

Game Mechanics as A Tool for Forming Cognitive Models of User Decision-Making

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Received: 29th Dec2025 | Received Revised Version: 04th Jan 2026 | Accepted: 29th Jan 2026 | Published: 21th Feb 2026

Volume 08 Issue 02 2026 | Crossref DOI: 10.37547/tajet/Volume08Issue02-14

Abstract

The article examines game mechanics as structural devices that shape cognitive models of decision-making rather than as entertainment-oriented rules. Relevance follows from the growing use of interactive systems where user choices emerge under uncertainty, time pressure, and reward contingencies, making the cognitive imprint of mechanics a design concern. Novelty consists in treating mechanics as cognitive interfaces that configure attention, inference, and action selection through repeated feedback cycles. The study aims to build an analytic account of how mechanic families (action-oriented and system-oriented) cultivate distinct decision strategies—reactive, planning-based, probabilistic, and systemic—through a stable core loop. The article applies analytical synthesis of recent research on game-based assessment, task-attention mechanisms, uncertainty management, and gamified system design. Results articulate a mechanics-to-model mapping that links feedback, constraints, and reward schedules to internal causal beliefs, risk heuristics, and transfer-ready strategies. The article targets researchers and designers working with gameful and decision-centric digital products.

Keywords: *game mechanics, decision-making, cognitive models, core loop, risk and reward, uncertainty, heuristics, attention, feedback, serious games.*

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Cite This Article: Petrov, M. (2026). Game Mechanics as A Tool for Forming Cognitive Models of User Decision-Making. The American Journal of Engineering and Technology, 8(2), 146–152. <https://doi.org/10.37547/tajet/Volume08Issue02-14>

1. Introduction

Game mechanics operate as structured interaction regimes that guide how users interpret signals, allocate attention, and select actions across repeated cycles. In decision-centric play, the user rarely receives explicit instructions about optimal behavior; instead, the system encodes causal hypotheses through constraints, feedback latency, reward schedules, and state transitions. Over

time, these elements cultivate internal models of “what causes what,” “what is worth doing next,” and “how risky a move is,” which later generalize to adjacent tasks that share similar informational structure. A central analytic target is the core loop as a repeatable cognitive schema: perception of state → evaluation of affordances → choice → feedback → belief update. Action-oriented structures privilege rapid stimulus–response coupling and short feedback horizons, often strengthening reactive control and fast heuristic choice. System-oriented

structures privilege planning, multi-step anticipation, and dependency tracking, strengthening mental simulation, probabilistic reasoning, and policy selection under uncertainty.

The purpose of the article is to explain how different mechanic families form different decision models and why the core loop functions as a stable scaffold for attention, learning, and transfer beyond the immediate game. The tasks are:

- 1) to derive an analytic mapping between mechanical properties and cognitive operations that underpin choice;
- 2) to describe how core-loop repetition forms internal causal, risk, and reward representations;
- 3) to synthesize design implications for building gameful systems that cultivate planning-based, probabilistic, or systemic decision strategies.

Novelty is expressed through an integrated mechanics-to-model framework that treats mechanics as cognitive interfaces that bias inference and action selection across repeated feedback cycles.

2. Materials and Methods

The material base consists of recent empirical reviews and design frameworks that connect gameplay structures with attention, learning, assessment, uncertainty management, and decision facilitation in gameful systems: A. Bijl [1] analyzes serious games in high-stakes assessment settings; J. Cutting [2] develops task-attention theory explaining how attentional selection during gameplay modulates learning; D. Gyaurov [3] synthesizes design frameworks and gameplay features that promote engagement and problem-solving under uncertainty; W. Huang [4] reviews gamified project-based learning research and its outcomes; T.J. Irabor [5] investigates serious-game use for systems thinking and decision formation; K. Ishaq [6] reviews personalized gamification evidence in learning settings; F. Naseer [7] proposes an AI-personalized framework integrating leveling, badges, and feedback; A. Schönbohm [8] connects serious gaming with strategic decision facilitation in crisis contexts; P. Siriaraya [9] presents a dual-loop design framework centered on the core-game loop; H. Yuan [10] reviews decision-making in repeated games through the lens of active inference and related cognitive mechanisms.

For writing the article, analytical synthesis and comparative analysis were applied, supplemented by structured source analysis, conceptual modeling, and

cross-source triangulation to align mechanical constructs with attention, inference, learning, and policy-selection processes.

3. Results

Across the reviewed literature, a convergent line appears: gameful systems elicit observable choices that reflect latent cognitive operations, yet those operations are not free-floating; they are shaped by mechanical constraints that define what information becomes salient, how quickly feedback arrives, and how future states depend on present actions. Serious games used for assessment provide a clear illustration: in-game behaviors can serve as performance indicators when the environment and task are authentic and when gameplay freedom and feedback are tuned to elicit capability-relevant behavior [1]. This positions mechanics as instruments that do more than reward activity; they can stabilize a cognitive model that a user relies on when selecting actions in recurring situations.

A first result is a mechanics-to-operations mapping that links mechanic families to clusters of mental operations that repeatedly activate within the core loop. Task-attention theory supports the claim that what players learn is moderated by what they attend to, and attentional selection is influenced by the demands and structure of tasks embedded in gameplay [2]. Mechanically, salience is not only visual; it is also functional: timers, scarcity, loss conditions, and reward gradients redirect information sampling toward action-relevant cues. When a loop repeatedly privileges “fast cue → immediate consequence,” the internal model that forms tends to compress state representations into a small set of diagnostic signals, supporting reactive choice and satisficing. When a loop privileges delayed outcomes, multi-step dependencies, and state persistence, the internal model expands toward causal graphs and policy sequences that require forward simulation, counterfactual testing, and contingency planning [3].

A second result concerns uncertainty management. A framework synthesis focused on uncertain gameplay scenarios indicates that specific gameplay feature configurations promote engagement while enabling complex problem-solving under uncertainty [3]. Under uncertainty, mechanics that expose partial information, enforce opportunity costs, or implement stochastic transitions push users toward probabilistic belief updating and exploration-exploitation control. In repeated decision environments, cognitive accounts

grounded in active inference emphasize inference over hidden states, policy selection, learning from outcomes, and adaptation under social or environmental uncertainty [10]. When mechanics embed repeated cycles with stable priors (consistent reward logic) and informative prediction errors (feedback that meaningfully updates beliefs), they train users toward model-based control where actions are selected to reduce uncertainty or secure expected value, depending on the structure of costs and rewards [10].

A third result distinguishes action-oriented and system-oriented mechanical structures as producing distinct decision styles through distinct feedback geometries. Action-oriented mechanics commonly compress the horizon: the user evaluates a narrow window of consequences, leading to rapid action selection, attentional filtering, and error correction via short-latency feedback. System-oriented mechanics expand the horizon: the user tracks resource stocks, delayed payoffs, and interdependent variables, developing causal attribution, planning, and risk aggregation through slower feedback and stronger state persistence [3]. Evidence from gamified learning research indicates that design choices that support sustained engagement and learning frequently rely on progress visibility, structured feedback, and coherent challenge–skill calibration, with

outcomes depending on how elements are combined and personalized [4], [6]. In this analytic frame, personalization does not merely alter motivation; it can reshape the cognitive model by changing which cues are diagnostic and which strategies remain viable under the user’s current constraints [7].

A fourth result concerns the core loop as a cognitive scaffold. Design work in mental health gamification formalizes a dual-loop view in which an intervention loop is integrated with a game loop, enabling designers to align game structure with target psychological processes [9]. Reframed for decision modeling, the core loop becomes the repeated cognitive routine that enforces how beliefs and preferences are updated. If feedback is immediate and unambiguous, the loop strengthens associative learning and stable heuristics. If feedback is delayed, noisy, or contingent on multi-step policies, the loop strengthens hypothesis testing, counterfactual reasoning, and strategic planning [2], [10]. In high-stakes decision facilitation contexts, serious games can provide a controlled environment that supports decision processes by externalizing complex tradeoffs and allowing safe exploration of alternatives, effectively making the core loop a rehearsal space for strategic cognition [8].

Figure 1 is integrated below as a compact conceptual scheme aligned with the reviewed models.

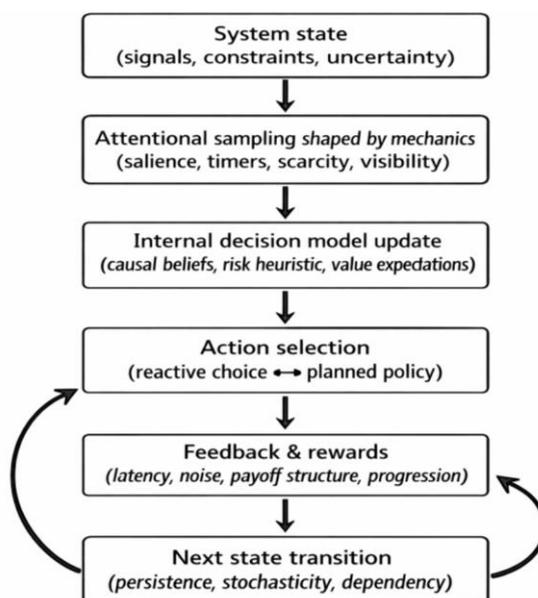


Figure 1. Mechanics-to-Model Core Loop for User Decision-Making (adapted from dual-loop core-game-loop design and task-attention accounts) [2], [9]

This scheme encodes a specific analytic claim: mechanics govern not only what users do, but what they infer. By shaping attentional sampling [2], mechanics determine which state variables enter the internal model, and by shaping feedback reliability and timing [9], they determine how strongly prediction errors revise beliefs [10]. The action-selection stage is where the action-oriented versus system-oriented distinction becomes legible: rapid-response systems compress deliberation and amplify cue-reactivity, whereas systems that enforce resource coupling and delayed consequences stimulate planning and policy comparison [3].

A fifth result concerns transfer and decision generalization. When mechanics repeatedly require users to track dependencies and anticipate delayed outcomes, the internal model tends to encode higher-order relationships (conditional rules, resource constraints, and tradeoff surfaces). Studies of gamified and game-based learning suggest that learning outcomes and cognitive gains depend on design coherence and sustained engagement, with personalization moderating effectiveness through fit between user characteristics and mechanic configuration [4], [6]. For decision modeling, the implication is precise: transfer is more plausible when the mechanic-imposed decision structure resembles the target structure outside the game—uncertainty type, feedback delay, and cost geometry—because the internal model learned in the core loop retains those structural priors. Systemic decision shifts observed in serious games focused on systems thinking similarly indicate that gameplay can reorient users from short-horizon choices toward long-horizon, interconnected reasoning when the mechanics repeatedly reward consideration of system-wide consequences [5].

Finally, the reviewed crisis-decision facilitation literature supports the view that serious gaming can function as a structured medium for strategic reasoning, enabling users to experiment with alternatives and observe consequences in a controlled setting [8]. Within the present analytic framework, that facilitation effect arises from mechanics that externalize hidden dependencies, make tradeoffs perceptible, and enforce iterative belief revision through the core loop. Taken together, the results establish that game mechanics act as cognitive interface structures: they parameterize attention, encode causal

hypotheses through feedback, and stabilize decision policies via repetition under uncertainty.

4. Discussion

The analytic synthesis supports a design-oriented interpretation: mechanics shape decision cognition through three coupled levers—attentional governance, feedback epistemics (how informative outcomes are), and horizon control (how far ahead the user must reason). Task-attention theory implies that attentional selection mediates what is learned from gameplay, so mechanics that control salience and sampling effectively control which features become “decision-relevant” in the user’s internal representation [2]. Systematic synthesis of uncertain gameplay features indicates that uncertainty-facing mechanics can be arranged to foster engagement while training problem-solving behaviors that resemble real-world ambiguity management [3]. In decision facilitation domains, serious gaming is positioned as a structured environment that enables safe exploration and rehearsal of strategic choices [8], aligning with the idea that mechanics can serve as cognitive scaffolding rather than merely decorative gamification.

Textual evidence across gamified learning reviews cautions that element lists alone are insufficient; outcomes depend on how elements combine and how they fit the learner or user [4], [6]. The AI-personalized mechanics framework strengthens this point by formalizing how feedback and progression can be tuned to individual trajectories [7]. In decision-model terms, personalization modifies the effective reward landscape and cue diagnosticity, which changes which heuristics appear successful and which policies the user adopts. The dual-loop framing around a core-game loop offers a practical bridge: it forces alignment between target psychological processes and the operational loop that users repeatedly execute [9].

The discussion specifies the comparison criterion used in the mapping: mechanics are classified by the dominant cognitive control they induce inside the loop—reactive (cue-driven), planning (sequence-driven), probabilistic (uncertainty-driven), or systemic (dependency-driven) (Table 1).

Table 1. Mechanic Families and the Dominant Cognitive Operations They Induce [2; 3; 5–10]

Mechanic family (examples)	Induced cognitive operations	Expected decision strategy profile
Time pressure, rapid feedback, combo streaks	attentional narrowing, fast cue utilization, error-driven adjustment	reactive, heuristic, short-horizon choice
Resource coupling, delayed payoffs, multi-step objectives	forward simulation, dependency tracking, tradeoff evaluation	planning-based, policy comparison
Partial information, stochastic transitions, fog-of-war analogs	probabilistic belief updating, exploration–exploitation regulation	probabilistic, adaptive strategy switching
System dashboards, interlocked variables, externalized causal links	causal attribution, model construction, long-horizon reasoning	systemic, integrative decision formation
Progression gates, adaptive difficulty, personalized feedback	calibration of effort, value learning, strategy stabilization under fit	individualized policy selection, persistence
Dual-loop intervention/game alignment	alignment of loop actions with the target cognitive process	structured cognitive rehearsal

Action-oriented families favor compressive representations and fast heuristic choice, while system-oriented families promote expansive representations that encode dependencies and delayed consequences. The probabilistic family sits between them, translating uncertainty into a demand for belief management and exploration policies, consistent with active-inference decision accounts in repeated games [10].

The discussion turns to operationalization: if mechanics form cognitive models, evaluation should focus on mechanism-aligned indicators rather than generic engagement. High-stakes assessment reviews indicate that in-game behaviors can reflect competencies when task authenticity and feedback design are adequate [1]. That provides a basis for proposing measurement proxies aligned with each cognitive operation (Table 2).

Table 2. Design Implications for Decision-Model Formation and Suggested Analytic Indicators [1–3; 5–10]

Design intent	Mechanic configuration implication	What the internal model should encode	Analytic indicators commonly discussed in the literature
Train reactive choice under pressure	short feedback latency, tight timers, clear success signals	cue–action associations, fast error correction	response-time distributions; error recovery patterns
Train planning and policy selection	delayed rewards, persistent state, explicit opportunity costs	multi-step causal chains, value of future states	sequence planning depth; policy consistency over trials

Train uncertainty reasoning	partial observability, stochastic outcomes, informative feedback	beliefs over hidden states; exploration policies	exploration rates; strategy shifts after prediction errors
Train systemic reasoning	interlocked variables, visible system dynamics, long-horizon scoring	causal models of dependencies; tradeoff surfaces	attribution patterns; stability of long-horizon choices
Sustain learning via fit	adaptive difficulty and personalized feedback	calibrated effort–value expectations	persistence under challenge; performance–engagement coupling
Align the loop with the target process	explicit loop mapping to intended cognition	Repeated rehearsal of target mental operations	coherence between loop actions and target outcomes

Two implications follow. First, mechanics should be selected by the cognitive form they impose on the loop, not by surface popularity; otherwise, the induced model can diverge from the intended decision competence. Second, analytic evaluation can remain non-experimental yet disciplined by tracing which loop constraints produce which observable choice regularities, drawing on assessment-oriented reasoning about in-game indicators and authenticity. In applied design, the dual-loop lens helps prevent category errors where reward and progression amplify engagement but fail to cultivate the intended inference pattern.

5. Conclusion

The first task is resolved through a mechanics-to-operations mapping that links mechanic families to attention control, belief updating under uncertainty, and policy selection regularities. The second task is determined by treating the core loop as a repeated cognitive routine in which feedback timing and informativeness shape causal beliefs, risk heuristics, and value expectations, consistent with dual-loop and repeated-game decision accounts. The third task is resolved through design implications and analytic indicators that show how action-oriented structures stabilize short-horizon heuristics, while system-oriented structures stabilize planning and systemic reasoning; personalization alters the effective reward landscape and, therefore, the selected decision policies.

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