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MARKOV CHAIN SIMULATION FOR ANALYZING THE INFLUENCE OF KNOWLEDGE ON DECISION-MAKING SYSTEM AND LONG-TERM HAPPINESS

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ABSTRACT

This study employs a Markov chain model to simulate the influence of knowledge on daily decision-making and long-term happiness. In the simulation, each individual is assumed to make 6,500 decisions per day over a 10-year period, with a total of 1,000 individuals categorized according to their levels of knowledge and awareness. Knowledge serves as a variable that influences the transition probabilities between good and bad decisions, as well as the emotional responses to those decisions (gratitude or regret). The simulation results indicate that individuals with higher levels of knowledge and awareness tend to maintain more stable happiness compared to those with lower levels of knowledge. The Markov chain model proves to be effective in mapping the dynamics of decision-making behavior and can be utilized as an analytical tool for developing behavior-based decision support systems in the context of industrial engineering.

INTRODUCTION

Happiness is an essential part of human life, shaped by the choices we make every day. These choices are strongly influenced by our knowledge and awareness [1], which transform happiness from being merely a feeling into the outcome of how we think and act [2]. Knowledge enables us to make better decisions, while awareness allows us to recognize the consequences of those decisions. On average, humans have approximately 6,500 decision-related cognitive envents per day [3], yet only about 10 to 20 of those events involve fully conscious, deliberative decisions [4], [5]. This highlights the crucial role of awareness in directing our lives.

When we make decisions consciously, we are, in fact, steering the direction of our thoughts [6]. By understanding and regulating thought processes—for instance, through practices such as gratitude [7], [8]—we can ensure that the majority of our daily decisions bring positive impacts to our lives, while the rest occur automatically [5]. However, possessing knowledge and awareness alone does not guarantee that every decision will be correct [9]. At times, we still make poor choices and experience their consequences.

In this study, happiness is defined as the feeling of gratitude when making good decisions and the feeling of regret when making poor ones. In other words, happiness is not only about experiencing pleasure but also about how we respond to the decisions we make. If happiness is rooted in daily decision-making, the key question becomes: how can we ensure that more of our decisions lead to happiness?

Although extensive research has examined the concept of happiness [1], [10], [11] and the factors that influence it [2], [7], [12], relatively few studies have explored how the process of daily decision-making shapes long-term happiness. To address this gap, this research applies a 10-year Markovian simulation involving 1,000 individuals with varying levels of knowledge. The purpose of the simulation is to predict how daily decisions influence the likelihood of achieving long-term happiness.

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To capture this process, the Markov chain [13] is employed as a statistical tool capable of modeling how one decision probabilistically affects the next. This study makes two key contributions. Theoretically, it advances the research field by modelling happiness not as a static outcome but as an emergent property of sequential decision-making processes. It integrates gratituted and regret into a dynamic Markov framework that captures how daily choices probabilistically shape long-term trajectories. Unlike prior regression-based or cross-sectional studies that treat happiness as a function of static predictors (e.g., income, education, or personality traits), the proposed Markov chain approach captures the sequential dependencies and probabilistic transitions between emotional states over time. This dynamic modeling reveals how the same individual may converge toward or diverge from happiness depending on their sequence of decisions—an insight that static models cannot provide. Practically, it translates this understanding into quantifiable insights. It demonstrates how targeted improvements in knowledge and awareness can systematically shift individuals toward more sustainable happiness. It bridges the gap between abstract theory and actionable intervention.

LITERATURE REVIEW

The pursuit of happiness is a universal goal, though its meaning can vary greatly. Happiness may develop across different levels, ranging from temporary physical pleasures (Level 1), satisfaction driven by ego (Level 2), a sense of purpose and connection with others (Level 3), to deeper and more meaningful happiness (Level 4). This progression suggests that true happiness is not merely about fleeting pleasure but rather about deeper, more enduring values.

From a philosophical perspective, Lala et al. (2023) discuss the concept of happiness according to Ibn Sina and Ibn Arabi [14]. Despite their differing views, both philosophers agree that true happiness lies in spiritual fulfillment. Similarly, Xin (2022) argues that happiness cannot be obtained easily but is instead the result of struggle. According to Xin, knowledge that is not applied in real life has no meaningful value [15]. Zamzami et al. (2021) also explore both physical and spiritual dimensions of happiness by analyzing the thoughts of earlier philosophers [16].

On the other hand, modern research on happiness has continued to expand. Czyz et al. (2021) employed the CARTSs approach to assess suicide risk factors with the aim of improving psychological assessment tools [17]. Babincak et al. (2018) measured happiness in Slovakia by testing the validity of the Subjective Happiness Scale (SHS). Their study, involving 977 respondents, found that happiness is not influenced by gender, religion, or education [18].

Another approach was introduced by Roessler et al. (2020), who developed a smart device called Happimeter to measure happiness and stress. In a three-month experiment with 22 participants, they found that individuals who received feedback on their mood became 16% happier and 26% more active compared to the control group, with no significant effect on stress levels [19], [20]. Weimann et al. (2015) investigated the relationship between happiness and economic well-being, challenging the "Easterlin Paradox." They argued that while high income does not guarantee happiness, it can improve one's quality of life.

Further research was conducted by Ludwigs et al. (2019), who reviewed various definitions of happiness and methods of measurement. Their study highlighted the global happiness database and provided practical guidance for researchers [21]. Lukoševičiūtė et al. (2022) systematically reviewed tools used to measure adolescent happiness and found that few studies had validated these instruments [22]. Meanwhile, Omar et al. (2021) analyzed the concept of moral happiness in the thought of Miskawayh, a Muslim philosopher influenced by Aristotle and other classical thinkers [23].

Despite the extensive body of research on happiness, one aspect remains underexplored—namely, happiness as the outcome of decision-making processes. Taking a novel approach, this study employs mathematical modeling based on Markov chains to map how daily decisions influence long-term happiness. Through this approach, the study seeks to provide new perspectives on understanding happiness.

RESEARCH AND METHODOLOGY

To understand how decision-making processes influence happiness, the Markov chain model is employed as an appropriate analytical tool. This model enables in-depth exploration and prediction of the cumulative effects of an individual's series of decisions. The application of the model follows these steps:

1. Defining Decision States

   In daily life, individuals continuously make decisions that can be classified as either good or bad. However, how a person responds to these decisions plays a critical role in the journey toward happiness. It is important to clarify that while prior literature estimates approximately 6500 thoughts per day, the present model operationalizes these as decision-related cognitive events rather than fully conscious, deliberative decisions. In this framework, a "decision" represents any cognitive instance where an individual encounters a choice point, which ranges from automatic, habitual responses to more deliberate selections. Those decision probabilistically influences subsequent emotional states and future behavioral tendencies. Thus, the 6500 daily events modeled here capture the continuum of cognitive processing that shapes happiness trajectories, not exclusively conscious volitional acts.

- If a person makes a good decision (D1), two outcomes are possible:
  - Gratitude (D1,1): Appreciating the good decision, thereby reinforcing positive habits.
  - Lack of gratitude (D1,2): Failing to appreciate the good decision, which prevents reinforcement of positive habits and may increase the likelihood of poor decisions in the future.
- If a person makes a bad decision (D2), two outcomes are also possible:
  - Regret (D2,1): Feeling regret for the poor decision, creating an opportunity for improvement and better choices in the future.
  - Lack of regret (D2,2): Failing to feel regret, leaving the individual more vulnerable to repeating the same mistake.

These outcomes are influenced by a person's level of knowledge (p) and awareness (k). The higher these two factors, the greater the likelihood of making decisions that contribute to happiness.

2. Determining Transition Probabilities

In this model, each individual makes approximately 6,500 decisions-related cognitive events per day. If a person's knowledge (p) and awareness (k) are both above 0.5, then 20 out of 6,500 decisions will automatically be good decisions. The remaining decisions follow these transition probabilities:

- If a person makes a good decision (D1):
  - 60% chance of feeling gratitude (D1,1), thus remaining in a state of happiness.
  - 40% chance of not feeling gratitude (D1,2), which increases the risk of moving toward a bad decision in the future.
- If a person makes a bad decision (D2):
  - 60% chance of feeling regret (D2,1), allowing a return to a better path.
  - 40% chance of not feeling regret (D2,2), which can reinforce negative habits.

Why 60% and 40%?

These assumptions are based on research in psychology, neurobiology, and behavioral economics:

1. Positivity Bias and Habit Persistence
   Fredrickson & Losada (2005) showed that the ratio of positive emotions to well-being indicates that individuals with more positive experiences are more likely to sustain good habits. In this context, approximately 60% of individuals who make good decisions continue positive thinking through gratitude, consistent with the "broaden-and-build theory" of positive psychology [24].
2. Behavioral Change Theory and the Effect of Regret
   Zeelenberg & Pieters (2007) found that regret has a strong corrective effect on decision-making. When individuals make poor decisions, about 60% experience regret and seek improvement, while 40% remain defensive or normalize their mistakes [25].
3. Neuroeconomic Studies on Gratitude and Regret
   Fox et al. (2015) demonstrated that individuals actively engaging in self-reflection have a 55–65% likelihood of experiencing corrective emotions (either gratitude or regret), while 35–45% are more inclined to ignore or rationalize their choices[26], [27].

In other words, the 60%/40% probabilities are illustrative assumptions for simulation purposes, reflecting general tendencies identified int the literature rather than empirically measured transition rates. They enable exploratory modelling of how emotional responding patterns might accumulate over time, with the acknowledgement that true population parameters may vary and require future empirical validation.

Mathematical Representation of Transition Probabilities are as follow:

- If $p > 0.5$ and $k > 0.5$:

Out of 6.500 daily decision, 20 good decisions occur automatically, while the remaining 6,480 follow this transition pattern:

- $P(H|H) = P(D1,1|H) * P(H|G)$
- $P(H|U) = P(D1,2|U) * P(U|NG)$
- $P(U|H) = P(D2,1|H) * P(H|R)$
- $P(U|U) = P(D2,2|U) * P(U|NR)$

Where:

- P(H|G) = 0.6 (probability of feeling gratitude after a good decision)
- P(U|NG) = 0.4 (probability of not feeling gratitude after a good decision)
- P(H|R) = 0.6 (probability of feeling regret after a bad decision)
- P(U|NR) = 0.4 (probability of not feeling regret after a bad decision)

3. **Setting Model Paramettets**

To test how these probabilities affect happiness within the population, the study divides individuals into two main groups:

1. Group with high levels of knowledge and awareness ($p > 0.5$, $k > 0.5$)
   - 500 individuals
   - 250 start the simulation in a happy state
   - 250 start the simulation in an unhappy state

2. Group with low levels of knowledge and awareness ($p \leq 0.5$ atau $k \leq 0.5$)
   - 500 individuals
   - 250 start the simulation in a happy state
   - 250 start the simulation in an unhappy state

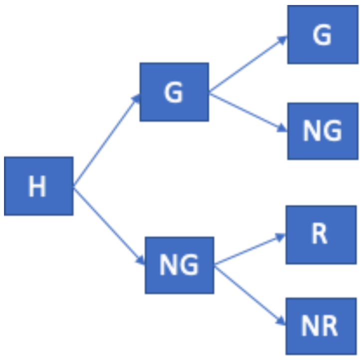

Figure 1. The decision tree begins from the happy state (H), followed by the choice between gratitude (G) and lack of gratitude (NG), and then proceeds to the choice between regret (R) and lack of regret (NR)

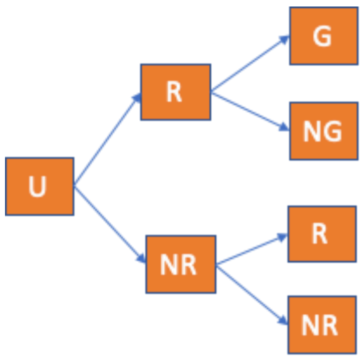

Figure 2. The decision tree begins from the unhappy state (U), followed by the choice between regret (R) and lack of regret (NR), and then proceeds to the choice between gratitude (G) and lack of gratitude (NG).

4. Decision Sequence Simulation

In the simulation stage, each individual undergoes a decision-making process over a 10-year period, with 6,500 decisions per day and 365 days per year.

In each simulation cycle, an individual's happiness state is updated based on transition probabilities. To better reflect the dynamics of real-life decision-making, the model also incorporates elements of uncertainty through probability distributions.

The simulation results include:

- The distribution of individuals who remain happy or unhappy over the 10-year period.
- Patterns of changes in happiness over time.
- Sensitivity analysis with respect to variations in key parameters (knowledge and awareness)

Through this simulation, the study seeks to provide deeper insights into how daily decisions shape long-term happiness, as well as the extent to which knowledge and awareness influence the journey toward happiness.

RESULT AND DISCUSSION

Result

The simulation was conducted on two main groups based on levels of knowledge and awareness: high and low. Each group was tested under three initial conditions: happy, unhappy, and 50:50. The simulation results and sensitivity analyses are described as follows:

1. Group with High Knowledge and Awareness

- Starting in a Happy State (Figures 3 and 4):
  A total of 62.4% of individuals remained happy until the end of the simulation. The happy state began to dominate from the fourth year onward. Sensitivity tests showed stability in the proportion of happiness at around 62%, reflecting the model's consistency under small parameter variations.

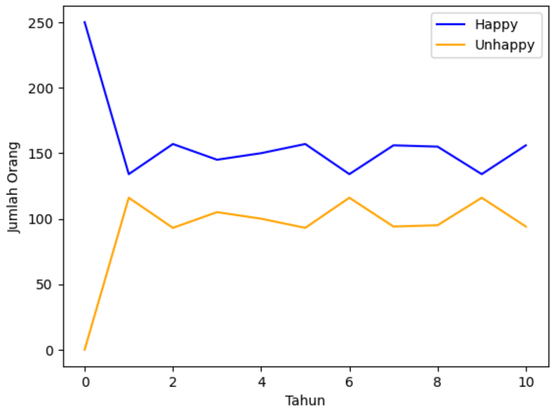

Figure 3. Simulation Results of "Smart" Individuals' Decision-Making on Happiness Starting from a Happy State

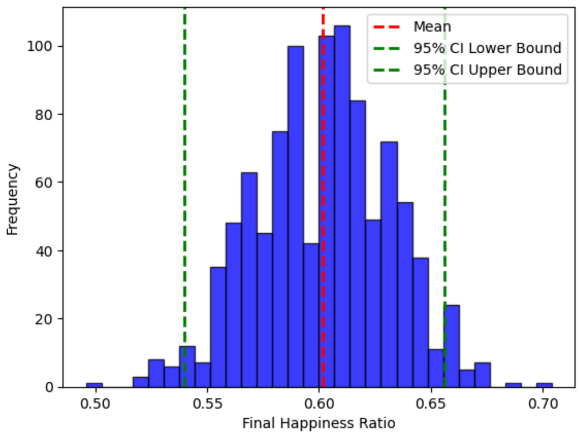

Figure 4. Sensitivity Test Results of the Happiness Ratio Distribution from 1,000 Simulations for the "Smart" Category Starting from Happiness

- Starting in an Unhappy State (Figures 5 and 6):
  A total of 59.6% of individuals achieved happiness by the end of the simulation, with significant changes occurring from the fifth year onward. Sensitivity tests indicated that the initial condition had a stronger influence in this scenario.

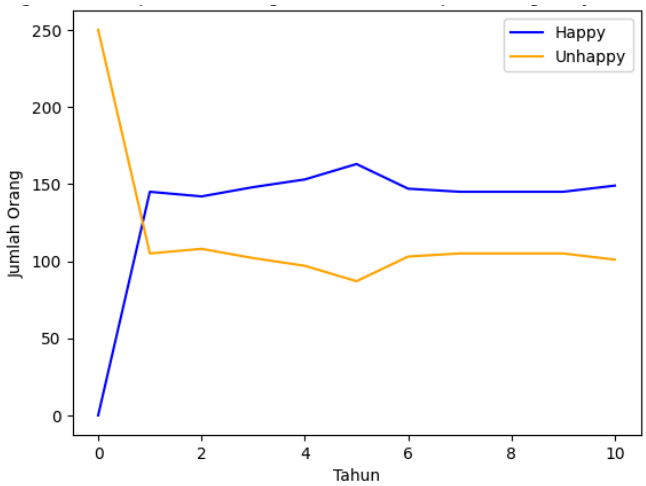

Figure 5. Simulation Results of "Smart" Individuals' Decision-Making on Happiness Starting from an Unhappy State

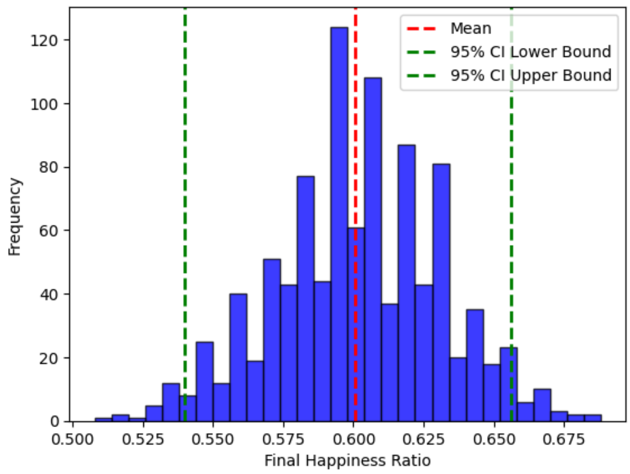

Figure 6. Sensitivity Test Results of the Happiness Ratio Distribution from 1,000 Simulations for the "Smart" Category Starting from Unhappiness

- Starting with a 50:50 Probability (Figures 6 and 7):
  A total of 60.2% of individuals ended in a happy state. Although unhappy individuals initially dominated, a turning point occurred in the eighth year. The results remained consistent, indicating model stability under random initial conditions.

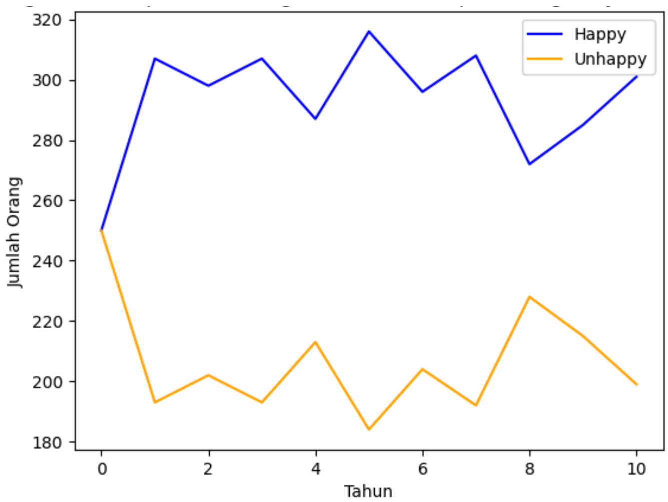

Figure 7. Simulation Results of "Smart" Individuals' Decision-Making on Happiness Starting from a 50:50 Condition

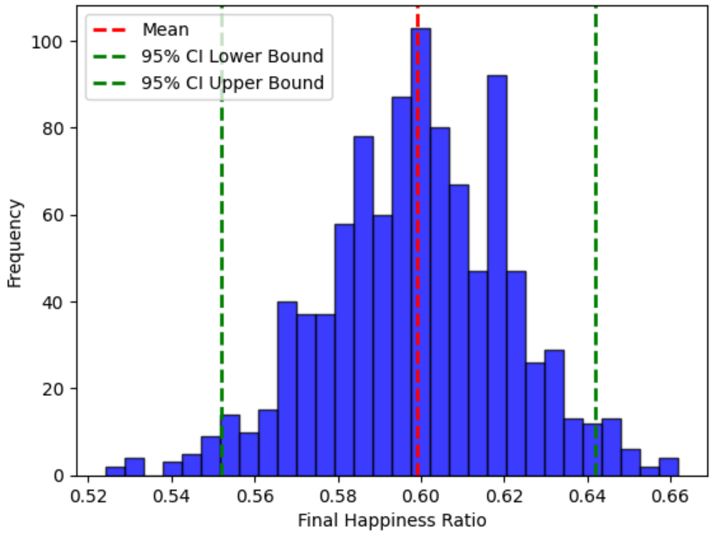

Figure 8. Sensitivity Test Results of the Happiness Ratio Distribution from 1,000 Simulations for the "Smart" Category Starting from 50:50

2. Group with Low Knowledge and Awareness

- Starting in a Happy State (Figures 9 and 10):
  Only 50.8% of individuals remained happy after 10 years of simulation. The number of unhappy individuals tended to dominate, suggesting that low levels of knowledge and awareness are insufficient to sustain happiness.

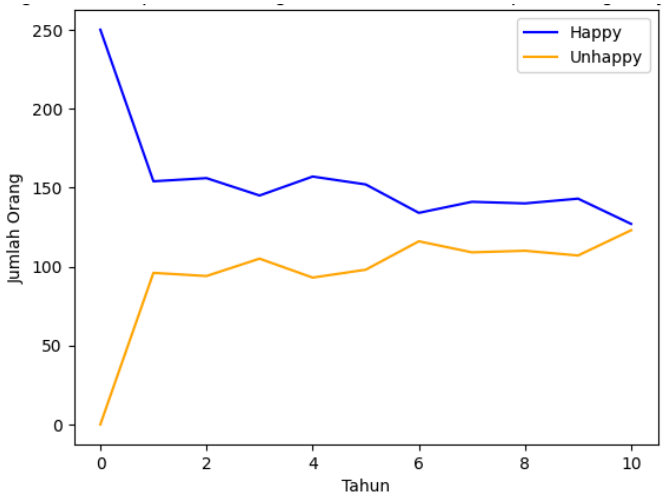

Figure 9. Simulation Results of "Not Smart" Individuals' Decision-Making on Happiness Starting from a Happy State

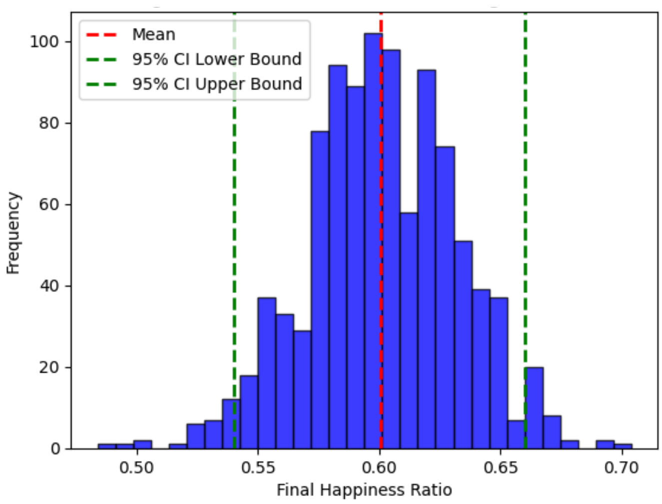

Figure 10. Sensitivity Test Results of the Happiness Ratio Distribution from 1,000 Simulations for the "Not Smart" Category Starting from Happiness

- Starting in an Unhappy State (Figures 11 and 12):

About 58% of individuals managed to shift to a happy state; however, unhappiness dominated for most of the simulation period. Sensitivity tests revealed high levels of fluctuation, reflecting instability in decision-making within this group.

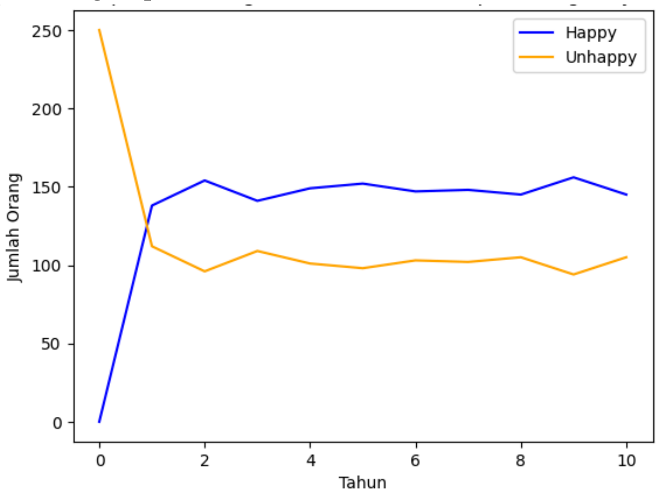

Figure 11. Simulation Results of "Not Smart" Individuals' Decision-Making on Happiness Starting from an Unhappy State

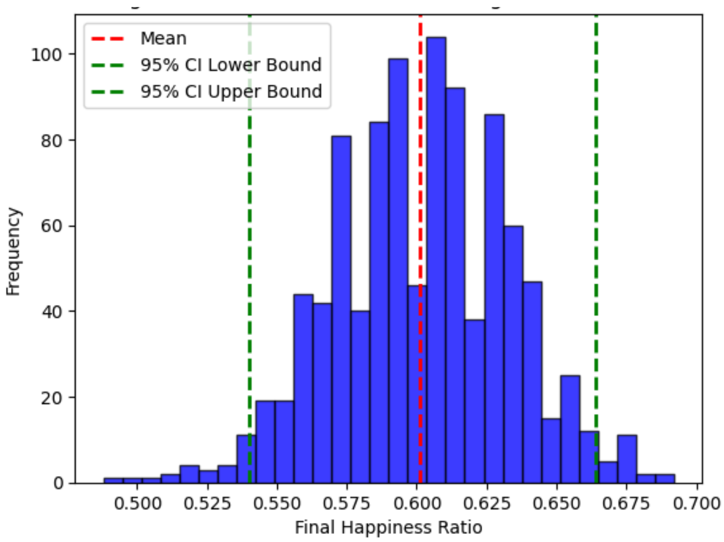

Figure 12. Sensitivity Test Results of the Happiness Distribution from 1,000 Simulations for the "Not Smart" Category Starting from Unhappiness

- Starting with a 50:50 Probability (Figures 13 and 14):
  A total of 53.8% of individuals ended in a happy state. However, unhappiness remained dominant during the majority of simulation cycles. The variation in results (ranging between 50%–60%) indicates that transition probabilities strongly influence outcomes in this group.

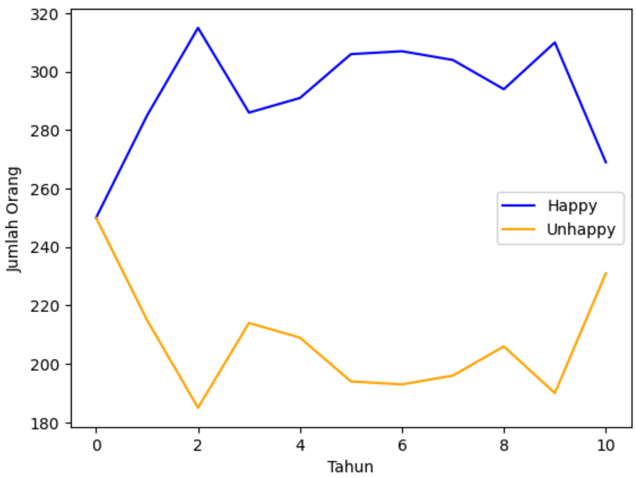

Figure 13. Simulation Results of "Not Smart" Individuals' Decision-Making on Happiness Starting from a 50:50 Condition

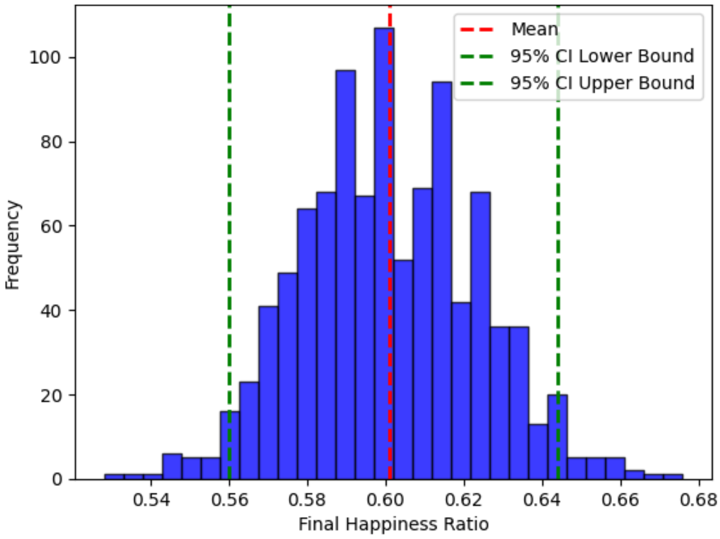

Figure 14. Sensitivity Test Results of the Happiness Ratio Distribution from 1,000 Simulations for the "Not Smart" Category Starting from 50:50

Discussion

The simulations demonstrate that individuals with higher levels of knowledge and awareness are more resilient in sustaining or achieving happiness. Conversely, individuals with lower knowledge exhibit greater vulnerability to unhappiness.

These findings align with Fredrickson and Losada (2005), who argued that positive experiences reinforced by awareness and self-reflection tend to form behavioral patterns oriented toward long-term well-being. In this context, expressing gratitude for good decisions strengthens the tendency to make further positive choices, as reflected in the Markov model applied here [28].

Moreover, Zeelenberg and Pieters (2007) emphasized the corrective role of regret in shaping future behavior [29]. They found that individuals who recognize poor decisions are more likely to make corrective adjustments, thereby achieving more positive long-term outcomes—a pattern also observed in the transition from unhappiness to happiness among high-knowledge individuals in this simulation.

From a neuropsychological perspective, the work of Perkins et al. (2015) in neuroeconomics supports the probabilistic assumption used in this model, showing that approximately 60% of individuals tend to respond to positive or negative experiences with constructive emotional reflection (such as gratitude or regret) [27]. This supports the 60%-40% probability assumption applied in the state transitions of the simulation.

The simulation reveals that initial conditions matter differentially across knowledge groups. High-knowledge individuals exhibit convergence behavior, meaning regardless of starting state, their happiness trajectories stabilize toward similar long-term distributions. It indicates that the transition matrix possesses a dominant eigenvalue associated with resilience. Conversely, low-knowledge individuals display persistent path dependence, where starting unhappy significantly increases the probability of remaining trapped in negative states. It suggests their transition matrices feature subdominant eigenvalues that slow convergence or create absorbing boundaries around unhappiness. These stability properties imply that knowledge and awareness do not simply increase happiness probabilities linearly; they fundamentally restructure the basin of attraction toward well-being, reducing sensitivity to initial conditions and shortening the mixing time required to reach steady-state happiness.

In sum, the simulation results not only remain consistent with theoretical and empirical evidence but also demonstrate that stochastic modelling using Markov chains is a valid and applicable approach for analysing the dynamics of happiness as shaped by daily decision-making. The Markov chain model effectively captures the dynamics of happiness transitions based on realistic probabilities, underscoring its potential as a tool for mapping the long-term consequences of everyday decisions.

Beyond theory, this model can be used to design practical interventions. For example, a digital app could ask users two quick questions after a decision: “Was this decision aligned with your knowledge?” and “Do you feel gratitude or regret?” By tracking responses over time, the app could identify patterns in a person’s behaviour and estimate how their decisions evolve. It could then offer personalized suggestions, such as encouraging gratitude journaling for someone who makes good decisions but does not feel grateful, or suggesting brief regret-reflection exercises for someone who tends to repeat poor choices. In organizational settings, similar ideas could be applied through simple daily programs, such as short five-minute mindfulness or awareness sessions focused on recognizing decisions and their outcomes. Over time, these small practices could help shift the balance between gratitude and regret in a positive direction. The Markov model provides a way to measure this process by showing how small, consistent changes can accumulate into meaningful improvements in long-term happiness, while also giving organizations a clear and practical way to evaluate whether their interventions are effective.

CONCLUSION

1. Main Finding: Long-term happiness emerges from cumulative daily decisions modeled via Markov chains. Individuals with higher knowledge and awareness demonstrate greater resilience in sustaining happiness regardless initial state. They also tend to achieve stable happiness-dominated distributions. The low-knowledge individual groups, however show persistent vulnerability to negative state trapping.
2. Theoretical implications: This study formalizes happiness as a dynamic, path-dependent process rather than a static outcome. It bridges philosophical constructs (Ibn Sina, Ibn Arabi) with psychological evidence of gratitude and regret, shifting focus from correlational determinants to sequential decision-emotion interactions.
3. Practical Implications: Interventions targeting knowledge and awareness may yield compounding long-term benefits by shifting individuals across critical tipping points. Decision-support tools that increase gratitude/regret ratios could systematically improve transition probabilities toward well-being. Concretely, three implementation pathways emerge from the simulation: (1) mobile applications that deliver daily reflection prompts and visualize users' happiness transition trajectories over time; (2) workplace training programs that integrate brief awareness exercises (e.g., 5-minute daily check-ins) to strengthen the probability of gratitude following good decisions; and (3) behavioural intervention protocols for clinical or coaching settings, where practitioners use Markov-based dashboards to monitor clients' decision-emotion patterns and tailor strategies (e.g., regret regulation techniques) when an individual shows persistent low-probability transitions from unhappiness. Each pathway translates the model's probabilistic insights into measurable, repeatable actions.
4. Limitations: The model uses simplified, literature-derived transition probabilities without empirical validation. It does not account for social influences, cultural variations, adaptive learning or the full distinction between automatic and deliberate cognitive processes.
5. Future research direction: Priorities include empirical validation of probabilities through experience-sampling methods, and model extensions incorporating heterogenous agents, adaptive learning, network effect, and cross-cultural parameterization.

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