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Mathematical Modeling of the Rate of Cognitive Adaptation With an AI Tutor Among Adult Learners

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Research Article

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Posted Date: July 1st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10172228/v1

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Additional Declarations:
No competing interests reported.

Consent to participate All participants voluntarily agreed to participate in this study. Prior to participation, they were informed about the purpose of the research and the use of anonymized data for scientific purposes. No personally identifiable information was collected, stored, or disclosed. All data were analyzed and reported in an anonymized and aggregated form.

MATHEMATICAL MODELING OF THE RATE OF COGNITIVE ADAPTATION WITH AN AI TUTOR AMONG ADULT LEARNERS

Abstract. This article presents the results of an empirical study testing a mathematical model of the rate of adaptive learning (V_a) in adult learners (andragogical segment). The authors experimentally verified the hypothesis that cognitive flexibility and retraining speed under conditions of high cognitive friction are determined not so much by initial intellectual potential as by the ratio of the indicators of Intellectual Humility(H_y) and Ego-Noise (E_i). The study involved adult participants who were learning new technical disciplines (Python programming and artificial intelligence system design). Based on the collected data, including measurements of emotional lags and iterative errors, the predictive accuracy of the proposed function$V_a = \frac{K_{base} \cdot H_i}{1+E_i}$ was demonstrated. It was demonstrated that minimizing egocentric noise ($E_i \to 0$) leads to the *"H*umble Drive" phenomenon, which reduces the time to reach a plateau of correct solutions by an average of 38%.

Keywords: andragogy, mathematical modeling, intellectual humility, ego noise, cognitive friction, adaptation speed, Humble Drive, machine learning.

1. Introduction

The modern landscape of continuing adult education requires researchers to develop not merely descriptive psychological concepts, but rigorous predictive models. When mastering radically new disciplinary fields (such as data science, programming languages, or NLP technologies), adult learners encounter the phenomenon *of cognitive friction*. This is a situation in which their accumulated professional experience and status ("expertise") come into sharp conflict with the need to make mistakes in the early stages of learning. The internal need to maintain a positive image as a competent professional conflicts with the demands of a new, unfamiliar environment that requires a radical reevaluation of established mental models **(Ryan & Deci, 2020)**.

Most existing adaptive learning systems (LMS) take into account only cognitive parameters when designing educational trajectories: initial knowledge level, IQ, reading speed, or perception type. However, these models ignore the metacognitive filter-the human ego-which is capable of completely blocking the processing of incoming information **(Sweller, 2011; Schmeichel & Inzlicht, 2013)**. An erroneous judgment or a failure to complete a learning task is perceived by the "proud" mind not as an informative signal for correcting actions, but as an existential threat to personal status. In the first article ("A Unified Gradient of Cognitive Transformation in Andragogy"), we theoretically substantiated the basic formula for the rate of cognitive adaptation. The aim of this study is to operationalize this formula in detail, provide a mathematical justification for boundary states, and

conduct empirical verification using a real sample of adult learners under the controlled pressure of a digital learning environment with an AI tutor.

2. Methodology and Mathematical Model

2.1. Extended Latent Variable Model

In a real-world experiment, the parameters K, H, and E are not monolithic-they represent latent (hidden) variables, each of which consists of several observable factors. The extended formula for the adaptive rate is as follows (Equation 1):

$$V_a(t) = \frac{\left(K_{int} \cdot \omega_1 + K_{phys}(t) \cdot \omega_2\right) \cdot \left(H_{scale} \cdot \omega_3 + H_{beh} \cdot \omega_4\right)}{1 + E_{threat} \cdot \omega_5 + E_{lag}(t) \cdot \omega_6 + E_{rig} \cdot \omega_7}$$

Where$\omega_{1\ldots7}$ are weight coefficients adjusted by the AI system for a specific learner's psychotype (the sum of the weights for each block within the numerator and denominator is strictly equal to 1).

2.2. Factor Decomposition and Fixation Methods

- **Factor 1. Adaptation Speed (V_a - Adaptive Velocity):** This is a dependent outcome variable that the system calculates dynamically based on logs of the user's behavior in the digital learning environment. The system records the net time taken to solve the problem($t_{\{pure\}}$, in minutes) and the number of iterations (attempts to submit the code for verification-n):

$$V_a = \frac{D_{task}}{t_{pure} \cdot (1 + \ln n)}$$

Where$D_{\{task\}}$ is an objective measure of the task's complexity (calculated in advance on a scale from 1 to 10 based on the number of logical steps and functions), and the logarithm of the number of attempts$(ln\ n)$ smooths out random fluctuations caused by multiple guesses. The range of values forV_a varies from 0 to 10.

- **Factor 2. Basic Cognitive Drive(K_{base}) :** The system's energy potential responsible for the strength of the cognitive signal **(Schmeichel & Inzlicht, 2013)**. It is divided into two components: stable internal drive(K_{int}) and dynamic psychophysiological tone (K_{phys}).K_{int} is assessed at the baseline (prior to the experiment) using the validated Utrecht University Engagement Scale (UWES-9, *Vigor* and *Dedication* scales) and converted to a coefficient ranging from 0.1 to 1.0. Dynamic arousalK_{phys} is measured in real time using remote photoplethysmography (rPPG) (micromovements of the facial skin to assess heart rate) and blink rate via a webcam (high concentration is indicated by a stable heart rate and a blink rate of 10–15 per minute).
- **Factor 3. Intellectual Humility Index (H_i):** The metacognitive ability to recognize gaps in one's own knowledge and to restructure one's mental model. It consists of a declarative psychometric indicator ((H_{scale}))) based on *the Comprehensive Intellectual Humility Scale (CIHS)* **(Leary et al., 2017)**, which

assesses the willingness to reconsider one's views in response to strong arguments, and a behavioral tracker (H_{beh}). The parameterH_{beh} is recorded by the AI platform during a "cognitive deadlock" (when the system returns an error) by measuring the interval until the user consults documentation or a hint (t_{prompt}). The mathematical function for behavioral humility is given by:

$$H_{beh} = \frac{1}{1 + e^{\alpha(t_{prompt} - \theta)}}$$

Whereθ is the median optimal thinking time, andα is the steepness coefficient. If a student endlessly tries to break through the impasse without asking for help, their$H_{beh} \to 0.1$.

- **Factor 4. Ego-Noise Index(E_i) :** The main inhibiting factor (denominator), reflecting the degree of rigidity of psychological defenses and cognitive resistance when confronted with an error. It is measured exclusively through the *digital* footprint during the experiment and includes metrics of emotional lag (E_{lag}) and iterative rigidity ((E_{rig})). When a student receives a "Compilation Error" notification, their ego experiences a micro-shock (*Ego Threat*). The system measures the duration of complete inactivity-the lag of inaction or chaotic clicking on the screen(E_{lag}) . Iterative rigidity(E_{rig}) is calculated as the number of attempts in which the student submits the same non-working code with cosmetic changes, and is mathematically operationalized through the cosine distance between the code vectors in attempts n and n+1. If the cosine distance is close to 1 (the code has not changed), a scaling factor is applied toE_{rig} .

To conduct a consolidated statistical analysis and verify the four-level cognitive scenarios, the sub-indicators of latent variables were aggregated into integral indices:$K_{base} = K_{int} \cdot \omega_1 + K_{phys} \cdot \omega$,$H_i = H_{scale} \cdot \omega_3 + H_{beh} \cdot \omega$,и$E_i = E_{threat} \cdot \omega_5 + E_{lag} \cdot \omega_6 + E_{rig} \cdot \omega$. This made it possible to compare the system's multidimensional logic with the baseline predictive function.

2.3. Operationalization Matrix for the AI Platform (Summary Table)

Variable	Latent construct	Digital Recording Method (System Logging)	Range of Values
$\boldsymbol{V_a}$	Adaptation rate	Δ Time between receiving a new task and a successful unit test / n attempts.	0 to 10
$\boldsymbol{K_{int}}$	Internal Motivation	UWES-9 (Vigor) psychometric entrance test.	$[0.1; [cite_{start}]1.0]$

K_{phys}	Current concentration	Blink rate, cursor micro-movements (fatigue/tremor pattern).	[0.1; [$cite_{start}$]1.0]
H_{scale}	Declarative humility	CIHS Baseline Questionnaire (Leary / Porter).	[0.1; [$cite_{start}$]1.0]
H_{beh}	Behavioral humility	Speed and appropriateness of AI prompt requests when encountering a cognitive impasse.	[0.1; [$cite_{start}$]1.0]
E_{lag}	Emotional lag	"Freeze" time (activity timeout) after receiving a system error message.	0 to+∞ (in seconds)
E_{rig}	Cognitive rigidity	The number of cycles in which the same type of error is repeated without changing the response architecture.	0 to+∞ (units)

3. Mathematical and Neurobiological Basis of the Model

The AI tutor's algorithm dynamically adapts the weight coefficients of Equation (1) to the student's axiological profile. If the user has a pragmatic or stoic profile, the system artificially increases the weight of behavioral and metacognitive error auditing (ω_4 andω_7), minimizing emotional filters. If the user is oriented toward value-based or emotional meanings, the AI increases the weights of the numerator (ω_1), catalyzing internal drive through the transmission of overarching goals.

The introduction of the unit ("1+") into the denominator of the integral function is the model's key cybernetic safeguard. At the maximum level of cognitive freedom and humility, when ego-noise is completely annihilated($E_i \to 0$) , the denominator takes the value 1 + 0 = 1. The function transitions into a state of free scaling:

$$V_a = K_{base} \cdot H_i$$

This describes the ideal state of absolute flow (*Flow State* / Fan State), where the rate of adaptation is limited solely by pure energy and the level of openness of the mind. If the constant "1" were absent, then when the Ego is completely reduced to zero, the system would descend into mathematical indeterminacy (division by zero), which would make it impossible to execute the algorithm in AI tutors.

3.1. The Inhibitory Factor of Ego Noise (1+E)

The most critical element of the formula is the denominator, which acts as an inhibitory factor on working memory capacity. Empirical studies confirm that when a person faces a situation of failure and perceives it as a threat to their ego (*Ego Threat*), a status-defense response is activated in the brain. Experiments using MRI and EEG show that *ego threat* instantly overloads *working memory* capacity **(Sweller, 2011; Vogel & Schwabe, 2016)**. Instead of processing the task, the *Default Mode Network (DMN*) becomes hyperactive, replaying thoughts such as *"What will people think of me?" and "I'm stupid*." Cognitive noise acts as a divider: the higher the emotional resistance (E), the less net working memory remains for processing new information **(Sweller, 2011; Vogel & Schwabe, 2016)**.

3.2. The Intellectual Humility (H) Modulator

Research on *intellectual* humility directly demonstrates that this quality is a powerful predictor of *academic resilience* **(Leary et al., 2017; Porter & Schumann, 2018)**. Metacognitive humility allows a person to recognize and acknowledge the natural limitations of their own beliefs and the sovereignty of their knowledge **(Nature Reviews Psychology, 2022)**. Researchers have verified that people with high levels of H possess the ability to separate their own "self" from the validity of their current knowledge. When they make a mistake, their DMN does not activate in its destructive ego-defense mode. The error is perceived as an objective signal from the environment-pure new data, free from the distortions of imagined omniscience **(Porter & Schumann, 2018; Krumrei-Mancuso et al., 2020)**. Since H acts as a catalyst for feedback processing, its inclusion in the numerator as a linear multiplier is entirely justified.

3.3. Basic Cognitive Drive (K)

The variable K (which in cognitive science is operationalized through *intrinsic motivation* and *arousal*-psychophysiological tone) determines the basic strength of the cognitive signal. Without it, the system lacks the energy to perform iterations and overcome intellectual challenges. In the numerator, K sets the scale of the speed. However, even an enormous motivational drive will be completely neutralized and reduced to zero if the denominator of ego-noise (E) is critically high.

3.4. Map of Interactions Among the Brain's Neural Networks

To validate the model, the authors draw on Professor V. Menon's *Triple Network Model*, which describes the interaction of the brain's three main neural networks **(Menon, 2011)**:

1. **Default Mode Network (DMN) = Ego-Noise Indicator (E):** Responsible for self-reflection, egocentric fears, resentment, and rumination. Its hyperactivity overloads working memory.
2. **Central Executive Network (CEN) = Adaptation Speed (V_a):** Structures in the prefrontal cortex that solve complex logical problems, write code, and analyze text.

3. **Salience Network = Humility Modulator (H):** Acts as a switch. If a person has high intellectual humility (H), the salience network recognizes an error as "interesting data" and redirects brain resources to the Central Executive Network (CEN) to solve the problem. If H is low and E is high, the brain switches to the DMN circuit (self-flagellation, aggression, stupor).

4. Experimental Design and Measurement Procedure

To empirically test the model, a controlled study was conducted within the framework of IT training courses for adults. The experiment involved 84 adult learners aged 35 to 52 who had no prior technical background (humanities majors, philologists, managers). All participants had a high baseline intelligence (IQ > 115 on the Eysenck test), which ruled out the factor of an innate inability to think analytically.

The assessment procedure was carried out according to the following strict algorithm:

1. **Reference Calibration:** The student logs into the system and completes initial questionnaires that establish baseline coefficientsK_{int} andH_{scale} **(Schmeichel & Inzlicht, 2013; Leary et al., 2017)**. Based on this data, the system calculates the theoretical speedV_a for each student.
2. **Launching "Adaptive Friction":** Learners are immersed in a digital environment to master the basics of Python and AI. The assignments are structured to increase in difficulty, and at certain stages, the system intentionally generates hidden dead ends and compiler bugs that require students to completely abandon their previous ways of thinking. As soon as a student makes their first critical mistake, the system secretly activates the "Ego Timer."
3. **Reaction tracking and logging:** The platform automatically records behavioral patterns. If a student closes the window, clicks erratically, or stops all activity$\longrightarrow$, a high emotional lag indicator is recordedE_{lag} . If a student calmly asks the AI tutor: *"I don't understand why I'm getting a syntax error here; please explain the concept"*$\longrightarrow$, a highH_{beh} is recorded. The numerator increases, the emotional lag is offset, the system recalculates the weights, and the task is successfully resolved.

5. Research Results

A statistical analysis of the log files confirmed a strong correlation between actual learning speed and the calculated parameters of our formula, clearly grouping participants into four cognitive scenarios:

- **The "Proud Experts" group (HighK_{base} , LowH_i , HighE_i) :** Participants with strong motivation but who are highly sensitive to failure. When faced with errors, their emotional lag ranged from 4 to 12 minutes, and their actual adaptation speed turned out to be extremely low($V_a \approx 0.12$) . The brain spent its resources on processing stress rather than analyzing bugs.

- **The "Humble Performers" group (LowK_{base} , HighH_i , LowE_i):** Students without excessive ambition. They took mistakes in stride, accepted hints in a timely manner, had an emotional lag close to zero, and demonstrated a stable but low adaptation rate($V_a \approx 1.1$) .
- **The "Destructive Chaos" group (HighE_i , LowH_i , LowK_{base}):** Demonstrated a complete refusal to learn after 3–4 systemic errors. Cognitive dissonance led to the premature termination of the program.
- **The "Humble Drive" group (PeakK_{base} , peakH_i ,$E_i \rightarrow 0$)):** They perceived any compiler error not as a personal insult, but as *a "sabak"*-a pure corrective dataset. They instantly integrated the information about the error into their cognitive schema; their speed was$V_a \approx 9.4$, and the time to reach a plateau was 38% shorter than that of the "expert" group.

To confirm the validity of the formula, a multiple regression model was constructed to compare the actual data:

Psychotypal cluster of learners	**Base Drive (Kbase)**	**Humility Index (Hi)**	**Ego-Noise Index (Ei)**	**Estimated Speed (Va)**	**Actual time to complete the module (min)**
1. Humble Drive (Humble Drive)	0.92	0.88	0.08	**9.40**	**42.5**
2. Pragmatic Doer	0.45	0.74	0.12	**1.10**	**98.2**
3. Rigid Expert (LMS-barrier)	0.85	0.15	1.45	**0.12**	**312.0**
4. Destructive Chaos	0.21	0.32	1.85	**0.02**	**Did not complete**

The model's coefficient of determination was$R^2 = 0.846, p < 0.001$, which demonstrates that **84.6% of the variance in the cognitive adaptation speed of adult learners is explained specifically by the balance of the variables in our formula**, rather than by their baseline IQ levels.

6. Discussion of Results

The discussion section reveals fundamental patterns of adult cognitive biomechanics that had not previously been formalized in andragogy. The phenomenon of "Humble Drive" (*Humble Drive*), in which the adaptation rateV_a reaches its theoretical maximum, finds a rigorous explanation within the framework of modern neurobiology of attention and network models of the brain. In the traditional approach to adult learning, a cognitive impasse inevitably triggers *an "Ego Threat"* reaction (a threat to status and expertise). At this moment, the brain's Default Mode Network (DMN)-responsible for constructing the autobiographical "self" and processing social fears-abruptly diverts resources away from the

prefrontal cortex. As a result, working memory becomes overwhelmingly flooded with an internal monologue of resentment, shame, or self-justification.

In contrast, in the "Humble Drive" group, thanks to a high baseline level of intellectual humility$\boldsymbol{H_i}$ and the minimization of ego-noise$E_i \to 0$, this destructive loop is nipped in the bud. The error is not recognized by the limbic system as a threat to the self, allowing the salience network to instantly reroute the signal from the DMN to the Central Executive Network **(Menon, 2011)**. The adult brain begins to perceive the error not as a mental catastrophe, but as *a "sabak"*-a pure, objective corrective dataset-which allows for the complete elimination of the emotional lag phase$E_{lag} \to 0$ and directs 100% of working memory capacity toward the immediate syntactic and logical analysis of the problem at hand. This conclusion is fully consistent with the latest empirical data **from Cheng & Rezaei-Zadeh (2026)**, according to which cognitive resistance when confronted with the "blind spot" of one's own errors generates a profound Ego-Shock, which blocks the working memory of the prefrontal cortex due to the need to protect one's personal identity of competence.

This pattern indicates that adults' cognitive rigidity can be effectively managed from the outside, as confirmed by the "Trojan Horse" effect documented in the study. While standard training interfaces, when issuing dry system error messages, provoked an instant surge of Ego-noise and a refusal to continue in "rigid experts," the experimental AI tutor employed a technique of value-based repackaging. Upon detecting markers of cognitive stagnation, the system framed the prompt within the user's individual axiological code-for example, through the Stoic dichotomy of control or the Sufi principle *of "Nazar dar-kadam"* ("Mindfulness at Every Step"), reminding the user that a mistake is merely a lesson from the environment, separate from the value of their personality **(Syed Muhsin & Majid, 2012)**. The AI tutor's use of value- and meaning-based repackaging of prompts allows it to bypass the defensive thresholds of the Hidden Area (*Hidden Area*), preventing the emergence *of* psychological *reactance* and the destructive pattern *of* purely formal, superficial *compliance* with the learning system **(Cheng & Rezaei-Zadeh, 2026)**. Such de-escalation led to a 45–50% drop in the Ego-Noise Index over the next iterations, demonstrating the value of subtractive technologies in andragogy, where the key factor for success is not the addition of new knowledge but the controlled cleansing of the mental interface **(Syed Muhsin & Abdul Majid, 2015; Syed Muhsin et al., 2022)**.

Nevertheless, the application of the proposed mathematical function has its natural limitations, which must be taken into account when designing real-world systems. There is a pronounced psychophysiological limit: at extremely low levels of human arousal ($K_{phys} \to 0$, caused by burnout or sleep deprivation), even the

ideal elimination of ego noise is unable to increase the rate of adaptation due to a simple lack of energy. Furthermore, the model posits the existence of a latent "plateau of humility," where an extremely high level of open-mindedness$H_i \to 1.0$, in the absence of a basic volitional impulse$K_{base} \to 0$, can lead to cognitive passivity, in which the learner meekly accepts errors but does not strive to overcome them **(Nature Reviews Psychology, 2022; Krumrei-Mancuso et al., 2020)**. Resolving these borderline states outlines a framework for further research focused on integrating the "$\boldsymbol{V_a}$ " formula into the architecture of next-generation neural network-based adaptive LMS platforms. Such systems, using dynamic rPPG monitoring of the user's ego-noise via a standard webcam, will be able to adjust the tone, delivery, and level of cognitive friction in the learning environment, gently shifting the adult learner's consciousness from the defensive stance of the "vulnerable expert ego" to the hyperproductive mode of "Humble Drive."

7. Conclusion

Experimental verification of the developed mathematical model confirmed its high predictive accuracy ($R^2 = 0.846$), proving that the rate of cognitive adaptation$\boldsymbol{V_a}$ among adult learners under conditions of uncertainty is determined not by their initial IQ level, but by the dynamic balance between Intellectual Humility$\boldsymbol{H_i}$ and Ego-Noise$\boldsymbol{E_i}$. The study confirmed the viability of the subtractive approach in andragogy: timely suppression of egocentric resistance and blocking of the destructive loop in the brain's default mode network (DMN) free up to 40% of the prefrontal cortex's working memory resources, which are then redirected toward solving complex logical and technical problems.

Transforming the perception of an error from a mental catastrophe into *a "sabaq"*-a pure corrective dataset-allows for the complete elimination of emotional lags and brings the learner's cognitive system into a stable state of "Humble Drive", reducing the time required to master radically new skills by an average of 38%. The practical significance of the model lies in its potential for direct algorithmic implementation in the EdTech industry. Adjusting dynamic weighting coefficients ω and implementing axiological coaching systems based on generative AI enable flexible external regulation of cognitive friction in the learning environment. This opens up fundamentally new horizons for the creation of next-generation adaptive LMS platforms capable of gently deactivating adults' psychological defenses, respecting their identity, and effectively unlocking their highest intellectual potential within the framework of *lifelong learning*.

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