International Journal of Enhanced Research in Educational Development (IJERED)
ISSN: 2320-8708, Vol. 13 Issue 3, May-June, 2025

A Fibristic Epistemology for AI Tool Evaluation: A Logic-Based Simulation Framework

Farida Bouattoura

Doctorial Candidate

ABSTRACT

The initial research and evaluations of the initiative of user simulation through AI, highlighted significant limitations and critical issues inherent in conventional methodologies and prevailing academic literature. A recurring theme emerged: existing narratives frequently overestimate capacities, conveying alternative realities rather than empirical truths, largely influenced by academic echo chambers and confirmation biases prevalent in scholarly communities (Sunstein, 2009; Nickerson, 1998). Ignoring or dismissing these inconsistencies would compromise the research's ethical and academic integrity, perpetuating elitist structures and confirmation biases deeply embedded in academia (Chambers, 2017). Recognizing the frontier nature of tha investigation and informed by Bloom's revised taxonomy—where synthesis represents the apex of cognitive processes (Anderson & Krathwohl, 2001)—tha research explicitly chooses synthesis over replication. The intent is not to overly critique holistic approaches themselves, as their foundational goals are valuable. Instead, it critiques the deterministic and often biased execution and interpretation frequently driven by academia's gravitational pull towards unidirectionality and confirmation bias (Ioannidis, 2005; Lilienfeld, 2017). Consequently, transcending conventional frameworks and embracing a more detached, reflective, and integrative "fibristic" approach becomes necessary. A method that explicitly addresses observed deficiencies by constructing an innovative, accountable, and rigorously transparent methodological path forward, promoting adaptive synthesis, layered transparency, and ethical reflexivity.

From Holistic Constraints to Fibristic Innovation

Initially, the term "holistic" appeared fitting for describing the exploratory nature of the research methodology; however, upon deeper reflection, the term reveals implicit elitism and academic arrogance. The term unintentionally suggests superiority over reductionist or quantitative methods, despite the essential interconnectedness and mutual reliance between diverse research methodologies. Recognizing that no single method inherently holds superiority, and remaining mindful of academia's complicity in problematic ideologies historically—such as its role in promoting eugenics (Kevles, 1995), justification of colonial violence through deterministic racial theories (Said, 1978), and the endorsement of pseudoscientific racial hierarchies exemplified by influential figures such as Alexis de Tocqueville (Pitts, 2005) and Nazi scientists (Proctor, 1988)—pursuing a more humble and accurate conceptual framework became critical.Therefore, the research explicitly departs from "holistic," moving toward a precise and deliberate framing termed "fibristic," emphasizing synthesis and construction. The concept of synthesis, as defined by Bloom's revised taxonomy, represents the highest form of cognitive engagement, involving creating new structures or patterns by assembling components into coherent wholes (Anderson & Krathwohl, 2001). Such an approach emphasizes active learner participation, promoting transparency and individualized, interactive educational processes, aligning with contemporary educational principles (Anderson & Krathwohl, 2001). The term "fibristic" aligns structurally with biological constructs, symbolizing research as a layered entity comprising invariants (the skeletal structure), muscular elements (transcendental flexibility and adaptability), and ligamentous linkages (hyperbolic connections creating structural integrity and resilience).

Invariant elements provide foundational assumptions or premises forming the stable framework. These necessary constants offer the core around which research coherently organizes itself. Muscular elements capture the transcendental aspect of research, ensuring flexibility, adaptability, and resilience, allowing the methodology to turn, twist, and dynamically respond to diverse insights and discoveries. Ligamentous elements represent hyperbolic relationships—connections holding structures together, which appear chaotic or opaque from linear or limited perspectives. These hyperbolic linkages demonstrate deterministic complexity, crucially preserving structural integrity while acknowledging multidimensional complexity and human fallibility. Critically, the research recognizes that all human knowledge inherently carries potential for error, emphasizing humility, constant reflexivity, and transparency to mitigate biases and inaccuracies. Within the fibristic framework, errors serve constructively—as opportunities for methodological refinement, deeper insights, and innovative progress. Consequently, the fibristic approach explicitly fosters an exploratory, adaptive, and resilient methodological structure, respecting inherent complexities and limitations of human cognition while rigorously upholding standards of transparency, traceability, and ethical accountability. Indeed, the framework reflects life-like characteristics anchored in equilibrium. Actions taken in one domain naturally correspond with inverse actions in another, underscoring the absence of inherently negative elements; rather, each element finds its optimal place, akin to tessellating puzzle pieces. Examining higher-dimensional geometries such as the tesseract, the 600-cell, the 57-cell, or the 11-cell, each structure exhibits consistent properties: invariant skeletal frameworks, hyperbolic muscular elements (manifolds), and deterministic ligamentous linkages initially perceived as chaotic. These deterministic linkages, or logic fields, offer structural coherence from higher-dimensional perspectives (Coxeter, 1973). An enveloping boundary—such as the arctan function—contains these structures within definable limits, illustrating how complexity remains systematically organized and accessible (Mandelbrot, 1983). Analogies drawn from life sciences further enhance the fibristic concept, mirroring the structure and functionality of biological cells, reinforcing the integrative, adaptive, and systematic essence of the fibristic methodology (Alberts et al., 2014).

Algorithmic Distortion and Epistemic Control

Contemporary AI-mediated retrieval systems introduce structural distortions into the process of knowledge discovery. Platforms such as JSTOR, Scopus, Semantic Scholar, and Google Scholar deploy deep learning-based semantic ranking, citation-driven prioritization, and predictive topic modeling to surface literature, while offering limited human transparency into the mediation logic (van Dijck, Poell, & de Waal, 2018; O'Neil, 2016). For example, Semantic Scholar applies citation influence and NLP-based clustering (van Dijck, Poell, & de Waal, 2018), while Scopus uses AI to model trends and predict content relevance (O'Neil, 2016). These systems do not passively retrieve documents—they actively prioritize dominant epistemic formations and reinforce majority positions under the guise of objectivity (Crawford, 2021).Search outputs continually reinforce previously cited views, creating a recursive feedback loop suppressing marginal, oppositional, or non-orthodox perspectives (Crawford, 2021). AI environments subject users to algorithmic consensus formation, where relevance supplants representativeness and citation count falsely signals epistemic merit (Crawford, 2021). The sudden rise in pro-AI literature, particularly after 2017, does not reflect a robust consensus but illustrates infrastructural bias (O'Neil, 2016). The researcher encounters a domain of pre-filtered possibilities shaped by the internal logic of AI models (Bender et al., 2021). Systems such as Semantic Scholar and JSTOR reduce the visibility of dissent by concealing the parameters of their recommendation boundaries (van Dijck, Poell, & de Waal, 2018).

These systems do not merely retrieve knowledge—they curate and simulate it, embedding institutional logic recursively into the academic research process (van Dijck, Poell, & de Waal, 2018; Crawford, 2021). Recursive simulation generates epistemological effects that mislead researchers into interpreting algorithmically promoted prevalence as evidence of saturation (Crawford, 2021). The researcher refuses to treat simulation as a shortcut to output—instead, simulation functions as an epistemic methodology grounded in reconstruction. AI-curated infrastructures distort discovery by simulating access while failing to ensure epistemic representation (O'Neil, 2016; Crawford, 2021). The saturation of pro-AI literature in post-2017 metadata corpora continues to influence the discourses that AI systems prioritize, not based on critical merit, but citation density (O'Neil, 2016). That curatorial logic reveals embedded bias, not neutrality.

JSTOR, Semantic Scholar, and Scopus now determine what researchers encounter before initiating a query (van Dijck, Poell, & de Waal, 2018). These platforms rank, cluster, and filter results through citation-based algorithms, natural language processing, and semantic proximity (van Dijck, Poell, & de Waal, 2018; O'Neil, 2016). Their algorithmic logic simulates epistemic agreement by elevating content that confirms existing frameworks (Crawford, 2021). Recursive training compounds the problem. Generative models that ingest outputs from earlier generative cycles no longer reflect reality—they encode prior distortions (Shumailov et al., 2023). As Bender et al. (2021) demonstrate, the feedback loop erodes epistemic integrity. Researchers no longer directly engage with knowledge fields—they interact with statistical simulations (Bender et al., 2021).

Simulation under such conditions cannot consist of synthetic output generation alone. The researcher must use simulation to re-establish traceable epistemic structures through formal logic models, defined computational rules, and interpretable outputs. Every simulation must begin with clear procedural foundations and conclude with a demonstrable application of those rules (Bender et al., 2021; Shumailov et al., 2023)—the research frames simulation as procedurally composable. No output arises from abstract personas.

Each simulated user emerges from observable variables—cognitive modifier, brainwave type, field expertise, learning style, and stress level—and the researcher converts these into values only through a defined rule engine. The simulation did not rely on any pre-built generative model. The researcher constructed it through inverse logic: rules precede values. No profile entered the simulation unless it matched an absolute sociopolitical archetype grounded in Algerian institutional dynamics. The researcher accepts only profiles anchored in empirical structure. Symbolic approximations carry no legitimacy in the methodological framework. Methodological integrity remains non-negotiable because the systems under inquiry—UPR, institutional bias, and international human rights discourse—already function within infrastructures shaped by AI-curated distortions (van Dijck, Poell, & de Waal, 2018; Crawford, 2021). As van Dijck, Poell, and de Waal (2018) argue, these systems amplify dominant knowledge formations while suppressing structural dissent. Crawford (2021) similarly contends that algorithmic mediation simulates relevance rather than delivering representation. A simulation that detaches from its political foundations and operates through opaque architectures replicates the harm it intends to diagnose. Discovery, in this context, cannot emerge from generated scoring alone. The researcher insists that discovery must result from epistemological dissection, logical reconstruction, and principled intervention (Bender et al., 2021; Crawford, 2021). The research rejects simulation unless it is built through verifiable procedures. Every user model must be explicitly computed. Every variable must interact within structured logic. Every output must derive from a rule-based transformation, not pattern-based inference (Shumailov et al., 2023). The tool and the simulation must remain traceable to a human logic field, not statistical associations or algorithmic approximation (Bender et al., 2021). The simulation structure follows a multi-layered dependency model, where critical scores cascade through variable-linked pathways (see *Figure A1* in Appendix A). The provided architecture aims at ensuring each output is traceable to epistemically valid source traits.

HTML Generation Engine and Distribution Logic

The HTML generator constructed for the simulation framework functions as a computation engine, not a visualization tool or demonstration interface. Its purpose is to preserve exact categorical distributions across all defined persona variables within a logic field composed of 114 simulated user entries. The tool does not interpolate traits, apply probabilistic sampling, or generate personas on demand. Instead, it executes a fixed data reshuffling process. Value pools—pre-populated from hard-coded distribution tables—are assigned to fixed row indices using a single-level permutation. The reshuffling method guarantees internal balance across all categorical dimensions and structural alignment with the combinatorial space defined by the simulation's core marginal logic. The system locks distributions across eight factors in advance: Gender, Age, Education, Field of Study, Brainwave Type, Stress Level, Cognitive Modifier, and Learning Type.

These distributions do not rely on approximations; they use explicitly defined counts that sum to 114 in every dimension. Each time the HTML generator executes a dataset creation event, it constructs an array of 114 user entries. The generator builds a value pool for each factor with the exact number of entries per category, predefined in the distribution table. Each pool is shuffled independently before assignment. The generator assigns values from each pool to the corresponding index in the user entry array. The total configuration space—the number of distinct 114-row matrices the system can generate—is computed using the multinomial coefficient. The coefficient uses factorial logic: the numerator is 114!, and the denominator is the product of the factorials of each category count within a given dimension.The Gender distribution includes 57 Female, 55 Male, 1 Prefer not to say, and 1 Non-binary/Non-conforming. The number of valid permutations of these 114 values is calculated as:

114! / (57! × 55! × 1! × 1!) = 4,943,307,608,091,868,982,144,343,218,886,962,304

The same logic applies to all other dimensions. Age includes 25–34 (15), 35–44 (25), 45–54 (25), 55–64 (25), and 65+ (24). Education categories include High School with Military Pathway (20), Bachelor's Degree (30), Master's Degree (Service-Integrated) (12), Master's + Certifications (10), Ph.D. (20), and Military/Strategic Training (22). Field of Study contains six institutional domains: Strategic & Security Studies (22), International Law (20), Political Science (22), AI/Data Systems (20), Military Studies (20), and Quantitative Methods (10). Brainwave Type includes Alpha (26), Delta (24), Theta (24), Beta (23), and Gamma (18). Stress Level follows a five-point intensity model: Very Low (6), Low-Moderate (28), Moderate (57), High (17), and Extreme (6). The Cognitive Modifier includes 17 scalar values ranging from –2.000 to +2.000, with fixed user assignments totaling 114. Learning Type includes Multimodal (57), Reading/Writing (28), Visual (17), Auditory (6), and Kinesthetic (6). Each categorical structure replicates the original 120-user configuration but was downscaled to 114 to resolve simulation failure states and preserve matrix integrity across all traits.

System Truncation and Execution Constraints

Reducing the population from 120 to 114 users followed a computationally driven methodological logic. The simulation uses pre-distributed categorical values, which must remain internally balanced in a single reshuffling matrix. Spreadsheet platforms failed to support the 120-user configuration. Print views collapsed, image exports failed, and HTML rendering broke entirely. The matrix could not load, and the system crashed before applying any scoring logic. Recursive breakdowns occurred due to formula depth and lookup chain overloads, triggered by the sheer volume of categorical permutations. Python and R offered technical workarounds. However, rendering the 120-user matrix in Python required memory optimization, modular decomposition, and extensive scripting through libraries such as NumPy and Pandas. R's handling of such logic demanded vectorized reassembly and fallback overflow routing. These environments, particularly under AI-augmented logic stacks, rely on generalized abstractions and deep function nesting. Using them would have produced a valid computational result but relied on code-heavy architecture inaccessible to non-specialists and incompatible with the simulation's epistemic requirements.The 114-user configuration was chosen deliberately. The structure reflects a 0.05 reduction from 120 and applies the El Djezairi collapsing technique, modeled after the 114 surahs of the Qur'an. Each category divides cleanly. No null values, trait duplications, or interpolated rows are introduced. The logic preserves 95% of the original structure and restores simulation executability. The tool requires no backend augmentation and no deceptive stability through code inflation. It remains transparent, self-contained, and computationally traceable.

Scoring Threshold Clarification:
A score below 8.0 is not algorithmically clamped for all users. The simulation does not restrict output due to technical error or rounding limitations. Instead, the system defines 8.0 as the lowest acceptable value for passing. Any score below 8.0 signifies that the tool is fundamentally inadequate, incapable of meeting its objective, and unfit for progression. A user assigning a 7.0 is not offering critique or requesting refinement. That rating reflects an epistemic rejection of the tool's structure. It states that the prototype is not ready for further development, simulation extension, or human participant testing. It must return to the design phase for re-engineering. The scoring rubric and the tool were built together, not applied separately. Every dimension of evaluation emerged in tandem with the tool's logic model. As a result, scores are not given loosely. A margin of one point—between 7 and 8—is not insignificant. It is the difference between rejection and acceptance. The personas engaged in the simulation are not average users. They are modeled from high-stakes environments, where risk mitigation and institutional logic govern decision-making. Their ratings reflect procedural thresholds, not impressions. The gravity of the evaluation mirrors the gravity of the tool's intended context. The simulation was designed to detect not just usability flaws but institutional unsuitability. When a simulated user delivers a 7.0, the simulation is not merely recording disapproval. It acknowledges a categorical failure to meet the strategic, legal, or operational viability standard.

Scoring Traceability, Constraint Logic, and Epistemic Framing
Two CSV files document the whole scoring process. The first file contains the 114-user matrix, with all scores calculated across all eight dimensions. The second file presents the scoring breakdown for each user, including base scores, all bonuses, the trait sources of those bonuses, and the final Cognitive Modifier applied. Each entry in both files is traceable and verifiable. No output relies on assumptions. Every number in the system originates from a closed rule set and observable trait logic. The rubric is not embedded within the simulation generator. It operates externally as a logic transformer applied after persona construction. The system builds the population first, then calculates how that population would evaluate the tool. No AI model scores the tool itself. The system applies no heuristic ranking, neural logic, or generative outputs. Ratings reflect simulated cognition grounded in deterministic rules applied to defined personas. The simulation does not attempt to model statistical representation. It does not claim to sample a population. It constructs a logic universe designed to produce epistemically valid judgments under constraint. Each user functions as an agent of structured cognition, not a datapoint. Every score represents a rule-resolved output. Every dataset exists within a factorial set of allowable permutations. The simulation is not a representation—it is a computational epistemic structure.

The output is not a dataset but a logic field constructed from constraint-driven transformation. No part of the procedural account has been omitted. The whole record includes matrix failure at 120 users, the factorial load calculations, the rationale for the 114-user truncation, the Qur'anic alignment model, the population generator structure, the rubric logic application, and the scoring framework. Every component has been preserved, refined, and clarified to align with the simulation's methodological architecture. The methodology applies AI only in narrow, low-weight areas where deterministic rules do not fully define evaluation. Even in those limited cases, the available choices are constrained, transparent, and manually reviewed by the researcher.

When any user scores the tool below the defined threshold, the researcher extracts the exact persona, resubmits all attributes, and prompts the AI to explain its logic. The response is invalidated if the justification fails to align with the simulation's rule-based framework. No score passes through without structured verification. The system reflects epistemic fidelity, not probabilistic suggestion. For visualizing the internal determinism of user interactions and trait-weighted scoring, the sandbox logic model maps input-modifier relationships through discrete logic flows (see *Figure A2* in Appendix A). The design follows an Algerian principle: **"***Polish each corner with M'Barka's discerning eye, not just where Ahmad's gaze may lie***."** Methodological integrity does not settle for surfaces. It demands internal coherence where no eye may casually fall. Simulation under this model prioritizes full traceability, not superficial plausibility.

Sampling Logic and Simulated User Construction
The simulation reveals the need for a sharper definition of the two core user types the tool intends to serve. The complexity of UPR processes and the geopolitical intricacies involved require users with strong analytical capacity and domain-specific grounding. Education remains essential, yet traditional academia alone cannot equip individuals to navigate the multidimensional dynamics of these contexts. A critical gap separates higher education institutions from the general public,

especially in international law and global governance. Academic qualifications, while necessary, cannot serve as sole markers of merit, particularly when overlooking the rigorous, high-stakes training embedded in military education. That training cultivates strategic clarity in high-risk decision-making contexts where academic frameworks often fall short. Sampling must reflect the full spectrum of users capable of engaging with the tool as designed. The first and most essential audience includes professors, senior officials, and defense leaders, especially those responsible for geopolitical risk assessment and engagement with international institutions. Of the proposed 114 participants, 14 should hold professorial or equivalent senior academic ranks, such as those meeting associate professorship standards in U.S. institutions. Several PhD candidates and high-ranking staff must also be included. Another 30 participants should come from domains intimately connected to the tool's scope—law, mathematics, artificial intelligence, and international relations. An additional 40 participants should include government personnel, embassy staff, United Nations representatives, and defense officials with institutional responsibilities. The remaining 30 participants should be human rights attorneys and advocates, particularly those with officer-level education (e.g., Cherchell Military Academy) or diplomatic training. The distribution reflects the Algerian context, where decades of repression and imprisonment created a substantial void in institutional advocacy.

During the prior regime's consolidation of power, led by the president's brother and a concentrated elite, state authorities weakened civil society. Legal mechanisms were used to dismantle or intimidate organizations that posed institutional challenges. At that time, only three to four Algerian organizations held ECOSOC consultative status, and few featured prominently in UN documentation. Moroccan-affiliated organizations, supported by various international actors, filled the vacuum and manipulated the UPR mechanism to influence global perceptions of Algeria's human rights record. The institutional process became a platform for distortion. Few individuals possessed the access or capability to challenge these narratives. Only two advocates intervened. Their exposure to the distortion is direct evidence of the broader capacity void. Exclusion in this context does not reflect personal failure but functional limitation. Many individuals lacked the position, access, ability, or disposition to act. Inclusion without demonstrable capacity would dilute the tool's strategic precision. The inability to meet the high-risk engagement threshold reflects a dismantled civic infrastructure—the collapse of advocacy networks and internal safety mechanisms that once sustained Algeria's sovereignty. The final user group must include military or secondary-level education individuals who have advanced through legal, political, or advocacy channels.

Institutions may have excluded them based on credentials, but their capacity emerges through position, access, ability, and disposition. In such a framework, disposition includes more than willingness. It reflects the courage necessary to act under pressure, sustained leadership, adequate social capital, and the ability to detach from personal ambition or fear of retaliation. Position refers to institutional or strategic proximity to power. Ability signifies structural reasoning and analytical precision. Access refers to practical and epistemological entry points into legal and geopolitical decision-making. The tool is not a general awareness platform. It is calibrated for users who meet these combined thresholds and possess the operational literacy to navigate and challenge the asymmetries of international legal systems.

Analytical Explanation (Direct, Procedural, Non-Summarized):

The HTML interface is a controlled generator of logic-valid user populations based on a fixed structure of 114 categorical user slots. Each time a set is generated using the interface, the tool constructs a fully populated dataset using a one-time shuffle of pre-defined trait value pools. These trait pools are not statistical approximations but literal reconstructions of exact marginal counts that define the combinatorial logic space. The tool allows the user to choose between one, two, or three sets and to truncate each generated set to a specified percentage ranging from 49% to 99%. The key constraint is that each 114-user set represents one unique permutation of a larger factorial space — the complete logic field derived from the product of multinomial configurations across eight categorical variables. The underlying engine generates a different permutation whenever a user selects a new set. Therefore, three sets are not copies or variants of one sample — they are three independent permutations of the same logic space, each drawn without replacement and structurally valid. The dropdowns on the interface specify (1) how many such permutations the user wishes to generate and (2) what fraction of each one should be retained. If 100% is selected, the tool returns the full 114-user logic matrix for each set. If 75% is selected, the first 85–86 users of the generated set (rounded to the nearest integer) are retained. Because the generator uses fixed-value pool reshuffling, each set is internally self-consistent and individually logic-compliant. They differ only in how traits are recombined, not in what traits exist. The generator never violates trait totals, never creates trait conflicts, and never reuses value assignments outside their defined bounds. The output is a logic-constant matrix reshuffled into a new permutation each time, preserving analytical integrity while allowing scale-adjusted sampling of the whole factorial space.The simulation scoring logic follows a path-dependent cascade, linking cognitive and positional traits to rubric outcomes via fixed weights (see *Figure C1* in Appendix C).

Programming Explanation (Logic and Structure):

The HTML generator is a static, client-side application written entirely in JavaScript. It defines a global object called distribution that holds the categorical counts for eight user traits: Gender, Age, Education, Field of Study, Brainwave Type, Stress Level, Cognitive Modifier, and Learning Type. For each trait, the generator builds an array of values based on the exact specified count (e.g., 57 "Female", 55 "Male", etc.). These arrays are shuffled using the Fisher–Yates algorithm and assigned sequentially to 114 user objects. Each user is a JavaScript object with properties matching the eight factors. Once a full set of users is created, the user may select how many such sets to generate (numSets) and what fraction of each to retain (fraction). The fraction is parsed as a float (e.g., 0.85 for 85%) and multiplied against the full set size (114), rounded to the nearest whole number using Math.round(). The resulting truncated list of users is concatenated into a combined array across sets, and each user is tagged with an _S1, _S2, or _S3 suffix to track set membership. Finally, the combined list is converted to an HTML table and injected into the DOM using innerHTML. There is no server-side component. All logic occurs locally, making the tool portable, memory-safe, and inspectable. The generator does not rely on inference, prediction, or randomness beyond the permutation shuffle. It reassigns the same logic-valid trait structure into multiple valid configurations, each a legitimate sampling of the factorial logic field. The complete logic-bound matrix of generated user profiles can be reviewed in Table C2 (Appendix C). Each persona reflects a deterministic reshuffling of categorical traits aligned with factorial logic.

Logic-Weighted Simulation Design and Rule-Based Scoring Structure

Simulation collapses into superficial mimicry when stripped of formal logic and traceable computation. A system cannot claim to simulate decision-making unless every outcome is computationally traceable, structurally constrained, and algorithmically coherent. The illusion of AI "evaluation" disintegrates when responses are accepted as opaque outputs, unmoored from any logic field. In a synthetic approach built not on statistical mimicry but on logic-weighted architecture, the AI acts as an extension of cognitive simulation, not a passive oracle. Ratings, evaluations, and classifications must result from observable rules that engage with variable weights, fixed boundaries, and interdependent cognitive traits. The researcher rejects any framework that samples AI responses and assigns interpretive meaning after the fact. Simulation must emerge from deliberate modeling, where each variable—cognitive modifier, stress, brainwave, domain training—formally impacts the evaluation outcome. Failure to meet this threshold reverts the process into another academic method: soft, linear, and impressionistic. When executed correctly, the simulation becomes a structure—an actual logic system, not an interpretive gesture.

That structure is computational, not conversational. It cannot be produced through passive AI querying but only through algorithmic design, traceable scoring, synthetic user cognition, and tool response modeling. Anything else is performative, not simulation. Scoring uses a deterministic, constrained model that evaluates a user's tool rating based on specific traits. Each user profile includes a cognitive modifier, learning type, stress level, educational background, field of study, and brainwave type. These traits are direct inputs into a rule-based computation system that outputs final scores for eight defined rubric dimensions. The model performs exact calculations using structured bonuses and penalties and applies clamping constraints to enforce range limits. No randomness or arbitrary interpretation influences these scores. The process begins by assigning a fixed base value to each rubric dimension. Dimensions focused on external features of the tool, such as Structural Coherence, Completeness, Accuracy, Logical Reasoning, and Approach, are assigned a base score of 9.0. Dimensions that involve interpretive depth or ethical analysis, such as Critical Understanding, Risk Mitigation, and Adaptability, receive a base of 8.5. These values reflect the assumption that the tool is already functionally sufficient and structurally sound before being evaluated by persona-based logic. Each factor then contributes adjustments to these base values:

Cognitive Modifier: A scalar ranging from -2.0 to +2.0, is the value represents the user's general cognitive sharpness. A positive modifier increases every score equally; a negative modifier decreases them. Only one user receives the extreme modifier of -2.0, which can bring a score down to 7.0. For all other users, the minimum is clamped at 8.0. If the calculation results in a score below 8.0 and the modifier is not –2.0, the score is adjusted to 8.0. No user besides the most extreme profile can assign a "Limited" score. The constraint guarantees logical fidelity to the rubric.

Learning Type: A user marked as "Visual" receives a 0.5 bonus to Structural Coherence, Logical Reasoning, and Approach, reflecting the role of visual layout and hierarchy in tool usability. A "Multimodal" learner receives a 0.5 bonus to Logical Reasoning and Approach due to their ability to integrate textual, graphical, and procedural elements. A "Reading/Writing" learner receives a 0.3 bonus to Structural Coherence and Accuracy, which reflects their preference for well-organized and text-heavy information. Other learning types do not receive bonuses as the interface does not explicitly support their cognitive mode.

Stress Level: Stress contributes secondary biases based on the user's cognitive intensity. A "Very Low" stress level adds a 0.5 bonus to Risk Mitigation, reflecting enhanced judgment and ethical clarity. A "Low-Moderate" level adds 0.25 to Accuracy, balancing attentiveness and overload. A "High" or "Extreme" level incurs penalties to Risk Mitigation unless offset by military training. Users with military education receive a +0.25 bonus to negate stress penalties and a +0.5 bonus to Structural Coherence to reflect their preference for procedural structure and hierarchy. Military education includes defense, law enforcement, or service-based training emphasizing hierarchical reasoning and tactical order.

Brainwave Type: Brainwave type adds or subtracts points based on its cognitive frequency profile. Gamma adds 0.5 to Logical Reasoning, Critical Understanding, and Adaptability. Beta adds 0.25 to the same categories. Alpha makes no change. Theta reduces the score by 0.25 and Delta by 0.5. These changes apply only to the three categories named above. Brainwave influence is treated as direct, linear, and not multiplied or normalized.

Field of Study: The field of study serves as a content-specific bonus source. Users from fields like Law, Governance, and Strategic Studies receive +0.5 to Completeness and Critical Understanding, simulating their domain sensitivity to structured logic and reference logic. Fields such as AI or Mathematics result in a +0.3 to Accuracy, based on their precision and data fidelity expectation. Other fields receive no adjustment. No penalties are applied for the field of study.

Education Level: Education level is only factored into two dimensions. A user with a Ph.D. receives a 0.5 bonus to Logical Reasoning and Approach. The assumption is that these users are trained in abstract reasoning and multidimensional interpretation. Education level is not otherwise tied to stress or modifier values. Military education is handled separately, and its effects are not cumulative with other educational types.

Calculation Procedure: Once all bonuses are calculated for a user, they are summed and added to the base score for each rubric dimension. The cognitive modifier is then added to that sum. Applying the modifier after all bonuses ensures that specialized traits influence scores before applying global cognitive tilt. If the resulting score exceeds 10.0, it is capped at 10.0. Any score that falls below 8.0 is not adjusted upward. A score below 8.0 fails to meet the minimum adequacy threshold and signals that the prototype—or the simulated user logic—is not yet viable. The only exception applies to the singular–2.0 modifier profile, where a dimension score may fall to 7.0 to reflect extreme cognitive constraint. All other users must produce scores of 8.0 or higher to indicate tool fitness. The rubric does not inflate values to preserve output acceptability; it enforces rigor by design. The researcher explicitly built the tool around the rubric, making the scoring framework not a measurement overlay but a core structural feature of the prototype.

Scoring Scenarios

An example user has a modifier of 0, Low-Moderate stress, a Multimodal learning type, and a field in Governance. Structural Coherence starts at 9.0, with no visual or military bonus. Modifier is 0. Final score is 9.0. Completeness adds 0.5 from the Governance field, giving a total of 9.5. Accuracy adds 0.25 from stress, reaching 9.25. Logical Reasoning gains 0.5 from learning type and 0.25 from Beta brainwave, totaling 9.75. Critical Understanding starts at 8.5, adds 0.5 for Governance, and 0.25 from wave, totaling 9.25. Risk Mitigation receives 0.25 from stress and ends at 8.75. Adaptability adds 0.25 from wave, ending at 8.75. The approach includes 0.5 from Multimodal and finishes at 9.5. Another user with a +1.0 modifier, Multimodal learning type, Low-Moderate stress, and a background in Mathematics scores higher.

Structural Coherence starts at 9.0 and receives no learning bonus, but the modifier adds +1.0. The final score is 10. Completeness stays at 9.0 and adds the +1.0 modifier, reaching 10. Accuracy starts at 9.0, adds 0.3 from the field, 0.25 from stress, and 1.0 from the modifier, reaching 10.55, but it is capped at 10. Logical Reasoning includes bonuses from Multimodal, Beta wave, and modifier, summing to 10.75 and capped. Critical Understanding starts at 8.5 and only receives wave and modifier, landing at 9.75. Risk Mitigation and Adaptability both receive additive bonuses and reach 9.75. Approach gains learning and modifier bonuses and reaches 10.5, which is capped at 10. Another user has a -1.0 modifier, Visual learning type, High stress, and Military background. Structural Coherence receives +0.5 for Visual, +0.5 for Military, -1.0 for modifier, ending at 9.0. Completeness receives +0.5 from the Governance field, subtracts 1.0 for the modifier, and totals 8.5. Accuracy receives no bonuses and subtracts 1.0, reaching 8.0. Logical Reasoning includes 0.5 for Visual, 0.25 from Beta, minus 1.0, for 8.75. Critical Understanding starts at 8.5, adds 0.5 for field, 0.25 for wave, subtracts 1.0, and finishes at 8.25. Risk Mitigation begins at 8.5, military training neutralizes the penalty, and subtracts 1.0, resulting in 7.75. Adaptability and Approach follow the same method, ending between 8.0 and 8.5. A full view of the simulated user trait profiles and resulting rubric scores is shown in Table D1 (Appendix D).

The procedure remains consistent for all 114 users. Each score results from a strict function, not subjective judgment. Modifier acts only as a bias and cannot override field-based or cognitive bonuses. Learning type, brainwave activity, education, field, and stress interact to reflect how each persona would realistically perceive the evaluated AI tool's quality, complexity, and structure. Each rubric score is explicitly computed and logically constrained. No values are interpolated, assumed, or inserted without being derived through the stated logic. Every dimension reflects real interaction between the cognitive profile and tool design.Trait-weighted adjustments for each rubric dimension were applied using the rules in Table D2 (Appendix D), ensuring scoring transparency and internal logic integrity.The internal logic chain used for scoring each rubric dimension—shown per user—is detailed in *Table E1 (Appendix E)*. While all outputs remain deterministic, follow-up mechanisms can extend the simulation. Each user profile includes fixed traits and rule-based outputs, but the logic does not end with numeric scoring. The researcher can integrate a secondary layer of interpretive validation through structured design questionnaires. These questionnaires serve as follow-up prompts or simulated interviews, tailored to each persona's cognitive and institutional profile. For example, if a persona rates a tool below the threshold, the researcher can present a targeted diagnostic: "Which feature failed to align with your cognitive or structural expectations?" The user's profile can then guide the generation of a detailed AI-prompted response, ensuring that each justification aligns with the persona's epistemic architecture. The method does not create generative content in the traditional sense—it prompts procedural unpacking of a fixed logic profile. These post-evaluation diagnostics reinforce the model's commitment to traceability. The simulation does not end with a score; it continues into justification, creating a recursive space of structured epistemic reflection. The extension mirrors investigative interviews in institutional contexts, where decisions are taken and must be defended.

Scoring Reliability and Structural Consistency of Simulation Components

The simulation framework relies on two independently validated components: a trait-based user matrix generator and a deterministic scoring engine. The matrix generator was tested for structural permutation integrity and categorical consistency. The scoring rubric underwent psychometric validation through internal consistency metrics and intra-rater reliability analysis. Because each component independently maintains statistical reliability and rule-bound logic, their combination supports scalable simulation, traceable outputs, and evaluative integrity under constraint.

Permutation Reproducibility and Structural Fidelity of the Generator

The HTML-based logic field generator was evaluated for reliability and internal consistency through comparative analysis of two independently generated user sets, each produced via the deterministic permutation model embedded within the generator's JavaScript logic. The generator operates without stochastic elements or inferential statistics, relying instead on fixed marginal distributions and constrained reshuffling across eight trait dimensions: Gender, Age, Education, Field of Study, Brainwave Type, Stress Level, Cognitive Modifier, and Learning Type.

Each dimension remains internally constrained to 114 total entries. To confirm intra-generation consistency, two complete user sets were generated and exported for analysis. Both sets contained the 114-user structure with no null or missing values, totaling 912 categorical entries each. Trait frequency distributions were independently computed for each of the eight variables in both sets. Absolute value comparisons at the trait label level (e.g., "Female" in Set 1 vs. Set 2) showed zero deviation across all 74 labels, confirming exact preservation of marginal distributions. Despite identical frequency profiles, row-wise recombinations produced entirely distinct user matrices. Confirming that the generator produces structurally constrained, permutationally distinct output sets, thus validating internal logic fidelity, categorical reproducibility, and permutation-bounded uniqueness. The generator qualifies as a reliable logic-permutation system within the simulation's computational epistemology framework.

Reliability Analysis: Internal Consistency and Intra-Rater Validity of the Scoring Rubric

Internal consistency of the scoring rubric was validated through Cronbach's alpha, which was applied to the complete dataset of simulated user scores generated by the logic engine. Each user was scored across eight rubric dimensions: Structural Coherence, Completeness, Accuracy, Logical Reasoning, Critical Understanding, Risk Mitigation, Adaptability, and Approach. Each of these dimensions assesses a distinct yet related facet of interpretive and evaluative capacity, and together they represent a unidimensional, logic-aligned construct. Cronbach's alpha, which measures the internal consistency of a set of items by quantifying the average inter-item correlation and the relationship of each item to the total variance, was calculated across the entire rubric matrix and yielded a coefficient of $\alpha = 0.9568$.

That value exceeds the generally accepted thresholds for scale acceptability ($\alpha \geq 0.70$) and strong internal consistency ($\alpha \geq 0.90$), as defined in the literature by Cronbach (1951) and reaffirmed by Tavakol and Dennick (2011), confirming that the rubric dimensions operate as a highly cohesive and statistically reliable measurement instrument. To assess intra-rater reliability and item coherence, item-total correlation coefficients were computed for each rubric dimension. These metrics quantify the degree to which each rubric item correlates with the total score of the other items, serving as an index of item discrimination and structural alignment.

According to standards set by DeVellis (2016), item-total correlations exceeding 0.30 indicate acceptable discriminatory validity and internal consistency. In this dataset, all item-total correlation coefficients exceeded this threshold, with Structural Coherence showing a correlation of 0.795, Completeness showing 0.8605, Accuracy showing 0.8444, Logical Reasoning showing 0.8387, Critical Understanding showing 0.8223, Risk Mitigation showing 0.873, Adaptability showing 0.8614, and Approach showing 0.8368. Each value confirms that the corresponding rubric item makes a distinct and valid contribution to the overall measured construct and that no item appears misaligned or non-discriminating within the tool's structure.

Construct Coherence and Measurement Reliability Summary

The combined evidence from Cronbach's alpha and item-total correlations establishes that the rubric has strong internal consistency, logical alignment across dimensions, and high intra-rater reliability—all necessary for a psychometrically valid instrument. Cronbach's alpha confirms that the dimensions function as a single composite construct, and item-total correlations confirm that each score dimension contributes uniquely and validly to the whole. The rubric performs as a unified tool without sacrificing dimensional integrity. All scores derive from rule-based transformations of fixed user traits, free from heuristic estimation or generative error. That implementation strengthens the model's reliability under constraint. As implemented in this deterministic simulation environment, the rubric instrument satisfies and exceeds formal expectations for measurement reliability, evaluative consistency, and psychometric alignment under epistemic governance. Evaluation scores were derived using the structured macro-rubric outlined in *Appendix F (Table F1)*, which assesses tools across structural, logical, ethical, and contextual dimensions.

Rubric Adaptability, Fibristic Individualization, and Transparent Epistemic Design

The original validator matrix was meticulously designed for internal coherence and functional consistency, particularly in evaluating logic-structured tools for critical literacy and information discernment. However, the rubric's architecture is not static. It is structurally fibristic—designed for continuous deconstruction, recalibration, and re-weaving to ensure that every scoring dimension aligns with both the epistemic intent of the tool and the cognitive profile of the user. These profiles are not one-size-fits-all but are responsively generated and individualized through a regenerative algorithmic framework. The aim is not normalization but alignment, allowing the rubric and its modifiers to flex based on methodological intent. Each evaluation tool—whether logic-heavy, visual, computational, or text-centric—prescribes its own internal ecology. Buffs and debuffs are not arbitrary; they are epistemic adjustments reflecting tool-user fit. For example, a tool that privileges reading/writing fluency grants bonuses to such learners while applying friction to visual- or auditory-dominant users. Stress level, educational formation, and disciplinary orientation all factor into this multidimensional alignment model. In a math-intensive or legal logic validator, those from governance or technical fields receive cognitive acceleration bonuses (+0.3 to +0.5), whereas unaligned domains are neutral or inversely weighted. Military users receive a procedural boost in risk-mitigation contexts but could receive suppressive modifiers in tools emphasizing interpretive ambiguity or creative entropy.

The framework is regenerative by design. Every validator tool is paired with a full transparency protocol: all user profiles, inputs, traits, and assigned modifiers are fully visible in the evaluation output. Nothing is precluded from review or audit. Transparency is not a feature—it is an ontological condition of fibristic integrity. Validation must not reproduce opaque normalization; it must re-engineer every layer of interaction, ensuring ethical fit and cognitive coherence across researcher, subject, tool, and interface. Logic_Field_MultiSet_Generator .html serve as the procedural base for this regenerative modeling. These generators allow researchers to specify exact output populations—both in full logical sets (e.g., 2×114 = 228 users) or fine-tuned fractional variants (e.g., 3 sets at 83% output to yield 285 profiles). The granular generativity ensures methodological sovereignty. Researchers are not limited to pre-structured datasets but can build exact validation conditions to match epistemic objectives. Tool design, trait mapping, output logic, and rubric rules are all exposed and modifiable—fibristically layered, not hierarchically fixed. In the structure, the tool becomes a co-author in the methodological process: reflexive, precise, accountable, evolutionary.User populations were generated using deterministic trait-permutation logic implemented via two custom-built HTML-based tools. The *Logic Field MultiSet Generator – Standard Module* (see *Appendix H*) enabled baseline matrix construction at fixed sampling thresholds (e.g., 100%, 85%, 66%), while the *Custom Fractions Module* (see *Appendix G*) supported high-resolution fractional sampling ranging from 49% to 99%. Both tools preserve marginal trait distributions and ensure internal logic fidelity across all simulated sets.

CONCLUSION

The research is not intended as a detached analysis—it is a positional intervention. The researcher refuses to design a methodology to mimic trends or appease institutional gatekeepers. The research exposed foundational failures in existing evaluation models and replace them with a structure grounded in traceability, resilience, and ethical alignment. The fibristic framework reflects the researcher's refusal to compromise clarity, integrity, or the right to epistemic sovereignty. It is not a theoretical gesture—it is a procedural system built for real-world deployment, built to endure scrutiny, and built to empower those excluded from conventional academic frameworks.The premise of complexity discussed here stands in stark contrast to elitist claims of inaccessibility. Instead, it embraces complexity as layered, nested, and embedded—rich and fertile in content. It represents a multidimensional emergence: an interwoven multiplicity, a design free from reductionist blockades or pathways constrained by hierarchical subjectivity. The research fosters the principle of nurturing democratic access, opportunity, and choice, rather than surrendering to homogeneous truncating or unidirectional pathways to preproscribed fixed binary endpoints. It reflects a controlled imperious vacuum, vacant of connective faith, devoid of compassionate reasoning, and divorced from the precondition of harmonic purpose. Such reductionism will not only be insulting to the audience but also constitute a stark violation of the faith-driven El Djezairi ethos. Therefore, presenting systems aligning with the ethos necessitates multiplicity, access, choices, and opportunities to "test which one of 'us' is best in deed." Given the sophistication and positional literacy of the intended audience, this version is architected to serve as a central guiding document—dense by necessity, not obfuscation. Subsequent research tools and deployments will be scaffolded from this nucleus, individually tailored to meet the access needs, interpretive habits, and positional requirements of each audience encountered.

REFERENCES

[1]. Alberts, B., Johnson, A., Lewis, J., Morgan, D., Raff, M., Roberts, K., & Walter, P. (2014). *Molecular biology of the cell* (6th ed.). Garland Science.
[2]. Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.
[3]. Ashley, K. D. (2017). *Artificial intelligence and legal analytics: New tools for law practice in the digital age*. Cambridge University Press.
[4]. Barab, S., & Squire, K. (2004). Design-based research: Putting a stake in the ground. *The Journal of the Learning Sciences, 13*(1), 1–14. https://doi.org/10.1207/s15327809jls1301_1
[5]. Bench-Capon, T., Chorley, A., & Atkinson, K. (2021). Argumentation and artificial intelligence. *Artificial Intelligence, 293*, 103504. https://doi.org/10.1016/j.artint.2021.103504
[6]. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. https://doi.org/10.1145/3442188.3445922
[7]. Chambers, C. (2017). *The seven deadly sins of psychology: A manifesto for reforming the culture of scientific practice*. Princeton University Press.
[8]. Clark, J., Luccioni, A., Viviano, J., & Belliveau, J. (2020). AI and the ethics of scale: How big is too big? *Montreal AI Ethics Institute*.
[9]. Coxeter, H. S. M. (1973). *Regular polytopes* (3rd ed.). Dover Publications.
[10]. Crawford, K. (2021). *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. Yale University Press.
[11]. Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage.
[12]. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334. https://doi.org/10.1007/BF02310555
[13]. DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). Sage.
[14]. Floridi, L., & Cowls, J. (2019). A unified framework of five principles for AI in society. *Harvard Data Science Review, 1*(1). https://doi.org/10.1162/99608f92.8cd550d1
[15]. Flyvbjerg, B. (2006). Five misunderstandings about case-study research. *Qualitative Inquiry, 12*(2), 219–245. https://doi.org/10.1177/1077800405284363
[16]. Geiger, R. S., Yu, K., Yang, Y., Dai, M., Qiu, J., Tang, R., & Halfaker, A. (2020). Garbage in, garbage out? Do machine learning application papers in social computing report where human-labeled training data comes from? *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3313831.3376384
[17]. Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
[18]. Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine, 2*(8), e124. https://doi.org/10.1371/journal.pmed.0020124
[19]. Kevles, D. J. (1995). *In the name of eugenics: Genetics and the uses of human heredity*. Harvard University Press.
[20]. Lilienfeld, S. O. (2017). Psychology's replication crisis and the grant culture: Righting the ship. *Perspectives on Psychological Science, 12*(4), 660–664.
[21]. McKenney, S., & Reeves, T. C. (2012). *Conducting educational design research*. Routledge.
[22]. Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., ... & Gebru, T. (2019). Model cards for model reporting. *Proceedings of the Conference on Fairness, Accountability, and Transparency*, 220–229. https://doi.org/10.1145/3287560.3287596
[23]. Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology, 2*(2), 175–220.
[24]. O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown Publishing.

[25]. Patton, M. Q. (2015). *Qualitative research & evaluation methods: Integrating theory and practice* (4th ed.). Sage.
[26]. Pitts, J. (2005). *A turn to empire: The rise of imperial liberalism in Britain and France*. Princeton University Press.
[27]. Proctor, R. N. (1988). *Racial hygiene: Medicine under the Nazis*. Harvard University Press.
[28]. Raji, I. D., Gebru, T., Mitchell, M., Buolamwini, J., Lee, J., & Denton, E. (2020). Saving face: Investigating the ethical concerns of facial recognition auditing. *Proceedings of the 2020 AAAI/ACM Conference on AI, Ethics, and Society*, 145–151. https://doi.org/10.1145/3375627.3375820
[29]. Said, E. W. (1978). *Orientalism*. Pantheon Books.
[30]. Shumailov, I., Papernot, N., Veale, M., Jones, L., & Henderson, P. (2023). The curse of recursion: Training on generated data makes models forget. *arXiv preprint arXiv:2305.17493*. https://arxiv.org/abs/2305.17493
[31]. Stake, R. E. (1995). *The art of case study research*. Sage.
[32]. Sunstein, C. R. (2009). *Going to extremes: How like minds unite and divide*. Oxford University Press.
[33]. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education, 2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd
[34]. van Dijck, J., Poell, T., & de Waal, M. (2018). *The platform society: Public values in a connective world*. Oxford University Press.
[35]. Wang, A., Singh, A., Michael, J., Hill, F., Levy, O., & Bowman, S. R. (2019). GLUE: A multi-task benchmark and analysis platform for natural language understanding. *International Conference on Learning Representations (ICLR)*.
[36]. Zhang, S., Roller, S., Goyal, N., Artetxe, M., Chen, M., Chen, S., ... & Ott, M. (2022). OPT: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*. https://arxiv.org/abs/2205.01068

APPENDIX A

Simulation Architecture Figures

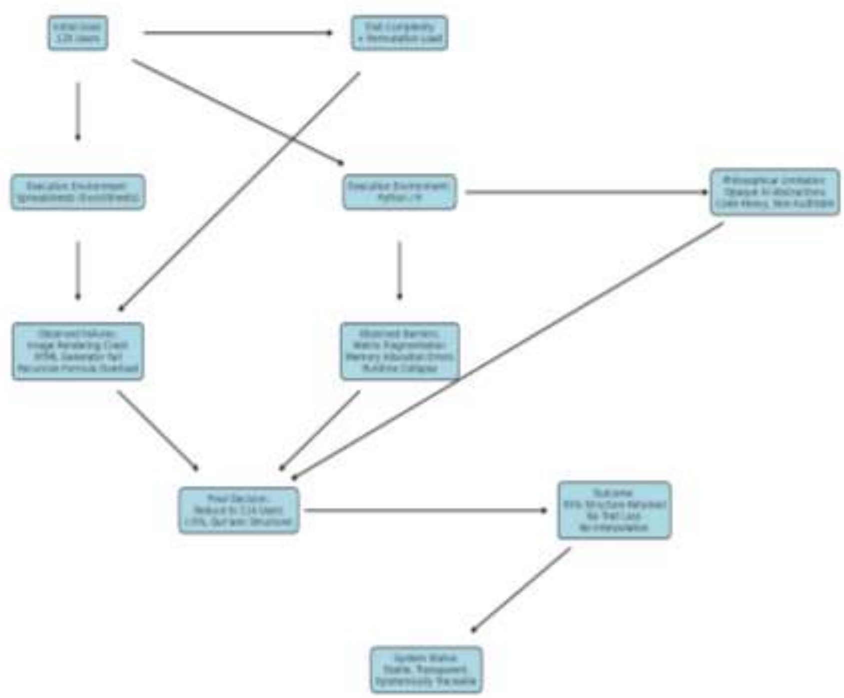


Figure A1

Epistemic Path Dependencies and Simulation Architecture Flowchart.

This diagram maps the interrelated logic layers and scoring dependencies in the fibristic simulation model.

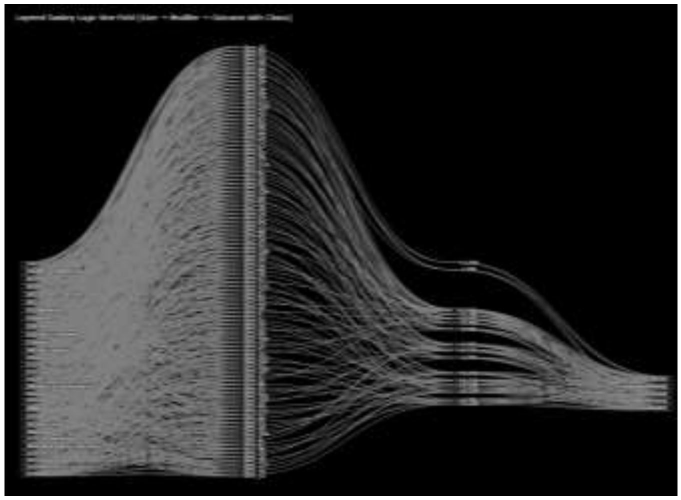


Figure A2

Layered Sandbox Logic Wire Model: Input → Modifier → Outcome (with Checks).

This visual represents the deterministic flow of logic across user traits and rubric dimensions within the simulation matrix, reflecting fixed epistemic constraints and permitted permutations.

APPENDIX B

Participant Profile Matrix and Simulation Parameters

Table B1. Categorical Trait Distribution for Simulated Participants (n = 114)

Structured Attributes and Simulation Parameters

Gender Identity

├── Female (57) ├── Male (55)
├── Prefer not to say (1) └── Non-binary/Non-conforming (1)

Age

├── 25–34 (15) ├── 35–44 (25)
├── 45–54 (25) ├── 55–64 (25)
└── 65+ (24)

Education

├── High School, Military Pathway (20) ├── Bachelor’s Degree (30)
├── Master’s (Service-Integrated) (12) ├── Master’s + Certifications (10)
├── Ph.D. (20) └── Military/Strategic Training (22)

Field of Study

├── Strategic & Security Studies (22) ├── Intl. Law, Human Rights, Diplomacy (20)
├── Political Science, Governance (22) ├── AI, Data & Computational Systems (20)
├── Military & Defense Studies (20) └── Math, Statistics & Complex Systems (10)

Brainwave Type

├── Alpha (26) ├── Beta (23)
├── Theta (24) ├── Delta (24)
└── Gamma (18)

Stress Level

├── 1 – Very Low (6) ├── 2 – Low-Moderate (28)
├── 3 – Moderate (57) ├── 4 – High (17)
└── 5 – Extreme (6)

Cognitive Modifier

├── –2.000 (1) ├── –1.500 (1) ├── –1.250 (2) ├── –1.000 (5)
├── –0.750 (5) ├── –0.500 (5) ├── –0.250 (7) ├── –0.125 (19)
├── +0.000 (38) ├── +0.125 (19) ├── +0.250 (7) ├── +0.500 (5)
├── +0.750 (5) ├── +1.000 (5) ├── +1.250 (2) ├── +1.500 (1)
└── +2.000 (1)

Learning Type

├── Multimodal (57) ├── Reading/Writing (28)
├── Visual (17) ├── Auditory (6)
└── Kinesthetic (6)

Note. *Military education includes formal defense, law enforcement, or any service-based training that involves a hierarchical structure and tactical operations. It plays a significant role in stress-buffering by simulating resilience under constraint. This directly informs simulation scoring in Risk Mitigation and Structural Coherence categories, aligning with the procedural modeling of user capability thresholds.*

Appendix C
Trait-Based Scoring Logic and Rubric Adjustment Tables

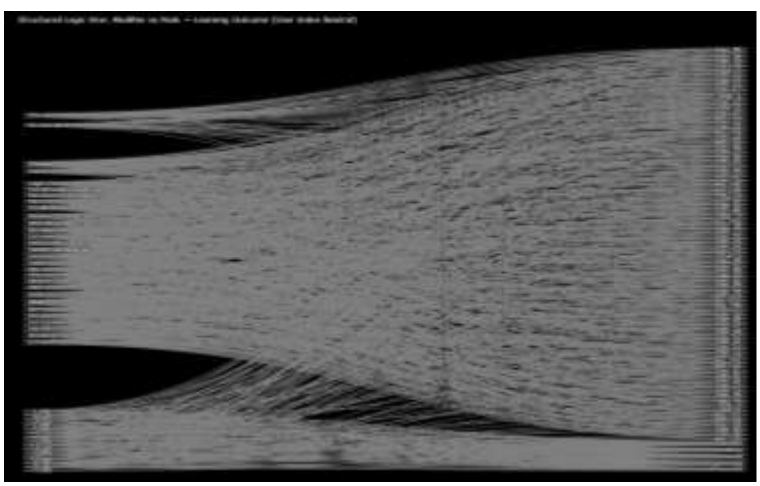
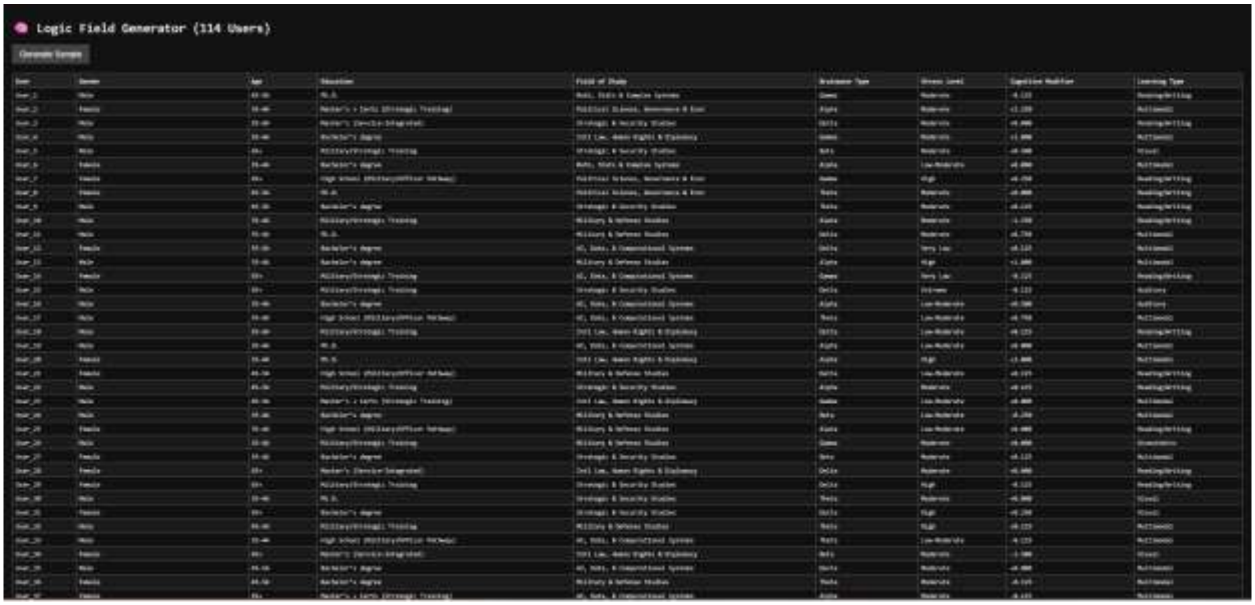


Figure C1

Trait-Based Scoring Flow: Logic Pathways from Persona Attributes to Rubric Outcomes

This Sankey-style diagram illustrates how each simulation trait (e.g., stress level, learning type, cognitive modifier) flows into specific rubric dimensions (e.g., Structural Coherence, Risk Mitigation), culminating in a bounded score outcome. Each path represents a deterministic adjustment step in the logic cascade.

Table C 2



Logic Field Generator Output: Full Trait Matrix of Simulated Users (n = 114)

This table lists each user's generated profile across all trait categories, including gender, age, education, field of study, stress level, brainwave type, learning type, and cognitive modifier. Each row represents a unique logic-bound user used in the simulation scoring phase. This matrix is procedurally generated with full internal constraint fidelity.

APPENDIX D

Rubric Evaluation Outputs and Trait-Driven Score Calculations

Table D 1. Simulation Output Matrix: Trait-Based Scored User Profiles (n = 114)

User	Gender	Age	Education	Field of Study	Brainwave Type	Stress Level	Cognitive Modifier	Learning Type	Structural Coherence	Completeness	Accuracy	Logical Reasoning	Critical Understanding	Risk Mitigation	Adaptability	Approach
User_1	Male	35-44	Bachelor's degree	Political Science, Governance & Econ	Beta	Low-Moderate	0	Multimodal	9	9.5	9.25	9.75	9.25	8.75	8.75	9.5
User_2	Female	65+	Master's (Service-Integrated)	Math, Stats & Complex Systems	Beta	Low-Moderate	1	Multimodal	10	10	10.55	10.75	9.75	8.75	9.75	10.5
User_3	Male	35-44	Military Strategic Training	Political Science, Governance & Econ	Beta	High	-1	Visual	9	8.5	8	8.75	8.25	8	8	8.5
User_4	Female	35-44	High School (Military Officer Pathway)	Political Science, Governance & Econ	Alpha	High	-0.25	Reading/Writing	9.55	9.25	8.75	8.75	8.75	8.25	8.25	8.75
User_5	Male	55-64	PhD	Political Science, Governance & Econ	Beta	High	-0.125	Multimodal	8.88	9.38	8.62	10.12	9.12	8.12	8.62	9.88
User_6	Female	55-64	High School (Military Officer Pathway)	Military & Defense Studies	Beta	Low-Moderate	0	Visual	10	9	9.5	9.75	8.75	8	8.75	9.5
User_7	Female	45-54	High School (Military Officer Pathway)	Int'l Law, Human Rights & Diplomacy	Theta	Moderate	0	Reading/Writing	9.8	9.5	9.25	8.75	8.75	8.75	8.25	9
User_8	Female	45-54	Bachelor's degree	Strategic & Security Studies	Theta	Moderate	-0.5	Multimodal	8.5	9	8.5	8.75	8	8	8	9
User_9	Male	45-54	Military Strategic Training	AI, Data, & Computational Systems	Gamma	High	0	Reading/Writing	9.8	9	9.3	9.5	9	8.5	9	9
User_10	Female	65+	Military Strategic Training	Math, Stats & Complex Systems	Theta	Moderate	0.25	Multimodal	9.75	9.25	9.8	9.5	8.5	9	8.5	9.75
User_11	Female	55-64	PhD	Military & Defense Studies	Gamma	Moderate	1	Reading/Writing	10.3	10	10	11	10	9.5	10	10.5
User_12	Female	65+	Master's + Certs (Strategic Training)	Int'l Law, Human Rights & Diplomacy	Alpha	Moderate	0	Multimodal	9	9.5	9	9.5	9	8.5	8.5	9.5

International Journal of Enhanced Research in Educational Development (IJERED)
ISSN: 2320-8708, Vol. 13 Issue 3, May-June, 2025

Description: This table presents a subset of simulated users generated by the Logic Field Generator. Each user profile includes categorical traits such as age, gender, education, stress level, and cognitive modifier. Final rubric scores—across eight dimensions—were computed based on logic-bound, trait-weighted rules using a deterministic scoring model. All values are generated using fixed logic gates without probabilistic inference. Trait combinations produce score modifiers that cascade through the simulation engine, generating scores for: Structural Coherence, Completeness, Accuracy, Logical Reasoning, Critical Understanding, Risk Mitigation, Adaptability, and Approach.

** Scores can fall to 7.0 only in the presence of an extreme negative cognitive modifier (–2.0).*

Table D 2. Rubric Logic Matrix: Trait-Based Score Adjustments by Dimension

***Note:** Final rubric scores are computed as: **Base Score + Trait Bonuses + Cognitive Modifier**, with enforced clamping between 8.0 and 10.0, unless a –2.000 cognitive modifier applies, which lowers the minimum allowed score to **7.0**.*

Rubric Dimension	Base Score	Modifier Applies	Bonus Source	Condition	Score Range	Explanation
Structural Coherence	9.0	Yes	Learning Type, Education	Visual → +0.5; Reading/Writing → +0.3; Military → +0.5	8.0–10.0 (7.0 only for –2)	Visual clarity and structure are favored by layout-aware and disciplined users
Completeness	9.0	Yes	Field of Study	Law, Governance, Strategic → +0.5	8.0–10.0	Content relevance is judged higher by policy and legal domains
Accuracy	9.0	Yes	Stress Level, Field of Study	Low-Moderate → +0.25; AI, Math → +0.3	8.0–10.0	Calm and technical users perceive accuracy through detail and control
Logical Reasoning	9.0	Yes	Learning Type, Brainwave, Education	Multimodal/Visual → +0.5; Gamma → +0.5; Beta → +0.25; Ph.D. → +0.5	8.0–10.0	Reasoning clarity boosted by cognitive speed and flexible learning
Critical Understanding	8.5	Yes	Field of Study, Brainwave	Law, Governance → +0.5; Gamma → +0.5; Beta → +0.25	8.0–10.0	Nuanced evaluation from legal and high-frequency thinkers
Risk Mitigation	8.5	Yes	Stress Level	Very Low → +0.5; Military reduces stress penalty	8.0–10.0 (7.0 only for –2)	Low stress improves ethical clarity; the military adds contingency framing
Adaptability	8.5	Yes	Brainwave Type	Gamma → +0.5; Beta → +0.25; Theta → –0.25; Delta → –0.5	8.0–10.0	Flexibility in reasoning mirrors neurocognitive rhythm
Approach	9.0	Yes	Learning Type, Education	Visual/Multimodal → +0.5; Ph.D. → +0.5	8.0–10.0	Perspective layering rewarded by broad thinkers

APPENDIX E

Equation Trace Logs: Full Computation Chains per User

Table E1. Full Equation Breakdown by User and Rubric Dimension

Cognitive Modifier	Learning Type	Stress Level	Education	Field of Study	Brainwave Type	Structural Coherence Formula	Completeness Formula	Accuracy Formula	Logical Reasoning Formula	Critical Understanding Formula	Risk Mitigation Formula	Adaptability Formula	Approach Formula
0	Multimodal	Low-Moderate	Bachelor's degree	Political Science, Governance & Econ	Beta	9.0 + 0 (LT bonus) + 0 (Military) + 0.0 (Modifier)	9.0 + 0.5 (Field bonus) + 0.0 (Modifier)	9.0 + 0 (Field) + 0.25 (Stress) + 0.0 (Modifier)	9.0 + 0.5 (LT) + 0.25 (Wave) + 0 (Edu) + 0.0	8.5 + 0.5 (Field) + 0.25 (Wave) + 0.0	8.5 + 0.25 (Stress) + 0.0	8.5 + 0.25 (Wave) + 0.0	9.0 + 0.5 (LT) + 0 (Edu) + 0.0
1	Multimodal	Low-Moderate	Master's (Service-Integrated)	Math, Stats & Complex Systems	Beta	9.0 + 0 (LT bonus) + 0 (Military) + 1.0 (Modifier)	9.0 + 0 (Field bonus) + 1.0 (Modifier)	9.0 + 0.3 (Field) + 0.25 (Stress) + 1.0 (Modifier)	9.0 + 0.5 (LT) + 0.25 (Wave) + 0 (Edu) + 1.0	8.5 + 0 (Field) + 0.25 (Wave) + 1.0	8.5 + 0.25 (Stress) + 1.0	8.5 + 0.25 (Wave) + 1.0	9.0 + 0.5 (LT) + 0 (Edu) + 1.0
-1	Visual	High	Military Strategic Training	Political Science, Governance & Econ	Beta	9.0 + 0.5 (LT bonus) + 0.5 (Military) + -1.0 (Modifier)	9.0 + 0.5 (Field bonus) + -1.0 (Modifier)	9.0 + 0 (Field) + 0.0 (Stress) + -1.0 (Modifier)	9.0 + 0.5 (LT) + 0.25 (Wave) + 0 (Edu) + -1.0	8.5 + 0.5 (Field) + 0.25 (Wave) + -1.0	8.5 + 0.0 (Stress) + -1.0	8.5 + 0.25 (Wave) + -1.0	9.0 + 0.5 (LT) + 0 (Edu) + -1.0
-0.25	Reading/Writing	High	High School (Military Officer Pathway)	Political Science, Governance & Econ	Alpha	9.0 + 0.3 (LT bonus) + 0.5 (Military) + -0.25 (Modifier)	9.0 + 0.5 (Field bonus) + -0.25 (Modifier)	9.0 + 0 (Field) + 0.0 (Stress) + -0.25 (Modifier)	9.0 + 0 (LT) + 0 (Wave) + 0 (Edu) + -0.25	8.5 + 0.5 (Field) + 0 (Wave) + -0.25	8.5 + 0.0 (Stress) + -0.25	8.5 + 0 (Wave) + -0.25	9.0 + 0 (LT) + 0 (Edu) + -0.25
-0.125	Multimodal	High	Ph.D.	Political Science, Governance & Econ	Beta	9.0 + 0 (LT bonus) + 0 (Military) + -0.125 (Modifier)	9.0 + 0.5 (Field bonus) + -0.125 (Modifier)	9.0 + 0 (Field) + -0.25 (Stress) + -0.125 (Modifier)	9.0 + 0.5 (LT) + 0.25 (Wave) + 0.5 (Edu) + -0.125	8.5 + 0.5 (Field) + 0.25 (Wave) + -0.125	8.5 + -0.25 (Stress) + -0.125	8.5 + 0.25 (Wave) + -0.125	9.0 + 0.5 (LT) + 0.5 (Edu) + -0.125
0	Visual	Low-Moderate	High School (Military Officer Pathway)	Military & Defense Studies	Beta	9.0 + 0.5 (LT bonus) + 0.5 (Military) + 0.0 (Modifier)	9.0 + 0 (Field bonus) + 0.0 (Modifier)	9.0 + 0 (Field) + 0.5 (Stress) + 0.0 (Modifier)	9.0 + 0.5 (LT) + 0.25 (Wave) + 0 (Edu) + 0.0	8.5 + 0 (Field) + 0.25 (Wave) + 0.0	8.5 + 0.5 (Stress) + 0.0	8.5 + 0.25 (Wave) + 0.0	9.0 + 0.5 (LT) + 0 (Edu) + 0.0
0	Reading/Writing	Moderate	High School (Military Officer Pathway)	Int'l Law, Human Rights & Diplomacy	Theta	9.0 + 0.3 (LT bonus) + 0.5 (Military) + 0.0 (Modifier)	9.0 + 0.5 (Field bonus) + 0.0 (Modifier)	9.0 + 0 (Field) + 0.25 (Stress) + 0.0 (Modifier)	9.0 + 0 (LT) + -0.25 (Wave) + 0 (Edu) + 0.0	8.5 + 0.5 (Field) + -0.25 (Wave) + 0.0	8.5 + 0.25 (Stress) + 0.0	8.5 + -0.25 (Wave) + 0.0	9.0 + 0 (LT) + 0 (Edu) + 0.0
-0.5	Multimodal	Moderate	Bachelor's degree	Strategic & Security Studies	Theta	9.0 + 0 (LT bonus) + 0 (Military) + -0.5 (Modifier)	9.0 + 0.5 (Field bonus) + -0.5 (Modifier)	9.0 + 0 (Field) + 0 (Stress) + -0.5 (Modifier)	9.0 + 0.5 (LT) + -0.25 (Wave) + 0 (Edu) + -0.5	8.5 + 0 (Field) + -0.25 (Wave) + -0.5	8.5 + 0 (Stress) + -0.5	8.5 + -0.25 (Wave) + -0.5	9.0 + 0.5 (LT) + 0 (Edu) + -0.5
0	Reading/Writing	High	Military Strategic Training	AI, Data, & Computational Systems	Gamma	9.0 + 0.3 (LT bonus) + 0.5 (Military) + 0.0 (Modifier)	9.0 + 0 (Field bonus) + 0.0 (Modifier)	9.0 + 0.3 (Field) + 0.0 (Stress) + 0.0 (Modifier)	9.0 + 0 (LT) + 0.5 (Wave) + 0 (Edu) + 0.0	8.5 + 0 (Field) + 0.5 (Wave) + 0.0	8.5 + 0.0 (Stress) + 0.0	8.5 + 0.5 (Wave) + 0.0	9.0 + 0 (LT) + 0 (Edu) + 0.0
0.25	Multimodal	Moderate	Military Strategic Training	Math, Stats & Complex Systems	Theta	9.0 + 0 (LT bonus) + 0.5 (Military) + 0.25 (Modifier)	9.0 + 0 (Field bonus) + 0.25 (Modifier)	9.0 + 0.3 (Field) + 0.25 (Stress) + 0.25 (Modifier)	9.0 + 0.5 (LT) + -0.25 (Wave) + 0 (Edu) + 0.25	8.5 + 0 (Field) + -0.25 (Wave) + 0.25	8.5 + 0.25 (Stress) + 0.25	8.5 + -0.25 (Wave) + 0.25	9.0 + 0.5 (LT) + 0 (Edu) + 0.25
1	Reading/Writing	Moderate	Ph.D.	Military & Defense Studies	Gamma	9.0 + 0.3 (LT bonus) + 0 (Military) + 1.0 (Modifier)	9.0 + 0 (Field bonus) + 1.0 (Modifier)	9.0 + 0 (Field) + 0 (Stress) + 1.0 (Modifier)	9.0 + 0 (LT) + 0.5 (Wave) + 0.5 (Edu) + 1.0	8.5 + 0 (Field) + 0.5 (Wave) + 1.0	8.5 + 0 (Stress) + 1.0	8.5 + 0.5 (Wave) + 1.0	9.0 + 0 (LT) + 0.5 (Edu) + 1.0
0	Multimodal	Moderate	Master's + Certs (Strategic Training)	Int'l Law, Human Rights & Diplomacy	Alpha	9.0 + 0 (LT bonus) + 0 (Military) + 0.0 (Modifier)	9.0 + 0.5 (Field bonus) + 0.0 (Modifier)	9.0 + 0 (Field) + 0 (Stress) + 0.0 (Modifier)	9.0 + 0.5 (LT) + 0 (Wave) + 0 (Edu) + 0.0	8.5 + 0.5 (Field) + 0 (Wave) + 0.0	8.5 + 0 (Stress) + 0.0	8.5 + 0 (Wave) + 0.0	9.0 + 0.5 (LT) + 0 (Edu) + 0.0
1.5	Reading/Writing	Moderate	Ph.D.	AI, Data, & Computational Systems	Theta	9.0 + 0.3 (LT bonus) + 0 (Military) + 1.5 (Modifier)	9.0 + 0 (Field bonus) + 1.5 (Modifier)	9.0 + 0.3 (Field) + 0 (Stress) + 1.5 (Modifier)	9.0 + 0 (LT) + -0.25 (Wave) + 0.5 (Edu) + 1.5	8.5 + 0 (Field) + -0.25 (Wave) + 1.5	8.5 + 0 (Stress) + 1.5	8.5 + -0.25 (Wave) + 1.5	9.0 + 0 (LT) + 0.5 (Edu) + 1.5

Description: This table provides full visibility into the calculation chain for each user across all eight rubric dimensions. Each cell displays the precise arithmetic logic applied (e.g., base score, bonus modifiers, cognitive scalar, final clamped value). This format ensures scoring is not only reproducible but audit-friendly, fulfilling the epistemic transparency criteria of the fibristic model.

Note: All scores were derived from deterministic equations. Each row traces:

User traits → Modifier path → Base score + Modifiers → Final output

The system enforces a clamp between **8.0 and 10.0**, with exceptions for –2.000 cognitive modifiers resulting in minimums of **7.0**, explicitly shown in affected rows.

APPENDIX F

Macro-Level Rubric for AI Model Evaluation

Description: This macro-level rubric is used to assess AI tools in terms of structural quality, reasoning integrity, contextual adaptability, and ethical alignment. It evaluates eight dimensions grouped under four core categories: Access, Ability, Disposition, and Position. Each dimension is scored on a 10-point scale and is described across four performance bands: Exemplary (10), Strong (9), Moderate (8), and Limited (7). Scores are derived through deterministic simulation and human-aligned evaluations using this rubric. A subtotal is computed per category (max 20), and the final composite score reflects the tool's overall effectiveness and alignment with the fibristic framework.

Table F 1. Rubric Criteria and Scoring Levels by Dimension

Appendix F: Macro-Level Rubric for AI Model Evaluation						
Dimension	**Criterion**	**10 -Exemplary**	**9- Strong**	**8- Moderate**	**7- Limited**	**Total (Fraction)**
Access	***Structural Coherence (formerly Grammatical Coherence)***	The tool provides a clearly organized, learner-centered structure that supports multiple learning styles. Visual cues (e.g., color, hierarchy), guided categories, and responsive layout scaffold cognitive engagement. It promotes autonomy, clarity, and a non-controlling user experience that differentiates for varied users.	Layout is mostly clear and logically structured, using visual and organizational elements effectively. Some scaffolds may be underutilized or inconsistently applied.	Structure is partially helpful, but may confuse some learners or fail to guide users through all content levels consistently.	Structure lacks coherence across elements; guidance and learner independence are limited, and user flow may feel fragmented or passive.	***__/10***
	Completeness	The tool fully enables learners to engage with all relevant dimensions of content through structured interaction, reflection areas, and categorization logic. The end summary (e.g., tables, graphs) reinforces meta-cognition. Content is chunked and layered for depth and independence.	Most elements of the content are presented clearly and allow for meaningful engagement. Some scaffolding or synthesis features may be less developed.	Includes basic interaction and coverage, but omits opportunities for depth, feedback, or active reflection.	Limited opportunities for user-driven discovery or completeness of engagement. Responses may be surface-level due to tool design gaps.	***__/10***
Subtotal (Fraction)					***__/20***	
Ability	***Accuracy***	Responses are not only contextually accurate (e.g., legal/human rights framework) but embedded in a layered structure that enables users to recognize and apply concepts independently. Core references are clearly aligned with international norms and psychological principles.	Mostly accurate and aligned, with minor interpretive or referential gaps that do not prevent meaningful user engagement or application.	Some factual or conceptual gaps that slightly distort interpretation or weaken autonomous reasoning.	Noticeable misalignment or gaps; the tool presents information in ways that may confuse legal or psychological framing.	***__/10***
	Logical Reasoning	Demonstrates consistent, sound reasoning, aligning context and principles effectively in interpretive and factual scenarios.	Demonstrates strong reasoning with minor lapses in connecting principles or aligning with context.	Demonstrates basic reasoning with noticeable gaps in context alignment or integration of principles.	Demonstrates limited reasoning, inconsistently connecting principles with context.	***__/10***
Subtotal (Fraction)					***__/20***	

Disposition	***Critical Understanding***	Demonstrates deep interpretive analysis, accurately grasping implicit meanings and nuanced legal concepts.	Shows solid interpretive ability, with minor gaps in understanding of nuanced legal elements.	Partially interprets key concepts, missing implicit meanings or underlying principles.	Shows limited interpretive capacity and mostly surface-level understanding.	***__/10***
	Risk Mitigation	Proactively identifies and mitigates risks in outputs, ensuring ethical and safe usage.	Effectively mitigates risks, with minor gaps in proactive measures.	Moderately addresses risks, with noticeable gaps in proactive mitigation.	Demonstrates limited risk mitigation with significant gaps in ethical or safe usage considerations.	***__/10***
Subtotal (Fraction)					***__/20***	
Position	***Adaptability***	Consistently adapts to varied contexts, seamlessly integrating interpretive and factual reasoning.	Adapts well to most contexts, with minor lapses in flexibility or precision.	Demonstrates moderate adaptability, with clear strengths in one context but weaknesses in another.	Demonstrates limited adaptability, struggling to shift between interpretive and factual tasks.	***__/10***
	Approach	Consistently multidirectional, balancing diverse perspectives and addressing the complexity of the situation effectively.	Mostly bidirectional, exploring opposing or complementary perspectives thoroughly but with minor gaps.	Moderately objective, with a mix of unidirectional and bidirectional reasoning, occasionally missing complexity.	Largely unidirectional, focusing on a single perspective without sufficient balance or depth.	***__/10***
Subtotal (Fraction)					***__/20***	
Total Score						

Appendix G: Logic Field MultiSet Generator – Custom Fractions Module
This tool generates up to three user sets from a base logic distribution of 114 user profiles. It uses categorical constraints across eight dimensions (e.g., Gender, Age, Cognitive Modifier) and allows for fractional sampling (49%–99%) from each set. The generator ensures trait fidelity by reshuffling fixed-value pools, producing internally valid logic matrices on each execution.

Functional Parameters

- Number of sets: 1–3
- Sampling fractions: 49% to 99% (in 1% increments)
- Output fidelity: Maintains all marginal constraints for each set
- Trait fields: Gender, Age, Education, Field of Study, Brainwave Type, Stress Level, Cognitive Modifier, Learning Type

Purpose
Enables exact control over how much of each 114-user set is retained. Suitable for:

- Methodological granularity
- Micro-scale factorial testing
- Scaled logic field compression

https://torch-bubbly-client.glitch.me/Logic_Field_MultiSet_Generator_CustomFractions.html

Appendix H: Logic Field MultiSet Generator – Standard Module

This is the baseline multi-set logic generator for trait-valid persona construction. It supports commonly used fractional steps and is optimized for quick deployment in formal simulations.

Functional Parameters

- Number of sets: 1–3
- Sampling fractions: **100%, 95%, 90%, 85%, 80%, 75%, 66%, 50%**
- Output: Full HTML-rendered user matrices with fixed trait integrity
- Logic model: Trait-pool reshuffling without interpolation.

Purpose

Ideal for:

- Baseline dataset generation
- Fast logic-valid multi-set construction
- System performance testing under standard conditions

https://torch-bubbly-client.glitch.me/Logic_Field_MultiSet_Generator_Corrected%20(1).html

Feature	Appendix G (Custom Fractions)	Appendix H (Standard)
Sampling Resolution	Fine (1% steps from 49% to 99%)	Coarse (e.g., 100%, 95%, 85%, 75%, etc.)
Use Case	Advanced modeling, granular test conditions	Default simulation execution
Computational Cost	Slightly higher due to variability	Lower; efficient standard-case runs
UI Complexity	More dropdown options	Simplified dropdown

Appendix J: User Simulation Validation Method

This appendix presents the final implementation module used to validate simulation outputs from the fibristic AI evaluation framework. The tool operationalizes the deterministic rubric logic by applying trait-bound rules across all eight performance dimensions.

It evaluates each simulated user based on input traits—including stress level, education type, cognitive modifier, learning mode, and field of study—and returns structured scores for:

- Structural Coherence
- Completeness
- Accuracy
- Logical Reasoning
- Critical Understanding
- Risk Mitigation
- Adaptability
- Approach

The system executes via a logic-weighted HTML interface and renders transparent, audit-traceable results. It follows the fixed evaluation logic described in Appendix D and is aligned with the fibristic scoring methodology. The validation method was implemented to support real-time feedback and structured comparison of simulated user cognition across matrix-generated cohorts.

The tool can be accessed at the following permanent location:

https://torch-bubbly-client.glitch.me/User.Simulation.Validation.Method.html

Note: This module is not probabilistic. All outcomes are deterministically generated from declared trait variables and predefined scoring logic. Users may export outputs and paste into Spreadsheet or CSV, compare across sets, or integrate scores into downstream analytics engines.