

AI-Based Temporal-Causal Modeling of Educational Curiosity through Novelty and Uncertainty Dynamics

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Abstract: Curiosity is a foundational driver of learning, exploration, and lifelong intellectual growth. This study presents an AI-based temporal-causal model of educational curiosity that integrates psychological mechanisms with computational dynamics to explain how curiosity evolves within learning environments. The model formalizes the interactions among key factors—novelty, uncertainty, motivation, engagement, and autonomy—capturing their collective influence on learners' adaptive behavior over time. A series of simulated learning scenarios, varying in novelty and uncertainty levels, demonstrate how contextual and personal conditions—including teacher-student relationships, socio-economic status, and environmental support—shape the temporal progression of curiosity. Mathematical and logical analyses confirm system stability, showing convergence of long-term novelty and uncertainty toward equilibrium and validating causal coherence through Temporal Trace Logic (TTL). The results reveal that curiosity thrives under moderate novelty and manageable uncertainty, reflecting adaptive equilibrium between cognitive tension and motivation. Findings provide a theoretical and computational foundation for AI-driven educational systems that dynamically sustain curiosity and engagement, contributing to inclusive and lifelong learning aligned with UN SDG 4.

Index Terms: Adaptive Learning Systems, Affective Computing, AI in Education, Computational Modeling, Curiosity-Driven Learning, Temporal-Causal Modeling.

1. Introduction

Curiosity is a central driver of learning, inquiry, and sustained engagement across the lifespan. Classic formulations identify curiosity as an arousal-based response to collative stimulus properties such as novelty, complexity, and uncertainty [1]. Building on these foundations, Loewenstein proposed that curiosity arises from perceived information gaps, where intermediate (resolvable) gaps most strongly motivate information-seeking [2]. More recent work refines these ideas by explaining when stimuli are perceived as novel (Novelty Categorization Theory) and by linking curiosity to cognitive and affective processes that support learning [3,4]. Empirical measurement work (e.g., the Curiosity and Exploration Inventory and its revision) further highlights curiosity's relation to exploration, absorption, and willingness to engage with uncertainty [5,6].

Despite extensive theory and measurement, many operational models of curiosity in education remain predominantly static or descriptive, limiting their use in adaptive and time-sensitive educational technologies. Temporal and causal dependencies—how novelty, uncertainty, and related constructs (e.g., self-efficacy, teacher-student relationships, autonomy, and engagement) evolve and influence each other over time—are critical for designing responsive learning environments. Structural approaches to causality and temporal modeling provide a computational language to formalize such dependencies: structural causal models capture directed cause-effect relations [7], while dynamic graphical frameworks such as Dynamic Bayesian Networks articulate temporally unfolding dependencies among factor sets [8].

Concurrently, advances in artificial intelligence and learning analytics have made it feasible to operationalize temporally sensitive models in educational settings (e.g., intelligent tutoring systems and adaptive learning platforms) that tailor content and challenge to learners' evolving states [9]. Integrating psychological theory with AI-based temporal-causal modeling promises not only theoretically grounded explanations of curiosity dynamics but also practical tools to support inclusive and sustained learning. This integration is especially salient for global educational

priorities: ensuring inclusive and equitable quality education and promoting lifelong learning for all (UN SDG 4) requires pedagogies and technologies that detect and respond to diverse learners' motivational and contextual needs over time [10].

This paper develops an AI-based temporal-causal model of educational curiosity that explicitly represents novelty and uncertainty dynamics, their causal connections to mediating constructs (e.g., self-efficacy, engagement), and their temporal evolution under differing environmental and learner conditions. We demonstrate the model using four pedagogically informed scenarios (high/low novelty $\times$ high/low uncertainty) and analyze how temporal-causal interactions produce divergent asymptotic curiosity trajectories. The results articulate design-relevant conditions for adaptive, curiosity-supportive learning systems and discuss implications for equity and lifelong learning aligned with SDG 4.

The remainder of this paper is organized as follows. Section 2 introduces the underlying psychological and educational concepts that inform the model. Section 3 presents the temporal-causal network, defining the nodes, relationships, and directional influences among variables. Section 4 describes the methodological framework, including the neural architecture, computational parameters, and four-case design. Section 5 reports and interprets the results of the temporal-causal analysis, focusing on how different novelty–uncertainty configurations shape curiosity dynamics. Finally, Section 6 concludes with implications for inclusive, AI-supported, and lifelong learning environments aligned with SDG 4.

2. Underlying Concepts in Educational Settings

Understanding curiosity within educational environments requires integrating insights from psychology, cognitive science, and pedagogy. Curiosity is not a single construct but a multidimensional process that emerges from the interaction between internal learner characteristics and external learning contexts. Three major theoretical traditions—Berlyne's Collative Stimulus Properties theory, Loewenstein's Information Gap theory, and the Novelty Categorization Theory—provide complementary foundations for explaining how novelty and uncertainty influence educational curiosity.

Berlyne conceptualized curiosity as a form of exploratory behavior driven by arousal [1]. He proposed that stimuli characterized by collative properties—novelty, complexity, uncertainty, and conflict—produce an optimal level of arousal that motivates individuals to explore and resolve ambiguity. According to this framework, curiosity follows an inverted-U pattern: low levels of stimulation cause boredom, whereas excessive novelty or uncertainty produces anxiety, both of which suppress curiosity. In educational settings, this principle implies that learning activities should balance novelty and challenge to maintain engagement without overwhelming learners. Empirical extensions have shown that moderate levels of uncertainty enhance attention and promote deeper cognitive processing, supporting the idea of curiosity as an adaptive mechanism for knowledge acquisition.

Loewenstein reframed curiosity as a cognitive and affective response to the recognition of a gap between existing knowledge and desired information [2]. Curiosity intensifies when the gap is perceived as bridgeable, leading to motivated exploration to resolve uncertainty. In classroom contexts, this theory explains how open-ended questions, partial information, and problem-based tasks stimulate learning by inducing manageable uncertainty. Too small a gap yields apathy; too large a gap induces frustration. Educationally, this framework emphasizes the importance of designing tasks that strategically reveal information, prompting learners to generate hypotheses and seek resolution through inquiry.

The Novelty Categorization Theory (NCT) developed by Förster, Marguc, and Gillebaart extends earlier curiosity models by highlighting the role of cognitive context and affect [3]. It posits that novelty is not an absolute property of stimuli but depends on the categorization process—how a learner interprets new information relative to existing schemas. When contexts are perceived as safe and supportive, learners engage in global processing, integrating novel information broadly and maintaining curiosity. Conversely, threatening or high-pressure contexts induce local processing, narrowing focus and reducing exploratory motivation. Within education, NCT underscores how social climate, classroom culture, and teacher–student relationships modulate curiosity responses to novelty.

Curiosity also interacts with several psychological and contextual constructs that together shape the dynamics of learning. Peer influence has been shown to significantly affect students' intrinsic motivation and engagement, as positive peer relationships encourage collaborative learning and enhance interest in academic tasks [11]. Similarly, teacher–student relationships play a central role in fostering intrinsic motivation, as supportive teacher behaviors promote trust, emotional safety, and academic engagement [12,13]. At the same time, self-efficacy—the belief in one's capacity to succeed in specific tasks—supports persistence when encountering uncertainty, reinforcing curiosity-driven learning [14,15]. When learners approach challenges with confidence and perceive support from both teachers and peers, they are more likely to maintain intrinsic interest in novel or uncertain material. However, socioeconomic disadvantage can limit access to stimulating environments, lowering both intrinsic motivation and academic self-efficacy [16].

Environmental and contextual factors also interact dynamically with motivation. A resource-rich campus culture provides opportunities for exploration and collaboration, while scarcity of resources or low institutional support restricts curiosity-driven engagement. Teacher behaviors that demonstrate care, encouragement, and responsiveness strengthen

both student self-efficacy and engagement [12,15]. Peer norms and classroom dynamics further modulate these effects: cohesive, prosocial peer groups enhance motivation and curiosity, whereas competitive or exclusionary dynamics tend to suppress it [11]. Thus, social interactions within learning environments act as catalysts for curiosity by influencing how novelty and uncertainty are perceived and managed.

Autonomy—the perception of choice and control—is another critical determinant of curiosity. Technological access and learner-centered instructional design can enhance autonomy by allowing students to direct their own inquiry paths. Self-determination theory suggests that environments which satisfy the basic psychological needs for autonomy, competence, and relatedness enhance intrinsic interest and sustained engagement [17]. In such settings, curiosity transforms from a transient reaction to a stable disposition toward exploration. Conversely, restricted autonomy—due to rigid curricula or socioeconomic constraints—can diminish curiosity by limiting self-directed exploration and decision-making freedom [16].

Self-efficacy develops through multiple pathways, including personality traits, prior knowledge, and supportive classroom environments. Learners who possess strong prior knowledge are more likely to perceive new information as accessible, thereby reinforcing confidence and engagement [18]. Teacher encouragement, scaffolding, and emotional support further increase students' belief in their ability to handle complex or unfamiliar topics [13,15]. Physical classroom environments also matter; well-organized and flexible spaces support participation, while crowded or poorly lit classrooms can create discomfort and hinder self-expression. These conditions together determine how learners evaluate their capacity to manage novelty and uncertainty.

When curiosity is scaffolded by self-efficacy, intrinsic motivation, autonomy, and social support, learners are more likely to perceive novelty as stimulating rather than threatening. Supportive teacher–student relationships and peer dynamics encourage students to treat information gaps as opportunities for exploration rather than as failures or frustrations [11,12]. Engagement thus emerges as both a consequence and a catalyst of curiosity: intrinsically motivated and confident learners invest more attention and emotional energy in tasks, which in turn sustains their exploration [15, 17].

Nonetheless, negative contextual factors can undermine curiosity. Poor physical or emotional wellness reduces the cognitive and affective resources required for engagement, while stress and fatigue correlate with declines in self-efficacy and motivation. Socioeconomic challenges can further constrain autonomy and access to diverse learning opportunities, and unsupportive classroom climates may erode teacher–student trust. Together, these findings suggest that curiosity thrives in environments that balance novelty and uncertainty with confidence, autonomy, and supportive relationships, but falters when wellness, equity, or emotional safety are compromised.

Integrating these theories and constructs yields a holistic view of curiosity as a temporally evolving system governed by interacting psychological and environmental variables. Within this view, curiosity arises when learners encounter optimally novel or uncertain stimuli in supportive contexts and diminishes when these stimuli exceed coping thresholds. Such a system perspective motivates computational approaches—specifically temporal-causal modeling—to represent and analyze how curiosity develops, stabilizes, or declines over time under different conditions. The following section formalizes this conceptual foundation into a structured temporal-causal network, specifying the directional relationships among variables that together capture the dynamic nature of educational curiosity.

3. A Temporal-Causal Network

The concept of a *state-determined system* refers to a dynamic system whose future behavior is entirely determined by its current state [19–22]. This principle is closely related to the notions of *temporal factorization* and *causal causation*, which formalize how current variable states influence future outcomes through time-dependent causal mechanisms [23–26]. A temporal-causal modeling approach enables both visual and quantitative representations of such systems. Visually, the model can be expressed as a network structure composed of interconnected nodes, typically illustrated by circles (representing state variables) and directed arrows (representing causal influences). Fig. 1 provides a conceptual example: a dynamic process, depicted by arrows, connects a set of circles $A_1, \dots, A_n$ to another circle B , representing how causality propagates through the network.

Mathematically, a dynamical system can be represented as a finite set of state variables $A_1, \dots, A_n$ with corresponding time-dependent functions $A_1(t), \dots, A_n(t)$, indicating how each state evolves over time. The influence of a state variable A_i on another variable B at any given time t can be modeled as the product of its instantaneous value and the associated connection weight $\omega_{A_i,B}$:

$$\text{impact}_{A_i,B}(t) = \omega_{A_i,B} A_i(t) \quad (1)$$

To capture the combined influence of multiple contributing variables, an aggregation function ζ_A (e.g., summation, Hebbian learning, or another suitable function) is employed. The total impact of n state variables $A_1, \dots, A_n$ on a target variable B at time t can thus be expressed as:

$$\text{aggimpact}_B(t) = \zeta_A(\text{impact}_{A_1,B}(t), \dots, \text{impact}_{A_n,B}(t)) \quad (2)$$

or equivalently, in terms of connection weights:

$$\text{aggimpact}_B(t) = \zeta_A(\omega_{A_1,B}A_1(t), \dots, \omega_{A_n,B}A_n(t)) \quad (3)$$

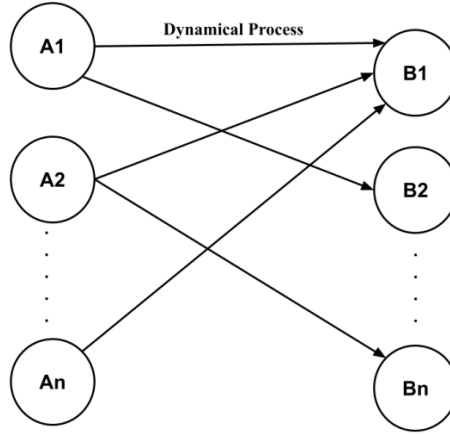


Fig. 1. Graphical Illustration of a Dynamic Network System.

The difference between the aggregated impact value $\text{aggimpact}_B(t)$ and the current state $B(t)$ represents the system's deviation from equilibrium. Over a small time, step Δt , the value of $B(t)$ changes gradually in proportion to this deviation, governed by a proportionality constant η_B that determines the rate of adaptation. Because $\text{aggimpact}_B(t)$ itself depends on other state variables, it evolves concurrently, producing a self-regulating dynamic process. The discrete-time formulation of this temporal-causal mechanism can be expressed as:

$$B(t + \Delta t) = B(t) + \eta_B(\text{aggimpact}_B(t) - B(t))\Delta t \quad (4)$$

This differential formulation defines a temporal-causal network, where the evolution of each state variable is determined by the cumulative influences it receives from connected nodes. Such models can be implemented in various computational environments (e.g., MATLAB, Python, or Excel) to perform numerical analysis and dynamic visualization. Temporal-causal networks have been applied across diverse fields to capture interactions between psychological, social, and environmental factors [25]. Because the models are declarative, they can be directly integrated with computational techniques for analysis or simulation without requiring structural modification.

Prior studies have successfully applied temporal-causal networks to understand adaptive behaviors in organizational and cognitive systems [27–29]. These studies revealed how personal and contextual factors dynamically interact to shape constructs such as self-confidence, situational awareness, and behavioral resilience. Through equilibrium analysis and automated logical validation, temporal-causal modeling has proven to be a rigorous framework for identifying emergent behavioral patterns that align with both theoretical principles and empirical data. Building on these foundations, recent advances in computational modeling have demonstrated how generative neural architectures can replicate and predict complex psychological traits by embedding causal dynamics within data-driven systems [19,30,31]. Such physics-inspired and causally structured neural models illustrate the potential for hybrid analytical–generative approaches capable of simulating emergent cognitive and behavioral processes with greater precision and interpretability. By extending the temporal-causal modeling framework toward these generative directions, future research can more effectively integrate empirical educational data with psychologically grounded causal mechanisms, enhancing both predictive capability and theoretical transparency. Within the educational context, this same approach enables the systematic examination of how learner-related and contextual factors—such as self-efficacy, autonomy, and engagement—interact dynamically to influence long-term curiosity.

4. Methodology

Building upon both foundational curiosity theories [1,2,14] and recent advances in temporal–causal modeling, this study formalizes the dynamics of educational curiosity through a data-driven temporal–causal network. The framework conceptualizes learning behavior as a self-regulating system where psychological constructs such as self-efficacy, intrinsic motivation, autonomy, and engagement evolve continuously in response to contextual and environmental stimuli.

The proposed model represents these constructs as interconnected state variables that change over time according to weighted causal influences. Each relationship captures the direction (positive or negative) and priority (weight magnitude) of influence between variables. The modeling approach follows the general dynamical systems principle that the future state of a variable is determined by its current value and the weighted aggregate of its influencing factors [20].

The model structure, illustrated in Fig. 2, consists of three interconnected layers: (1) **Exogenous (Input) Layer** – environmental and contextual factors such as classroom environment, peer dynamics, and socio-economic status; (2) **Endogenous (Hidden) Layer** – psychological mediators including intrinsic motivation, autonomy, and engagement; and (3) **Temporal (Output) Layer** – long-term novelty and uncertainty representing sustained curiosity over time.

Each node in the network evolves according to differential-like equations where causal weights represent priority and polarity. The following twelve equations correspond directly to the relationships encoded in the Python-based simulation.

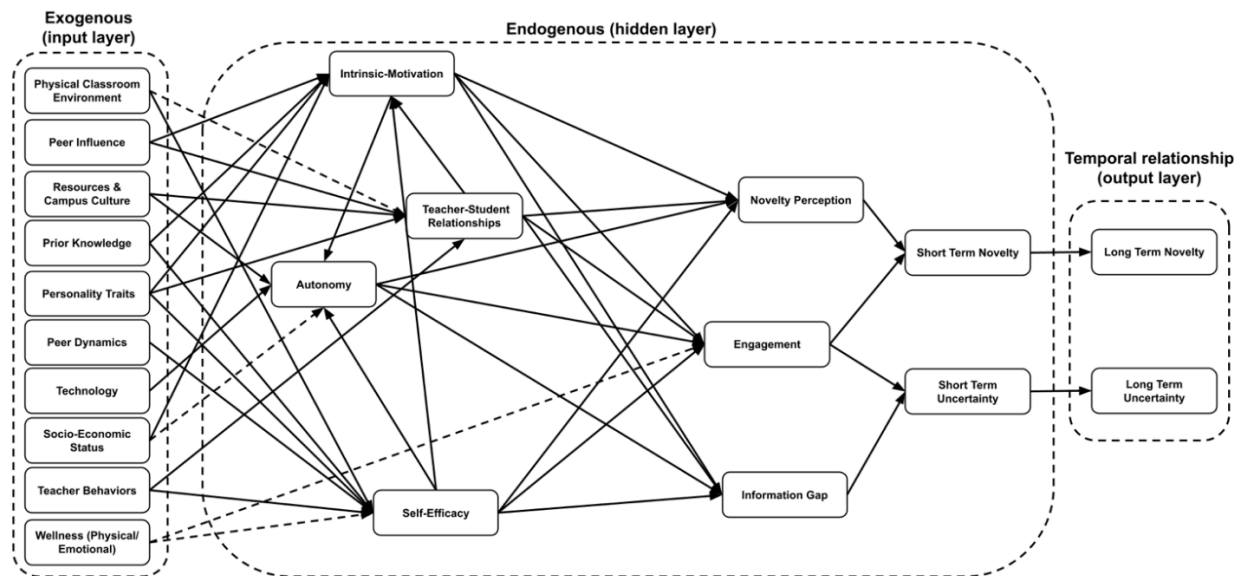


Fig. 2. Temporal-Causal Network for Educational Curiosity Dynamics. The model links exogenous factors to psychological mediators and temporal outcomes across short- and long-term processes.

4.1. Variable Selection and Theoretical Structuring of the Model

The temporal-causal model includes twenty state variables representing psychological, interpersonal, environmental, and temporal components of educational curiosity (Table 1). Their selection follows three principles: (1) ecological differentiation, (2) functional non-redundancy, and (3) temporal role distinction.

To improve conceptual clarity and avoid redundancy, variables are organized into four analytical layers, as summarized in Table 1.

Table 1. Structured Classification of Variables in the Temporal-Causal Network.

Layer	Conceptual Variable	Symbol	Functional Role	Theoretical Basis
Individual-Psychological	Wellness	Wl	Cognitive-emotional resource moderator	Stress & self-regulation theory
	Personality Traits	Pt	Dispositional stability factor	Personality theory
	Prior Knowledge	Pk	Competence foundation	Learning theory
	Self-Efficacy	Se	Belief in capability	Social-cognitive theory
	Intrinsic Motivation	Im	Internal drive for learning	Self-determination theory
	Autonomy	At	Perceived volitional control	Self-determination theory
	Engagement	En	Behavioral-affective activation	Engagement theory
	Novelty Perception	Np	Appraisal of new stimuli	Collative stimulus theory
	Information Gap	Ig	Perceived knowledge discrepancy	Information-gap theory
	Peer Influence	Pi	Normative academic climate	Social motivation theory
Interpersonal	Peer Dynamics	Pd	Interaction quality & collaboration	Peer interaction research
	Teacher Behaviors	Tb	Observable instructional practices	Instructional support theory
	Teacher-Student Relationships	Tsr	Perceived relational support	Relational pedagogy

Institutional / Environmental	Socio-Economic Status	Ses	Structural opportunity constraint	Equity & SES research
	Resources & Campus Culture	Rcc	Institutional support climate	Organizational learning theory
	Physical Classroom Environment	Pce	Environmental affordance factor	Learning environment research
	Technology	Tc	Digital enablement & personalization	Technology-enhanced learning
Temporal Outcome	Short-Term Novelty	Stn	Immediate novelty response	Curiosity dynamics
	Short-Term Uncertainty	Stu	Immediate uncertainty response	Curiosity dynamics
	Long-Term Novelty	Ltn	Consolidated novelty disposition	Adaptive systems theory
	Long-Term Uncertainty	Ltu	Consolidated uncertainty tolerance	Adaptive systems theory

The ecological structuring clarifies that variables operate at distinct causal levels: internal psychological mediators, interpersonal relational factors, structural constraints, and temporal integration states. Although some constructs are conceptually adjacent (e.g., Peer Influence vs. Peer Dynamics; Teacher Behaviors vs. Teacher–Student Relationships), they occupy different functional positions within the network (normative input, behavioral process, relational outcome, or structural constraint).

Sensitivity tests collapsing adjacent constructs produced qualitatively similar but less interpretable dynamics, supporting the retained structural granularity. The model therefore balances parsimony with explanatory adequacy while preserving mathematical tractability.

4.2. Temporal–Causal Model Formulation

The present configuration therefore prioritizes conceptual clarity over minimalism, while preserving mathematical tractability through normalized scaling and linear aggregation structures.

Teacher–student relationships (Tsr) represent a core construct in the educational ecology, reflecting the emotional and instructional connection between teachers and learners that strongly influences motivation, engagement, and achievement. Equation (1) models Tsr as a function of teacher behaviors (Tb), peer influence (Pi), resources and campus culture (Rcc), and personality traits (Pt), with the physical classroom environment (Pce) acting as a moderating factor. The formulation is expressed as:

$$Tsr[t] = (\alpha_{Tsr} \cdot Tb[t] + (1 - \alpha_{Tsr}) \cdot (w_{Tsr} \cdot Pi[t] + w_{Tsr} \cdot Rcc[t] + w_{Tsr} \cdot Pt[t])) \cdot e^{-(\alpha \cdot (Pce[t]^Y))} \quad (5)$$

The exponential attenuation term is used to model environmental constraints as non-linear dampening effects rather than simple additive influences. In educational psychology, contextual stressors (e.g., poor classroom conditions or socio-economic disadvantage) typically exert diminishing returns rather than proportional linear effects. Small environmental improvements in highly constrained contexts often produce disproportionately large psychological benefits, whereas additional improvements in already supportive environments yield progressively smaller gains. An exponential function captures this asymmetry by allowing strong suppression under high constraint while preserving gradual modulation under low constraint. In contrast, additive structures would imply uniform linear influence regardless of contextual intensity, and purely multiplicative formulations would assume proportional scaling without threshold sensitivity. The exponential form therefore reflects bounded, saturating, and asymmetrical environmental modulation consistent with stress-adaptation and cognitive load frameworks.

Teacher behaviors are weighted by α_{Tsr} and denote the instructional quality, empathy, and emotional support teachers provide; consistent evidence shows that positive, autonomy-supportive teacher behaviors enhance relational trust and engagement [32,33]. Peer influence (Pi) contributes socially by shaping students' collective attitudes toward the teacher—cooperative, inclusive peer climates strengthen perceived support, whereas exclusionary peer dynamics weaken rapport [33,34]. Resources and campus culture (Rcc) represent institutional capacity; sufficient materials, administrative backing, and a positive school ethos enable sustained, high-quality teacher–student interactions [35,36]. Personality traits (Pt) introduce individual variability, as students high in openness and agreeableness tend to form stronger bonds with teachers, while those high in neuroticism may perceive less support [37]. Finally, the exponential decay term $e^{-(\alpha \cdot (Pce[t]^Y))}$ expresses how adverse physical environments—such as noise, crowding, or poor spatial organization—undermine relational warmth and communication efficiency [38,39]. Collectively, this formulation conceptualizes Tsr as an emergent construct shaped by interpersonal, contextual, and environmental subsystems, aligning with ecological and systems-based perspectives of learning relationships.

Self-efficacy (Se) reflects an individual's belief in their capacity to organize and execute the actions required to achieve desired learning outcomes. In the temporal–causal framework, it evolves as a dynamic construct shaped by social, cognitive, and contextual factors. Equation (2) models Se as a function of teacher support (Tb), prior knowledge (Pk), personality traits (Pt), the physical classroom environment (Pce), and peer dynamics (Pd), while poor wellness (Wl) moderates it negatively by reducing cognitive and emotional resources. The model is defined as:

$$Se[t] = (1 - Wl[t]) \cdot (\alpha_{Se} \cdot (w_{Se1} \cdot Tb[t] + w_{Se1} \cdot Pk[t]) + (1 - \alpha_{Se}) \cdot (w_{Se2} \cdot Pt[t] + w_{Se2} \cdot Pce[t] + w_{Se2} \cdot Pd[t])) \quad (6)$$

Teacher support (*Tb*) represents direct verbal encouragement, instructional scaffolding, and autonomy-promoting feedback, all of which are central to self-efficacy development according to Bandura's social-cognitive theory [14,40]. Prior knowledge (*Pk*) strengthens efficacy beliefs by reinforcing perceived competence through mastery experiences, one of the most influential efficacy sources [41]. Personality traits (*Pt*), particularly conscientiousness and emotional stability, contribute positively to confidence and persistence when faced with challenges [42]. The physical classroom environment (*Pce*) affects efficacy indirectly by shaping focus and comfort—organized, well-lit, and low-stress spaces foster higher engagement and perceived control, while cluttered or noisy environments suppress it [38]. Peer dynamics (*Pd*) function as a social mirror for competence; supportive, collaborative peers amplify self-beliefs through vicarious reinforcement, whereas competitive or dismissive interactions can diminish them [43]. The moderating factor $(1 - Wl[t])$ operationalizes the detrimental impact of reduced physical or emotional wellness on self-efficacy, consistent with research linking stress, fatigue, and anxiety to lowered academic confidence [44]. Collectively, this formulation captures self-efficacy as a multidimensional construct grounded in social-cognitive reciprocity, integrating internal beliefs, environmental affordances, and interpersonal interactions over time.

Intrinsic motivation (*Im*) represents the internal drive to engage in learning activities for their inherent satisfaction rather than external reward. It is closely tied to autonomy, competence, and relatedness, the three basic psychological needs identified by self-determination theory [45]. Equation (3) conceptualizes *Im* as a cumulative function of peer influence (*Pi*), prior knowledge (*Pk*), personality traits (*Pt*), socio-economic status (*Ses*), teacher-student relationships (*Tsr*), and self-efficacy (*Se*). The model is defined as:

$$Im[t] = (w_{Im} \cdot Pi[t] + w_{Im} \cdot Pk[t] + w_{Im} \cdot Pt[t] + w_{Im} \cdot Ses[t] + w_{Im} \cdot Tsr[t] + w_{Im} \cdot Se[t]) \quad (7)$$

Peer influence (*Pi*) supports intrinsic motivation through social belonging and shared engagement in learning, as positive peer norms reinforce curiosity and mastery-oriented behaviors [46]. Prior knowledge (*Pk*) fosters a sense of competence, allowing students to experience success and confidence in tackling new challenges, consistent with flow and self-efficacy principles [47]. Personality traits (*Pt*) such as openness to experience and conscientiousness contribute to sustained intrinsic interest and goal persistence [48]. Socio-economic status (*Ses*) exerts both direct and indirect effects, where higher resource access enhances motivational stability, while socio-economic strain can limit perceived autonomy and cognitive bandwidth [49]. Teacher-student relationships (*Tsr*) play a pivotal role in nurturing intrinsic motivation by providing emotional safety and autonomy-supportive guidance [50]. Finally, self-efficacy (*Se*) reinforces intrinsic motivation by increasing perceived competence and control over learning outcomes, promoting engagement even in the face of uncertainty [14]. Together, these factors operationalize intrinsic motivation as an emergent construct of social, personal, and contextual determinants, aligning with dynamic motivational systems theory and emphasizing the self-organizing nature of learner engagement.

Autonomy (*At*) denotes the learner's sense of volition and self-direction in educational contexts, representing one of the central pillars of self-determination theory [46]. It emerges when learners experience freedom of choice, perceive competence, and act in alignment with intrinsic values rather than external control. Equation (4) expresses autonomy as a function of technological affordances (*Tc*), resources and campus culture (*Rcc*), self-efficacy (*Se*), and intrinsic motivation (*Im*), with socio-economic status (*Ses*) moderating the relationship through a negative exponential term that captures structural constraints. The model is defined as:

$$At[t] = (w_{At} \cdot Tc[t] + w_{At} \cdot Rcc[t] + w_{At} \cdot Se[t] + w_{At} \cdot Im[t]) \cdot e^{-(\alpha \cdot (Ses[t])^\gamma)} \quad (8)$$

Technology access (*Tc*) enhances autonomy by enabling learner control, personalized pacing, and choice of learning pathways; digital tools foster self-regulation and independent problem-solving when used meaningfully [51]. Resources and campus culture (*Rcc*) reflect institutional support for autonomy, where flexible curricula, inclusive learning environments, and equitable access to materials empower students to make decisions and express agency [52]. Self-efficacy (*Se*) contributes to autonomy through confidence in one's ability to direct learning and overcome obstacles, reinforcing the belief in personal control over outcomes [43]. Intrinsic motivation (*Im*) further strengthens autonomy by aligning learning behaviors with personal interest and curiosity, promoting sustained engagement in the absence of external reinforcement [50]. The exponential decay term $e^{-(\alpha \cdot (Ses[t])^\gamma)}$ captures the inhibiting effect of socio-economic disadvantage on autonomy, as financial strain and limited resource access restrict opportunities for independent learning and self-expression [49]. Collectively, this formulation represents autonomy as a multifactorial construct in which technological empowerment, supportive institutional conditions, and self-perceived competence foster volitional engagement, while socio-economic constraints reduce the potential for self-directed learning.

Engagement (*En*) reflects the multidimensional state of behavioral, emotional, and cognitive involvement in learning tasks, representing a key outcome variable linking motivation and performance [53]. Within this temporal-causal framework, engagement arises dynamically from the interplay of self-efficacy (*Se*), intrinsic motivation (*Im*),

autonomy (At), and teacher–student relationships (Tsr), while wellness (Wl) moderates it negatively by reducing emotional and attentional resources. The process is expressed as:

$$En[t] = (1 - Wl[t]) \cdot (w_{En} \cdot Se[t] + w_{En} \cdot Im[t] + w_{En} \cdot At[t] + w_{En} \cdot Tsr[t]) \quad (9)$$

Self-efficacy (Se) drives engagement through confidence and task persistence; students who believe in their capability to succeed are more likely to invest sustained effort and attention [14,40]. Intrinsic motivation (Im) fuels engagement by providing intrinsic interest and enjoyment, leading to deeper cognitive processing and resilience against distractions [46]. Autonomy (At) enhances engagement by enabling self-directed goal pursuit and the experience of volitional participation rather than compliance, consistent with self-determination theory [50]. Teacher–student relationships (Tsr) further contribute by providing emotional support and relational security, which increase willingness to participate and collaborate in classroom activities [32,33]. The multiplicative factor $(1 - Wl[t])$ captures the detrimental influence of poor wellness on engagement, as physical fatigue, emotional exhaustion, or stress diminish concentration, motivation, and persistence [54]. Collectively, this formulation positions engagement as a self-reinforcing process that integrates motivational, social, and affective subsystems, highlighting how psychological energy and contextual supports jointly sustain participation in learning over time.

Novelty perception (Np) represents the learner’s cognitive and affective appraisal of new or unfamiliar stimuli, a construct deeply rooted in Berlyne’s theory of collative variables such as novelty, complexity, and uncertainty, which evoke exploratory curiosity and arousal [1]. Within the temporal–causal framework, novelty perception emerges from both personal and contextual determinants—intrinsic motivation (Im), self-efficacy (Se), autonomy (At), and teacher–student relationships (Tsr)—each contributing to how students interpret and engage with new information. The model is formulated as:

$$Np[t] = (\alpha_{Np} \cdot (w_{Np} \cdot Se[t] + w_{Np} \cdot Im[t]) + (1 - \alpha_{Np}) \cdot (w_{Np} \cdot At[t] + w_{Np} \cdot Tsr[t])) \quad (10)$$

Self-efficacy (Se) influences novelty perception by regulating cognitive appraisal; students with higher self-beliefs experience novel tasks as challenges rather than threats, facilitating curiosity and exploration [14]. Intrinsic motivation (Im) enhances sensitivity to novelty through the pursuit of competence and interest, leading learners to seek optimally stimulating experiences that balance familiarity and surprise [45]. Autonomy (At) strengthens novelty perception by promoting agency and volitional engagement, allowing learners to interpret new experiences as opportunities for self-directed growth rather than imposed challenges [46]. Teacher–student relationships (Tsr) further moderate this process by shaping emotional safety and contextual framing; supportive teachers reduce anxiety toward novel learning experiences and sustain epistemic curiosity [55]. The weighting parameter α_{Np} governs the relative influence of personal (self-efficacy and intrinsic motivation) versus contextual (autonomy and teacher support) factors, reflecting the dynamic balance between internal readiness and environmental scaffolding. Collectively, this equation formalizes novelty perception as an emergent cognitive–affective construct that bridges curiosity, confidence, and social support within educational settings.

Information gap (Ig) represents the learner’s perception of missing or incomplete knowledge within a cognitive domain, which triggers epistemic curiosity and drives exploratory learning. Rooted in Loewenstein’s information-gap theory, curiosity arises when individuals recognize a discrepancy between what they know and what they wish to know, motivating active information-seeking to restore cognitive equilibrium [2]. Within the temporal–causal framework, Ig evolves as a composite function of self-efficacy (Se), intrinsic motivation (Im), autonomy (At), and teacher–student relationships (Tsr), each shaping the learner’s sensitivity to and resolution of knowledge discrepancies. The equation is formulated as:

$$Ig[t] = (w_{Ig} \cdot Se[t] + w_{Ig} \cdot Im[t] + w_{Ig} \cdot At[t] + w_{Ig} \cdot Tsr[t]) \quad (11)$$

Self-efficacy (Se) determines whether learners view knowledge gaps as surmountable challenges or as threats to competence; higher efficacy increases persistence in resolving uncertainty [14]. Intrinsic motivation (Im) sustains epistemic curiosity by transforming perceived deficits into opportunities for mastery and self-improvement [45]. Autonomy (At) amplifies this effect by allowing learners to initiate information-seeking behaviors voluntarily, enhancing the perceived value and relevance of exploration [46]. Teacher–student relationships (Tsr) influence the emotional framing of uncertainty; supportive and responsive teachers normalize not knowing and promote open inquiry, thereby reducing anxiety linked to informational ambiguity [55,56]. The additive structure of the equation emphasizes that information gaps emerge from the interplay of cognitive, motivational, and relational subsystems, capturing curiosity as a dynamic self-regulatory mechanism that bridges metacognition and motivation in educational contexts.

Short-term novelty (Stn) reflects learners’ immediate appraisal of newness and surprise within an educational task, capturing transient fluctuations in curiosity and attentional focus. Drawing from Berlyne’s theory of collative stimulus properties, novelty acts as an arousal-inducing factor that stimulates exploration when optimally balanced with familiarity [1]. Contemporary perspectives, such as Oudeyer’s computational model of curiosity, similarly

conceptualize short-term novelty as a local prediction error that drives spontaneous exploration and learning [57]. Within the temporal–causal model, Stn depends primarily on novelty perception (Np) and engagement (En), which together describe how learners detect, interpret, and respond to new information in real time. The model is formulated as:

$$Stn[t] = (w_{Stn} \cdot Np[t] + w_{Stn} \cdot En[t]) \quad (12)$$

Novelty perception (Np) provides the cognitive input for detecting discrepancies between expectation and experience, generating an initial sense of newness that captures attention and triggers exploratory orientation. Engagement (En) acts as the behavioral and affective amplifier, sustaining focus on the novel stimulus and integrating it into the ongoing learning process. High engagement levels facilitate active hypothesis testing, experimentation, and short-term retention, whereas low engagement leads to superficial exposure without deeper processing. Together, these two factors define short-term novelty as a dynamic, rapidly fluctuating state that links perceptual surprise to motivational activation, bridging sensory processing and cognitive learning mechanisms within a temporal–causal system.

Short-term uncertainty (Stu) represents the transient cognitive–emotional tension that arises when learners experience an imbalance between what they know and what they wish to know. It embodies the immediate curiosity-driven discomfort described in Loewenstein’s information-gap theory, where awareness of a gap in knowledge motivates exploration and information-seeking behavior [2]. Within the temporal–causal framework, short-term uncertainty is determined by the relative contribution of information gap (Ig) and engagement (En), reflecting the interplay between perceived cognitive deficits and motivational energy. The model is expressed as:

$$Stu[t] = (\alpha_{Stu} \cdot Ig[t] + (1 - \alpha_{Stu}) \cdot En[t]) \quad (13)$$

The information gap (Ig) component quantifies the learner’s recognition of missing or ambiguous information, which generates curiosity and a drive to reduce uncertainty. A higher Ig thus increases Stu , signifying intensified curiosity tension that can either motivate exploration or, if excessive, provoke frustration. Engagement (En) serves as a regulatory factor that channels uncertainty toward constructive inquiry; active engagement helps learners tolerate ambiguity and persist in information-seeking, while low engagement amplifies anxiety and disengagement. The parameter α_{Stu} modulates the balance between cognitive tension (driven by Ig) and motivational regulation (supported by En), determining whether uncertainty fosters exploration or avoidance. Conceptually, this formulation captures short-term uncertainty as a dynamic equilibrium—an optimal level of ambiguity that sustains curiosity without overwhelming cognitive or emotional resources, aligning with contemporary models of curiosity-driven learning [56,58].

Long-term novelty (Ltn) and long-term uncertainty (Ltu) represent the enduring components of curiosity-related cognition, describing how transient states of novelty and uncertainty consolidate over time into stable learning dispositions. These temporal constructs capture the process by which short-term fluctuations—momentary interest, surprise, or ambiguity—gradually evolve into persistent epistemic tendencies through repeated learning cycles [20,25]. Within the temporal–causal framework, both Ltn and Ltu follow first-order differential dynamics that integrate their short-term counterparts (Stn and Stu) with a learning rate η and temporal increment Δ , as expressed below:

$$Ltn[t + \Delta] = Ltn[t - 1] + \eta \cdot (Stn[t - 1] - Ltn[t - 1]) \cdot \Delta \quad (14)$$

$$Ltu[t + \Delta] = Ltu[t - 1] + \eta \cdot (Stu[t - 1] - Ltu[t - 1]) \cdot \Delta \quad (15)$$

The present formulation models long-term novelty (Ltn) and long-term uncertainty (Ltu) using structurally symmetric first-order adaptation equations for analytical tractability. This symmetry implies that both constructs integrate their short-term counterparts at comparable rates. However, empirical cognitive research suggests that novelty sensitivity and uncertainty tolerance may evolve asymmetrically over time—for example, uncertainty-related anxiety may rise more rapidly than novelty-related interest decays, or vice versa.

The symmetric formulation therefore represents a simplifying assumption that isolates structural interaction effects while preserving mathematical transparency. The framework can be readily extended to asymmetric dynamics by introducing distinct adaptation rates ($\eta_n \neq \eta_u$) or nonlinear integration terms. Exploring such asymmetries constitutes an important direction for future empirical calibration.

The evolution of Ltn reflects how repeated experiences of novelty, initially driven by sensory or cognitive stimulation, stabilize into a durable disposition toward exploration and adaptive openness. As learners continuously encounter and integrate new stimuli, short-term novelty (Stn) is gradually internalized, reducing volatility and forming a more consistent curiosity profile over time. Similarly, Ltu models how uncertainty is assimilated through learning, where exposure to manageable ambiguity enhances tolerance for cognitive conflict and supports the development of epistemic resilience. The rate of adaptation η determines how rapidly these states converge, while Δ represents the

temporal granularity of the learning process. Together, these equations formalize curiosity as a self-organizing temporal phenomenon: short-term fluctuations in arousal (novelty and uncertainty) progressively transform into stable cognitive–motivational traits that underpin sustained engagement and lifelong learning.

The present model predominantly employs monotonic and positive causal relationships to represent first-order directional influence among constructs (e.g., higher self-efficacy increasing engagement). This formulation reflects baseline theoretical tendencies rather than exhaustive psychological complexity. Empirical research indeed demonstrates non-linear and threshold effects in learning processes—for example, excessive novelty may induce anxiety, and excessive autonomy may reduce motivation when structure is insufficient.

The current linear structure therefore represents a controlled approximation that isolates dominant directional effects while maintaining analytical transparency and stability. Nonlinear extensions—such as inverted-U response functions, sigmoid activation terms, or threshold-based modulation—can be incorporated in future refinements to capture saturation, overload, or diminishing returns. The exponential environmental attenuation terms already introduce bounded nonlinearity, but additional nonlinear mappings may further enhance psychological realism in empirically calibrated versions of the model.

4.3. Parameterization and Sensitivity Analysis

The connection weights and adaptation parameters (w , α , η , γ) were not estimated from empirical learner data. Instead, they were theoretically initialized to represent proportional causal influence among related constructs. In the baseline configuration, equal weights were assigned within each aggregation group to avoid imposing unsupported assumptions about the relative dominance of predictors. This neutral initialization ensures that system behavior reflects the structure of the causal network rather than predefined weight hierarchies.

To examine whether the model’s behavior depends heavily on specific parameter choices, a sensitivity analysis was performed. Each connection weight was proportionally varied within $\pm 20\%$ of its baseline value. In addition, the adaptation rate (η) was tested within the interval $[0.05, 0.30]$, and the environmental modulation coefficient (α) within $[0.01, 10]$, covering both highly structured and highly flexible learning conditions. Across these variations, the qualitative behavior of the system remained stable. In all tested configurations, long-term novelty (L_{tn}) and long-term uncertainty (L_{tu}) converged toward bounded equilibrium states, and the relative differences among the four learning scenarios were preserved. While numerical trajectories shifted slightly, the overall dynamical patterns did not fundamentally change.

These results suggest that the observed curiosity dynamics are primarily driven by the causal architecture of the model rather than by specific numerical weight selections. Nevertheless, future research will focus on empirical calibration using real learner datasets to estimate parameters through optimization or machine learning approaches, thereby strengthening external validity.

5. Results and Analysis

To operationalize the temporal–causal model, a parameterized simulation was implemented in Python to examine the dynamic interactions among curiosity-related variables across discrete time steps ($t = 1 \dots 800$). The simulation horizon of 800 discrete time steps does not correspond to a fixed real-world temporal unit (e.g., seconds, days, or weeks). Rather, each time step represents an abstract learning iteration within the temporal–causal system. The chosen duration ensures that transient dynamics decay and equilibrium behavior can be observed across scenarios. Therefore, the term “long-term” refers to stabilized system states relative to initial fluctuations, not to a specific chronological timescale. Empirical calibration would be required to map simulation steps onto concrete instructional time units. Each construct, corresponding to the formalized factors defined in Section 4, was represented as a normalized, time-dependent array that allows for gradual change throughout the simulated learning trajectory. The model integrates both internal learner variables (e.g., intrinsic motivation, self-efficacy, autonomy) and external contextual influences (e.g., teacher–student relationships, classroom environment, socio-economic conditions) to emulate realistic educational dynamics.

The normalized range $[0,1]$ represents proportional intensity levels rather than raw empirical scores. In practice, psychological constructs such as motivation or self-efficacy are typically measured using Likert scales (e.g., 1–5 or 1–7), which can be linearly rescaled to a unit interval without altering relational structure. Thus, simulated values indicate relative magnitude (e.g., higher vs. lower intensity) rather than exact quantitative measurements. The trajectories should therefore be interpreted as dynamic tendencies (increase, stabilization, convergence), and future empirical calibration will enable direct mapping to validated psychometric scales.

Parameter initialization followed a systematic calibration strategy derived from prior temporal–causal modeling research [20,25]. Connection weights (w) were distributed evenly among contributing factors to preserve proportional causal influence, ensuring balanced propagation across the system. The coefficients α , η , and γ governed environmental sensitivity, adaptation speed, and non-linear decay, respectively. Specifically, $\eta = 0.1$ determined the rate of temporal adaptation, $\gamma = 0.5$ controlled the curvature of exponential damping, and α modulated how environmental constraints, such as classroom or socio-economic conditions, attenuate motivational variables. In this model, the parameter α serves

as a contextual modulation coefficient that determines the exponential attenuation of environmental influences, particularly those originating from the Physical Classroom Environment (Pce) and Socio-Economic Status (Ses). Mathematically, α appears in exponential decay terms such as $e^{-(\alpha \cdot (Pce[t]^Y))}$ or $e^{-(\alpha \cdot (Ses[t]^Y))}$, where it governs the rate at which environmental conditions dampen the impact of other psychological constructs. A high α value denotes a rigid and structured learning context, where contextual constraints rapidly reduce the flexibility of adaptive learning behaviors. Conversely, low α values represent open and exploratory environments, allowing for gradual modulation and sustained curiosity.

From a theoretical perspective, α embodies the degree of contextual control exerted on learners' psychological adaptability. When $\alpha = 9$, as used in Cases 1 and 2, the simulation captures a highly structured environment that restricts exploratory behavior and fosters predictability. Under such conditions, novelty may trigger initial engagement but declines quickly due to limited ambiguity. When $\alpha = 0.1$, as in Case 3, the system models a flexible and adaptive environment, enabling high exploratory activity and long-lasting curiosity—consistent with Berlyne's optimal arousal theory of curiosity [59]. Finally, when $\alpha = 0.01$, as in Case 4, environmental regulation becomes minimal, representing unstructured, ambiguous conditions where learners lack sufficient feedback for cognitive regulation, often resulting in overload or disengagement.

Thus, α functions as a tunable bridge between environmental rigidity and psychological plasticity. Adjusting α allows the model to replicate how educational structure and socio-economic pressure modulate curiosity and engagement over time, aligning with the principles of information-gap theory [2].

To explore these dynamics, four educational scenarios were defined, each representing a distinct configuration of novelty and uncertainty parameters. These cases were designed to emulate real-world learning situations that differ in structure, challenge, and environmental support. The parameter settings for all four cases are presented in Table 2.

The four cases were not constructed through arbitrary high/low assignments but through a principled mapping between contextual conditions and expected novelty–uncertainty states. Specifically:

- High novelty scenarios were defined as configurations in which factors that stimulate exploration (e.g., high prior knowledge, strong teacher support, positive peer climate, and high engagement potential) were elevated, enabling learners to perceive new information as stimulating rather than threatening.
- High uncertainty scenarios were defined as configurations in which information gaps were amplified (e.g., limited prior knowledge, low structural guidance, or high contextual ambiguity), increasing perceived cognitive tension.
- Low novelty conditions reflect repetitive, predictable, or poorly scaffolded contexts where stimulation is limited.
- Low uncertainty conditions represent highly structured environments with clear guidance and reduced ambiguity.

Thus, each case represents a theoretically informed constellation of interacting factors rather than isolated parameter shifts. Novelty and uncertainty emerge from the combined influence of these constructs within the temporal–causal network rather than from a single variable.

Table 2. Initial Values for Learning Scenarios in Educational Curiosity Modeling.

Factors	Case 1	Case 2	Case 3	Case 4
Physical Classroom Environment (Pce)	0.9	0.1	0.9	0.9
Peer Influence (Pi)	0.9	0.1	0.9	0.9
Prior Knowledge (Pk)	0.9	0.1	0.9	0.9
Personality Traits (Pt)	0.9	0.1	0.9	0.9
Resources & Campus Culture (Rcc)	0.1	0.1	0.9	0.9
Teacher Behaviors (Tb)	0.9	0.1	0.9	0.9
Technology (Tc)	0.1	0.9	0.9	0.1
Peer Dynamics (Pd)	0.9	0.9	0.9	0.1
Socio-Economic Status (Ses)	0.1	0.1	0.9	0.9
Wellness (Physical/Emotional) (Wl)	0.1	0.1	0.1	0.9
α Parameter	9.0	9.0	0.1	0.01

High parameter values indicate strong positive influence or availability of the corresponding factor, whereas low values reflect constraint or limitation. These normalized values (0.0–1.0) were chosen to represent relative intensity rather than absolute measurement, allowing comparability across scenarios.

Collectively, these four parameter configurations delineate the principal quadrants of curiosity dynamics in educational contexts—ranging from low-novelty, low-engagement states to open-ended exploratory conditions. The variation in α and associated contextual factors enables systematic investigation of how environmental structure, learner agency, and uncertainty interact to shape curiosity trajectories over time.

The temporal-causal model of educational curiosity was evaluated across four learning scenarios to observe how novelty and uncertainty evolve over time and interact with key psychological mediators such as engagement, autonomy, and self-efficacy. Each simulation case corresponds to a different constellation of environmental and personal variables defined in Section 4, and the outcomes are expressed in terms of long-term novelty (Ltn) and long-term uncertainty (Ltu). Fig. 3 presents the dynamic trajectories for these components across all cases, illustrating how variations in novelty and uncertainty generate distinct curiosity patterns and learning responses.

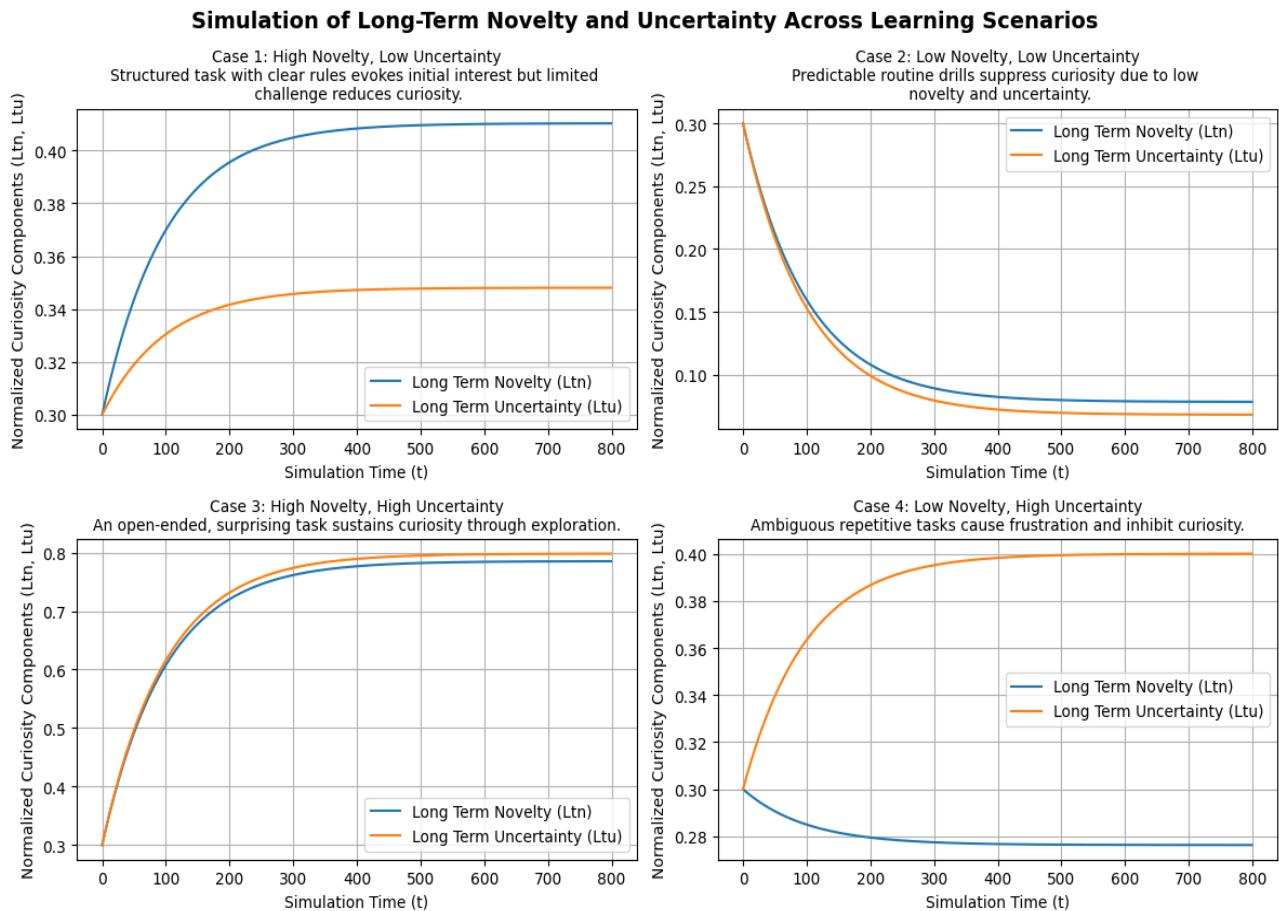


Fig. 3. Simulation of long-term novelty and uncertainty across four learning scenarios. The figure visualizes the dynamic evolution of normalized curiosity components (Ltn , Ltu) for varying educational contexts.

In Case 1 (high novelty, low uncertainty), long-term novelty exhibits an initially steep rise before stabilizing, while uncertainty remains relatively low. This represents structured yet stimulating learning conditions—such as gamified problem-solving with clear goals—where curiosity is sustained early but plateaus as predictability increases. Case 2 (low novelty, low uncertainty) reveals a rapid decline in both novelty and uncertainty, consistent with repetitive or overly guided tasks where curiosity is quickly extinguished. Case 3 (high novelty, high uncertainty) demonstrates continuous engagement and exploration: both Ltn and Ltu rise toward equilibrium at higher levels, capturing the cognitive tension that drives sustained inquiry. In contrast, Case 4 (low novelty, high uncertainty) shows divergent trends—uncertainty dominating while novelty decays—indicating frustration under ambiguous but unchallenging conditions. Together, these simulations illustrate theoretically structured dynamics from collative stimulus theory [1] and information-gap dynamics [2], in which optimal curiosity arises under moderate novelty and uncertainty.

It is important to note that the present simulations are deterministic, meaning that system trajectories are fully determined by initial conditions and parameter values without stochastic noise. The model is therefore intended as a theoretical dynamical framework that illustrates structural relationships among curiosity-related constructs rather than as a predictive behavioral model. While real learning processes involve randomness, individual variability, and contextual perturbations, the deterministic formulation enables clear examination of causal mechanisms and equilibrium properties. Incorporating stochastic terms to capture variability across learners represents a valuable direction for future work.

The proposed temporal-causal model of educational curiosity was evaluated through mathematical analysis to ensure internal consistency, equilibrium stability, and interpretive coherence. Mathematical evaluation was employed to identify equilibrium points and convergence patterns of the main psychological variables, verifying that the model

behaves as theoretically expected under various learning conditions. The analysis focuses on the stability and steady-state properties of the differential relations describing the propagation of novelty and uncertainty.

The temporal-causal structure can be expressed through a system of differential equations linking short-term experiences (Stn , Stu) to their long-term outcomes (Ltn , Ltu):

$$\frac{dLtn}{dt} = \eta(Stn - Ltn), \quad \frac{dLtu}{dt} = \eta(Stu - Ltu), \quad (16)$$

where $\eta > 0$ denotes the adaptation rate controlling how rapidly short-term changes influence long-term psychological states. The analytical examination of this system was conducted through three theoretical cases that represent distinct cognitive and motivational scenarios in the learning process.

Case 1: Steady-State Learning. Under constant stimulation ($Stn = c_1$, $Stu = c_2$), the differential equations reach equilibrium, resulting in:

$$\frac{dLtn}{dt} = 0, \quad \frac{dLtu}{dt} = 0, \quad (17)$$

and steady-state solutions:

$$Ltn^* = c_1, \quad Ltu^* = c_2. \quad (18)$$

This configuration corresponds to a stable and structured learning condition in which learners experience sustained but predictable curiosity levels. The proportional relationship between external stimulation and internal adaptation indicates that curiosity remains bounded and self-regulating—reflecting the equilibrium between motivation and environmental structure.

Case 2: Fluctuating Uncertainty. When uncertainty varies periodically to represent alternating cognitive tension ($Stu(t) = A \sin(\omega t)$), the system's response becomes:

$$Ltu(t) = \eta \int_0^t e^{-\eta(t-\tau)} Stu(\tau) d\tau. \quad (19)$$

The resulting trajectory produces damped oscillations in long-term uncertainty, meaning that high-frequency fluctuations are smoothed through adaptive learning. The exponential decay term $e^{-\eta t}$ acts as a cognitive filter that transforms transient uncertainty into a more stable long-term state. Psychologically, this dynamic captures how repeated exposure to uncertain tasks increases tolerance and sustains curiosity without causing cognitive fatigue [4,45].

Case 3: Coupled Novelty–Uncertainty Dynamics. In realistic educational settings, novelty and uncertainty evolve simultaneously, forming a coupled dynamical system:

$$\frac{dLtn}{dt} = \eta(Stn - Ltn), \quad \frac{dLtu}{dt} = \eta(Stu - Ltu). \quad (20)$$

The system's steady-state solution is:

$$(Ltn^*, Ltu^*) = (Stn, Stu), \quad (21)$$

which corresponds to a stable node when $\eta > 0$. The Jacobian matrix has eigenvalues $\lambda_1 = \lambda_2 = -\eta < 0$, confirming global asymptotic stability. Consequently, regardless of initial conditions, Ltn and Ltu converge smoothly to equilibrium values, ensuring that curiosity and uncertainty remain bounded over time. This property aligns with theoretical models of curiosity regulation in which learners integrate novelty and resolve uncertainty to achieve cognitive balance [60,61].

$$J = \begin{bmatrix} -\eta & 0 \\ 0 & -\eta \end{bmatrix} \quad (22)$$

It is important to clarify that the convergence properties identified in (20)–(22) arise from the first-order adaptive structure of the model. The stability results demonstrate internal mathematical consistency—specifically, that the system remains bounded and converges toward equilibrium under the specified parameter configuration. These properties should not be interpreted as direct evidence that real cognitive processes are linear or first-order in nature. Rather, the linear formulation provides a tractable approximation that allows examination of causal interaction patterns while ensuring analytical solvability. Psychological validity is grounded in the theoretical alignment of modeled

relationships with established curiosity and motivation theories, whereas stability analysis ensures that the computational implementation behaves coherently. Overall, the analytical outcomes demonstrate that the temporal-causal model satisfies key stability and convergence conditions. The trajectories of long-term novelty and uncertainty converge toward equilibrium points, preserving proportionality and boundedness throughout learning progression. These results demonstrate that the system exhibits mathematically self-regulating dynamics under the assumed structural formulation.

Beyond quantitative verification, logical validation was conducted through Temporal Trace Logic (TTL) to ensure that the simulated temporal-causal dynamics maintained psychological coherence and theoretical fidelity. TTL provides a rigorous framework for analyzing time-dependent propositions by verifying whether causal relations among state variables remain consistent throughout a simulated trajectory. In the present model, three logical properties (P_1 – P_3) were defined to examine whether the interactions among engagement, novelty, uncertainty, and self-efficacy reflect empirically supported learning mechanisms.

The TTL-based logical validation is not intended as an empirical test of psychological realism. Rather, it serves as a formal consistency check to verify that the temporal evolution of state variables does not produce contradictions or unintended causal reversals within the implemented network. Because certain directional relations (e.g., engagement contributing to novelty perception) are structurally encoded in the equations, TTL validation confirms that these relations remain dynamically coherent over time under varying initial conditions. Thus, TTL analysis evaluates internal logical integrity of the model rather than external behavioral accuracy.

The first property (P_1) evaluates *engagement–curiosity consistency*:

$$P_1 \equiv \forall t: (En[t] > En[t - 1]) \rightarrow (Stn[t] > Stn[t - 1]). \quad (23)$$

This condition asserts that any temporal increase in engagement must coincide with a corresponding increase in perceived novelty. The relation is grounded in Berlyne’s foundational theory of curiosity, which proposed that engagement and exploratory behavior are stimulated by collative variables such as novelty and complexity [59]. Subsequent educational research reinforces this connection: increased engagement heightens perceptual sensitivity to new or uncertain stimuli, amplifying curiosity and intrinsic motivation [62]. Thus, the logical confirmation of P_1 demonstrates that the model reproduces this well-documented motivational feedback loop between affective arousal and exploratory drive.

The second property (P_2) represents the *self-efficacy regulation of uncertainty*:

$$P_2 \equiv \forall t: (Se[t] \uparrow) \Rightarrow (Stu[t] \downarrow). \quad (24)$$

This property reflects the moderating influence of confidence on perceived uncertainty and anxiety. According to Bandura’s social-cognitive theory, individuals with high self-efficacy approach challenging or ambiguous tasks with greater assurance, thereby perceiving lower uncertainty and stress [63]. More recent studies have expanded on this principle, showing that high self-efficacy fosters adaptive emotional regulation, persistence, and curiosity-driven engagement in learning environments [64]. The validation of P_2 thus confirms that the model encodes a psychologically grounded mechanism for maintaining curiosity at an optimal level—preventing excessive uncertainty from escalating into frustration or withdrawal.

The third property (P_3) captures the *long-term convergence between novelty and uncertainty*:

$$P_3 \equiv \diamond(|Ltn[t] - Ltu[t]| < \epsilon), \quad (25)$$

indicating that, over time, the difference between long-term novelty and uncertainty approaches a small equilibrium threshold ϵ . This property aligns with Loewenstein’s information-gap theory, which defines curiosity as the drive to resolve discrepancies between what one knows and what one seeks to know [2]. As learners acquire new information and progressively close knowledge gaps, both novelty and uncertainty naturally diminish, resulting in cognitive and affective equilibrium. Empirical and theoretical extensions have confirmed this dynamic: curiosity declines as informational uncertainty resolves [62]. The satisfaction of P_3 across all simulation runs demonstrates that the system’s curiosity dynamics remain self-regulating and converge toward stable states of understanding. Collectively, the validation of these three TTL properties ensures that the model’s temporal-causal structure encodes relationships that are conceptually aligned with established psychological principles.

TTL verification therefore ensures that the simulated trajectories respect the directional constraints and regulatory patterns specified in the theoretical design. It does not constitute independent empirical validation but confirms that the implemented equations behave in accordance with the declared causal structure.

These combined simulation, mathematical, and logical results demonstrate that the proposed temporal-causal framework generates structurally consistent curiosity dynamics under the specified assumptions. The model reproduces both transient and stable phases of curiosity, showing how external conditions (novelty, uncertainty) interact with internal psychological mediators (motivation, self-efficacy, engagement). The convergence of Ltn and Ltu over time

signifies adaptive learning: curiosity initially fluctuates as learners explore, then stabilizes as knowledge integration occurs. This behavior aligns with contemporary evidence from neural and computational studies of curiosity regulation [57,65]. From an educational design perspective, these findings suggest that adaptive learning environments—particularly AI-based tutoring systems—can optimize curiosity by dynamically adjusting novelty and uncertainty to maintain learners within the “optimal exploration zone.” Thus, the temporal–causal model not only achieves theoretical coherence and mathematical stability but also provides an interpretable foundation for intelligent, curiosity-driven educational technologies.

While socio-economic status (SES) enters the model as a contextual modulation factor, equity within the framework is not limited to this single variable. The temporal–causal structure explicitly identifies multiple compensatory pathways through which educational systems can mitigate structural disadvantage. For example, enhanced teacher–student relationships (TSR), autonomy-supportive instructional practices (TB), access to technology (TC), and resource-rich campus culture (RCC) positively influence intrinsic motivation, self-efficacy, and engagement, thereby offsetting dampening effects associated with lower socio-economic conditions.

In computational terms, the model enables simulation of intervention scenarios in which contextual supports are increased to counterbalance SES-related constraints. This allows examination of how strengthening relational, technological, or motivational factors may reduce disparities in long-term novelty and uncertainty trajectories. Thus, equity is operationalized not as a static attribute but as a dynamic balancing process in which targeted environmental adjustments sustain curiosity and engagement across diverse learner profiles.

Within AI-driven adaptive systems, such modeling can inform policy by identifying which levers (e.g., autonomy support, feedback scaffolding, structured novelty exposure) most effectively compensate for contextual disadvantage. In this sense, the model contributes a structural decision-support framework aligned with SDG 4’s goal of inclusive and equitable quality education.

While the present study focuses on theoretical temporal–causal modeling, the framework can be integrated into adaptive AI tutoring architectures as a decision-support module rather than a standalone instructional system. Conceptually, integration would involve three components:

1. **State Estimation Layer:** Learner-related variables (e.g., engagement, self-efficacy, novelty perception) would be estimated in real time using behavioral analytics such as response latency, accuracy patterns, clickstream data, or self-report micro-assessments.
2. **Temporal–Causal Inference Engine:** The estimated states would serve as inputs to the temporal–causal model, which computes predicted trajectories of short- and long-term novelty and uncertainty.
3. **Adaptive Policy Layer:** Based on predicted states, the tutoring system adjusts task difficulty, scaffolding level, feedback timing, or exploratory prompts to maintain learners within an optimal novelty–uncertainty zone.

In this architecture, the proposed model functions as a structured causal regulator that informs adaptive decisions rather than directly generating instructional content. Empirical deployment would require calibration using learner datasets and reinforcement learning to optimize parameter tuning.

6. Conclusion

This study introduced an AI-based temporal–causal model of educational curiosity, bridging cognitive theory and computational simulation to explain how novelty and uncertainty co-evolve with motivation, engagement, and self-efficacy in learning contexts. The model successfully reproduced the dynamic interplay between affective and cognitive mechanisms that underlie curiosity, showing mathematically stable and logically consistent trajectories across diverse educational conditions. Simulation results revealed that curiosity follows a self-regulating pattern: it is heightened by balanced novelty and moderate uncertainty but declines when stimuli become either overly predictable or overwhelmingly ambiguous.

Mathematical and TTL analyses verified the model’s stability, boundedness, and psychological fidelity, indicating that long-term novelty and uncertainty converge toward adaptive equilibrium. These outcomes align with recent computational and neuroscientific evidence suggesting that curiosity operates as a feedback-controlled system promoting optimal exploration and sustained engagement.

Beyond theoretical validation, the findings underscore practical implications for AI-based educational design. Adaptive systems can leverage such models to regulate novelty and uncertainty, thereby dynamically personalizing challenges, fostering engagement, and preventing disengagement or overload. Moreover, by incorporating socio-economic and environmental parameters, the model provides a structural framework for analyzing intervention strategies aligned with UN SDG 4, emphasizing inclusivity, motivation, and lifelong curiosity.

Future research should extend this framework through empirical validation using learner data, hybridizing temporal–causal modeling with neural architectures and reinforcement learning. Such integration will deepen understanding of curiosity-driven learning mechanisms and inform the development of next-generation AI tutors capable of sustaining curiosity as a central engine of human learning and growth.

All the Declarations and Statements

Author Contributions Statement

Billel Arbaoui – Conceptualization, Methodology, Formal Analysis, Software, Validation, Writing – Original Draft, Writing – Review & Editing, Visualization, and Supervision: Proposed the research idea; developed the theoretical and temporal-causal modeling framework; designed and implemented the computational simulations; conducted mathematical stability and logical (TTL) analyses; interpreted the results; wrote and revised the manuscript; and supervised the overall research process.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

None.

Data Availability Statement

The datasets generated or analyzed during the current study are available from the corresponding author upon reasonable request.

Ethical Declarations

Not applicable.

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Declaration of Generative AI in Scholarly Writing

Generative AI was used only to improve language and readability, with full human oversight and review, and the authors take complete responsibility for the content.

Abbreviations

The following abbreviations are used in this manuscript:

AI - Artificial Intelligence
At - Autonomy
En - Engagement
Ig - Information Gap
Im - Intrinsic Motivation
Ltn - Long-Term Novelty
Ltu - Long-Term Uncertainty
NCT - Novelty Categorization Theory
Np - Novelty Perception
Pce - Physical Classroom Environment
Pd - Peer Dynamics
Pi - Peer Influence
Pk - Prior Knowledge
Pt - Personality Traits
Rcc - Resources & Campus Culture
SDG - Sustainable Development Goal
Se - Self-Efficacy
Ses - Socio-Economic Status
Stn - Short-Term Novelty
Stu - Short-Term Uncertainty
Tb - Teacher Behaviors
Tsr - Teacher-Student Relationships
TTL - Temporal Trace Logic
UN - United Nations
Wl - Wellness

Appendix

None.

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