education is increasingly rooted in data-driven allocation models, where resource distribution, risk stratification, and program evaluation are governed by large-scale analytics and algorithmic decision rules (Williamson, 2017; Perrotta & Williamson, 2018). Within this emerging framework of algorithmic governance, these systems convert diverse aspects of student experience and institutional life into standardized data objects—such as risk scores, engagement indices, and progression metrics—that can be monitored and acted upon at scale. This approach institutionalizes an audit-oriented rationality, where student well-being and program quality are made visible and actionable primarily through pre-defined indicators, dashboards, and performance benchmarks. Instead of complementing professional judgment, these data infrastructures risk supplanting it, as effective administration becomes increasingly equated with adherence to model outputs and indicator targets, even when these fail to capture the relational, affective, and contextual dimensions of students' lives and educational trajectories (Espeland & Sauder, 2024).

V. The historical genealogy of Autolligence: The factory school model and teaching machines

To fully comprehend the conceptual framework of Autolligence, its provenance must be analyzed utilizing a historico-hermeneutic methodology. Drawing upon Searle's classic Chinese Room thought experiment, it is obvious that the manipulation of syntax according to predetermined rules completely lacks semantic "aboutness" or true intentionality (Searle, 1980). Searle establishes that primary intentionality belongs exclusively to living, biological organisms, whereas artificial systems display merely derivative or metaphorical variants.

The rise of the factory model of schooling during the late 19th and early 20th centuries directly pioneered this mechanized ethos. Driven by the rapid expansion of the Industrial Revolution, educational reformers systematically restructured schools to mirror the structural efficiency, discipline, and mass organization of industrial manufacturing plants. Students were conceptualized as uniform raw materials moving along an assembly line of age-graded classrooms, where teachers appended discrete components of standardized knowledge before processing individuals into finished, graduated products (Tyack & Cuban, 1995). This structural transformation, critiqued by thinkers such as Michel Foucault as a disciplinary apparatus for producing a compliant labor force, prioritized institutional uniformity over personal cultivation (Davis et al., 2020). Targeted government policies explicitly aligned technical, mechanical, and vocational education frameworks to cultivate a disciplined workforce capable of operating within highly regimented environments (Focacci & Perez, 2022).

Historical precedents underscore this pervasive standardization. In Germany, the handicraft movement (Knabenhandarbeit) of the 1880s led to the establishment of the Association for Manual Training in 1886 and the Teachers' Training College in Leipzig in 1887, specifically designed to integrate manual standardization into pedagogical training (Dittrich, 2018). In Prussia and the United States, compulsory attendance laws enacted between 1850 and 1930 engineered a massive demographic shift from agrarian labor to skilled industrial and clerical positions, permanently aligning childhood with the administrative mandates of the state (Becker et al., 2009).

This structural mechanization was accompanied by the parallel evolution of physical learning apparatuses. Beginning with rudimentary instructional devices such as 19th-century hornbooks and correspondence courses, the mid-20th century witnessed the explicit rise of the mechanical teaching machine. Sidney Pressey's work in the 1920s introduced the first automated multiple-choice testing devices, paving the way for B.F. Skinner's highly influential innovations in the 1950s and 1960s. Skinner applied the rigorous psychological tenets of operant conditioning and reinforcement to programmed instruction, fracturing instructional content into measurable, incremental steps (Ferster, 2014). By the 1960s, programmed instruction emerged as a massive systemic movement, defining learning via behavioral objectives and immediate, automated feedback loops (Ilankumaran, 2023). A major milestone of this era was the University of Illinois' PLATO program (1959–1976), which established the world's first generalized computer-assisted instruction system, laying the foundational codebase and infrastructural precedents for contemporary online learning platforms (Cope & Kalantzis, 2023 ; Canales & Polenghi, 2019).

This systemic reductionism established the foundational paradigm necessary for contemporary machine learning architectures. Modern algorithmic optimization—manifested via Maximum Likelihood Estimation (MLE) and cross-entropy loss functions—constitutes the technical apex of this tradition. By training neural networks to mathematically minimize a loss function against pre-existing distributions, contemporary Autolligence effectively forces human language and learning into the same sterile, predictable analytical frameworks originally devised by industrial-era technocrats (Mao et al., 2023 ; Chen et al., 2025). By integrating this insight with philosophical hermeneutics, we can trace how modern Autolligence represents the technical culmination of a centuries-old endeavor to mechanize the human learning process within specific socio-political contexts (Grondin, 2016; Rogers, 2016).

VI. The techno - administrative regime: Standardized assessment and categorization

The institutionalization of automated pedagogy experienced significant acceleration due to mid-century geopolitical restructuring. In the early 1960s, the OECD played a crucial role in shifting European and international education from a focus on holistic cultural development to a predominantly technocratic model. By integrating educational governance with labor market forecasting, extensive statistical auditing, and standardized accountability benchmarks, the OECD initiated a comprehensive process of systemic standardization aimed at maximizing economic efficiency (Tröhler, 2014).

This context directly reinforced the practice of high-stakes testing, establishing it as the primary mechanism for monitoring, regulating, and controlling the pace of learning. Standardized metrics inherently prioritize rote memorization and mechanical uniformity over critical inquiry. Critical educational theorists argue that high-stakes examination regimes fundamentally perpetuate entrenched systemic inequalities, actively marginalizing students from diverse, economically disadvantaged, or non-normative backgrounds while discouraging pedagogical flexibility in favor of teaching to the test (McLaren, 2015; Tarlau, 2014).

Historically, this relentless drive toward educational examination highlights a profound transformation within educational science, characterized by three recurring historical patterns:

The reductions of children: Converting children into passive repositories of measurable, fragmented traits such as intelligence, morality, and adaptability.

The systemic deployment of examination tools: Utilizing examination instruments for institutional sorting, hierarchical streaming, and exclusion from mainstream classrooms, which directly led to the medicalization of learning differences and the creation of isolated segregated diagnostic facilities.

The construction of a techno-administrative regime: Fashioning a regime where childhood is viewed as a strictly quantifiable entity, and learning is reduced to predictable, comparable analytical tasks tailored exclusively to administrative convenience.

This historical categorization was frequently executed under the banner of state welfare, employing a medicalized language of testing to manage population cohorts perceived as disparate or non-normative. The rapid expansion of Lewis Terman's intelligence testing movement in the United States and Europe during the 1910s and 1920s specifically targeted marginalized, immigrant, and economically disadvantaged children for institutional tracking and deficit classification (Bakker, 2020; Ellis, 2013; Omori, 2018). This pseudo-scientific obsession with hierarchical ranking extended into colonial contexts; for instance, Depaepe's analysis of psychological testing in the Belgian Congo during the 1950s illustrates how standardized tools were weaponized to reinforce racist tropes and mechanically construct a narrow intellectual elite rather than providing genuine educational advancement (Depaepe, 2018).

VII. Discussion and conclusions: Demystifying the Illusion of intelligence

The historical and bibliographical evidence supports our central thesis: labeling contemporary automated algorithmic systems as intelligent is more a political and rhetorical maneuver than an objective ontological truth. This terminology seeks to construct an artificial lineage of computation, tracing back to Gottfried Wilhelm Leibniz's 17th-century vision of the Calculus Ratiocinator and the Characteristica Universalis, which aimed to replace human argumentation with systematic mathematical calculation (Benzmüller et al., 2017). In the realm of educational history, pedagogical science has been progressively adapted to align with this trajectory, evolving from teaching machines to programmed instruction, and ultimately leading to modern Autolligence.

To break free from this historical constraint and effectively challenge the anthropomorphic simplifications of automated education, critical pedagogy must shift towards radically post-anthropocentric, biocentric educational frameworks. By embracing a paradigm of critical enbiagogy—an approach that combines the Greek roots en (within), bios (life), and agoge (guidance/education) to signify a life-centered pedagogical framework—educational theory can conceptualize interspecies, praxeological communication that transcends purely human constructs and corporate metrics. This approach systematically dismantles the mechanical, quantitative reductionism inherent in autolligent systems (Hourdakis, Ieronymakis, & Souka, 2025).

To prevent enbiagogy from remaining a purely theoretical abstraction within corporate-dominated educational ecosystems, educators must operationalize it through counter-hegemonic pedagogical practices. Functionally, this involves shifting the locus of learning from centralized digital platforms to localized, living environments. For example, rather than deploying proprietary LLM chatbots to simulate ecological systems—a practice that enforces cognitive dependence—enbiagogy can manifest through community-governed, open-source projects mapping local biodiversity and conducting interspecies field observations. By tying literacy and inquiry to the material, non-human world, students actively reclaim autonomy from corporate data infrastructures, subverting the surveillance metrics of the techno-administrative condition through local, collaborative acts.

Therefore, to resolve the contemporary terminological crisis, we must steadfastly reject misleading anthropomorphisms in favor of technically precise, philosophically rigorous vocabulary:

Probabilistic pattern correlation: This phrase must strictly replace the notion of "machine reasoning." As Autolligence lacks conscious rationale, its internal process is one of mathematical transformation, executing probabilistic induction and computational pattern synthesis to map incoming inputs to statistically optimized outputs. It functions as a data-processing accelerator, not a thinking agent.

Computational classification of verbal indicators: This term must supersede "sentiment analysis" or "emotional intelligence." Devoid of conscious experience (qualia), the machine cannot feel emotion. It merely detects semantic loads, mapping syntactic references to keywords that human programmers have categorized as positive or negative. It is a purely quantitative appraisal of linguistic conventions.

Consciousness and autonomous will remain the impenetrable boundaries separating human intelligence from Autolligence. Human cognition is defined by the capacity to pose entirely new, unprogrammed problems, to contest existing rules, and to reflect critically upon the underlying "why" of a solution through complex metacognition. Autolligence can only replicate linguistic regularities and generate an increasingly sophisticated illusion of intellect. Lacking internal purpose, volition, or subjective intent, Autolligence is an artifact, not a moral subject. It possesses no ethical neutrality, as its training data is profoundly laden with the values, political choices, and structural biases of its human creators. Ultimate evaluative responsibility, moral accountability, and intellectual agency reside entirely with the human scholars, educators, and historians directing the algorithm—preserving the vital critical distance required to employ the machine as an instrument of precision rather than succumbing to its automated constraints.

REFERENCES

[1]. Anderson, B. R., Shah, J. H., & Kreminski, M. (2024b). Homogenization Effects of large language models on human creative ideation. *Creativity and Cognition,* 413–425. https://doi.org/10.1145/3635636.3656204

[2]. Bakker, N. (2020b). Professional competence and the classification and selection of pupils for schools for “feebleminded” children in the Netherlands (1900–1940). *Paedagogica Historica*, 57(6), 728–744. https://doi.org/10.1080/00309230.2020.1762681

[3]. Becker, S. O., Hornung, E., & Woessmann, L. (2011). Education and catch-up in the industrial Revolution. *American Economic Journal Macroeconomics*, 3(3), 92–126. https://doi.org/10.1257/mac.3.3.92

[4]. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots. In FAccT ’21: *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*. https://doi.org/10.1145/3442188.3445922

[5]. Benzmüller, C., Weber, L., & Paleo, B. W. (2017). Computer-Assisted analysis of the Anderson–Hájek ontological controversy. *Logica Universalis*, 11(1), 139–151. https://doi.org/10.1007/s11787-017-0160-9

[6]. Berzal, F. (2025). DL101 Neural Network Outputs and loss Functions. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2511.05131

[7]. Canales, A. F., & Polenghi, S. (2019b). Classifying children: a historical perspective on testing and measurement. *Paedagogica Historica*, 55(3), 343–352. https://doi.org/10.1080/00309230.2019.1611890

[8]. Chalmers, D. J. (1995). Facing up to the problem of consciousness. Journal of Consciousness Studies, 2(3), 200–219.

[9]. Chang, D. H., Lin, M. P., Hajian, S., & Wang, Q. Q. (2023). Educational design principles of using AI chatbot that supports Self-Regulated learning in education: goal setting, feedback, and personalization. *Sustainability*, 15(17), 12921. https://doi.org/10.3390/su151712921

[10]. Chang, P. (2024). Struggling with exactitude in a fragmented state: Intelligence testing in early twentieth-century China. *History of Science*, 63(1), 73–100. https://doi.org/10.1177/00732753241235432

[11]. Chen, F., Huang, A., Golowich, N., Malladi, S., Block, A., Ash, J. T., Krishnamurthy, A., & Foster, D. J. (2025). The coverage principle: How Pre-Training Enables Post-Training. *ArXiv.org*. https://doi.org/10.48550/arxiv.2510.15020

[12]. Chourdakis, A. (2021). Notes on the Postgraduate Program in Critical Pedagogy. In P. Kalogiannaki (Ed.), *Education and society* (p. 352). Diadrasi.

[13]. Cope, B., & Kalantzis, M. (2023b). A little history of e-learning: finding new ways to learn in the PLATO computer education system, 1959–1976. *History of Education*, 52(6), 905–936. https://doi.org/10.1080/0046760x.2022.2141353

[14]. Davis, R. A., Conroy, J. C., & Clague, J. (2020). Schools as factories: The limits of a metaphor. *Journal of Philosophy of Education*, 54(5), 1471–1488. https://doi.org/10.1111/1467-9752.12525

[15]. Depaepe, M. (2018b). Tests, measurements, and selection in the Belgian Congo during the 1950s: the end of racist clichés? *Paedagogica Historica*, 55(3), 493–510. https://doi.org/10.1080/00309230.2018.1538253

[16]. Dittrich, K. (2018b). “The center of the manual training movement in Germany”: die Deutsche Lehrerbildungsanstalt für Knabenhandarbeit in Leipzig, 1887–1914. *Paedagogica Historica*, 55(5), 671–693. https://doi.org/10.1080/00309230.2018.1538251

[17]. Ellis, J. (2013). “Inequalities of Children in Original Endowment”: How Intelligence Testing Transformed Early Special Education in a North American City School System. *History of Education Quarterly*, 53(4), 401–429. doi:10.1111/hoeq.12035

[18]. Espeland, W. N., & Sauder, M. (2024). *Audit culture: How indicators and rankings are reshaping the world*. Pluto Press.

[19]. Ferster, B. (2014). *Teaching machines: Learning from the intersection of education and technology*. JHU Press.

[20]. Focacci, C. N., & Perez, C. (2022). The importance of education and training policies in supporting technological revolutions: A comparative and historical analysis of UK, US, Germany, and Sweden (1830–1970). *Technology in Society*, 70, 102000. https://doi.org/10.1016/j.techsoc.2022.102000

[21]. Franceschelli, G., & Musolesi, M. (2024). On the creativity of large language models. *AI & Society*, 40(5), 3785–3795. https://doi.org/10.1007/s00146-024-02127-3

[22]. Griot, M., Hemptinne, C., Vanderdonckt, J., & Yuksel, D. (2025). Large Language Models lack essential metacognition for reliable medical reasoning. *Nature Communications*, 16(1), 642. https://doi.org/10.1038/s41467-024-55628-6

[23]. Grondin, J. (2016). The Hermeneutical Circle. In N. Keane & C. Lawn (Eds.), *A companion to hermeneutics* (pp. 299–305). John Wiley & Sons, Inc.

[24]. Guan, R., Raković, M., Chen, G., & Gašević, D. (2024). How educational chatbots support self-regulated learning? A systematic review of the literature. *Education and Information Technologies*, 30(4), 4493–4518. https://doi.org/10.1007/s10639-024-12881-y

[25]. Guilford, J. P. (1967). The nature of human intelligence. New York, NY: McGrawHill.

[26]. Haase, J., Hanel, P. H. P., & Pokutta, S. (2025). Has the Creativity of Large-Language Models peaked? An analysis of inter- and intra-LLM variability. a*rXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2504.12320

[27]. Hourdakis, A. (2020). Critical-Praxical Pedagogy. Reflections on the experience of the Postgraduate Program in Teacher Education of the Pedagogical Department of Primary Education of the University of Crete. *Education Sciences*, 2020, 191–216.

[28]. Hourdakis, A., Ieronymakis, Y., & Souka, M. (2025). Critical enbiagogy (Εμβιαγωγική): Biocentric (interspecies) critical-praxical education & communication beyond human beings – de-anthropocentrism. In *Education and New Developments* 2025 – Volume 2 (pp. 96-100).

[29]. Ilankumaran, M. (2023). Programmed Instruction is a System for Sustainable Development of Language Skills. *Migration Letters*, 20(S9), 1643-1654.

[30]. Jin, Y., Li, Y., Wang, S., & Zhang, W. (2022). Automatic classification of learning objectives based on Bloom’s Taxonomy. *Studies in Educational Evaluation*, 74, 101178.

[31]. Kozbelt, A., Beghetto, R. A., & Runco, M. A. (2010). Theories of creativity. In J. C. Kaufman & R. J. Sternberg (Eds.), *The Cambridge handbook of creativity* (pp. 20–47). New York, NY: Cambridge University Press.

[32]. Mao, A., Mohri, M., & Zhong, Y. (2023). Cross-Entropy Loss Functions: Theoretical analysis and applications. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2304.07288

[33]. Mason, L. M., & Society, E. P. (2025). The nonidentity of human beings and artificial intelligence. *Philosophia Christi*, 27(1), 143–162. https://doi.org/10.5840/pc202527110

[34]. Mayer, R. E. (2024). The past, present, and future of the Cognitive Theory of Multimedia Learning. *Educational Psychology Review*, 36(1). https://doi.org/10.1007/s10648-023-09842-1

[35]. McLaren, P. (2015). *Life in schools: An introduction to critical pedagogy in the foundations of education*. Routledge.

[36]. Michell, J. (2021). “The art of imposing measurement upon the mind”: Sir Francis Galton and the genesis of the psychometric paradigm. *Theory & Psychology*, 32(3), 375–400. https://doi.org/10.1177/09593543211017671

[37]. Mirchandani, S., Xia, F., Florence, P., Ichter, B., Driess, D., Arenas, M. G., Rao, K., Sadigh, D., & Zeng, A. (2023). Large language models as general pattern machines. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2307.04721

[38]. Mogi, K. (2024). Artificial intelligence, human cognition, and conscious supremacy. *Frontiers in Psychology*, 15, 1364714. https://doi.org/10.3389/fpsyg.2024.1364714

[39]. Nicolas, S., Andrieu, B., Croizet, J., Sanitioso, R. B., & Burman, J. T. (2013). Sick? Or slow? On the origins of intelligence as a psychological object. *Intelligence*, 41(5), 699–711. https://doi.org/10.1016/j.intell.2013.08.006

[40]. Oguz, H. (2025b). Authoritarian Recursions: How fiction, history, and AI reinforce control in education, warfare, and discourse. *ArXiv.org*. https://doi.org/10.48550/arxiv.2504.09030

[41]. Omori, M. (2018). The discovery of feeblemindedness among immigrant children through intelligence tests in California in the 1910s. Paedagogica Historica, 54(1–2), 221–235. https://doi.org/10.1080/00309230.2017.1411959

[42]. Onyeukaziri, J. N. (2025). Artificial Intelligence and Suppositum: a critique of the critique of the notion of selfhood. *Scientia Et Fides*, 13(1), 57–74. https://doi.org/10.12775/setf.2025.004

[43]. Panadero, E. (2017). A review of Self-regulated Learning: Six models and four directions for research. *Frontiers in Psychology*, 8, 422. https://doi.org/10.3389/fpsyg.2017.00422

[44]. Perrotta, C., & Williamson, B. (2016). The social life of Learning Analytics: cluster analysis and the ‘performance’ of algorithmic education. *Learning Media and Technology*, 43(1), 3–16. https://doi.org/10.1080/17439884.2016.1182927

[45]. Polák, M., & Marvan, T. (2018). Neural correlates of consciousness meet the theory of identity. *Frontiers in Psychology*, 9, 1269. https://doi.org/10.3389/fpsyg.2018.01269

[46]. Rogers, B. (2016). Historicity and temporality. In N. Keane & C. Lawn (Eds.), *A companion to hermeneutics* (pp. 105–113). John Wiley & Sons, Inc.

[47]. Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. *Creativity Research Journal*, 24(1), 92–96. https://doi.org/10.1080/10400419.2012.650092

[48]. Ryan, R. M., & Deci, E. L. (2017). *Self determination theory: Basic psychological needs in motivation, development, and wellness*. New York, NY: Guilford Press.

[49]. Searle, J. R. (1980). Minds, brains, and programs. *Behavioral and Brain Sciences*, 3(3), 417–424. https://doi.org/10.1017/s0140525x00005756

[50]. Steyvers, M., Tejeda, H., Kumar, A., Belem, C., Karny, S., Hu, X., Mayer, L. W., & Smyth, P. (2025). What large language models know and what people think they know. *Nature Machine Intelligence*, 7(2), 221–231. https://doi.org/10.1038/s42256-024-00976-7

[51]. Tarlau, R. (2014). From a language to a theory of resistance: Critical pedagogy, the limits of "framing," and social change. *Educational theory*, 64(4), 369-392. https://onlinelibrary.wiley.com/doi/abs/10.1111/edth.12067

[52]. Tröhler, D. (2014). Change management in the governance of schooling: the rise of experts, planners, and statistics in the early OECD. *Teachers College Record the Voice of Scholarship in Education*, 116(9), 1–26. https://doi.org/10.1177/016146811411600903

[53]. Tyack, D. B., & Cuban, L. (1995). *Tinkering toward utopia: A century of public school reform*. Harvard University Press.

[54]. United States. Office of Educational Technology. (2023). *Artificial intelligence and the future of teaching and learning: Insights and recommendations. US Department of Education*, Office of Educational Technology.

[55]. Ward, T. B., Smith, S. M., & Finke, R. A. (1999). Creative cognition. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 189–212). New York, NY: Cambridge University Press.

[56]. Wechsler, D. (1981). *Historical Review: The Psychometric Tradition. Developing the Wechsler Adult Intelligence Scale*. Contemporary Educational Psychology.

[57]. Williamson, B. (2017). *Big data in education: The digital future of learning, policy and practice*. SAGE

[58]. Zeide, E. (2017). The structural consequences of Big Data-Driven education. *Big Data*, 5(2), 164–172. https://doi.org/10.1089/big.2016.0061