

Convergence of Automatic Operations to Controlled Operations via Internal Capacity Building

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Abstract

Despite the extensive literature on dual-process theories of cognition, there remains limited understanding of how automatic operations (System 1) can converge toward controlled operations (System 2) over time, and under what conditions such alignment improves individuals' quality of life. This study addresses this gap by developing a nonlinear dynamic model of automatic-controlled system interaction, drawing on expectancy-disconfirmation theory and behavioral frameworks such as prospect theory. Methodologically, we formulate a first-order nonlinear difference equation to capture the updating of automatic processes based on discrepancies with controlled goals. Using stability analysis, we identify conditions under which individuals' automatic operations converge to their controlled operations, and when they instead exhibit cyclical or unstable patterns. To extend the model, we incorporate an internal capacity building (or "internal work") parameter that reflects practices such as mindfulness, boundary setting, and present-moment awareness. Our analytical results reveal significant heterogeneity: some individuals naturally achieve convergence, while others require internal work to reach stable alignment. Increasing internal work expands the proportion of individuals whose automatic operations converge with their controlled system, effectively shifting cognitive processing toward greater deliberation. The implications are twofold. Theoretically, this research contributes a mathematical framework for linking internal psychological processes with dual-system models of cognition. Practically, it highlights the potential of capacity-building interventions—such as mindfulness-based practices—to foster self-alignment, enhance autonomy in decision-making, and improve overall well-being.

Keywords

Quality of Life, Internal Capacity Building, Dual-Process, Stability Analysis,

1. Introduction

Human decision-making involves an ongoing interplay between automatic impulses and deliberate control. A person may instinctively reach for unhealthy food, respond defensively to criticism, or buy a product on impulse. At the same time, the same individual aspires to act according to higher-order goals such as maintaining health, cultivating good relationships, or managing finances responsibly. This tension between the automatic and the deliberate is at the heart of both psychological theories of cognition and marketing theories of consumer behavior.

As revisited by Csikszentmihalyi (1990), people who learn to control inner experience will be able to determine the quality of their lives, which is as close as any of us can come to being happy. When a person feels in control of life and feels that it makes sense, there is nothing left to desire, the person can listen and stay emotionally balanced in the face of every event in life. In other words, aligning our automatic impulsive system to conscious operations will be able to improve the quality of life.

The dual-process framework, popularized by Kahneman (2011) and refined by Evans and Stanovich (2013), distinguishes between two broad systems. System 1 is fast, intuitive, and emotional. System 2 is slower, effortful, and logical. While both systems are essential, conflicts between them create inconsistencies in behavior. Although the literature richly describes the two systems, less attention has been devoted to the dynamics of alignment: under what conditions does System 1 gradually adapt to System 2? How can impulsive tendencies be shaped so they support deliberate goals?

Marketing research on expectancy-disconfirmation (Anderson, 1973; Oliver, 1980; Parasuraman et al., 1985) provides an analogy: consumers compare products to expectations. We extend this analogy to the intrapersonal level. Automatic operations are like performance, deliberate goals like expectations. Disconfirmation dynamics shape cognition, just as they shape consumer evaluations.

The contribution of this paper is fourfold: 1) we develop a nonlinear dynamic model of automatic-to-controlled convergence, 2) we identify heterogeneity between stable and oscillating individuals, 3) we introduce internal work as a parameter that expands convergence, and 4) we provide cross-disciplinary insights linking marketing, psychology, and management.

2. Literature Review

Our work builds on and integrates four streams of research: 1) dual-process theories in psychology, 2) expectancy-disconfirmation models in marketing, 3) reinforcement learning and cognitive dynamics, and 4) internal work and mindfulness. Together, these literatures provide the foundation for our dynamic model of

convergence between automatic and controlled operations.

Research on dual-process theories has established a central distinction in human thought. [Kahneman \(2011\)](#) describes System 1 as fast, intuitive, and effortless, while System 2 is slow, deliberate, and effortful. This division explains why people can make quick judgments in familiar settings but struggle in unfamiliar or complex environments. [Evans and Stanovich \(2013\)](#) refine these ideas, arguing that dual-process models should not only contrast intuition and reasoning but also consider the conditions under which each system dominates.

Dual-process theories are widely applied to explain consumer and managerial biases: heuristics, framing effects, and myopic choices often emerge from System 1 dominance. Yet these theories remain largely descriptive. They tell us that the two systems exist and differ, but not how dynamically interact over time. What remains unclear is whether, and under what conditions, System 1 can be “trained” by System 2 to align impulses with deliberate goals. Our model addresses this gap by embedding dual-process cognition in a dynamic updating framework, enabling formal analysis of convergence and oscillation.

In marketing, Expectancy-Disconfirmation Theory (EDT) has been central for decades. [Anderson \(1973\)](#) and [Oliver \(1980\)](#) argue that satisfaction depends on the gap between expectations and actual performance. [Parasuraman et al. \(1985\)](#) extend this to service quality, showing how consistent under- or over-performance influences loyalty.

Recent research refines these ideas. [Rust et al. \(1999\)](#) emphasize that distributions of expectations matter: customers evaluate not only mean performance but also variance. [Evangelidis and Van Osselaer \(2018\)](#) highlight the role of common versus distinctive attributes in generating disconfirmation, while [Peña-Marin and Wu \(2019\)](#) show that imprecise expectations may paradoxically increase trust by making disconfirmation less damaging.

EDT thus provides a rigorous model of how consumers evaluate firms over time. Yet this literature has remained focused on external interactions between consumers and firms. Our contribution is to adapt the same logic inward: just as customers compare products to expectations, individuals compare automatic responses to deliberate standards. This intrapersonal disconfirmation is, to our knowledge, not yet modeled, but it opens a new perspective linking marketing science to psychology.

The Rescorla-Wagner rule ([Rescorla & Wagner, 1972](#)) posits that associative learning follows an error-correction process: expectations are updated proportionally to the difference between predicted and actual outcomes. This principle has shaped decades of research in psychology, neuroscience, and decision sciences ([Sutton & Barto, 1998](#)).

In decision-making contexts, [Busemeyer and Stout \(2002\)](#) applied RL to the Iowa Gambling Task, decomposing behavior into learning-rate components. [Yechiam and Busemeyer \(2005, 2008\)](#) compared alternative assumptions in experience-based decision-making, showing that memory and learning rate critically

shape outcomes. Meta-analyses (Wulff et al., 2018) confirm systematic differences between description-based and experience-based learning, further highlighting the role of updating dynamics.

We further link the model to control-theoretic intuitions via a target-adjustment mechanism (“internal work”), consistent with recent tutorial bridges from control models to cognition (e.g., Smith et al., 2022).

Our emphasis on stability and identifiability resonates with work on model identifiability in cognitive modeling (Moran, 2016). Moreover, it links dynamics to testable cognitive invariants (e.g., Robinson et al., 2023).

Our model draws directly on this tradition. We interpret a memory parameter as analogous to a learning rate: low memory means heavy weighting of recent experiences (volatile adjustment), while high memory means smoothing across history (stable adjustment). This interpretation links our model to a large body of empirical work on learning parameters and provides testable predictions about heterogeneity in convergence.

A final stream of literature concerns internal work, broadly defined as practices that build self-awareness, resilience, and reflective capacity. In psychology, Brown and Ryan (2003) show that mindfulness enhances well-being by fostering present-moment awareness. Kabat-Zinn (2005) developed Mindfulness-Based Stress Reduction (MBSR), which has been applied in clinical, organizational, and educational settings. More recently, Maymin and Langer (2021) argue that mindfulness systematically reduces cognitive biases by shifting individuals toward more deliberate processing.

Kauffman (2012) describes the Yemima Method, a structured awareness practice with psychological and spiritual roots, emphasizing self-regulation and personal growth. From a managerial perspective, mindfulness has been linked to employee resilience, decision quality, and leadership effectiveness.

Despite this growing evidence, formal modeling is limited. Existing research documents benefit but do not explain how internal work changes cognitive dynamics. Our contribution is to embed internal work as a parameter in a dynamic system, showing mathematically how it expands the region of convergence between System 1 and System 2. This bridges practical interventions with formal modeling.

Taken together, these four streams highlight both insights and gaps. Dual-process theories explain cognitive differences but not dynamics. Expectancy-disconfirmation formalizes updating but only in consumer-firm contexts. Reinforcement provides mathematical tools but is rarely applied to intrapersonal alignment. Mindfulness shows benefits but lacks formal integration.

By uniting these literatures, our paper provides a new framework for understanding how individuals achieve—or fail to achieve—harmony between automatic impulses and deliberate goals. The dynamic model presented in the next section builds directly on these foundations.

Recent contributions further refine dual-process and cognitive-control theories by modeling how attention and effort dynamically allocate between automatic and

deliberative systems (see also [Robinson et al., 2023](#)). Integrating these advances strengthens the bridge between our dynamic formulation and current neuroscience-inspired approaches that quantify learning, control allocation, and convergence processes.

3. The Dynamic Model

To explain how automatic operations (System 1) adjust in response to controlled operations (System 2), we build a dynamic model grounded in expectancy-disconfirmation logic and reinforcement learning. The model highlights three central building blocks: 1) the updating mechanism, 2) the stability condition, and 3) the effect of internal work. Each is formalized in a simple equation and motivated with analogies from consumer behavior, psychology, and management.

3.1. Updating Mechanism: The Core Adjustment Process

At the heart of our model is the idea that automatic responses do not remain static. They evolve over time as individuals repeatedly compare their impulses to their deliberate goals. If automatic behavior falls short of deliberate standards, System 2 exerts corrective pressure; if it exceeds, System 2 may relax standards or adjust expectations. We capture this with the updating equation:

$$x_{t+1} = f(x_t) = x_t + (1 - \lambda)g(Y - x_t). \quad (1)$$

where, x_t is the automatic operation at time t , Y is the controlled standard, and λ is a memory parameter, $\lambda \in [0, 1)$, more exactly, $(1 - \lambda)$ captures the weight ascribed to the effect of disconfirmation gap, similar to the learning rate parameter in computational models of learning (see [Collins & Shenhav, 2021](#) for a review). The function $g(\cdot)$ transforms the gap between deliberate and automatic processes into an adjustment term. To be consistent with prospect theory (i.e., loss aversion; [Kahneman & Tversky, 1979](#)), the gap function must be asymmetric, i.e., negative gap (loss) is weighed more heavily than positive gap (gain). Such asymmetric properties were also considered, for example, for reference-price effects by [Fibich et al. \(2003\)](#).

A potential functional form g could be,

$$g(Y - x(t)) = \begin{cases} k \left[(Y - x(t)) + c(Y - x(t))^b \right], & Y - x(t) \geq 0 \text{ (positive gap)} \\ -k \left[(x(t) - Y) + c(x(t) - Y)^a \right], & \text{otherwise} \end{cases},$$

with $k > 0$. We specified the gap function g as a nonlinear function of a satisfying experiences (in the case of $Y - x(t) \geq 0$) or a dissatisfying experiences (otherwise). This function can be approximated by combining two additive parts, one linear and one (the residual) nonlinear component¹. Whereas the former represents the direct effect of experienced gains or losses, the nonlinear component

¹The specific proposed approximation of the nonlinear updating function also has some favorable mathematical properties because the linear component with the same slope around the equilibrium $Y = x$ makes the gap function g differentiable at this point.

accounts for the concavity of the gain and the convexity of the loss function. We posit, and develop intuitions in our subsequent analyses, that the idiosyncratic scale factor k (which corresponds to $g'(0)$), relates to an individual's general sensitivity to disconfirmation (gap) between expectations and observed (perceived) quality performances (i.e., satisfying or dissatisfying experiences), while the correction factor c indicates an individual's degree of loss-averse behavior. The parameter c also reflects the role or the importance that an individual attaches to the specific product/service class under consideration. Notice that when c moves toward zero, the effect of the second component of the gap function vanishes, while large absolute values of c mean that the nonlinear part of the updating function clearly dominates the linear effect. Thus, the interaction or cross-effect of k with c acts as a scale factor for the effect sizes of the disconfirmation gap on the expectation updating process, where increasing k and decreasing absolute values of c exert a larger overall updating effect.

In **Figure 1**, we plot the mapping of the gap function on the vertical axis (the updating effect) in response to negative/positive disconfirmation on the horizontal axis for two illustrative parameterizations of c and k .

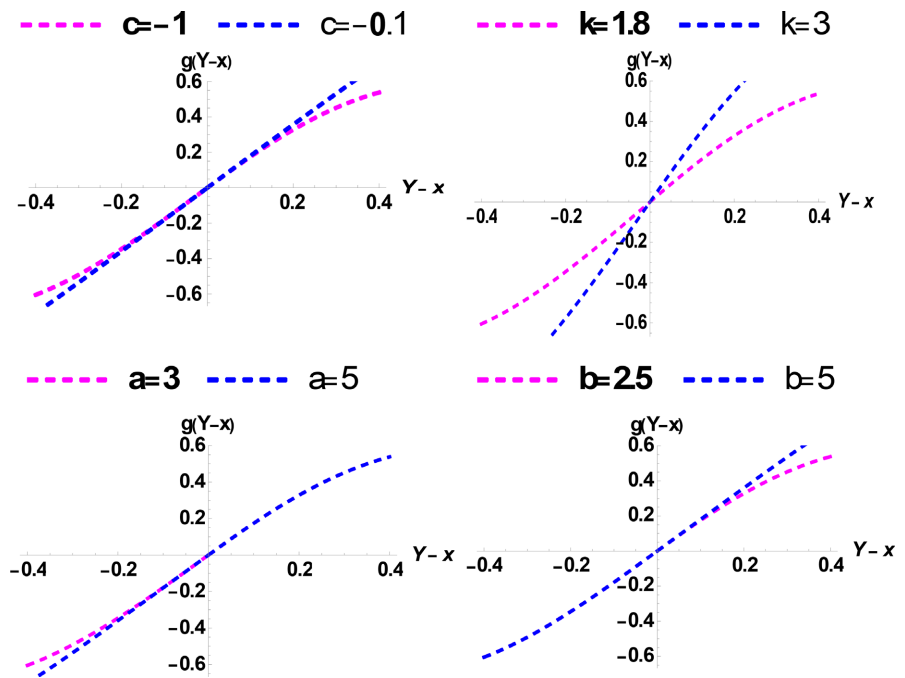


Figure 1. The effect of the parameters on the gap function.

The parameters a and b (with the constraint that $a > b$) are responsible for making the gap function consistent with prospect theory, i.e., diminishing marginal effects and loss aversion. As can be seen from the graphs in the second row of **Figure 1**, to be consistent with prospect theory, smaller values of a and b lead to a decay of the relative loss or gain effects, respectively. To fulfill property, losses weigh more than gains, we require that $a > b$ for $|Y-x| < 1$, thus in a small enough neighborhood of Y .

To avoid singularity of the second derivative of g with respect to x when $x = Y$, we need $a > b > 2$. In addition, our scaling factors are required to be $k > 0$ and $c < 0$. Let K be the parameter space of g . Then,

$$K = \{(k, c, b, a) : k > 0, 2 < b < a, c < 0\}.$$

Note that Equation (1) is a generalization of delta learning rule, also known as Rescorla-Wagner rule (Rescorla & Wagner, 1972), that has been employed in connectionist theories of learning (Gluck & Bower, 1988; Rumelhart et al., 1986; Sutton & Barto, 1998), IGT studies (e.g., Busemeyer & Stout, 2002; Yechiam & Busemeyer, 2005), and binary choice studies (Yechiam & Busemeyer, 2008). Other reinforcement-learning models include Ahn et al. (2008) and Steingroever et al. (2013). Similar conceptualizations to (1) were used in marketing literature by Oliver (1980), Sivakumar, Li, and Dong (2014), and recently by Fruchter et al. (2023).

In the current model, Equation (1) reflects a fundamental principle: learning is discrepancy-driven. Automatic behavior updates in proportion to the difference between what “is” and what “should be”. These parallels consumer learning models, where customers adjust expectations after comparing product performance with prior beliefs. If λ is low, individuals overweight recent experiences: a single gap between impulse and goal provokes a strong reaction. If λ is high, individuals smooth across time: a single discrepancy is not enough to shift behavior.

The gap function $g(\cdot)$ reflects sensitivity. A steeper slope implies higher responsiveness, while asymmetry captures loss aversion—negative gaps (impulse < goal) weigh more than positive ones.

This mechanism mirrors how consumers evaluate brands. A customer who is highly reactive (low λ) may churn after one bad service encounter. Another with greater memory (high λ) integrates experiences and remains loyal despite fluctuations. Similarly, individuals differ in how much they let single impulses derail their longer-term standards.

In self-regulation, the updating rule parallels how people adapt habits. Someone trying to quit smoking may relapse after a single stressful event if they react too strongly (low λ), while another with greater resilience (high λ) maintains progress despite setbacks. The discrepancy-driven update thus generalizes across domains.

Alternative alignment pathways, such as procedural learning and habit formation through repetition, can also lead to stability by gradually automatizing deliberate responses. However, the present model adopts a discrepancy-driven mechanism because it provides an analytically tractable link between perceived gaps, adjustment strength, and convergence behavior. This formulation captures the essence of expectancy-disconfirmation and reinforcement-learning principles while remaining flexible enough to incorporate slower habit dynamics in future extensions.

3.2. Stability Condition: Convergence versus Oscillation

While Equation (1) explains how adjustments occur, the key question is whether

these adjustments lead to stability. Do automatic operations settle at alignment with deliberate goals, or do they overshoot and oscillate indefinitely? Linearizing around the fixed-point x^* yields the stability condition:

$$\left| 1 - (1 - \lambda)g'(Y - x^*) \right| < 1. \quad (2)$$

This inequality specifies when convergence occurs. If adjustments are too aggressive (steep $g'(\cdot)$, small λ), the system overshoots. Automatic responses swing from “too much” to “too little”, creating cycles. If adjustments are balanced, the inequality holds, and the system converges smoothly.

Stability analysis of nonlinear system dynamics has been successfully employed in a number of fields in operations research and management science (e.g., Feichtinger et al., 1994; Hommes, 1994; Kopel et al., 1998; Thiétart & Forgues, 1995; Bischi et al., 2000).

This mirrors consumer satisfaction dynamics. Some customers, with moderate expectations and memory, gradually stabilize in loyalty. Others, highly reactive, cycle between over-enthusiasm and disappointment, never settling. Firms often observe these oscillations in satisfaction surveys and churn metrics.

At the psychological level, the condition explains why some people stabilize in their habits and others fluctuate. A dieter with balanced adjustments gradually adopts sustainable habits; one who reacts too strongly cycles between restriction and bingeing. Stability emerges not only from goals but from the *rate* at which individuals update toward them.

3.3. Heterogeneity: Type-1 vs. Type-2 Individuals

The stability condition generates natural heterogeneity. We classify: Type-1 individuals (balanced λ and sensitivity): achieve convergence, smoothly aligning impulses with deliberate goals. Type-2 individuals (short memory, high sensitivity): oscillate indefinitely, unable to stabilize.

So, after some periods/episodes of “learning”, as shown in **Figure 2**, Type-1 is capable of accurately aligning their automatic processes with the System2 of the

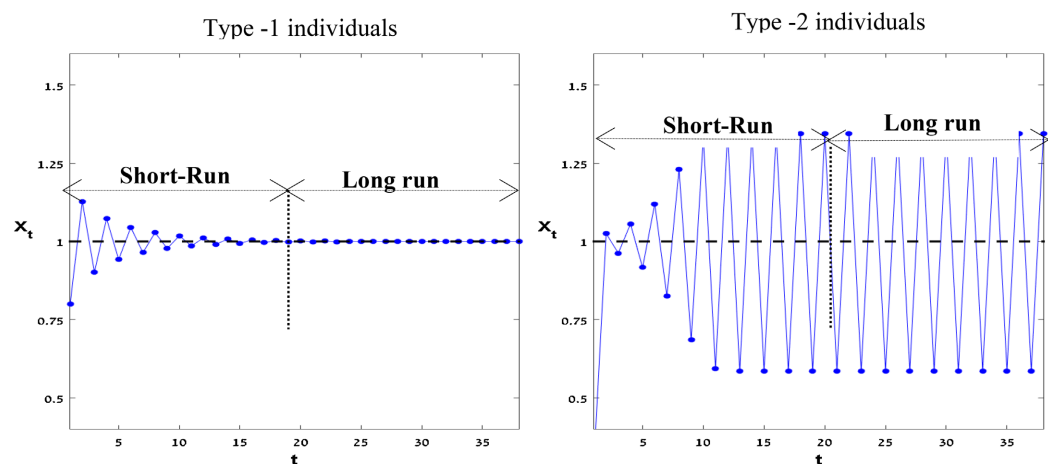


Figure 2. Time series of automatic operations in the short and long run.

individual. Type-2 is unable to align her automatic processes with System 2 of herself and will continue with stable sequences of fluctuations in the long run, see **Figure 2**.

This heterogeneity is not random but structurally determined. It parallels observed differences in consumer behavior (loyal vs. switcher segments) and in psychology (resilient vs. impulsive personalities).

Just as firms cannot expect every customer to stabilize without intervention, not every individual will achieve cognitive alignment unaided. Heterogeneity motivates the search for interventions.

Mathematically, from stability analysis (Equation (2)), we obtain that Type-1 individuals belong to,

$$\{(\lambda, g') : 0 < (1 - \lambda)g'(0) < 2\} \text{ or } 1 - \frac{2}{g'(0)} < \lambda < 1, \quad (3a)$$

and Type-2 individuals belong to

$$\{(\lambda, g') : (1 - \lambda)g'(0) > 2\} \text{ or } 0 < \lambda < 1 - \frac{2}{g'(0)}. \quad (3b)$$

3.4. Internal Work: A Capacity-Building Stabilizer

While natural heterogeneity exists, individuals are not bound by type. Practices such as mindfulness, awareness training, or boundary setting—collectively called internal work—enable individuals to alter the dynamics. We formalize this as:

$$Y = Y_0 + (x_t - Y_0)u, u \in [0, 1] \quad (4)$$

where Y_0 is the baseline-controlled standard, and $u \in [0, 1]$ is the *internal work parameter*. When $u = 0$, the standard remains fixed at Y_0 . Automatic impulses are judged against an unchanging benchmark. When $u = 1$, the controlled standard adapts perfectly, guaranteeing convergence. Intermediate values represent partial adjustment enabled by internal work.

Internal work reduces the effective discrepancy between impulses and goals. By expanding awareness and lengthening perspective, it prevents overreaction. In stability terms, u enlarges the region of convergence: more individuals who would otherwise oscillate can now stabilize.

In marketing, loyalty programs stabilize consumer behavior by reinforcing long-term relationships. Even if short-term disappointments occur, the relationship persists. Internal work plays an analogous role inside the individual, stabilizing cognition despite fluctuations.

Mindfulness practices train individuals to observe impulses without acting immediately. This effectively increases deliberation weight, raising effectiveness. System 2 has more influence, reducing volatility. The result is greater harmony between automatic responses and deliberate standards.

3.5. Expanded Dynamics with Internal Work

When u is introduced, the updating equation becomes:

$$x_{t+1} = x_t + (1 - \lambda)g((u - 1)(x_t - Y_0)). \quad (5)$$

This expression shows that internal work dampens the discrepancy term, adjusting less extreme. In graphical terms, the stability region in the parameter space (λ, g') expands as u increases. This explains why mindfulness and awareness interventions are effective: they reshape the adjustment process itself, not just outcomes. Internal work changes the *rules of updating*, enabling stability for a broader set of individuals.

The dynamic model thus consists of three key building blocks: 1) Updating Mechanism (Equation (1)): Automatic operations adjust based on discrepancies, much like consumer expectations. 2) Stability Condition (Equation (2)): Convergence depends on the balance between memory and sensitivity, explaining heterogeneity. 3) Internal Work Parameter (Equation (3)): Awareness practices expand convergence, stabilizing individuals who would otherwise oscillate.

Together, these building blocks offer a unified account of cognitive alignment, bridging psychology, marketing, and management. They set the stage for the propositions and results that follow.

In empirical settings, the internal work parameter u can be operationalized as the observed or induced intensity of reflective regulations such as the frequency of mindful pauses, adherence to guided reflection prompts, or average decision latency before action. It can be measured through validated awareness or non-reactivity scales, digital logs of “pause-before-act” events, or composite indices combining self-report and behavioral traces. Experimentally, u may be manipulated by brief mindfulness or reflection interventions, or by interface designs that insert a short reflection window before commitment, thereby strengthening deliberative control and expanding the convergence region predicted by the model.

4. Results and Propositions

Building on the dynamic model, we derive three central propositions that formalize the behavioral consequences of our framework. Each proposition highlights a distinct insight into how automatic operations align with deliberate standards, and how internal work changes this alignment. We present each formally, then provide intuitive explanations, psychological and marketing analogies, and managerial implications. All the proofs are in **Appendix**.

Proposition 1 (Natural Heterogeneity in Convergence): *Assume an individual uses internal work as in (4).*

1) *The individual's automatic operations converge to the conscious system (an individual will converge to a fixed point) if and only if the slope of the individual's gap function multiplied by the weight ascribed to recent disconfirmation gaps satisfies*

$$0 < (1 - \lambda)g'(0) < \frac{2}{1 - u} \quad \text{or} \quad 1 - \frac{2}{(1 - u)g'(0)} < \lambda < 1 \quad (6a)$$

2) *Otherwise, i.e., when*

$$0 < \lambda < 1 - \frac{2}{(1-u)g'(0)} \quad (6b)$$

the individual's automatic operations will oscillate between a small number of points.

Without internal work ($u = 0$), convergence of automatic operations to controlled standards occurs only if the memory parameter λ is sufficiently high and the sensitivity parameter g' is moderate. Individuals with these balanced parameters (Type-1) converge, while those with short memory or high sensitivity (Type-2) oscillate.

In other words, Type 1 individuals belong to (6a) and Type 2 to (6b). Thus, based on (6a), some individuals' automatic System converges to their System 2 without any help ($u = 0$). These individuals belong to

$$1 - \frac{2}{g'(0)} < \lambda < 1. \quad (7a)$$

The group that needs a “push” (*internal work*) to converge to its actual System 2 belongs to

$$1 - \frac{2}{g'(0)(1-u)} < \lambda < 1 - \frac{2}{g'(0)}. \quad (7b)$$

This result captures heterogeneity. Some individuals naturally stabilize their impulses (Type-1), while others fluctuate (Type-2). These differences emerge not from random noise but from structural parameters of the updating process.

Consider self-control in dieting. A Type-1 dieter gradually adopts stable habits, smoothly aligning meals with health goals. A Type-2 dieter alternates between restriction and bingeing, never stabilizing.

In consumer loyalty, Type-1 customers integrate experiences and form stable brand attachments. Type-2 customers overreact to single encounters, switching providers repeatedly. Firms observe this in churn data: some consumers are loyal “rocks”, others are volatile “butterflies”.

Heterogeneity is predictable and structural. Firms and policymakers cannot assume all individuals will converge. Recognizing this heterogeneity motivates targeted interventions—such as nudges, training, or loyalty-building—aimed at Type-2 individuals.

Proposition 2 (Internal Work Expands Convergence): *By increasing u or using more internal work to our automatic operations, more individuals will be able to accurately adjust their long-run automatic System 1 to System 2 or get closer to themselves.*

When $u > 0$, the set of parameters (λ, g') for which convergence occurs expands. Internal work reduces the effective discrepancy between impulses and goals, dampening oscillations and allowing more individuals to stabilize.

Internal work functions as a stabilizer. It enables individuals who would otherwise oscillate to converge. Rather than changing personality traits, internal work alters the updating process itself, making stability achievable for a broader set of

individuals.

Mindfulness training helps individuals pause before reacting. A person prone to anger may oscillate between outbursts and regret (Type-2). With mindfulness, the same person moderates reactions, gradually stabilizing into calmer responses.

Loyalty programs serve as external stabilizers. A customer prone to switching may remain loyal if the program provides consistent reinforcement. Internal work plays the same role interpersonally, expanding the set of “loyal” impulses.

This result justifies interventions. Stability is not fixed by natural type but can be cultivated. Firms may design consumer-facing interventions (apps, nudges, reminders) that mimic internal work by dampening reactivity. Organizations may embed mindfulness programs to stabilize employee performance.

Proposition 3 (Internal Work Expands Personality): *Internal work, $0 \leq u \leq 1$, changes the weight we put to our System 2 vs. System 1, mathematically from λ to $\bar{\lambda}$, where*

$$\lambda \leq \bar{\lambda} = u(1 - \lambda) + \lambda < 1. \quad (8)$$

Proposition 3 proves mathematically that internal work effectively increases the weight of memory λ , shifting cognition toward deliberation and reducing volatility. Thus, by listening to ourselves, separating it from the automatic system, we can increase λ value, thus use a more deliberative approach in information processing, thus better control our mind, and getting closer to ourselves. By getting closer to ourselves, we achieve the *real quality of life and happiness*.

Internal work does not merely reduce oscillations; it qualitatively shifts cognition. Individuals become less reactive to single events and more guided by accumulated goals. System 2’s influence strengthens, producing deeper deliberation.

In mindfulness practice, individuals learn to lengthen the “pause” between impulse and action. This temporal extension allows them to incorporate more memory into decisions. The result is less volatility and greater alignment with long-term goals.

Consider brand reputation. Strong brands create a memory buffer: consumers do not overreact to one bad review because long-term reputation weighs more. Internal work creates the same buffer internally, enhancing deliberation over time.

Internal work is not just a short-term stabilizer but a structural shift. By embedding mindfulness and resilience practices, organizations create longer decision horizons. This reduces employee reactivity to feedback shocks and aligns decisions with strategic goals.

Together, the propositions yield a coherent picture: 1) Without intervention, individuals naturally divide into convergent (Type-1) and oscillating (Type-2) groups. 2) Internal work expands the set of convergent individuals, stabilizing even those prone to volatility. 3) Internal work enhances deliberation, making cognition more forward-looking and less reactive.

This dynamic framework explains both why some individuals naturally achieve well-being and why interventions like mindfulness are effective in stabilizing oth-

ers. It provides formal grounding for psychological observations and marketing practices, offering a cross-disciplinary bridge between the two domains.

5. Discussion and Managerial Implications

This section translates the model's results into actionable insights for marketing science, psychology, managerial practice, digital/platform design, and public policy. We emphasize testable predictions, measurement strategies, and practical design choices that follow from the three building blocks: updating, stability, and internal work.

5.1. Implications for Marketing Science

Consumer loyalty and satisfaction dynamics. Proposition 1 formalizes a long-observed split between stable and volatile consumers. Customers with balanced memory and moderate sensitivity (high λ , moderate g') integrate experiences and converge toward a steady evaluation; those with short memory or high sensitivity oscillate. The model predicts that loyalty metrics (retention, repeat purchase, NPS stability) will correlate with individual-level updating parameters estimated from panel data. Researchers can recover λ and an effective g' by fitting state-space models to satisfaction time series.

Expectation management. Expectancy-disconfirmation emphasizes performance vs. expectations; our model adds that the path of expectations matter. Firms serving volatile segments (low λ) should smooth perceived variability (consistent service scripts, proactive communication, post-failure recovery cadences) to avoid oscillations. For stable segments (high λ), firms can innovate more boldly because evaluations integrate over time.

Segmentation by stability. Segment not only by value but by stability type. Signals of Type-2 dynamics include high variance in satisfaction, frequent provider switching, and sharp responses to single incidents. Tailored interventions include recovery guarantees, follow-up messaging, and "cooling-off" prompts that increase deliberation before defection.

Testable predictions. 1) Interventions that mimic internal work (reflective prompts, habit trackers, "are you sure?" confirmations) should raise effective λ and the probability of convergence. 2) Treatments that reduce perceived discrepancy slopes (flatten g' via expectation setting and service consistency) will damp oscillations and reduce churn among Type-2 consumers.

5.2. Implications for Psychology and Well-Being

Explaining individual differences. The stability condition provides a structural basis for heterogeneity in self-control, habit formation, and emotional regulation. Individuals outside the stability region oscillate between impulsive action and compensatory restraint. This aligns with observed relapses of cycles (e.g., dieting, smoking) and inconsistent study habits.

Interventions as dynamics, not willpower. Proposition 2 reframes mindfulness,

boundary setting, and awareness practices as changes to the updating rule. Rather than exhorting willpower, interventions expand the region in which ordinary updates lead to alignment—shifting the goal from “try harder” to “update smarter”.

Measurement. Practitioners can estimate λ from the weight placed on recent outcomes in sequential tasks and infer effective g' from the slope of responses to discrepancies in longitudinal logs. Validated scales (mindfulness, delay of gratification, cognitive reflection) should correlate with higher λ and lower effective g' .

5.3. Implications for Managerial Practice

Employee training and resilience. Treat internal work as a capability that reduces volatility in performance. Mindfulness-based programs, reflective debriefs, and boundary-setting workshops raise effective λ , making teams less reactive to short-term shocks. Expect steadier throughput, fewer errors during turbulence, and improved retention.

Performance management. Highly reactive employees (low λ) show boom-bust cycles in KPIs after reviews: Pair feedback with reflection prompts and goal-anchoring exercises to flatten g' and raise λ , reducing oscillations. Scheduling buffers (e.g., 24-hour response windows) serve as internal-work levers.

Change management and leadership. During transformations, leaders can institutionalize rituals that increase deliberation weight: pre-mortems, post-mortems, decision memos, and “pause points” before irreversible actions. These practices are organizational analogs of the u parameter.

The notion of *internal work* aligns conceptually with emerging managerial approaches that emphasize developing individual abilities as strategic resources. In particular, the “Management by Abilities” (MBA) framework (Peter Drucker & Vilfredo Pareto, 2021) extends the classical *Management by Objectives* of Drucker and the efficiency logic of Pareto by focusing on self-regulatory and adaptive capacities as drivers of sustainable performance. Within our dynamic formulation, such ability-based investments operate analogously to an increase in the internal-work parameter u , enhancing stability and convergence across organizational processes

5.4. Digital and Platform Design

Friction as a feature. High-frequency feedback loops (notifications, variable rewards) push users toward low λ and high effective g' . Platforms seeking healthy engagement can add purposeful friction—confirmation dialogs, reflection timers, and session summaries—that operationalize internal work at the UI level.

Recommenders and stability. Recommender systems can incorporate stability signals: penalize items that induce large, short-term discrepancies for users identified as Type-2, and promote content that supports convergence to stated long-term goals. Experiments should track variance and damped-oscillation metrics, not only means.

Ethics and transparency. Because internal-work-like features influence cognition, platforms should disclose intent and offer opt-outs. The aim is to enhance users' autonomy (higher deliberation weight), not manipulate outcomes.

A practical illustration is a timed “cooling-off” feature embedded before major or irreversible actions—such as confirming a purchase, sending a sensitive message, or closing an account. The brief delay (e.g., 30 - 90 seconds) accompanied by a short goal-reminder prompt gives users a moment for reflection, effectively operationalizing internal work u by increasing deliberation time and attenuating impulsive responsiveness. In model terms, this design temporarily raises the effective memory weight λ and flattens the sensitivity $g'(\cdot)$, thereby promoting convergence toward controlled behavior.

5.5. Policy and Societal Well-Being

Public health and finance. Oscillations produce costs: diet cycling, credit churn, stress. Public programs that teach reflective updating can expand convergence at scale. Schools and community centers can deliver light-touch curricula that raise λ and reduce effective g' through routines of pause, reflect, and plan.

Measurement for policy. Track stability metrics (variance, autocorrelation, damped oscillations) alongside means in program evaluations. Cost-benefit analyses should include avoided churn (e.g., healthcare lapses, loan defaults) attributable to improved cognitive stability.

5.6. Summary

Stability is a dynamic property that organizations and policymakers can influence. By raising effective memory (λ) and flattening discrepancy responsiveness (g') through internal-work levers (u), managers can convert oscillation-prone behavior into aligned, goal-consistent action—improving loyalty, performance, and well-being.

Although the model centers on internal dynamics, external environments can modulate the same parameters that govern convergence. Under high stress, uncertainty, or social pressure, the effective memory parameter λ typically declines, giving disproportionate weight to recent impulses, while the sensitivity g' steepens, amplifying fluctuations. Supportive or low-stress contexts, by contrast, stabilize behavior by sustaining higher λ and dampening g' . Integrating such contextual modulation, through time-varying λ_t or g'_t —would extend the model toward a more ecological account of cognitive stability.

6. Conclusion and Future Research

This paper has developed a dynamic framework to explain how automatic operations (System 1) may converge—or fail to converge—toward controlled operations (System 2), and how internal work alters this process. Our model adapts well-established insights from expectancy-disconfirmation theory and reinforcement learning to the intrapersonal level, showing how the interplay of memory, sensitivity,

and internal capacity building shapes cognitive stability. By integrating dual-process theories with expectancy-disconfirmation and reinforcement-learning insights, the framework yields cross-disciplinary implications for marketing science, psychology, management, and policy.

The contributions of this research are fourfold: 1) We formalized the adjustment process of automatic operations using a nonlinear difference equation. This brings mathematical clarity to dual-process theories, which are often described narratively. 2) The model identifies two broad types of individuals: those who naturally achieve convergence (Type-1) and those who oscillate (Type-2). This heterogeneity, often observed in consumer and psychological contexts, emerges naturally from the stability condition. 3) By introducing an internal work parameter, we demonstrated how practices such as mindfulness systematically expand convergence. Internal work does not erase impulses but reshapes the updating process, so that deliberate goals exert greater influence. 4) The framework bridges marketing, psychology, and management. It explains consumer loyalty and expectation dynamics, illuminates mechanisms of well-being, and provides actionable implications for firms and policymakers seeking to foster stability.

Like all modeling efforts, our framework abstracts from reality. Three limitations deserve attention: We model the interaction between Systems 1 and 2 as a single updating rule with parameters λ and u . In practice, cognition may involve multiple interacting processes, nonlinearities, and feedback loops that extend beyond our specification. While the model generates testable predictions, we have not yet provided empirical tests. Designing experiments that perfectly align with the model is challenging. We therefore leave empirical validation for future work. Our model treats internal work as a personal parameter. In reality, cultural, organizational, and environmental factors shape the extent to which individuals can engage in mindfulness or self-regulation. Future research should incorporate these contextual influences.

In conclusion, this paper advances the study of cognition and decision-making by moving beyond static descriptions of dual processes to a dynamic model of convergence. By highlighting heterogeneity and the transformative role of internal work, it offers both theoretical depth and practical relevance. Ultimately, the model underscores a hopeful message: while some individuals naturally align their impulses with their goals, others can learn to do so through practices that enhance awareness, resilience, and deliberation. Internal work is thus not a marginal intervention but a fundamental lever for fostering autonomy, stability, and long-term happiness.

Conceptually, the equilibrium described in our model resembles the “atomic balance” principle emphasized in economic systems (Lordkipanidze, 2025). Just as stability in an atom arises from a proportional balance between opposite forces, sustainable cognitive or organizational alignment requires a comparable harmony between regulating and self-regulating mechanisms. This analogy underscores the broader relevance of our stability condition beyond the psychological domain, sug-

gesting that the same logic of balanced interaction governs both individual cognition and systemic equilibrium.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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Appendix: Proofs

Proof of Proposition 1

Part 1) is implied directly from the definition of stability at fixed point (condition: $|1 - (1 - \lambda)g'(Y - x^*)| < 1$), and Part 2) from the instability.

Proof of Proposition 2

Let us denote by $L(u)$ the measure of the set of individuals from (6a); i.e., the set of individuals who will get closer to themselves, using internal work u . To calculate $L(u)$, we need the distribution of the Type 1 individuals' characteristics in the population. Consider a continuous distribution with a density function $f(\lambda)$. Then, by (3), the measure of the set of individuals that became closer to themselves is,

$$L(u) = \int_{1 - \frac{2}{(1-u)g'(0)}}^1 f(\lambda) d\lambda.$$

If F is the distribution function of λ ; i.e., $F(\tau) = \int_0^\tau f(\lambda) d\lambda$, then

$$L(u) = F(1) - F\left(1 - \frac{2}{(1-u)g'(0)}\right).$$

Taking the derivative of $L(u)$, we have

$$L'(u) = \frac{2}{g'(0)(1-u)^2} f\left(1 - \frac{2}{(1-u)g'(0)}\right) > 0.$$

Last inequality completes the proof.

Proof of Proposition 3

Considering (6a), if $u > 0$, then

$$\begin{aligned} 0 < (1-\lambda)g'(0) &< \frac{2}{1-u} \\ \Rightarrow 0 < (1-\lambda)(1-u) &< \frac{2}{g'(0)} \\ \Rightarrow 0 < 1 - \frac{2}{g'(0)} < \lambda + u(1-\lambda) &= \bar{\lambda} < 1 \end{aligned}$$

But if $u = 0$, then $1 - \frac{2}{g'(0)} < \lambda < 1$. Thus, $u > 0$ transforms λ to $\bar{\lambda} = \lambda + u(1-\lambda) > \lambda$.

This completes the proof.