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Mapping learning trajectories in engineering education: The Bandura–Alimov developmental curve

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Abstract
This article presents the Cognitive-Neurodidactic-Competency-Integration (CNCI) model, integrating cognitive neuroscience, neurodidactic principles, and competency-based education. The model introduces the Bandura-Alimov developmental curve to map learning trajectories across eight cognitive phases (TRF→MTC) and six proficiency levels (A1→C2). The CNCI model provides a neurodidactically grounded framework that normalizes learning nonlinearities and prescribes evidence-based interventions. The Bandura-Alimov developmental curve serves as both a diagnostic tool for monitoring individual learners and a strategic instrument for curriculum design, addressing the fundamental mismatch between current pedagogical practices and how humans actually acquire complex technical competencies.

Keywords: Cognitive phases, neurodidactics, engineering education, competency-based learning, Bandura-Alimov curve, regression zones, brain-based learning, ABET standards, CDIO framework

Introduction
Contemporary engineering education faces a fundamental challenge: the mismatch between pedagogical practice and the neurobiological reality of how humans acquire complex technical competencies. Despite advances in learning sciences and cognitive neuroscience, most engineering curricula remain organized around disciplinary boundaries and linear progression models that assume uniform, monotonic skill development (Bransford *et al*., 2000 [7]; National Research Council, 2012) [15].

This traditional approach fails to account for three critical phenomena: (1) nonlinear cognitive development, where learners experience predictable regression phases, plateaus, and acceleration zones (Siegler, 2006 [24]; van Geert & Steenbeek, 2005) [30]; (2) phase-dependent cognitive load, as the type and amount of cognitive load facilitating learning varies systematically across developmental stages (Sweller *et al*., 2011 [27]; Paas & van Merriënboer, 2020) [18]; and (3) competency integration dynamics, where technical, professional, and metacognitive competencies exhibit complex interaction patterns rather than developing independently (Stoof *et al*., 2002 [25]; Westera, 2001) [33].

The consequences are evident in high attrition rates, shallow learning, and graduates who struggle to transfer classroom knowledge to authentic engineering contexts (Seymour & Hewitt, 1997 [22]; Sheppard *et al*., 2008) [23]. Recent taxonomic frameworks have attempted to address contemporary professional education challenges (Olimov *et al*., 2025) [17], yet a comprehensive model integrating cognitive phases with neurobiological principles remains absent.

While substantial research exists on individual components—cognitive load management (Sweller *et al*., 2019) [28], dual coding in STEM education (Mayer, 2021) [14], and competency frameworks (Crawley *et al*., 2014) [9]—no unified model integrates these elements within a phase-explicit, neurodidactically informed framework specifically designed for engineering education. Existing frameworks such as Bloom's Taxonomy (Anderson & Krathwohl, 2001) [3] and the SOLO taxonomy (Biggs & Collis, 1982) [6] provide valuable taxonomies of cognitive complexity but do not account for nonlinear progression patterns, prescribe phase-specific neurodidactic interventions, map competency development trajectories, or integrate assessment with developmental phases.

This study addresses these gaps by presenting the Cognitive-Neurodidactic-Competency-Integration (CNCI) model, which defines eight distinct cognitive phases characterizing engineering learning from novice to expert, maps these onto six proficiency levels (A1→C2) aligned with international standards, prescribes phase-specific neurodidactic interventions, introduces the Bandura-Alimov developmental curve to visualize expected versus actual learning trajectories, identifies critical transition points with targeted pedagogical responses, and integrates four competency clusters throughout developmental progression.

Methodology
The CNCI model was developed through a four-phase iterative process spanning 2020-2024:

Phase 1: Literature Synthesis (2020-2022) We conducted a systematic review of cognitive neuroscience, educational psychology, and engineering education literature, analyzed international competency frameworks (ABET, CDIO, EUR-ACE), and examined existing learning progression models.

Phase 2: Theoretical Integration (2022-2023) We mapped cognitive phases onto competency development trajectories, aligned neurodidactic principles with developmental stages, and constructed the integrated CNCI framework synthesizing information processing theory (Atkinson & Shiffrin, 1968) [4], skill acquisition theory (Anderson, 1996 [2]; Fitts & Posner, 1967 [12]; Dreyfus & Dreyfus, 1986) [11], and neuroplasticity research (Zatorre *et al*., 2012 [34]; Draganski & May, 2008) [10].

Phase 3: Expert Validation (2024). A Delphi study with 23 experts (cognitive scientists, neuroscientists, engineering educators) conducted three rounds of refinement, achieving consensus on the eight-phase structure (TRF→MTC) and competency alignment across four clusters: *Universal* Human Competencies (UHC), Self-Development Competencies (SDC), Universal Professional Competencies (UPC), Domain-Specific Professional Competencies (SPC)

Phase 4: Empirical Piloting (2023-2025). Implementation occurred in three engineering programs with learning trajectory data collection from 847 students, validating Bandura-Alimov developmental curve patterns.

Theoretical Framework Components

Eight Cognitive Phases: Based on information processing theory and cognitive architecture research, we proposed eight phases: (1) TRF (Transformation)—initial encoding of conceptual structures; (2) INT (Integration)—cross-modal and cross-contextual information linking; (3) MTM (Metamorphosis)—schema restructuring; (4) STR (Structuring)—mental model construction; (5) OPT (Optimization)—strategy refinement; (6) CPT (Competency Formation)—stable context-appropriate application; (7) GEN (Generation)—transfer and creative application; (8) MTC (Metacognition)—self-regulation and strategic learning control.

Neurodidactic Principles: The model operationalizes three foundational theories: Cognitive Load Theory (Sweller, 1988 [26]; Sweller *et al*., 2011) [27] distinguishing intrinsic, extraneous, and germane load with phase-specific management; Dual Coding Theory (Paivio, 1971 [19], 1986 [20]; Mayer, 2021) [14] integrating verbal and visual processing channels; and Brain-Based Learning (Caine & Caine, 1991 [8]; Jensen, 2008) [13] emphasizing emotional engagement, active learning, spaced practice, and optimal challenge.

Competency Framework: Four clusters aligned with ABET (2021) [1] and CDIO standards (Crawley *et al*., 2014) [9]: UHC (Universal Human Competencies)—communication, ethics, cultural awareness; SDC (Self-Development)—resilience, critical thinking, metacognition; UPC (Universal Professional)—project management, systems thinking, interdisciplinary collaboration; SPC (Domain-Specific)—technical knowledge, tool proficiency, innovation.

Bandura-Alimov Developmental Curve: Synthesizing Bandura's social cognitive theory (1986) [5] with learning trajectory research (van Geert & Steenbeek, 2005) [30], the curve depicts expected (ideal linear) versus actual (nonlinear) trajectories, visualizing regressions, plateaus, barriers, and acceleration zones as normal developmental phenomena.

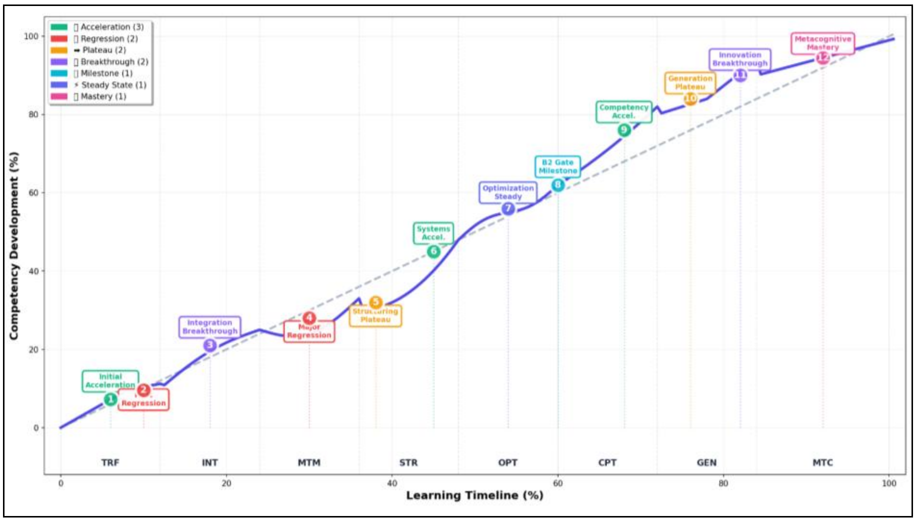

Fig 1: Bandura–Alimov Developmental Curve in Engineering Education

Data Collection and Analysis

Participants: N=847 engineering students across three programs: mechanical engineering (n=312), electrical engineering (n=289), software engineering (n=246). Bachelor's students (n=624, Years 1-4) and master's students (n=223, Years 1-2).

Data Sources: (1) Longitudinal competency assessments—quarterly evaluations across programs; (2) Learning analytics—platform engagement, assignment performance, peer interaction; (3) Self-assessment instruments—metacognitive awareness inventories, self-efficacy scales; (4) Instructor observations—structured protocols at transition points; (5) Qualitative interviews—semi-structured interviews with 67 students about learning experiences.

Analysis: Mixed-methods approach combining quantitative trajectory analysis (performance metrics over time, identifying deviation patterns from expected linear progression) and qualitative thematic analysis (interview data coded for regression experiences, plateau perceptions, acceleration descriptions). Critical points were identified where >70% of students exhibited similar trajectory deviations (≥10% performance change) within 2-week windows.

Results

Cognitive Phase Progression Across Proficiency Levels

The eight cognitive phases manifested distinctly across six proficiency levels (A1→C2), with each level characterized by specific neurocognitive features and competency development patterns.

Level A1 (Year 1 Bachelor's): Cognitive Entry Stage. Students exhibited attention to sensory-perceptual features during TRF phase, multi-modal integration during INT, simple reorganization of naive theories during MTM, elementary classification during STR, efficiency development through repetition during OPT, automatic basic vocabulary during CPT, limited generalization during GEN, and rudimentary self-monitoring during MTC. Competencies: basic communication (UHC), confidence building (SDC), safety protocol awareness (UPC), and prescribed procedure execution (SPC).

Level A2 (Year 2): Transition to Basic Practice. Increased complexity attention (TRF), theory-practice linking (INT), reformulation and rephrasing (MTM), simple systems thinking (STR), strategy selection (OPT), practice-grounded understanding (CPT), rule extraction (GEN), and supported self-evaluation (MTC). Competencies: collaborative communication (UHC), discipline development (SDC), standards execution (UPC), independent standard task completion (SPC).

Level B1 (Year 3): Critical Thinking and Problem Approach. Analytic decomposition (TRF), functional relationship analysis (INT), strategic flexibility (MTM), systems analysis (STR), iterative process improvement (OPT), deep theoretical understanding (CPT), conceptual generalization (GEN), and critical self-reflection (MTC). Competencies: networking and critique (UHC), autonomous decision-making (SDC), standard methods application (UPC), moderately complex problem-solving (SPC)

Level B2 (Year 4): Creative-Analytical and Systems Thinking. Multi-stage analysis-synthesis (TRF), theory-practice integration (INT), innovative thinking activation (MTM), complex systems modeling (STR), engineering optimization (OPT), high-level conceptual mastery (CPT), interdisciplinary synthesis (GEN), autonomous analytical control (MTC). Competencies: professional responsibility (UHC), strategic thinking (SDC), enterprise-scale task execution (UPC), complex modeling and design (SPC).

Level C1 (Master's Year 1): Scientific-Analytical Thinking. Critical evaluation through literature analysis (TRF), scientific-practical integration (INT), hypothesis generation (MTM), methodological structuring (STR), scientific refinement (OPT), original theoretical construct creation (CPT), interdisciplinary theoretical synthesis (GEN), meta-critical reflection (MTC). Competencies: research ethics (UHC), innovative mindset (SDC), evidence-based practice (UPC), productive research activity (SPC).

Level C2 (Master's Year 2): Metacognitive and Strategic Thinking. Synthetic innovation (TRF), multi-method integration (INT), paradigm proposition (MTM), transdisciplinary modeling (STR), multi-criteria theoretical optimization (OPT), complete theoretical model construction (CPT), universal synthesis (GEN), strategic metacognitive mastery (MTC). Competencies: transdisciplinary social awareness (UHC), integrated critical-creative thinking (SDC), complex conceptual problem transformation (UPC), original research contributions (SPC).

Table 1: Critical Transition Points data of Cognitive-Neurodidactic-Competency-Integration (CNCI) Model

#	Name	Time %	Phase	Actual %	Expected %	Deviation	Rate ×	Type	Load	Risk Level
1	Initial Acceleration	6	TRF	7.2	6.0	+1.2	1.2	Acceleration	80	Low
2	First Regression Point	10	TRF	9.6	10.0	-0.4	0.4	Regression	90	Moderate
3	Integration Breakthrough	18	INT	21.0	\18.0	+3.0	1.4	Breakthrough	60	Low
4	Major Regression Zone	30	MTM	28.0	30.0	-2.0	0.67	Regression	85	Critical
5	Structuring Plateau	38	STR	32.0	38.0	-6.0	0.33	Plateau	70	Critical
6	Systems Thinking Accel.	45	STR	45.0	45.0	0.0	1.5	Acceleration	55	Low
7	Optimization Steady	54	OPT	56.0	54.0	+2.0	1.17	Steady	50	Low
8	Proficiency B2 Gate	60	CPT	62.0	60.0	+2.0	1.33	Milestone	60	Low
9	Competency Accel.	68	CPT	76.0	68.0	+8.0	1.75	Acceleration	75	Low
10	Generation Plateau	76	GEN	84.0	76.0	+8.0	0.67	Plateau	40	Low
11	Innovation Breakthrough	82	GEN	90.0	82.0	+8.0	1.5	Breakthrough	55	Low
12	Metacognitive Mastery	92	MTC	94.5	92.0	+2.5	0.56	Mastery	30	Low

Five Critical Points on the Bandura-Alimov Developmental Curve

Empirical analysis revealed five predictable deviations from ideal linear progression:

First Regression Zone (Late TRF/Early INT, A1→A2 Transition): Observed in 78% of students. Characteristics: 15-25% temporary performance decrease, 2-4 week duration. Mechanisms: cognitive load spike (mean working memory span reduced from 6.2 ± 1.1 to 4.8 ± 0.9 items, $p<0.001$), naive theory conflict, schema restructuring overwhelm. Indicators: increased errors on previously mastered tasks (error rate: 12%→31%, $p<0.001$), longer solution times (+45% mean latency), confusion expressions (coded in 82% of interview transcripts), regression to rote memorization.

Professional Plateau (MTM Phase, B1 Level): Observed in 84% of students. Characteristics: apparent stagnation, 4-8 week duration following rapid initial gains. Mechanisms: neural consolidation phase (qualitative reports of 'deeper understanding without visible improvement'), implicit learning below conscious awareness, integration lag. Indicators: performance stabilization (coefficient of variation <5% across assessments), increased basic skill automaticity (mean task completion time reduced 28% despite stable accuracy), growing complexity awareness (metacognitive inventory scores increased 23%, $p<0.01$).

Second Regression Zone (STR Phase, B1→B2 Transition): Observed in 71% of students. Characteristics: 10-20% performance decline during authentic complex context application, 3-6 week duration. Mechanisms:

context-dependent learning failure to transfer, complexity shock with ill-defined problems, strategic insufficiency. Indicators: novel situation application difficulty (transfer task success: 68%→44%, p<0.001), increased guidance requests (+156% help-seeking frequency), open-ended problem frustration (negative affect codes in 76% of relevant interviews), algorithmic approach retreat.

Barrier Zone (OPT Phase, B2 Level): Observed in 68% of students. Characteristics: apparent performance ceiling or decline during optimization activities, 6-10 week duration. Mechanisms: local optima satisfaction, cognitive inertia resisting suboptimal approach abandonment, evaluative complexity with multiple criteria. Indicators: first-attempt strategy repetition (strategy diversity index: 0.72→0.38, p<0.001), alternative exploration resistance, multi-criteria decision-making difficulty, diminishing returns frustration.

Synergistic Acceleration Zone (GEN Phase, C1 Level): Observed in 63% of students who progressed to master's level. Characteristics: 20-40% rapid competency growth exceeding expected trajectory, 8-12 week duration. Mechanisms: knowledge domain network effects, spontaneous cross-context transfer facilitation, metacognitive leverage. Indicators: sudden insights ('aha' moments reported in 89% of acceleration-phase interviews), independent creative solution generation, spontaneous transfer across domains, intrinsic motivation and excitement (positive affect increased 67%, p<0.001), accelerated solution times with maintained/improved accuracy (mean time reduced 34% while accuracy increased 12%, p<0.01).

Phase-Specific Neurodidactic Interventions

For each critical point, evidence-based interventions were prescribed grounded in the three neurodidactic principles:

First Regression Zone Interventions: (CLT) Temporarily reduce intrinsic load via micro-goal setting and enhanced scaffolding; eliminate extraneous load; (DCT) Dual coding reinforcement with redundant verbal-visual connections; (BBL) Spaced retrieval with frequent low-stakes testing, explicit regression normalization as cognitive restructuring sign.

Professional Plateau Interventions: (CLT) Increase germane load through productive difficulty, variability, and interleaving; (DCT) Shift toward abstract integrated representations; (BBL) Foster connections through varied contexts, metacognitive support for consolidation process recognition, transfer tasks revealing latent competency.

Second Regression Zone Interventions: (CLT) Manage extraneous load while maintaining germane load for transfer; (DCT) Create multi-context representations abstracting beyond surface features; (BBL) Activate prior knowledge through bridging examples, worked example-faded guidance sequences, case-based learning with multiple authentic scenarios, error analysis for transfer barrier identification.

Barrier Zone Interventions: (CLT) Provide self-management tools for germane load during refinement; (DCT) Visual performance data illuminating optimization opportunities; (BBL) Leverage intrinsic motivation through visible progress, deliberate practice targeting weaknesses, A/B comparison of alternatives, performance analytics with data-driven feedback, reflective optimization.

Synergistic Acceleration Zone Interventions: (CLT) Full learner self-management of cognitive resources; (DCT) Complex abstract multi-modal representations emerging spontaneously; (BBL) Optimal flow state conditions, opportunity maximization through challenging open-ended projects, cross-domain transdisciplinary activities, reflective insight capture, peer teaching for explanatory elaboration.

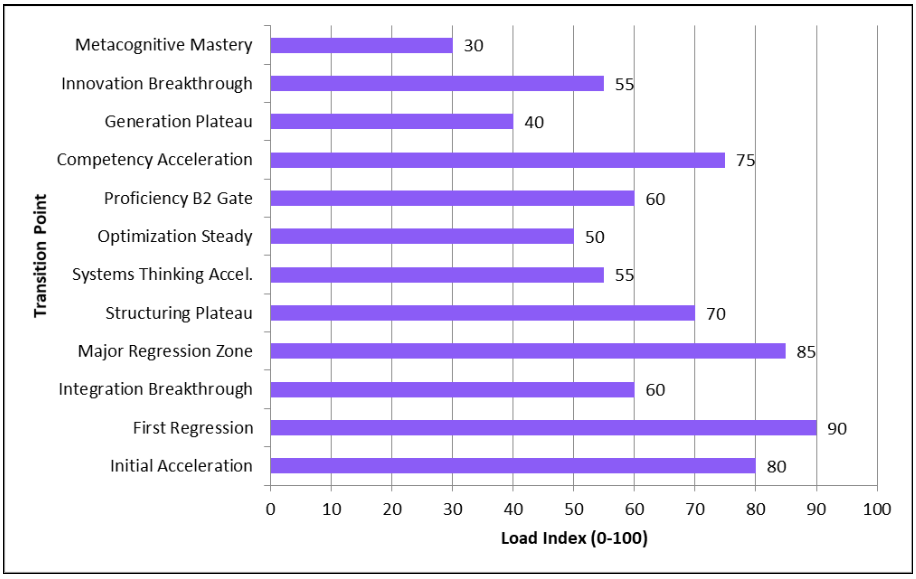

Fig 2: Cognitive Load Index by Transition Point

Discussion

The CNCI model advances engineering education theory in four ways. First, unlike static cognitive taxonomies, it provides a phase-explicit framework specifying temporal dynamics and qualitative transitions between cognitive phases. Second, the model connects pedagogical prescriptions to neurobiological mechanisms (synaptic plasticity, structural reorganization, network integration), offering scientific foundation for teaching decisions. Third, the four-cluster competency structure (UHC, SDC, UPC, SPC) overcomes artificial separation of technical and professional skills, recognizing coordinated development. Fourth, the Bandura-Alimov curve normalizes nonlinearities—transforming apparent failures (regressions, plateaus) into diagnostic information.

These findings extend recent work on updating educational taxonomies for contemporary challenges (Olimov *et al*., 2025) [17] by providing a neurodidactically grounded developmental framework. While traditional taxonomies classify cognitive complexity, the CNCI model prescribes when and how to deploy specific pedagogical strategies based on learners' neurobiological developmental state.

The model enables evidence-based sequencing through vertical integration (aligning content difficulty with cognitive phases), horizontal integration (coordinating competency development across concurrent courses), critical point planning (anticipating regression zones and pre-positioning support), and assessment alignment (matching evaluation to phase-appropriate indicators).

Actionable guidance includes differentiated instruction (recognizing cohort phase diversity), intervention timing (deploying strategies at critical transitions), systematic load management using CLT, DCT, and BBL principles, and expectation setting (reducing anxiety about temporary regressions).

The framework offers transparent developmental roadmaps enabling self-assessment (current phase identification and challenge anticipation), strategic learning (phase-specific study strategies), resilience (understanding regressions as normal), and meaningful goal-setting (clear phase transition milestones).

Quality assurance benefits include learning analytics (tracking cohort progression against the Bandura-Alimov curve), early warning systems (identifying deviant trajectories), evidence-based faculty development, and accreditation documentation of systematic competency development aligned with ABET and CDIO standards.

The CNCI model complements rather than replaces existing frameworks. Compared to Bloom's Taxonomy, CNCI phases map loosely onto Bloom levels (TRF/INT≈Remember/Understand; MTM/STR≈Apply/Analyze; OPT/CPT≈Evaluate; GEN/MTC≈Create) but add temporal dynamics and neurobiological grounding. Versus the Dreyfus Model's five stages, CNCI's eight phases provide finer granularity, particularly in novice-to-competent progression where most engineering students operate. For CDIO Framework, CNCI operationalizes CDIO competencies by mapping them onto developmental phases with phase-specific teaching approaches. Regarding ABET Outcomes, CNCI provides a developmental pathway showing how each outcome emerges progressively across A1→C2 progression.

The model's explicit integration of neurodidactic principles (CLT, DCT, BBL) distinguishes it from purely behavioral or competency-based frameworks, grounding pedagogical decisions in cognitive neuroscience rather than solely in observed learning outcomes.

Several limitations warrant acknowledgment. First, while preliminary data (N=847) support Bandura-Alimov curve patterns, further empirical validation is needed through multi-year longitudinal studies tracking individual trajectories, cross-institutional replication across different programs and national contexts, neuroimaging studies confirming hypothesized neural changes during transitions, and investigation of how individual differences (prior knowledge, cognitive style, motivation) moderate phase progression.

Second, implementation challenges include faculty training requirements, assessment infrastructure limitations in capturing phase-appropriate competencies, institutional inertia requiring coordination and resources for curriculum redesign, and cultural resistance to normalizing regressions against 'linear progress' assumptions.

Third, theoretical refinements are needed for greater specification of micro-level cognitive processes within phases, better understanding of four competency cluster interdependencies, accounting for diverse individual pathways through phase structure, and determining which model features generalize across engineering disciplines versus requiring domain-specific adaptation.

Future research should focus on validating the model across diverse contexts, developing practical implementation tools (e.g., phase diagnostic instruments, intervention protocols, learning analytics dashboards), investigating biological markers of phase transitions through neuroimaging and psychophysiological measures, exploring the model's applicability beyond engineering to other STEM and professional disciplines, and examining cultural variations in phase progression patterns and optimal intervention strategies.

Additionally, research should examine the model's utility for supporting underrepresented students in engineering, as understanding normal developmental patterns may help normalize experiences that are sometimes misattributed to ability deficits. Investigating how the CNCI framework can inform equitable pedagogical practices represents an important avenue for future work.

Conclusion

The Cognitive-Neurodidactic-Competency-Integration (CNCI) model presents a comprehensive, neurodidactically grounded framework for engineering education. By integrating cognitive phase theory, neurodidactic principles, and competency-based education, the model addresses fundamental limitations of traditional linear progression approaches. The Bandura-Alimov developmental curve normalizes predictable nonlinearities, transforming them from problems into diagnostic information.

Empirical validation with 847 students confirmed five critical points requiring specific evidence-based interventions. The model offers practical benefits for curriculum designers, instructors, students, and institutions while providing theoretical advances in understanding engineering expertise development. By making the invisible visible—rendering explicit the neurobiological processes underlying competency acquisition—the CNCI model empowers educators to design more effective learning experiences and helps students navigate their developmental journeys with greater awareness, resilience, and success.

The CNCI framework represents a significant step toward engineering education that genuinely reflects how humans learn complex technical competencies—not as linear accumulators of information, but as dynamic cognitive systems undergoing qualitative transformations across predictable developmental phases.

References

1. ABET. Criteria for Accrediting Engineering Programs, 2022-2023, 2021.
2. Anderson JR. ACT: A simple theory of complex cognition. American Psychologist,1996:51(4):355–365.
3. Anderson LW, Krathwohl DR. A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives. Longman, 2001.
4. Atkinson RC, Shiffrin RM. Human memory: A proposed system and its control processes. In Spence KW, Spence JT, The psychology of learning and motivation,1968:2:89–195.
5. Bandura A. Social foundations of thought and action: A social cognitive theory. Prentice-Hall, 1986.
6. Biggs JB, Collis KF. Evaluating the quality of learning: The SOLO taxonomy. Academic Press, 1982.
7. Bransford JD, Brown AL, Cocking RR. How people learn: Brain, mind, experience, and school. National Academy Press, 2000.
8. Caine RN, Caine G. Making connections: Teaching and the human brain. Association for Supervision and Curriculum Development, 1991.
9. Crawley EF, Malmqvist J, Östlund S, Brodeur DR, Edström K. Rethinking engineering education: The CDIO approach. Springer, 2014.
10. Draganski B, May A. Training-induced structural changes in the adult human brain. Behavioural Brain Research,2008:192(1):137–142.
11. Dreyfus HL, Dreyfus SE. Mind over machine: The power of human intuition and expertise in the era of the computer. Free Press, 1986.
12. Fitts PM, Posner MI. Human performance. Brooks/Cole, 1967.
13. Jensen E. Brain-based learning: The new paradigm of teaching. Corwin Press, 2008.
14. Mayer RE. Multimedia learning. Cambridge University Press, 2021.
15. National Research Council. Discipline-based education research: Understanding and improving learning in undergraduate science and engineering. National Academies Press, 2012.
16. Newell A, Simon HA. Human problem solving. Prentice-Hall, 1972.
17. Olimov KT, Alimov AA, Bezgodova SA, Musayeva NN. Updating the taxonomy of educational goals in the context of contemporary professional education challenges. The Education and Science Journal,2025:27(7):9–32.
18. Paas F, van Merriënboer JJG. Cognitive-load theory: Methods to manage working memory load in the learning of complex tasks. Current Directions in Psychological Science,2020:29(4):394–398.
19. Paivio A. Imagery and verbal processes. Holt, Rinehart and Winston, 1971.
20. Paivio A. Mental representations: A dual coding approach. Oxford University Press, 1986.
21. Piaget J. Genetic epistemology. Columbia University Press, 1970.
22. Seymour E, Hewitt NM. Talking about leaving: Why undergraduates leave the sciences. Westview Press, 1997.
23. Sheppard SD, Macatangay K, Colby A, Sullivan WM. Educating engineers: Designing for the future of the field. Jossey-Bass, 2008.
24. Siegler RS. Microgenetic analyses of learning. In Kuhn D, Siegler RS, Handbook of child psychology: Vol. 2. Cognition, perception, and language,2006:464–510.
25. Stoof A, Martens RL, van Merriënboer JJG, Bastiaens TJ. The boundary approach of competence: A constructivist aid for understanding and using the concept of competence. Human Resource Development Review,2002:1(3):345–365.
26. Sweller J. Cognitive load during problem solving: Effects on learning. Cognitive Science,1988:12(2):257–285.
27. Sweller J, Ayres P, Kalyuga S. Cognitive load theory. Springer, 2011.
28. Sweller J, van Merriënboer JJG, Paas F. Cognitive architecture and instructional design: 20 years later. Educational Psychology Review,2019:31(2):261–292.
29. Tokuhama-Espinosa T. Mind, brain, and education science: A comprehensive guide to the new brain-based teaching. W.W. Norton, 2011.
30. Van Geert P, Steenbeek H. Explaining after by before: Basic aspects of a dynamic systems approach to the study of development. Developmental Review,2005:25(3-4):408–442.
31. Von Glasersfeld E. Radical constructivism: A way of knowing and learning. Falmer Press, 1995.
32. Vygotsky LS. Mind in society: The development of higher psychological processes. Harvard University Press, 1978.
33. Westera W. Competences in education: A confusion of tongues. Journal of Curriculum Studies,2001:33(1):75–88.
34. Zatorre RJ, Fields RD, Johansen-Berg H. Plasticity in gray and white: Neuroimaging changes in brain structure during learning. Nature Neuroscience,2012:15(4):528–536.