Psychology of games

Part 1: Reward-seeking behavior

(computational rationality, behavioral game design, reward design, limits of perception, cognition & action)

Perttu Hämäläinen 2024

Disclaimer: This content is perpetually work-in-progress, updated every year.

Teaser: Curtis et al. 2022

Toward Believable Acting for Autonomous Animated Characters

https://www.youtube.com/watch?v=0RB6DASdUP8

Cassidy Curtis
14 tilaajaa

Tilaa

13 Jaa Lataa Klippi Tallenna

Longer version of the talk with more details

https://www.youtube.com/watch?v=4T-FJ1KI9Lo

Discussion

- Is this a good way to model behavior, motivation, and emotion in animals and/or humans?
- What aspects of the system are realistic?
- What might be missing?

Discussion

- Is this a good way to model behavior, motivation, and emotion in animals and/or humans?
- What aspects of the system are realistic?
- What might be missing?

In the following, I will go deeper into these questions. According to current knowledge, this system gets many things right, although some aspects are overly simplified

Actual lecture begins…

Overview

- Playing games (and other human behavior) as reward-seeking behavior
- Why? Reward-seeking both explains many aspects of player behavior, and can be implemented in software for non-player characters
- What affects our reward seeking (limitations of perception, cognition, and memory)
- How to design game rewards?

Overview

- This lecture: Principles that work independent of the reward type (game score, virtual currency, game objects, satisfaction of beating a challenge…)
- Next lectures: But what is the "human reward function"? What do players really find satisfying/rewarding and care about?
    - This will lead us to deeper topics such as intrinsic motivation, emotion, and transformative games—but those can still benefit from the principles of this first lecture!

Structure

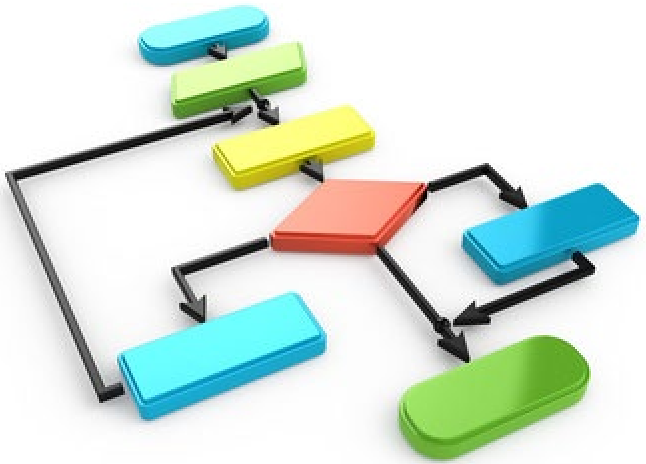
- **Theory: two types of thinking, computational rationality, limits of human cognition, perception, and action**.
- Practice: Game design principles based on the theory.

Computational rationality

- Classical economics: Humans are rational, choosing optimal actions that maximize utility
- Behavioral economics: Humans are not rational. Decision making is plagued by cognitive biases such as sunk cost fallacy
- Computational rationality (a.k.a. bounded rationality, ecological rationality): Humans try to act optimally, but it is hard. In practice, we make errors and are only approximately rational, limited by the capabilities of perception, cognition, and memory.

Two types of thinking

SYSTEM 2: EXPLICIT/CONSCIOUS:
SLOW, ALGORITHMIC, EFFORTFUL



ATTENTION,
PRIMING,
INHIBITION

IDEAS,
ASSOCIATIONS,
IMPULSES,
INTUITIONS

SYSTEM 1: IMPLICIT/UNCONSCIOUS:
FAST, ASSOCIATIVE, EFFORTLESS,
INTUITIVE

ASSOCIATION

And you will read this at the end

You will read this first

And then you will read this

Then this one


Rate Your Experience
Enjoying Dungeon Keeper?
5-Star ratings from you help us provide free updates!
How would you rate Dungeon Keeper?
1-4 Stars
5 Stars

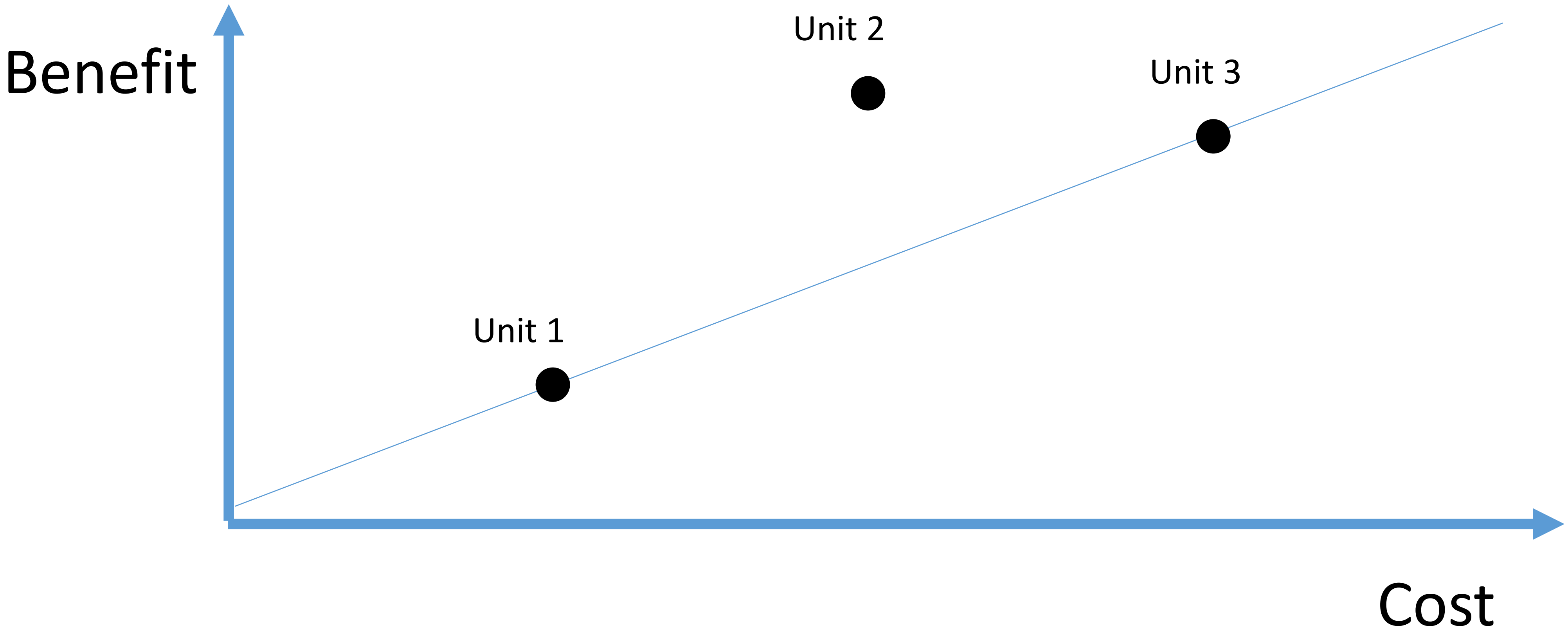
What limits us?

- Slow speed and high effort of analytical decision making (System 2)
  (finite computing resources and time)
- Inaccuracy and biases of intuition (System 1)
- Inaccuracy of memory
- Limited attention (we time-slice instead of multitasking!)
- Incomplete information
- Relativity, subjectivity, and adaptivity of perception or evaluation of things like reward value, beauty, time…

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility.

We already talked about this



Game design problems and utility

- Problems are often about **players and designers having different perceptions of utility (or cost)**
- Designers have more knowledge => does the game communicate all that’s needed?

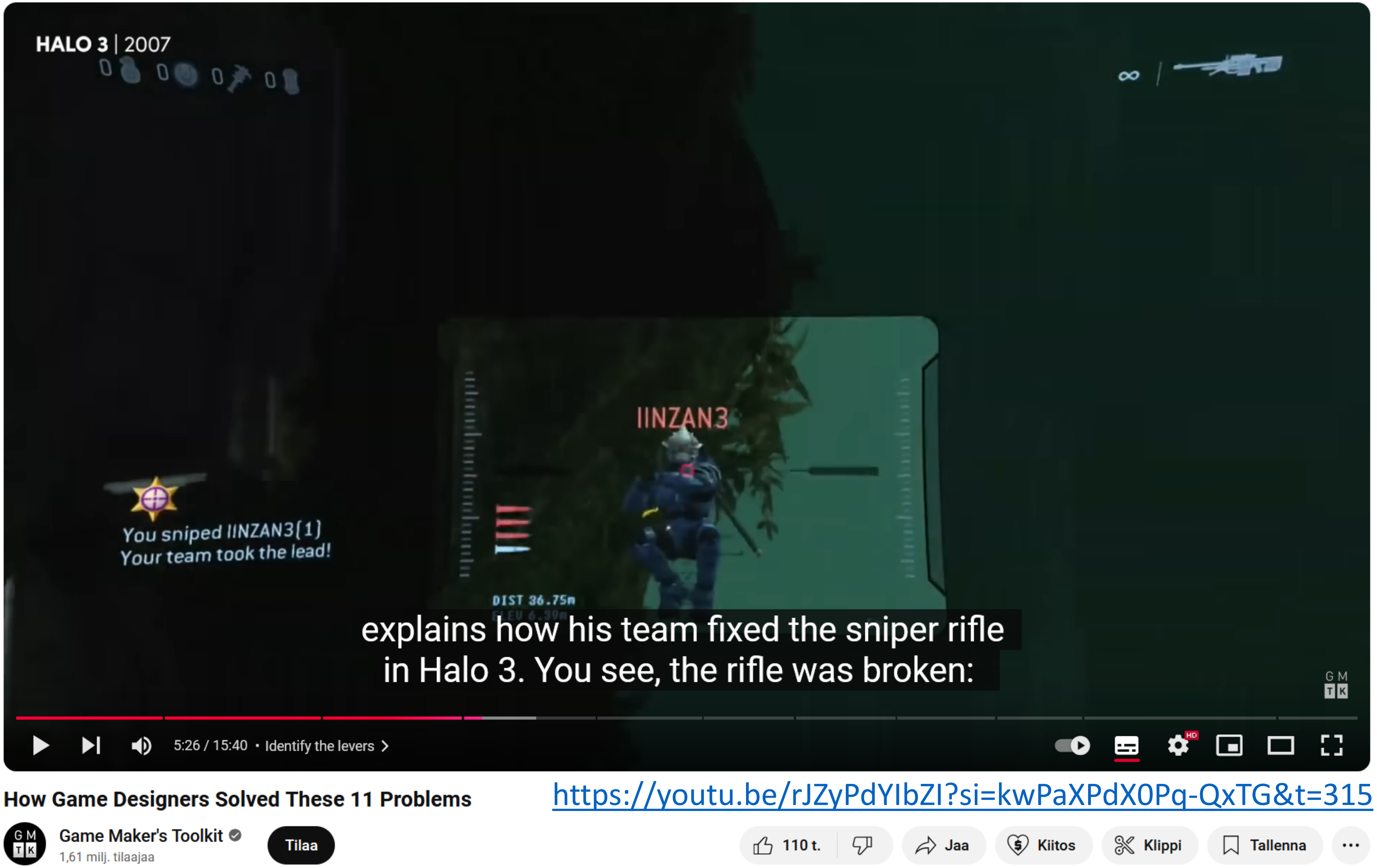
Utility can be contextual and interdependent

How Game Designers Solved These 11 Problems

https://youtu.be/rJZyPdYIbZI?si=Qkh-51L5tyBIPFob&t=751

Game Maker's Toolkit
1,61 milj. tilaajaa
Tilaa
110 t. | Jaa | Kiitos | Klippi | Tallenna

Crucial: Identify the right parameters to tune



https://youtu.be/rJZyPdYIbZI?si=kwPaXPdX0Pq-QxTG&t=315

Total utility = benefit – cost (You can adjust both)

How Game Designers Solved These 11 Problems

https://youtu.be/rJZyPdYIbZI?si=CEIVW6EbanBsT-9g&t=224

Game Maker's Toolkit
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What is utility?

A mathematical definition

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: **The expected sum of rewards for our current and future actions**

Why is this a good model?

- A lot of empirical support for humans and animals choosing actions of (approximately) highest perceived utility
- Compatible with AI methods such as Deep Reinforcement Learning

  => Data from AI player models can make useful predictions of human players
- Reward-based modeling also allows “other” types of behavior:
  - Random behavior: Add noise to the utility estimates of actions
  - Rule-based (moral codes): Impose a punishment (negative reward) for violating the rules
  - Goal-driven behavior: Define rewards for reaching the goals.

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \gamma^t r(a_t, o_t)\right]$$

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \gamma^t r(a_t, o_t)\right]$$

DISCLAIMER: The math is only essential for technical designers who might build game AI or player behavior simulations. Optional material for others.

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_{\boxed{t}} \gamma^{\boxed{t}} r(a_{\boxed{t}}, o_{\boxed{t}})\right]$$

Time, with *t=0* denoting the current time and increasing towards the future

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \gamma^t r(\boxed{a_t,} o_t)\right]$$

Action at time *t*

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \gamma^t r(a_t, \boxed{o_t})\right]$$

Observation of the world at time *t*

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \gamma^t \boxed{r(}a_t, o_t)\right]$$

Reward function: What do we perceive as rewarding/satisfying?

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\boxed{\sum_t} \gamma^t r(a_t, o_t)\right]$$

Sum over time: We do not only care about the reward for our next action, but also about all the actions possible after that

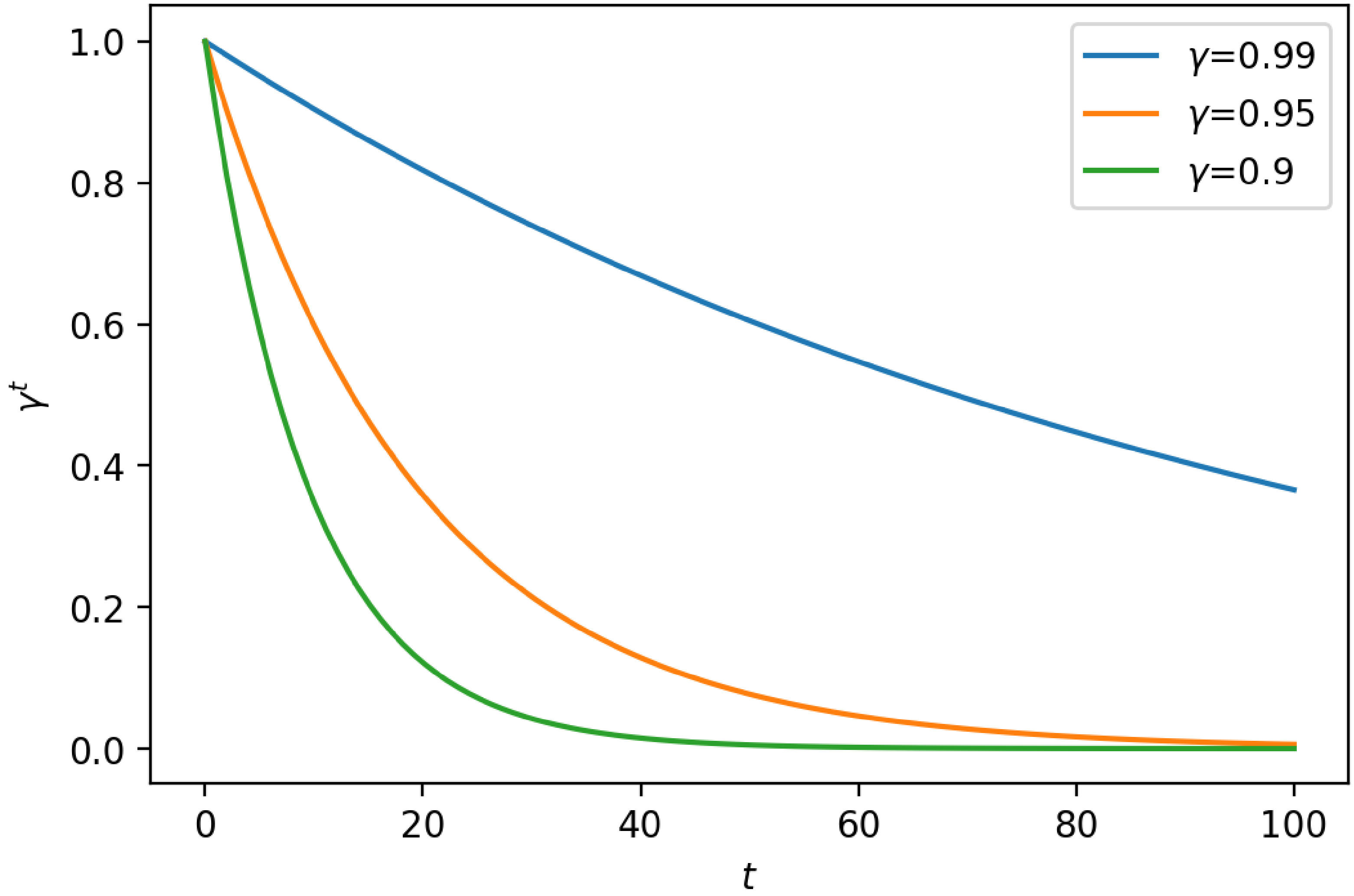
Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\sum_t \boxed{\gamma^t r}(a_t, o_t)\right]$$

Future discounting of rewards:
γ is in range 0…1. At *t*=0, γ^t=1.
When *t* grows, γ^t decreases to zero.

Small discount γ: Immediate rewards matter more



Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\mathbb{E}\left[\boxed{\sum_t \gamma^t r(a_t, o_t)}\right]$$

This sum of discounted future rewards is also called "return", denoted *R*

Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

$$\boxed{\mathbb{E}}\left[\sum_t \gamma^t r(a_t, o_t)\right]$$

Expectation: If the results of our actions are more or less random, we want to take actions yield maximal return, on average.

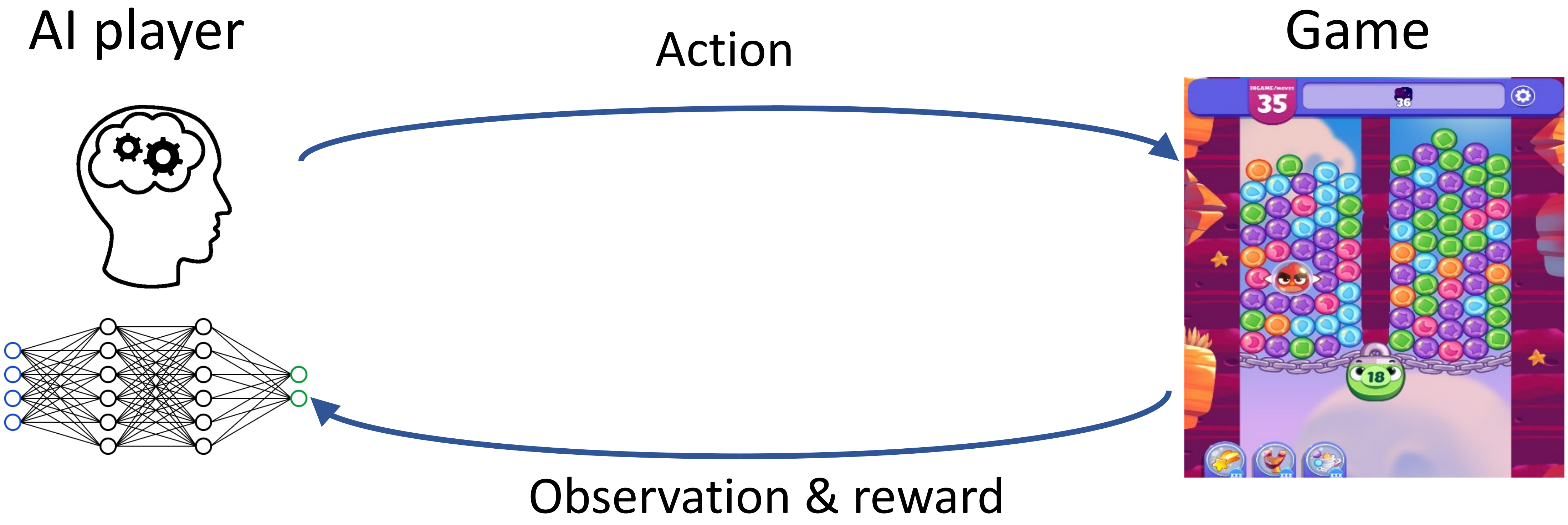
Computational rationality

Behavior emerges from (approximate and limited) optimization of utility: The expected sum of rewards for our current and future actions

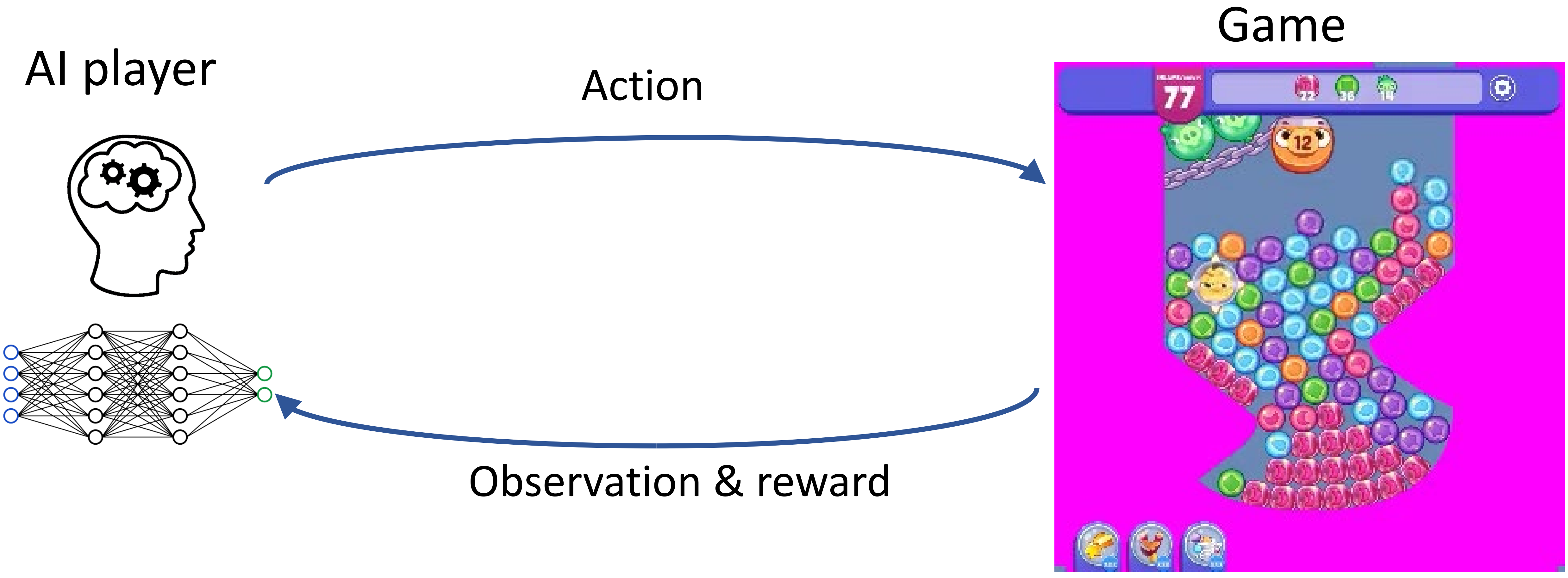
$$\mathbb{E}\left[\sum_t \gamma^t r(a_t, o_t)\right]$$

Optimizing this is at the heart of many AI systems => we can use AI players for playtesting etc.

Game-playing AI



Game-playing AI



We optimize and learn through interaction

Computational Rationality as a Theory of Interaction

Antti Oulasvirta
Aalto University
Finland

Jussi P.P. Jokinen
University of Jyväskylä
Finland

Andrew Howes
University of Birmingham
UK

ABSTRACT

How do people interact with computers? This fundamental question was asked by Card, Moran, and Newell in 1983 with a proposition to frame it as a question about human cognition – in other words, as a matter of how information is processed in the mind. Recently, the question has been reframed as one of adaptation: how do people adapt their interaction to the limits imposed by cognition, device design, and environment? The paper synthesizes advances toward an answer within the theoretical framework of *computational rationality*. The core assumption is that users act in accordance with what is best for them, given the limits imposed by their cognitive architecture and their experience of the task environment. This theory can be expressed in computational models that explain and predict interaction. The paper reviews the theoretical commitments and emerging applications in HCI, and it concludes by outlining a research agenda for future work.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models; User models.**

KEYWORDS

Cognitive modeling, computational rationality, interaction, reinforcement learning, adaptation, individual differences

menu selection [16], distraction [104], and visual search [67]. Such theories, while abstractions, are central to the practical aims of HCI and have made contributions to computational design [38, 87], human factors [126], design practice [96], and design education [84]. Recently, human–AI cooperation has added another area in which there is a need for theories of cognition [25, 46, 53].

The theory presented in this paper has grown out of difficulties experienced by the authors, cognitive scientists by training, in applying cognitive architectures. We repeatedly faced the issue that each model needs the modeler to hypothesize how the task is completed, and to code this knowledge as production rules. In other words, the modeler must specify a "recipe", a rule set that specifies the user's procedural skill. Writing these rules is challenging, in part because users are clever at generating unexpected strategies that are hard to identify. This difficulty stems from the fact that architectures such as EPIC [66] and ACT-R [3] admit a very large space of possible strategies. They are not sufficiently constrained for ascertaining which strategies users will actually choose. Moreover, rule systems are brittle. They must be updated if the design or environment changes, and a different rule set is needed for each type of user, limiting applications for design and intelligent interfaces.

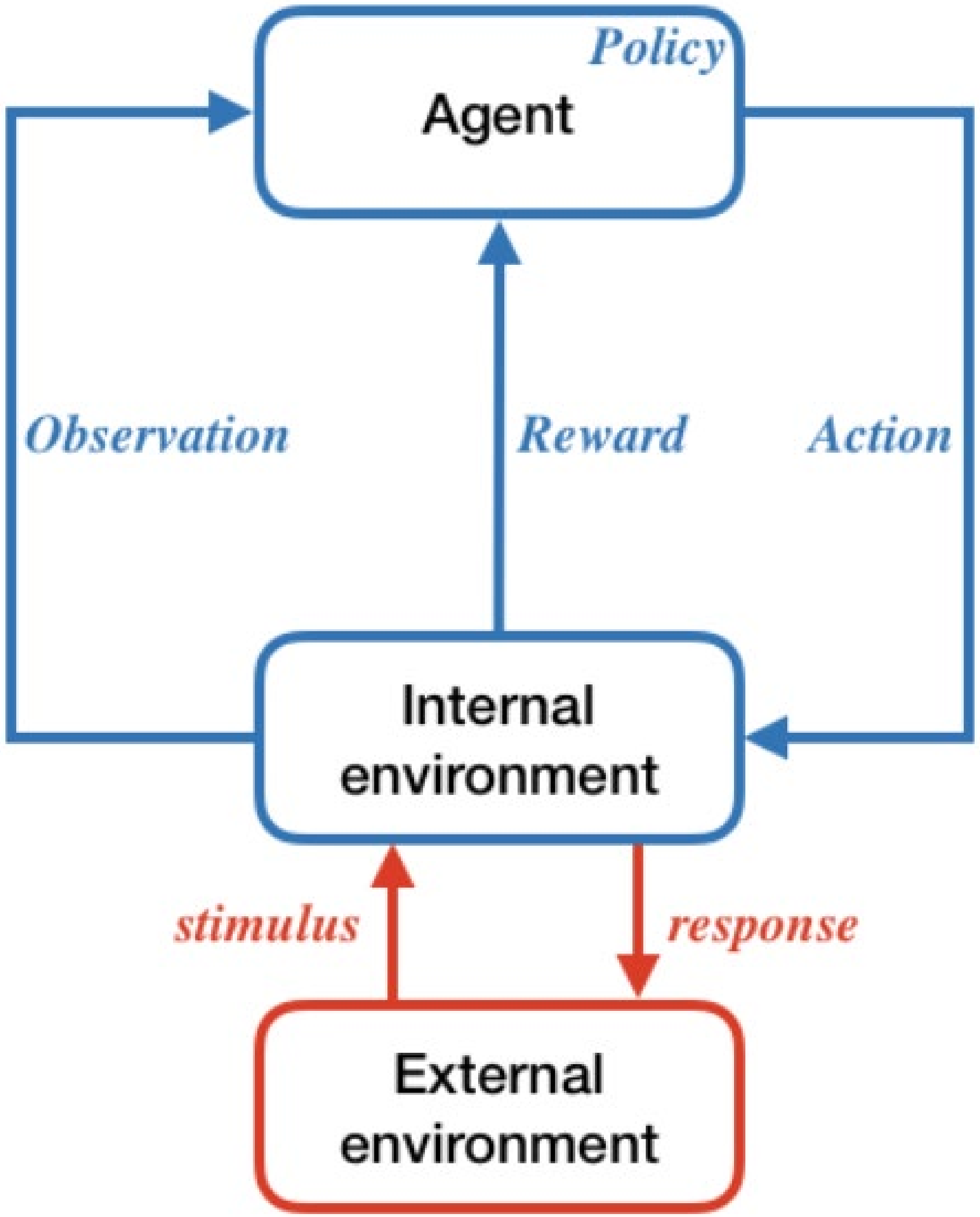
These issues have recently been addressed by a new class of theories in efforts to explain *why* people choose some strategies in interaction and not others [1, 22–24, 56, 59, 61, 63, 91]. Consider, for example, explaining why people make certain text-entry errors

https://dl.acm.org/doi/abs/10.1145/3491102.3517739

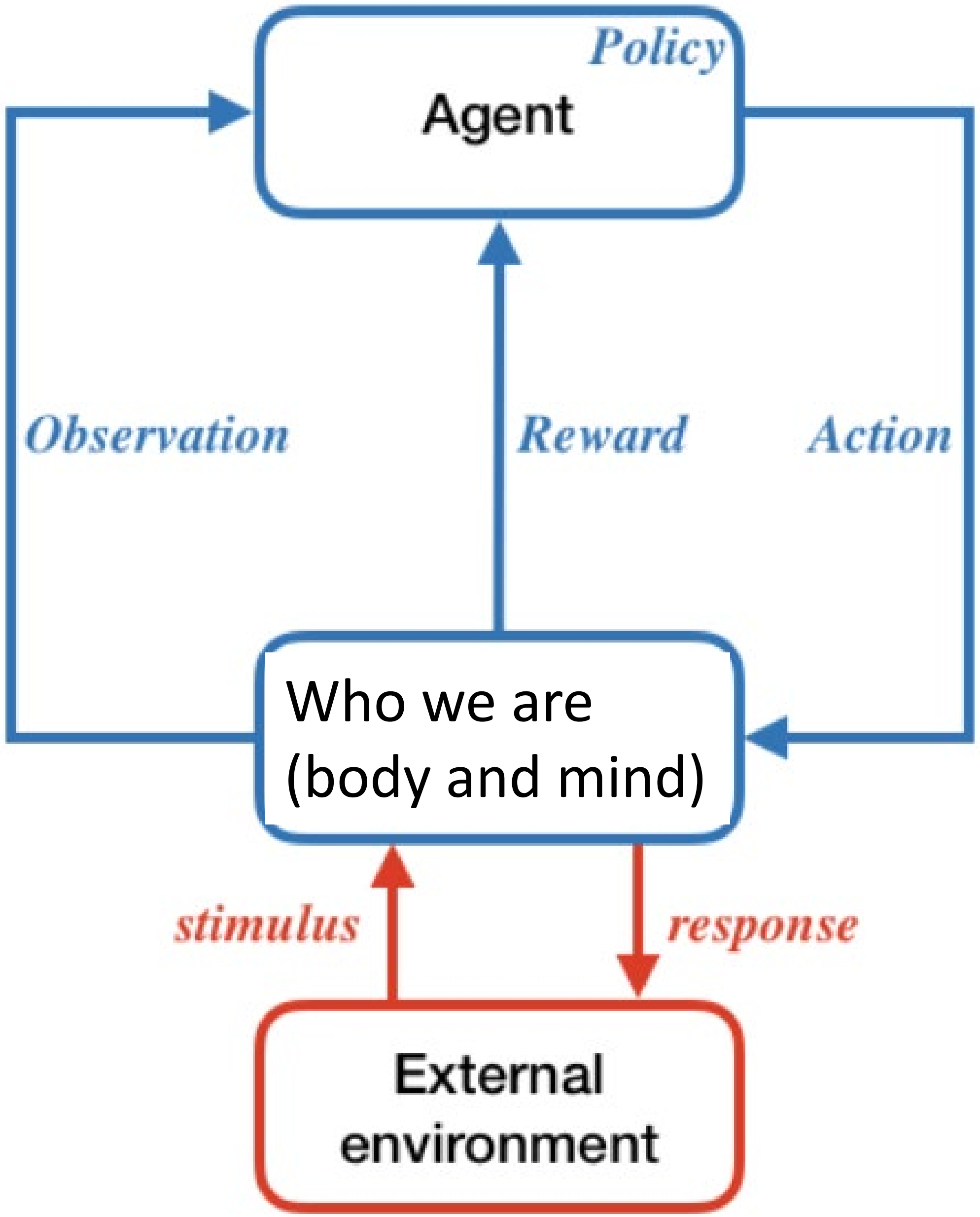
Game playing AI interacting with a game

- First, try random actions
- Gradually start to repeat the actions that yield highest utility
- Fundamentally, learning iteratively through trial and error

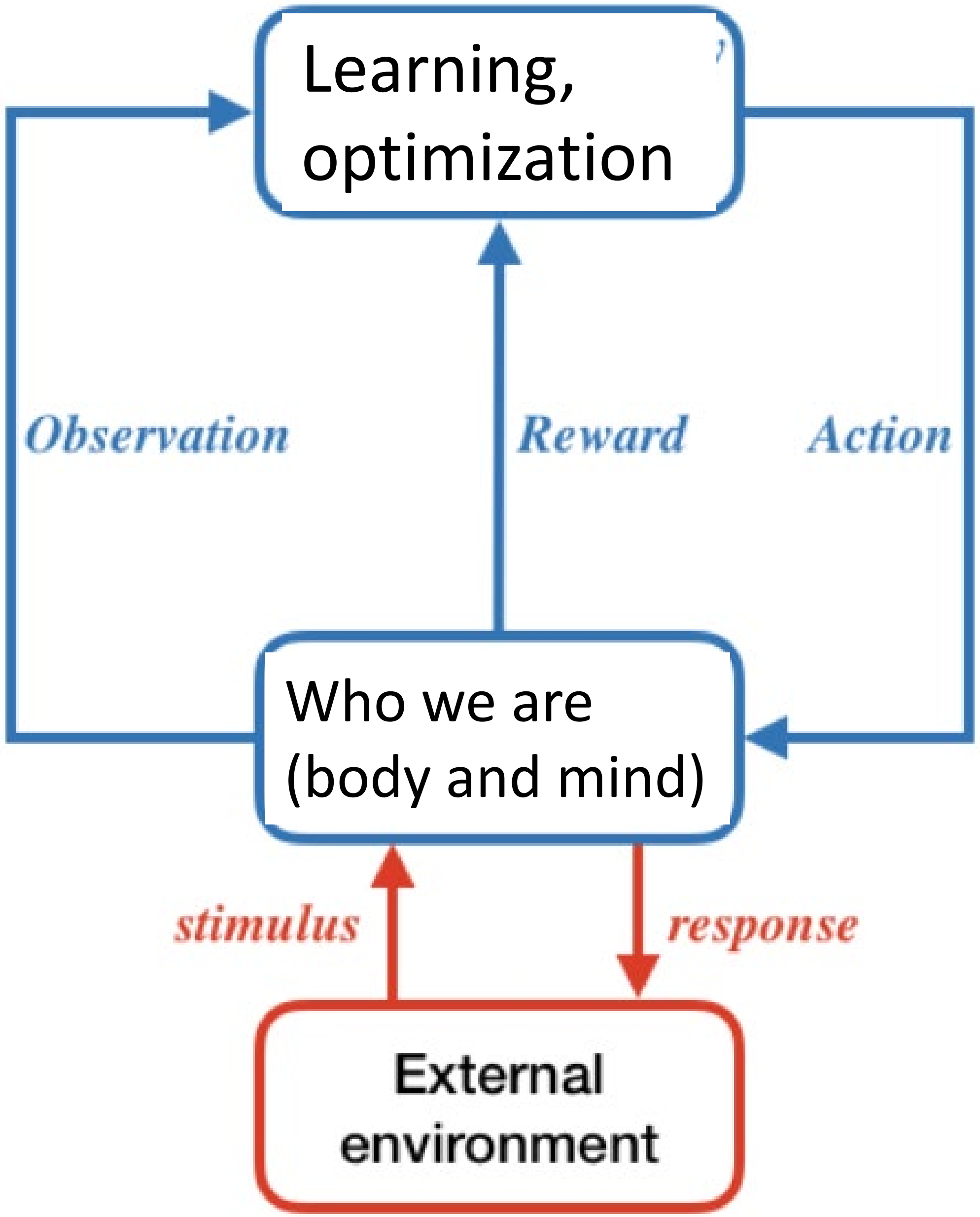
What about humans?



“Internal environment” = who we are



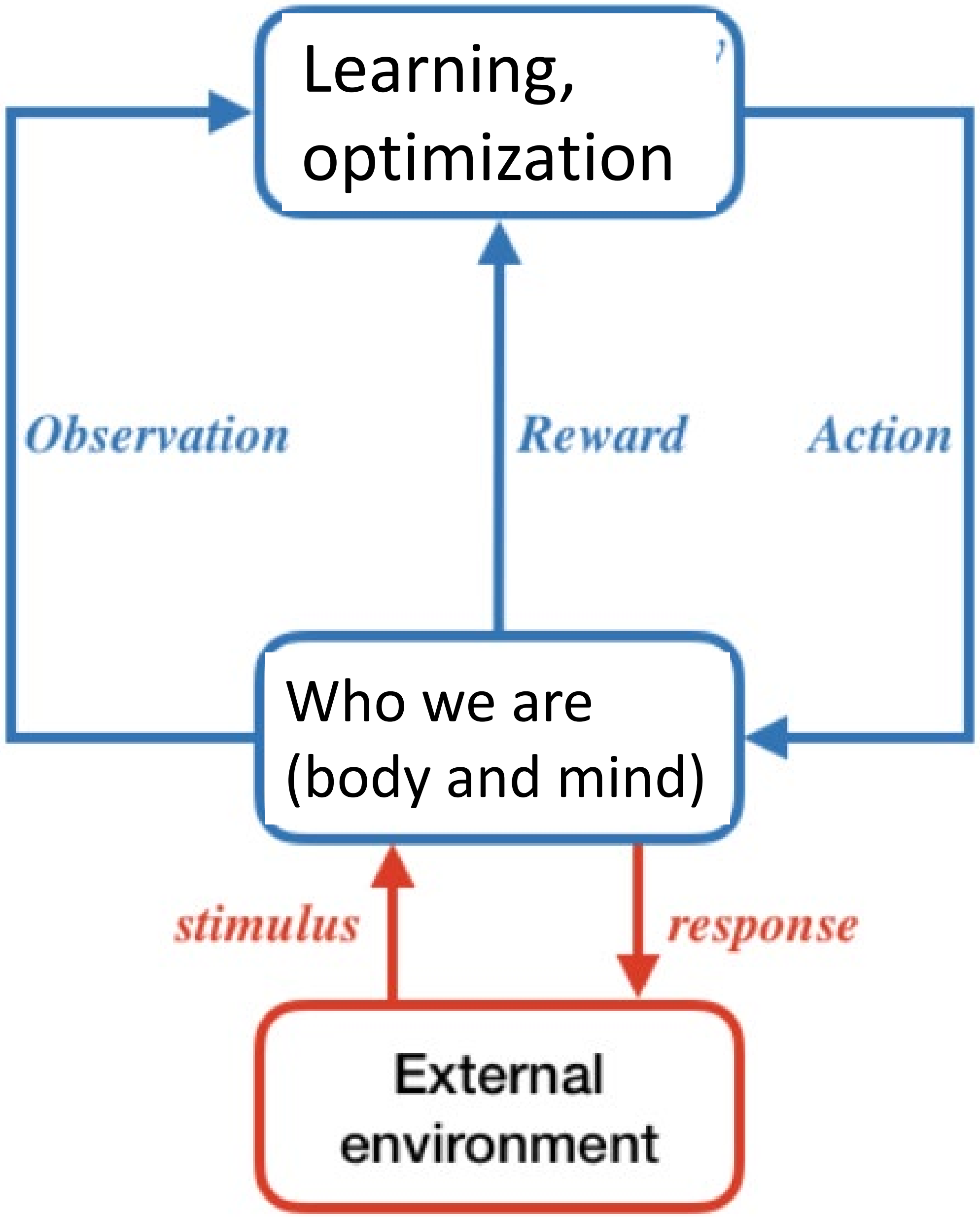
“Agent” = learning & optimization/search



How do we learn and optimize?

System 1: Evaluate and choose actions based on intuition or "what feels right" (intuitive and sometimes irrational predictions of utility)

System 2: Think of every option, e.g., using some mental model that lets us predict the results of actions



System 1 and evolution

- Intuitive/instinctive System 1 preferences are both learned and innate
- During the most of our evolution, energy has been a scarce resource
- High-calorie foods have provided a survival advantage => we're genetically built to seek them and experience them as rewarding, innately and irrationally/suboptimally

JOURNAL ARTICLE

Sweet taste preferences are partly genetically determined: identification of a trait locus on chromosome 16 FREE

Kaisu Keskitalo, Antti Knaapila, Mikko Kallela, Aarno Palotie, Maija Wessman, Sampo Sammalisto, Leena Peltonen, Hely Tuorila ✉, Markus Perola

The American Journal of Clinical Nutrition, Volume 86, Issue 1, July 2007, Pages 55–63, https://doi.org/10.1093/ajcn/86.1.55

Published: 01 July 2007 **Article history** ▾

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ABSTRACT

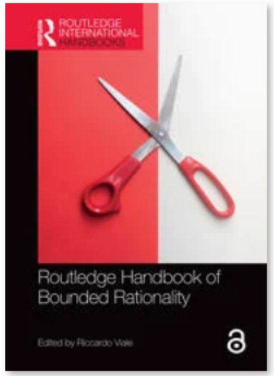
Background: Humans have an innate preference for sweet taste, but the degree of liking for sweet foods varies individually.

Objective: The proportion of inherited sweet taste preference was studied. A genome-wide linkage analysis was performed to locate the underlying genetic elements in the genome.

Design: A total of 146 subjects (32% men, 68% women) aged 18–78 y from 26 Finnish families evaluated the intensity and pleasantness of 3 suprathreshold solutions of sucrose (3.0%, 7.5%, and 18.75%) and plain water and the intensity of filter paper impregnated with 6-*n*-propylthiouracil (PROP). The subjects also reported the pleasantness and the use frequency of 5 sweet foods (chocolate, candy, ice cream, sweet desserts, and sweet pastry) and completed a food-behavior questionnaire that measured their craving for sweet foods.

Results: Of the chemosensory functions, the pleasantness rating of the strongest (18.75%) sucrose solution and the intensity rating of PROP yielded the highest heritability estimates (41% and 66%, respectively). The pleasantness and the use frequency of sweet foods (both variables calculated as a mean of ratings for 5 food items) and the craving for sweet foods showed significant heritability (40%, 50%, and 31%, respectively). A logarithm of odds score of 3.5 (P = 0.00003) was detected for use frequency of sweet foods on chromosome 16p11.2 (marker D16S753).

Conclusions: Sweet taste preferences are partly inherited. Chromosome 16p11.2 may harbor genetic variations that affect the consumption of sweet foods.



Chapter

Ecological rationality

Bounded rationality in an evolutionary light

By Samuel A. Nordli, Peter M. Todd

Book Routledge Handbook of Bounded Rationality

Edition	1st Edition
First Published	2020
Imprint	Routledge
Pages	11
eBook ISBN	9781315658353

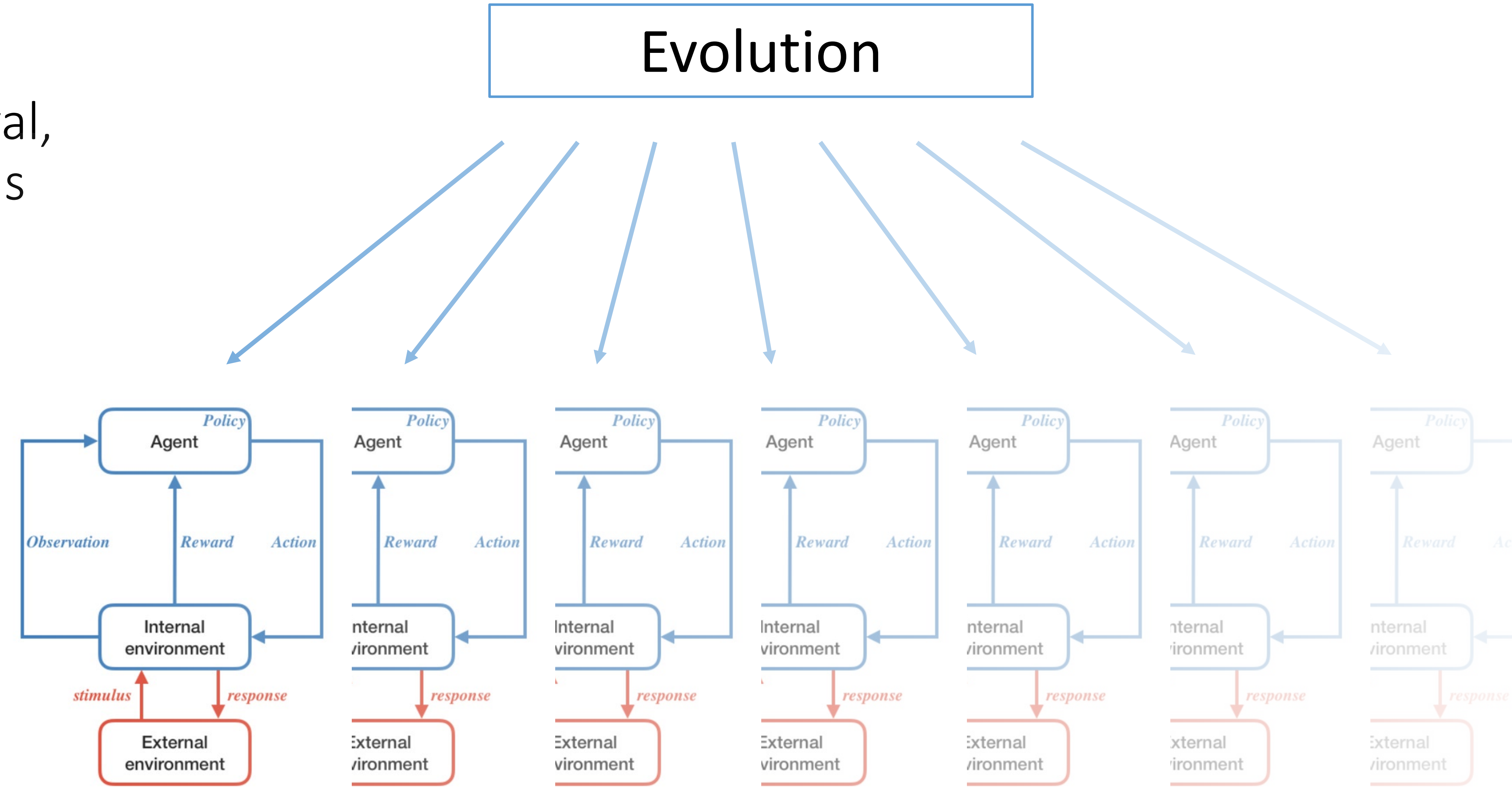
ABSTRACT

The study of ecological rationality situates Simon's notion of bounded rationality within the framework of natural selection, emphasizing that the evolved capacities of decision-making organisms have been shaped by and are adapted to the structure and fitness pressures of ancestral environments. Research in ecological rationality considers the fit between decision mechanisms and the structure of decision environments in order to understand behavioral outcomes in specific decision contexts. This chapter focuses on the importance of goals in decision making, highlighting how decision makers use cues about environment structure to efficiently determine which behaviors or strategies will best serve goal pursuit; research in ecological rationality, behavioral ecology, and neuroscience is used to draw connections between fast and frugal heuristics, fixed action patterns, rules of thumb, and habits, framing each as examples of cue-driven iteration/variation of past behavior used to pursue goals in present contexts. The chapter closes with a review of specific examples from ecological rationality research, an overview of how the ecological rationality perspective can help understand behavior that fails to match classically rational expectations, and finally with a discussion on future directions for research in ecological rationality.

The big picture: Two nested optimization processes

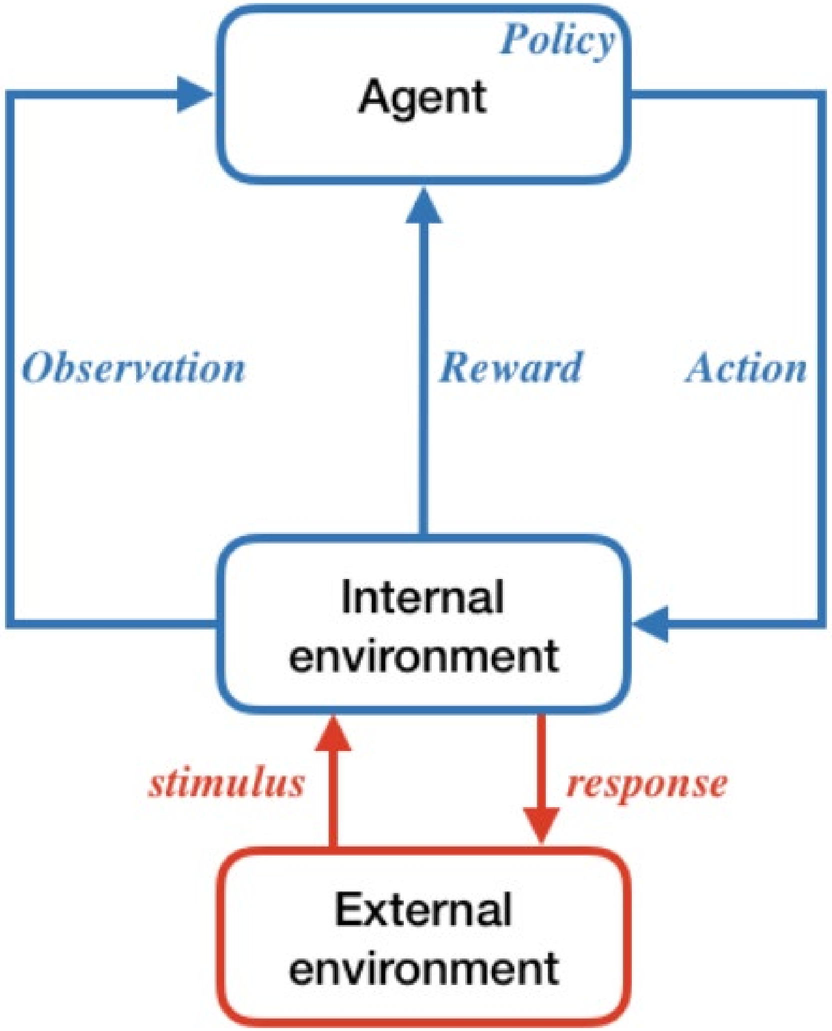
Evolution:
Optimization of genes for survival, over generations

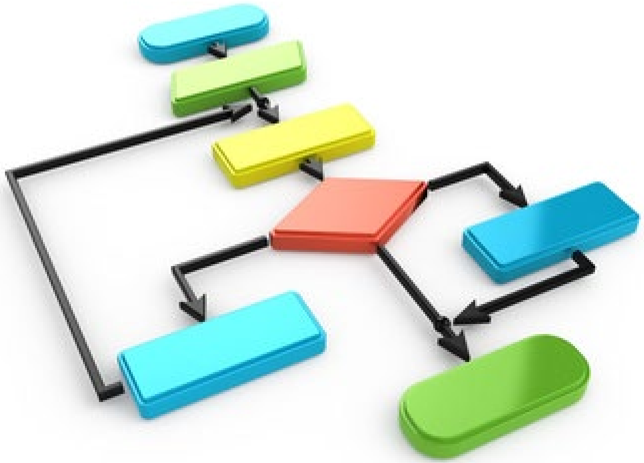
Computational Rationality:
Optimization of behavior during each individual's lifespan



CR limitations defined by evolution: cognitive architecture, innate preferences and other System 1 biases…

CR recap: We optimize utility, but with limitations





ATTENTION,
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IDEAS,
ASSOCIATIONS,
IMPULSES,
INTUITIONS

ASSOCIATION

Questions? (also: short break)

Structure

- Theory: two types of thinking, computational rationality, limits of human cognition, perception, and action.
- **Practice: Game design principles based on the theory.**

Example games: Walking Dead No Man’s Land & Clash Royale

- In the following slides, I’ll be using examples from WDNML and Clash Royale.
- I assume you have played both games:
  - WDNML: Complete first two episodes or play until you run out of virtual currency.
  - Clash Royale: Play at least through the tutorial and the first arena so that you get to unlock some cards and start to get an idea of the reward and progress mechanics

Design principles and implications

- **Core reward design principles (anticipation and discounting of rewards)**
- Avoiding thinking (System 1 vs. System 2, cognitive biases affecting reward evaluation)
- Perception and attention (contrast, Halo effect, confirmation bias)
- Memory (storing and retrieving information)
- Social (effect of other people)

Behavioral game design

https://www.gamedeveloper.com/design/10-years-of-behavioral-game-design-with-bungie-s-research-boss

10 Years of Behavioral Game Design with Bungie's Research Boss

Bungie's head of user research takes another look at his decade-plus old article, which has become both influential and infamous for its suggestion that games can be better when developers take the psychology of players into account.

John Hopson
Blogger

June 15, 2012

[*Bungie's head of user research takes another look at his decade-plus old article, which has become both influential and infamous for its suggestion that games can be better when developers take the psychology of players into account.*]

A lone scientist labors late into the night in his lab, assembling his creation piece by piece, and then releases it to rampage across an unsuspecting world! Muwhahahaha!

No, not *Frankenstein*. Behavioral Game Design!

When I wrote that article a decade ago, I was a psychology graduate student and amateur game designer who had never worked in the games industry. Since then, the article has run amok, living an almost completely independent existence in the wilds of the internet.

It's been translated into multiple languages and assigned as homework. It's been cited by academics, pilloried by the Huffington Post, and even lampooned by my childhood favorite, Cracked magazine.

[Footnote: This actually makes me the second of Bungie's employees to be called out by Cracked. Their treatment of our security chief was much more complimentary.]

And as anniversaries tend to do, the 10 year anniversary of this article has spurred a lot of reflection on my part. The industry has changed almost beyond recognition since 2001, and I'd like to take the opportunity to ruminate publicly about where this topic has gone in the past decade.

Reinforcement learning has been acknowledged as a

powerful force in game design.

The biggest change is that it's hard to find a game today that doesn't take its reward structure seriously. At the time of the article, it was a radical idea to say that games contained rewards and that the way those rewards were allotted could affect how people played. Now it's simply a given.

The clearest example of the acceptance of reinforcements in game design is the widespread use of achievements. Achievements are a really interesting case for study because there often isn't any

Rewards only motivate us if we anticipate/predict them

- Computational Rationality: players choose actions that yield highest expected utility (sum of future rewards)

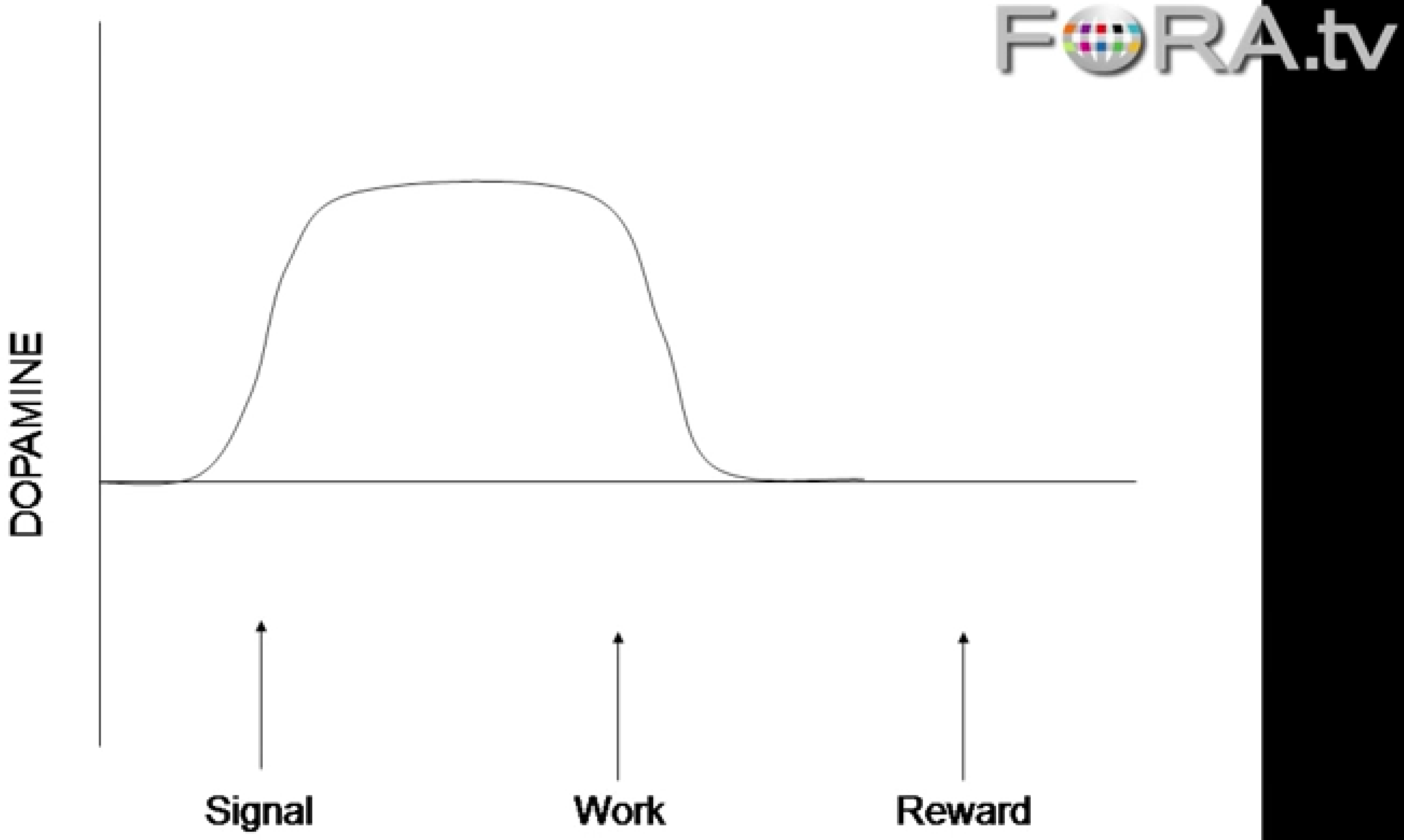
$$\mathbb{E}\left[\sum_t \gamma^t r(a_t, o_t)\right]$$

- However, players' information, search capabilities and mental models are limited => they might not anticipate the rewards

Anticipating rewards and the brain

- Dopamine is the key neurotransmitter, linked to seeking reward and pleasure in games, gambling, work, sex...
- Dopamine peaks when anticipating reward (based on previous experience or some mental model), not when getting the reward. The rise of dopamine drives us to action.

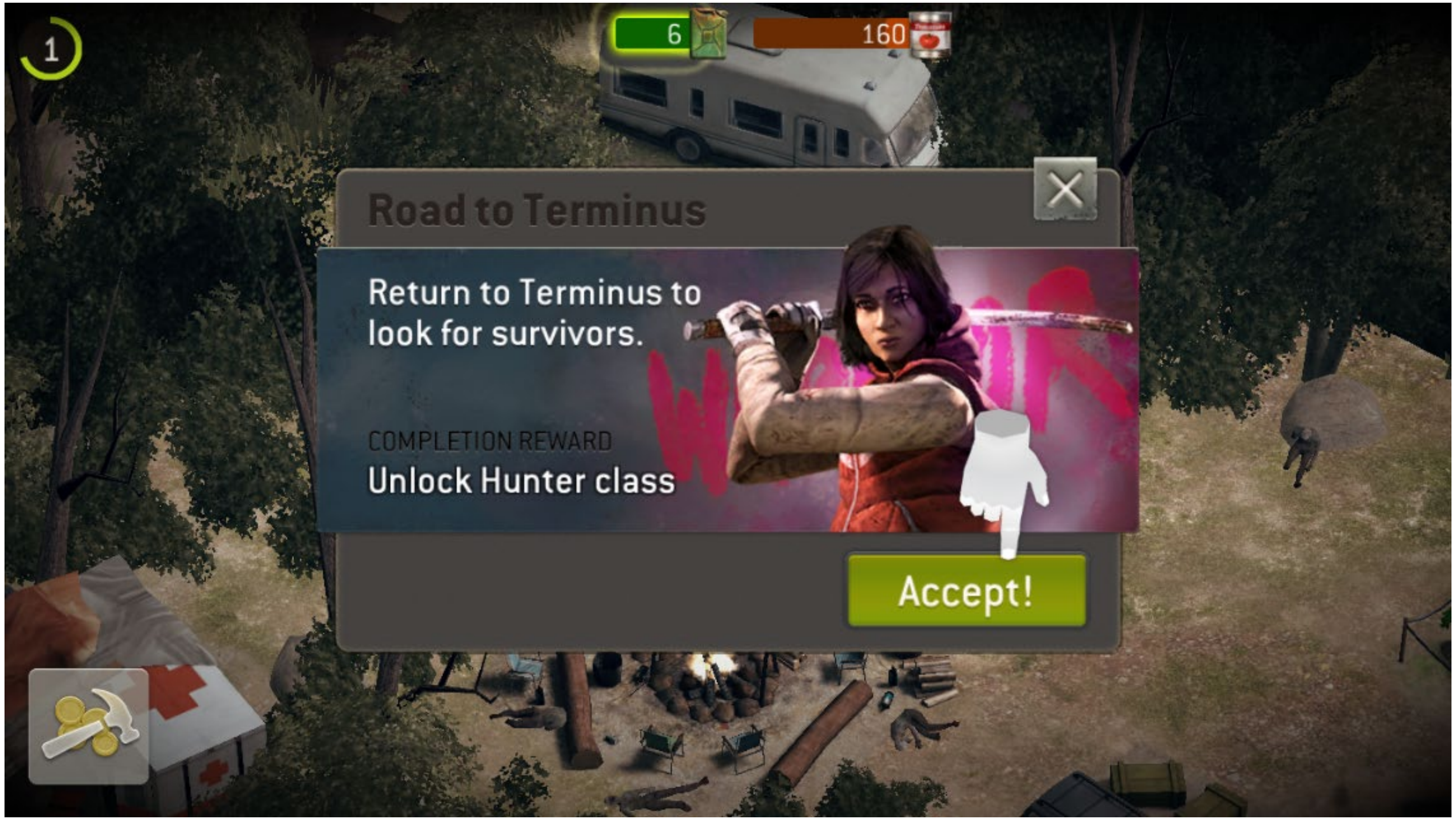
https://www.youtube.com/watch?v=axrywDP9Ii0



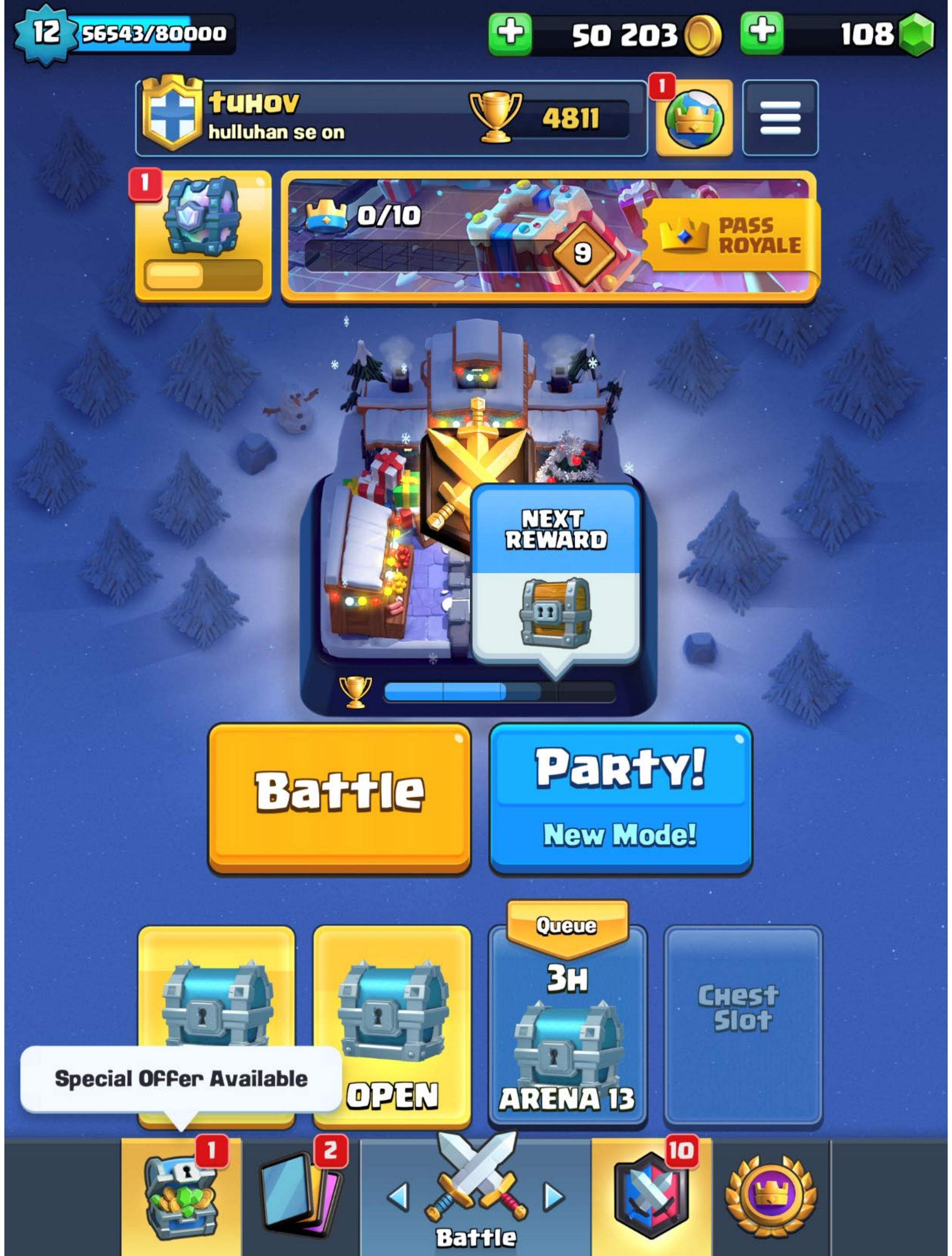
Design principle: Build anticipation

- The player’s information, search capabilities and mental models are limited => they might not anticipate the rewards
- Design implications:
  - Communicate/advertise future rewards to increase motivation!
  - Often: Communicate next reward already before previous one reached.

Communicate future rewards



WDNML: Clearly state the reward that the player will get, e.g., after completing an episode



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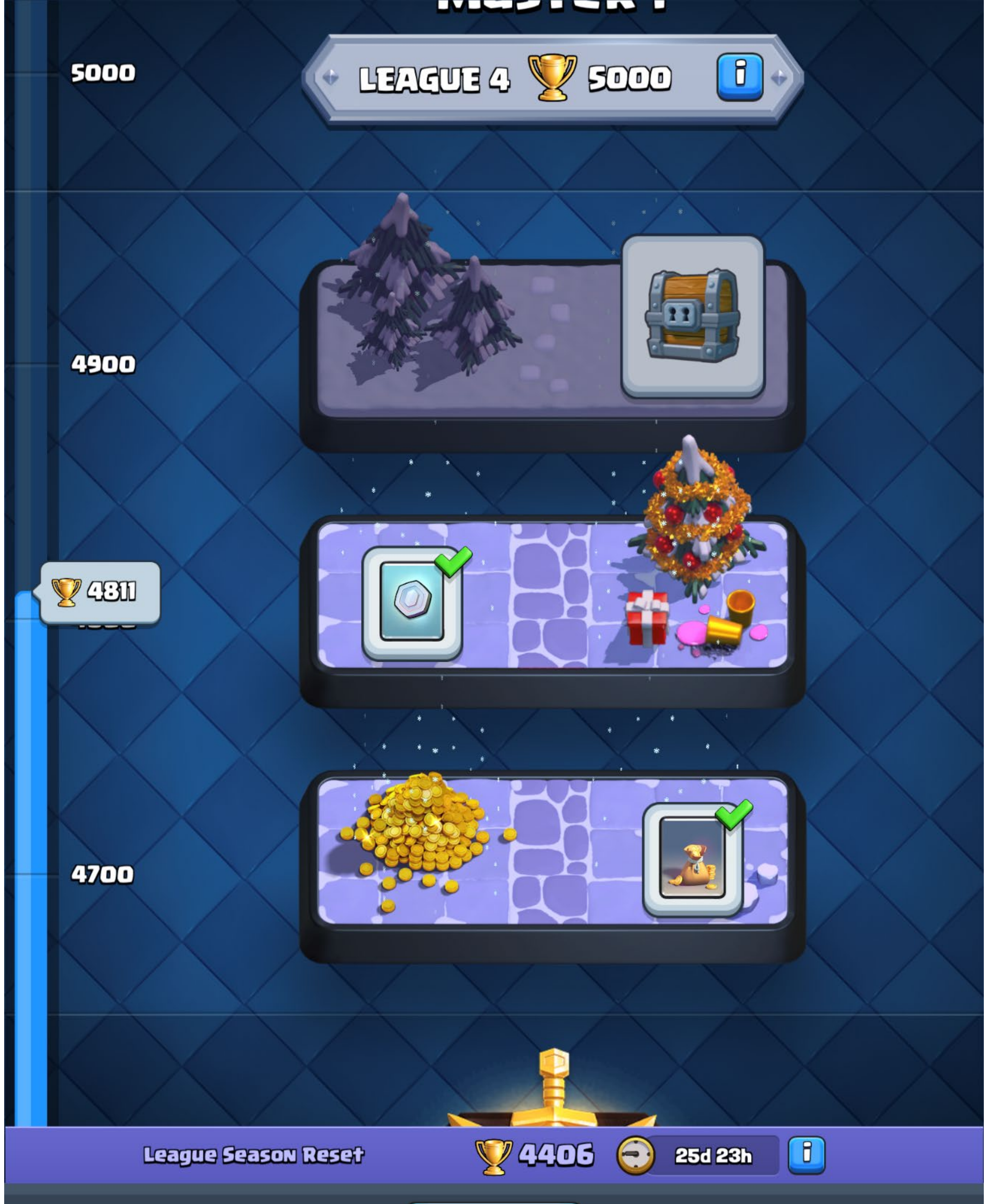
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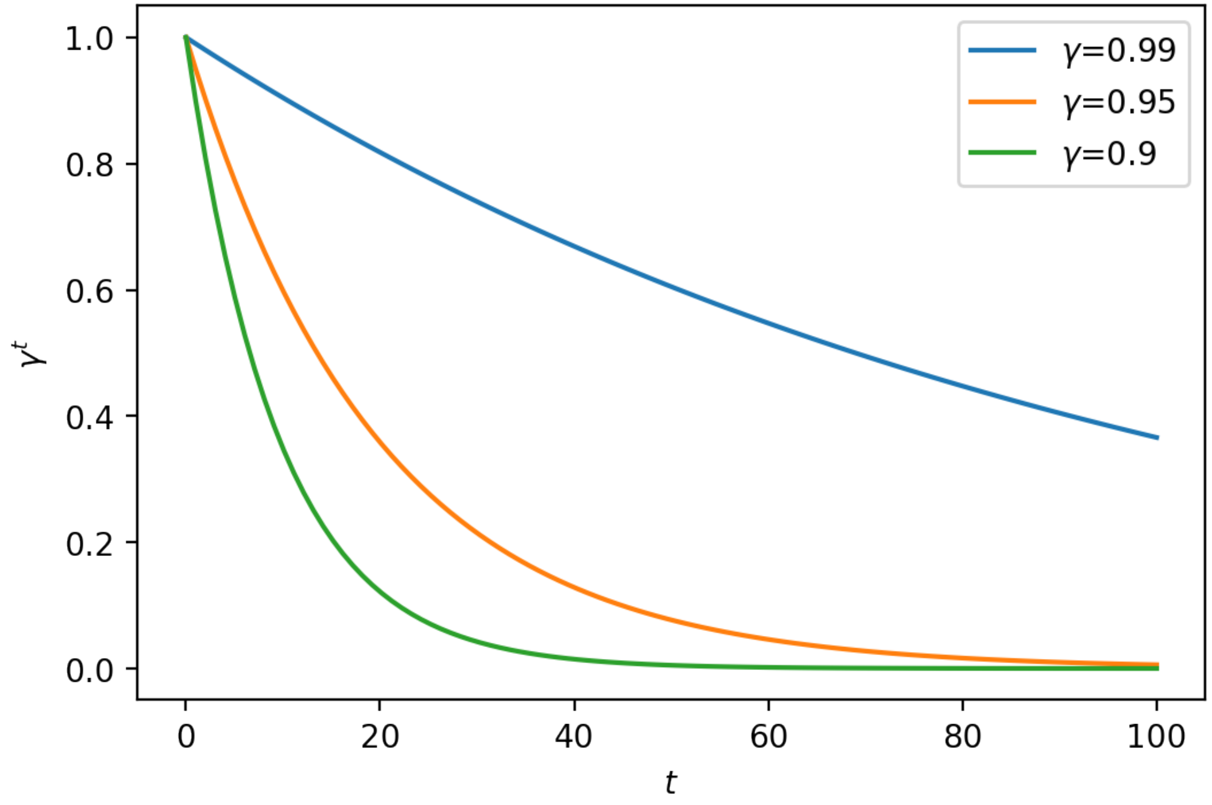
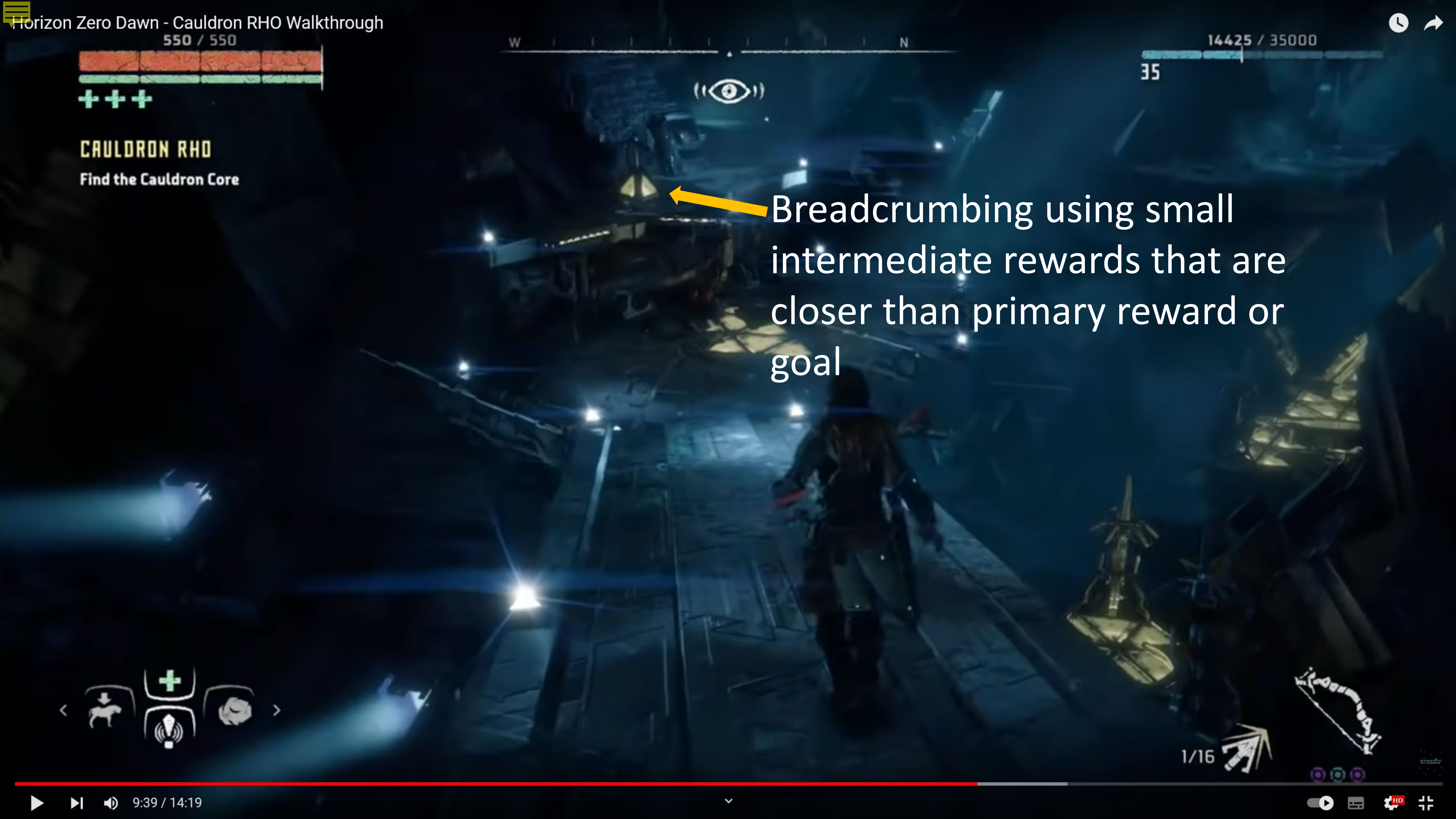
Design pattern: Rewards that unlock later

WDNML: Many rewards cannot be used immediately, player has to first reach some other goal(s).

Motivation increases when the reward or goal is near

- Computational Rationality model: future discounting through the gamma parameter => far-future rewards feel smaller and less motivating
- Design principles:
  - Breadcrumbing: even small intermediate rewards guide the player towards a bigger reward that is so far that it might not feel motivating
  - Break tasks into subtasks that have rewards.
  - Rewards at multiple time scales (e.g., core loop and daily login rewards)




Horizon Zero Dawn - Cauldron RHO Walkthrough
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CAULDRON RHO
Find the Cauldron Core
Breadcrumbing using small intermediate rewards that are closer than primary reward or goal
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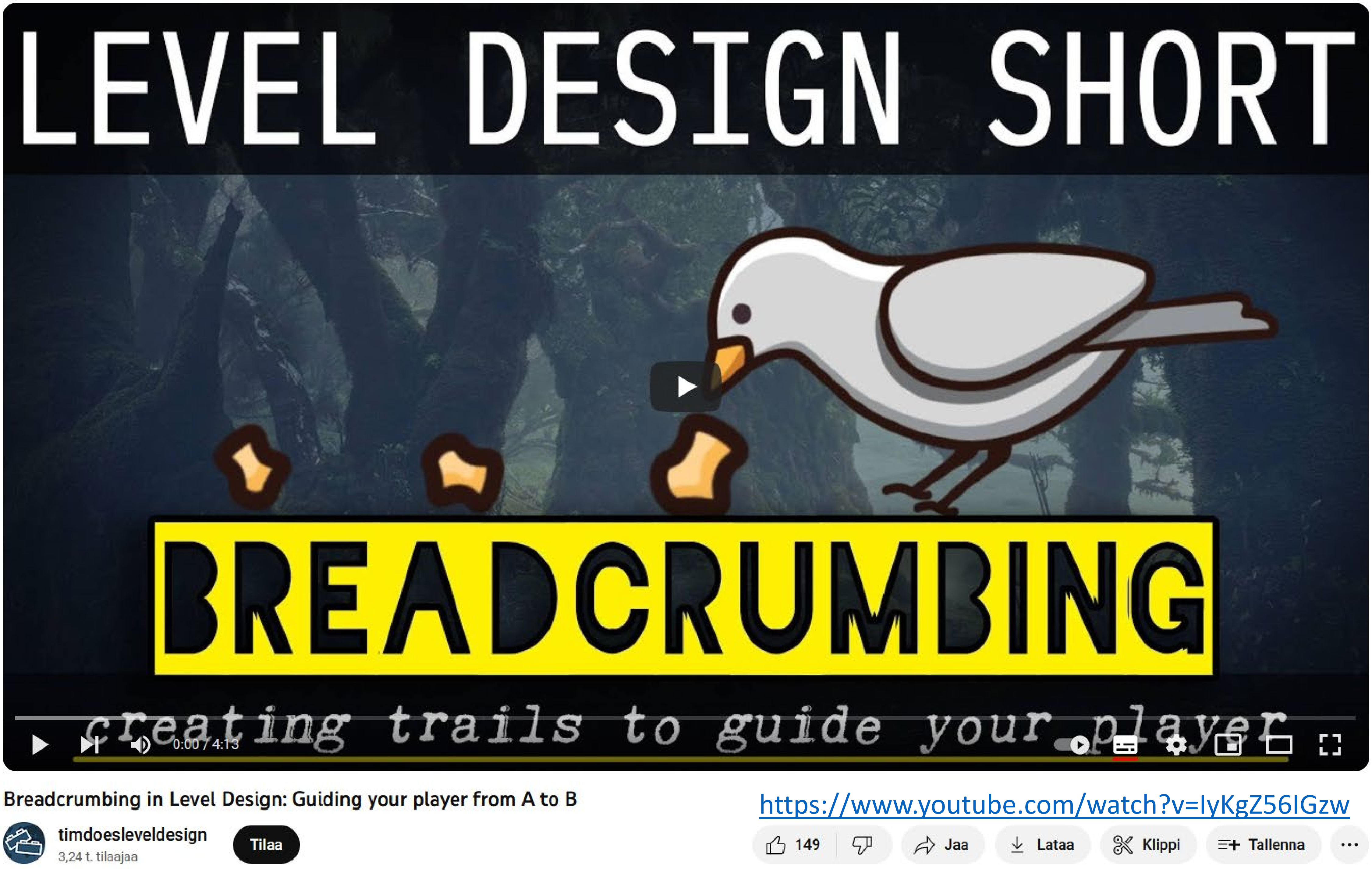
9:39 / 14:19



https://www.youtube.com/watch?v=IyKgZ56IGzw

Perception of time is subjective

Endowed progress effect: perceived time-to-reward can be manipulated.

An illusion of already having made progress towards a goal can make the goal seem nearer and more motivating (remember the discounting of rewards that are far)

The Endowed Progress Effect: How Artificial Advancement Increases Effort

JOSEPH C. NUNES
XAVIER DRÈZE*

This research documents a phenomenon we call the *endowed progress effect*, whereby people provided with artificial advancement toward a goal exhibit greater persistence toward reaching the goal. By converting a task requiring eight steps into a task requiring 10 steps but with two steps already complete, the task is reframed as one that has been undertaken and incomplete rather than not yet begun. This increases the likelihood of task completion and decreases completion time. The effect appears to depend on perceptions of task completion rather than a desire to avoid wasting the endowed progress. Moderators include the reason, if any, offered for the endowment and the currency in which progress is recorded.

Consumers often persist in their efforts to achieve goals that are accompanied by discrete, extrinsic rewards. For example, they might delay purchasing a cellular phone a determinate number of months in order to get the newest product with the latest features. They might forgo various small discretionary purchases in order to save enough money to buy a big-ticket item such as a plasma TV. Or they might steer multiple purchases toward a particular air carrier with the hope of earning enough miles for a free flight. The notion that goals motivate individuals, making them work harder and perform better than people without goals, has been supported broadly in the literature (Locke and Latham 1990).

This research documents a phenomenon we call the *endowed progress effect*, whereby people provided with artificial advancement toward a goal exhibit greater persistence toward reaching the goal. By artificial advancement, we are referring to moving someone toward a goal while simultaneously moving the goal away such that the task requirements and reward remain unchanged. For example, consider reframing a frequency program that requires eight purchases in order to earn a specific reward as a program requiring 10, but with two purchases awarded upon enrollment. Both programs require eight purchases and provide the same reward, yet for two reasons, we expect those who receive the endowed progress to exert more effort.

First, by framing the task as one that has been undertaken and is incomplete rather than one not yet begun, we expect people to be more committed to completing the task. Zeigarnik (1927) demonstrated that interrupted or uncompleted actions engender a strong motivation to complete the action, and psychologists agree that once a person accepts a task, for whatever reason, he or she tends to stay on that course until the goal is achieved (Fox and Hoffman 2002). Second, according to the *goal gradient effect* (see Hull 1932), people who are closer to their goal should exert comparatively more effort. Hence, we expect the initial momentum provided by the endowed progress to be compounded as effort increases with each step taken toward the goal.

The concept of persistence as a component of goal-directed behavior has been an integral part of motivation research for decades. Two central paradigms in the literature seek to explain persistence and have formed the foundation for modern approaches. First, Atkinson's work on achievement motivation (1957) depends on two fundamental elements: *inertial tendency* and *expectancy*. Inertial tendency is a psychological analog to Newton's first law of motion. Just as motion instigated in the physical world persists indefinitely unless acted upon by external forces, Atkinson believed a goal-directed tendency would persist until satisfied. Hence, inertial tendency reflects persistence and must be taken into account when evaluating other aspects of motivation. Expectancy is determined by the likelihood of success and the perceived value of attaining the goal. As the distance from the goal decreases, both the desirability and the feasibility of completion are believed to increase (Atkinson and Birch 1974). Models in this tradition have been

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Endowed progress effect

Perception of time is subjective

- A reward seems closer if we don’t understand how far it is, or remember or foresee all the hurdles that lie ahead
- The initial enthusiasm of a game project: Many projects would not even start if people realistically anticipated the difficulties.
- Game design: Some games like WDNML obfuscate the time-to-reward

WDNML time-to-reward obfuscation:

- Reward: a new weapon
- Needs leveling up a character
- Leveling up a character needs higher-level training ground
- Leveling up the training ground needs a council upgrade
- Council upgrade needs lot’s of supplies => need to upgrade supply storage
- Hard to keep the whole cascade in mind and anticipate how much grinding/waiting/gold needed => boosts the anticipation of getting to use the new weapon.

Daily Quests or Daily Pests? The Benefits and Pitfalls of Engagement Rewards in Games

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REGAN L. MANDRYK, University of Saskatchewan, Canada

Many games use engagement rewards as incentives for players to engage, e.g., daily login rewards, repeatable challenges, or seasonal rewards like holiday skins. These rewards may serve players by facilitating enjoyment or motivation; however, they may also be considered differently by skeptical players, e.g., as dark patterns that do not benefit players, and may detract from—or even harm—player experiences. As they are widely prevalent in a variety of games, it is important to understand how such rewards are experienced by players to inform potential pitfalls, such as when they are negative for gaming experience or lead to unhealthy gaming behaviours. 178 participants completed a mixed-methods survey and described such rewards in games they play, the tasks required to acquire them, and their experience qualitatively and with validated scales of motivation regulation and passion orientation. We found that players perceived these rewards as beneficial (e.g., as motivation), as negative (e.g., by promoting fear of missing out), or even as an obligation or chore. Quantitative results further support the dualistic experience of such rewards. We contribute findings and design recommendations that are useful for understanding and designing widely used but potentially detrimental reward mechanics.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Computer games**; • **Software and its engineering → Interactive games.**

Additional Key Words and Phrases: games, reward, daily, quests, engagement, motivation, passion, lootbox

ACM Reference Format:
Julian Frommel and Regan L. Mandryk. 2022. Daily Quests or Daily Pests? The Benefits and Pitfalls of Engagement Rewards in Games. *Proc. ACM Hum.-Comput. Interact.* 6, CHI PLAY, Article 226 (October 2022), 23 pages. https://doi.org/10.1145/3549489

https://dl.acm.org/doi/abs/10.1145/3549489


4
6
1095
810
83
XP
4
Map


4
6
1311
810
83
219
4
Map


4
6
1314
908
83
109
4
Map


4
6
1314
919
XP
83
4
Map

Clash Royale rewards?

- Battle (core loop) win?
- Battle fail?
- Login rewards?
- Daily retention rewards?
- Weekly?
- Longer term?

Clash Royale rewards

- Battle win: chests, xp
- Battle fail: crowns for crown chest, xp
- Login: chest timers have expired, you can open. Free cards in shop.
- Daily: get 10 crowns for crown chest, the 2-day structure of clan wars (collection day + war day, very bad socially to miss either – you might get kicked out from the clan)
- Weekly: Epic Sunday (can request and donate epics with clan, free epic in shop, more epics and legendaries to buy in shop)
- Longer term: Getting to new arenas, clan war season rewards, challenger season rewards

Reward design checklist

- Rewards are a key tool for motivating players => Reward all desired behavior
  - Reward for winning or reaching goals (WDNML: loot boxes,)
  - Reward for playing (failing to reach the goals, trying again) (WDNML rewards for failing: XP from killed walkers, timers that complete while playing)
  - Reward for coming back the next day (WDNML: upgrade timers, XP & can producers, random walkers)
  - Reward long-term retention (WDNML: episodic structure and episode rewards, character leveling, episodes too long to be completed in a single session. Also: achievements/trophies)
- Rewards motivate more when closer (breadcrumbing, endowed progress effect, other possible manipulations of perceived time-to-reward)
- Build anticipation – don't assume your players are prescient (WDNML: announcing episode completion rewards in the beginning of episode)

Design principles and implications

- Core reward design principles (anticipation and discounting of rewards)
- **Avoiding thinking (System 1 vs. System 2, cognitive biases affecting reward evaluation)**
- Perception and attention (contrast, Halo effect, confirmation bias)
- Memory (storing and retrieving information)
- Social (effect of other people)

Avoiding thinking, going with the default

- Analytic System 2 thinking requires mental effort, which people tend to avoid
- Implication: people often go with the default, intuitive/automatic response, especially when tired or intoxicated
- Game design principle: Frame the desired player behavior as the default
- Game monetization: Many games frame paying as the default

The power of the default

- In many countries, getting a driver’s license includes indicating whether you are a willing organ donor in case of accidental death
- Even in such an important decision, people go with the default, avoiding thinking.
- Checking a box to opt out: nearly 100% of people become donors
- Checking a box to opt in: donor rate drops near or below 10%

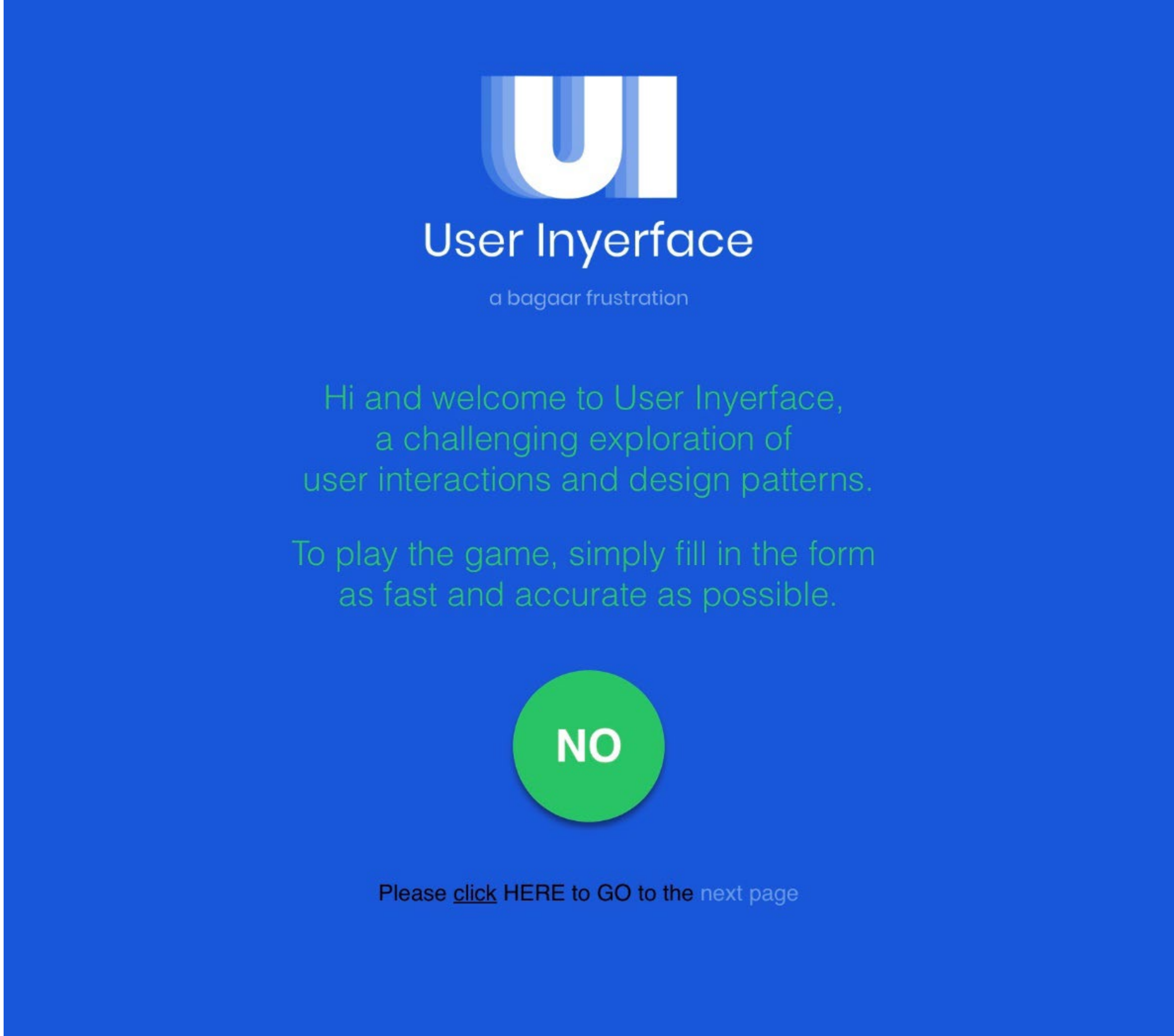

6
1087
690
94
EPISODE 1
ROAD TO TERMINUS
TERMINUS
Hello there!
Are you enjoying The Walking Dead: No Man's Land so far? Would you like to recommend us in the App Store?
Write a review
No, thanks
World map
Camp
3


Rate Your Experience
X
Enjoying Dungeon Keeper?
5-Star ratings from you help us provide free updates!
How would you rate Dungeon Keeper?
1-4 Stars
5 Stars

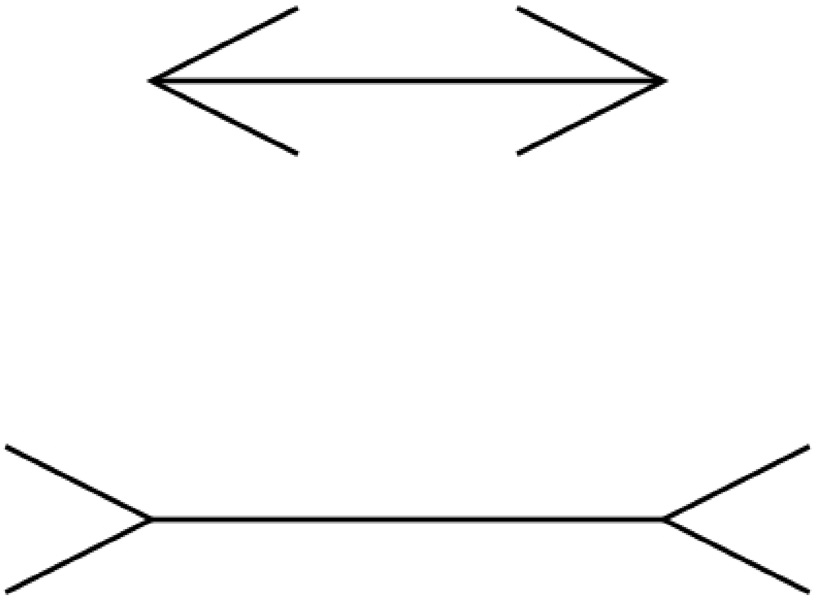
Common ”default designs” in games?

- Menu flow that gets you into the game if you don’t want to think and just keep pressing ’X’
- When the game starts or a saved game is loaded, the player’s initial facing direction is towards the next goal
- Clear landmarks that intuitively guide navigation

https://userinyerface.com/



System 1 biases affecting reward evaluation



System 1 biases affecting reward evaluation

- The biases may be suboptimal for a given individual and situation, but optimal on average, from an evolutionary perspective
- Often exploited in game reward design and monetization
- Biases covered in the next slides: desirability of random rewards, loss aversion, artificial scarcity, sunk cost fallacy

Desirability of random or unpredictable rewards

- Random rewards (e.g., loot boxes) are more desirable and motivating than fully predictable rewards.
- Computational rationality: Increased perceived value of rewards => actions that produce random rewards appear more optimal.
- Behavioral psychology term: Variable ratio reinforcement
- Design implication: Good to have both randomness and skill-based play
- Can also be abused—the irrational desirability of random rewards is one explanation for gambling addiction

Evolutionary basis for random rewards

- We didn't evolve in the presence of slot machines and other forms of artificial randomness!
- Gambler's fallacy: "I've lost so many times now that I'll win next time"

NBER Working Paper #3769
July 1991

THE "GAMBLER'S FALLACY" IN LOTTERY PLAY

ABSTRACT

The "gambler's fallacy" is the belief that the probability of an event is lowered when that event has recently occurred, even though the probability of the event is objectively known to be independent from one trial to the next. This paper provides evidence on the time pattern of lottery participation to see whether actual behavior is consistent with this fallacy. Using data from the Maryland daily numbers game, we find a clear and consistent tendency for the amount of money bet on a particular number to fall sharply immediately after it is drawn, and then gradually to recover to its former level over the course of several months. This pattern is consistent with the hypothesis that lottery players are in fact subject to the gambler's fallacy.

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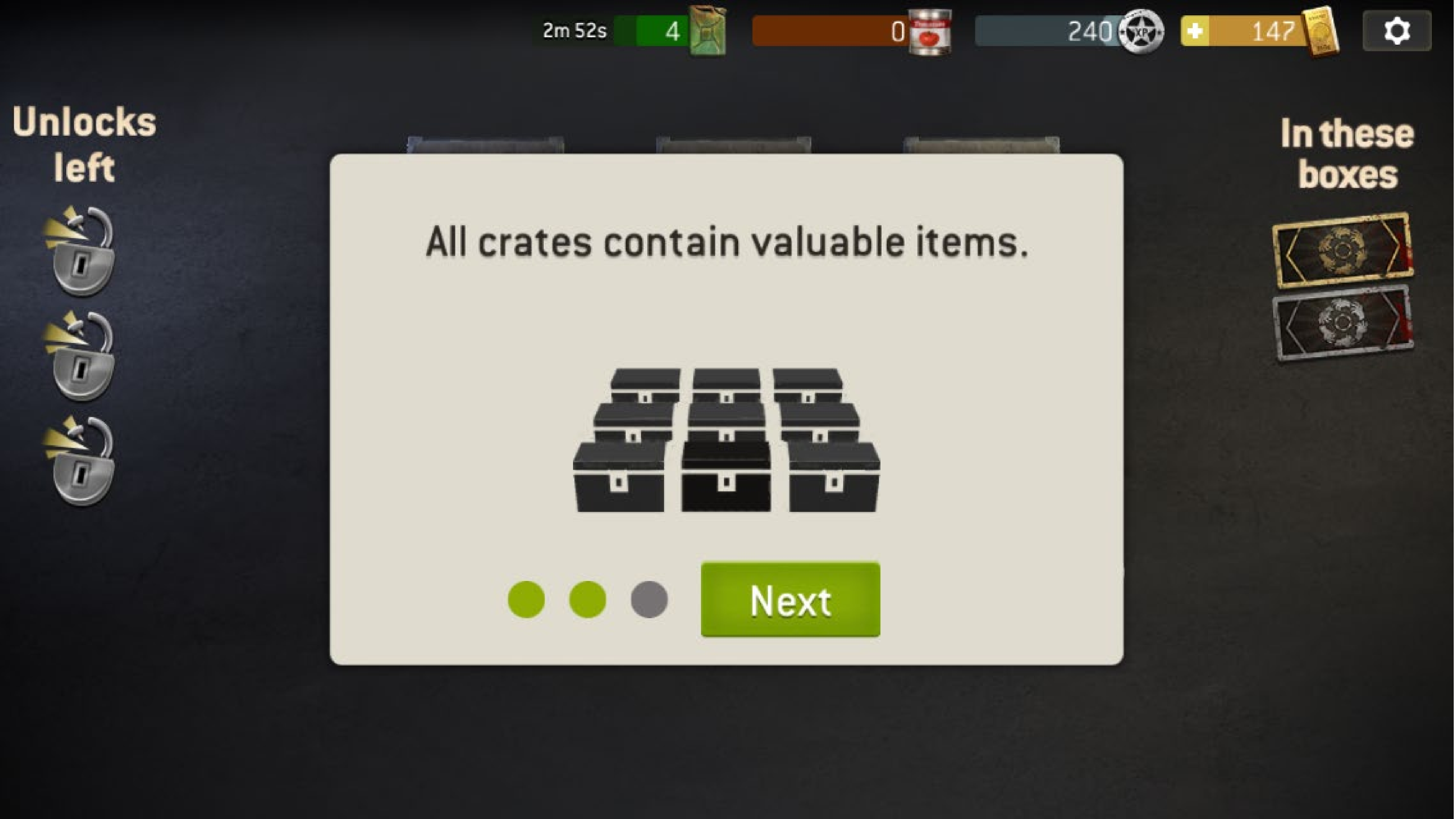
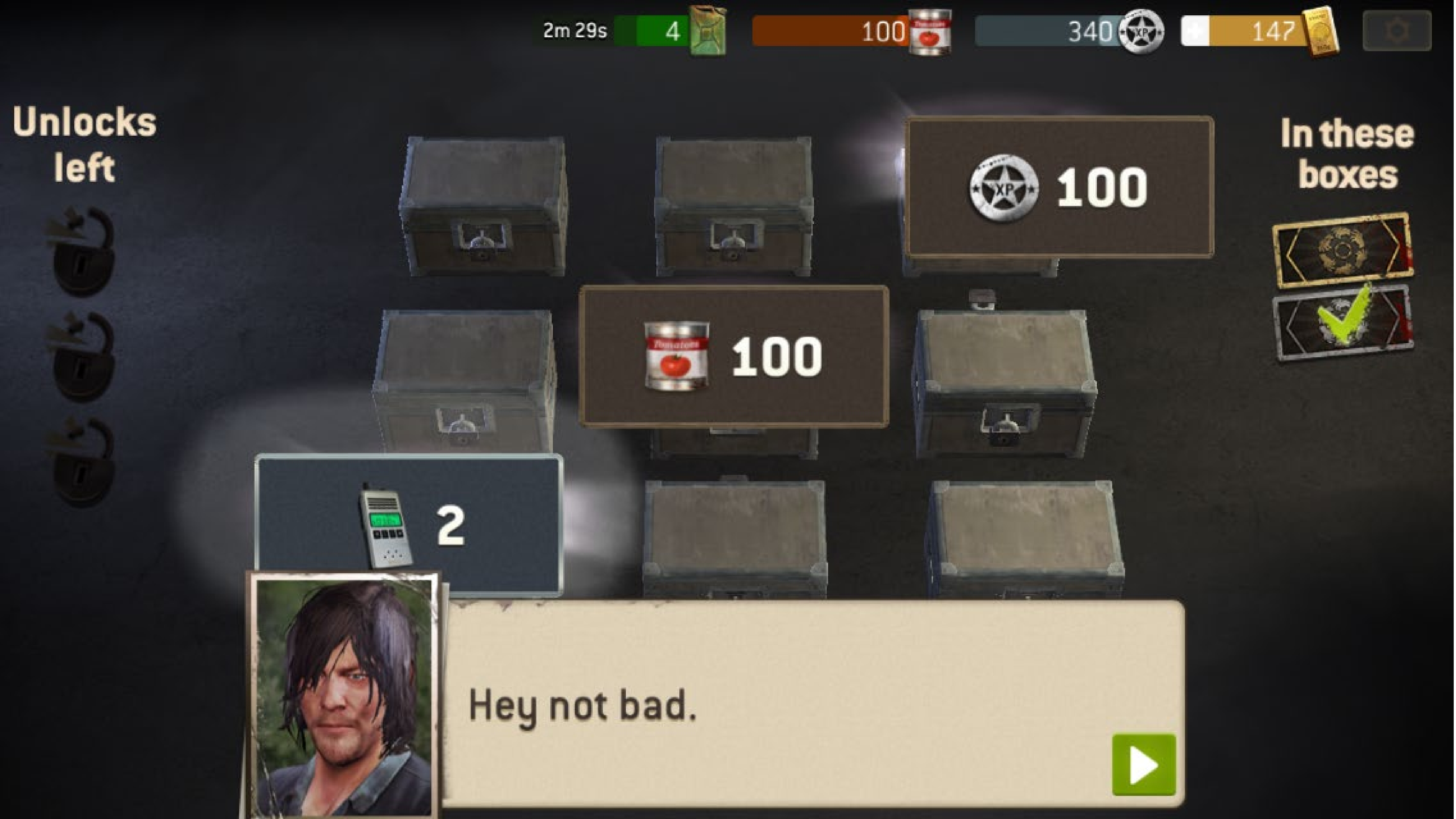
https://www.nber.org/system/files/working_papers/w3769/w3769.pdf


2m 56s
4
0
240
XP
147
Unlocks left
In these boxes
After a mission you get 3 free unlocks.
Next

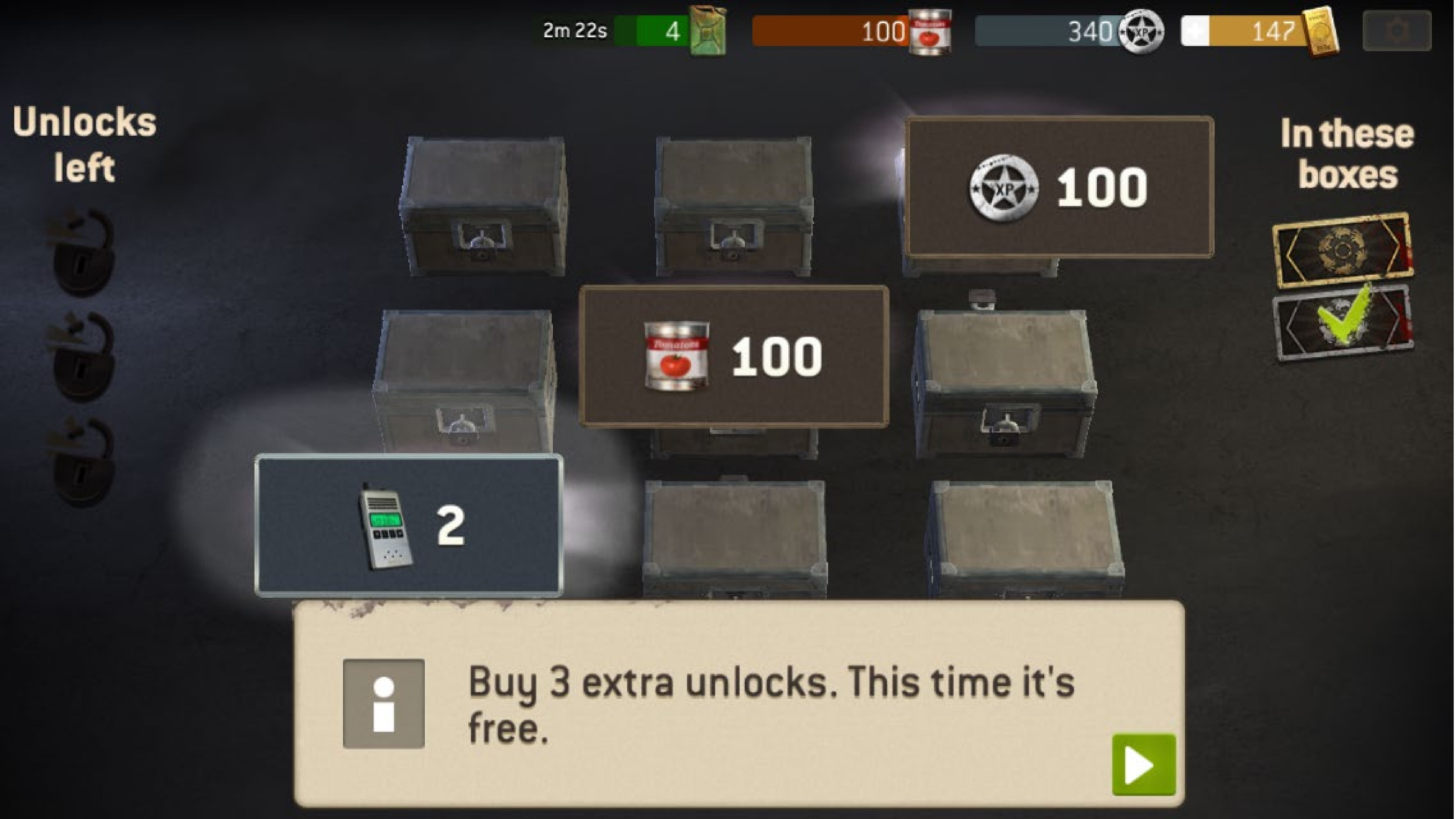

2m 52s
4
0
240
147
Unlocks left
In these boxes
All crates contain valuable items.
Next


2m 39s
4
0
240
147
Unlocks left
In these boxes


2m 33s
4
56
34
147
Unlocks left
In these boxes
100
100
100
100
2


2m 29s
4
100
340
147
Unlocks left
In these boxes
100
100
2
Hey not bad.


2m 25s
4
100
340
147
Unlocks left
In these boxes
100
100
2
The golden crate is still out there.


2m 22s
4
100
340
147
Unlocks left
In these boxes
100
100
2
Buy 3 extra unlocks. This time it's free.


2m 16s
4
100
340
147
Get 3 more
Free
100
100
2
In these boxes


2m 12s
4
100
340
147
Unlocks left
In these boxes
100
100
2
Alright, open 3 more!

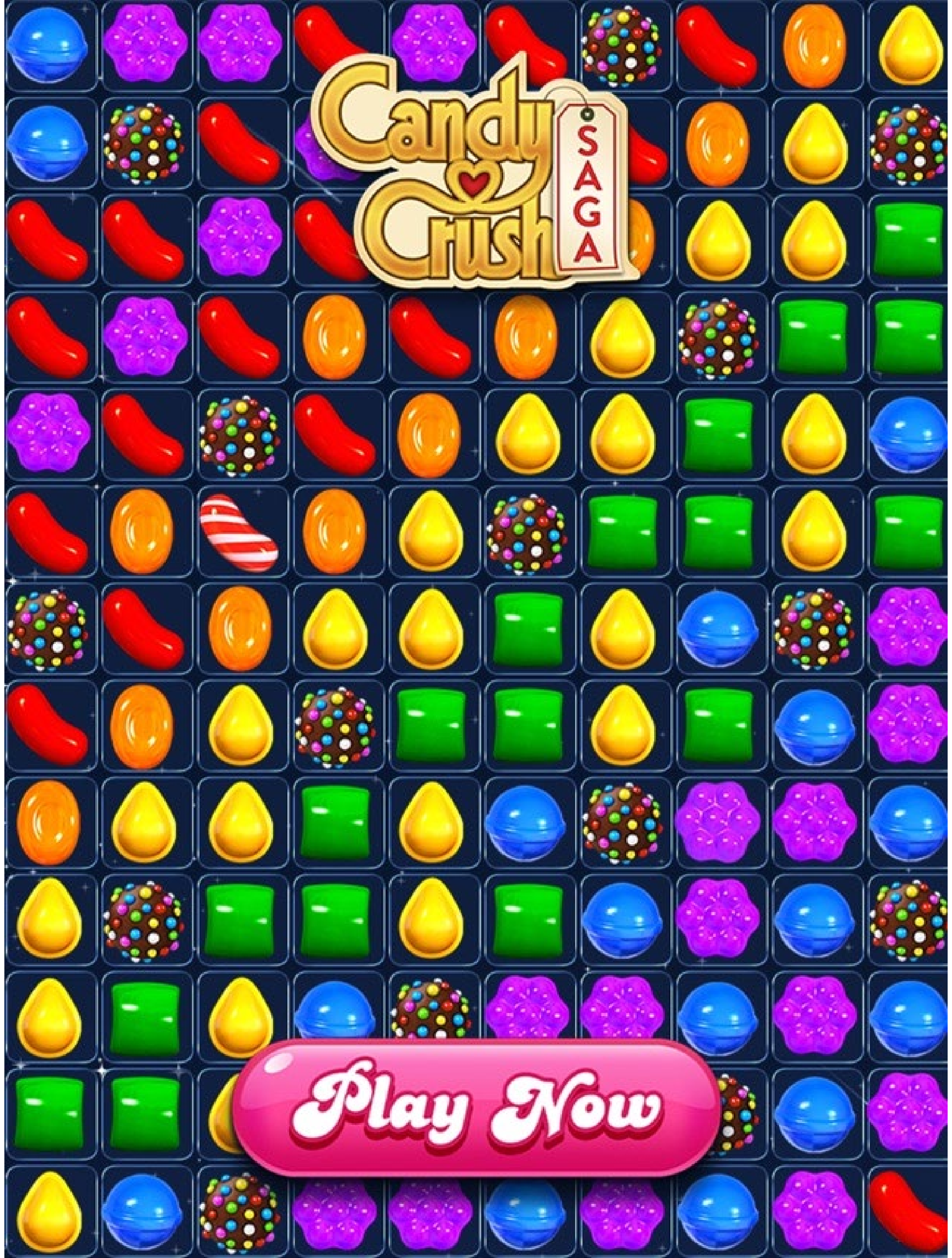

2m 3s
4
110
340
147
Unlocks left
In these boxes
100
100
2
100


2m
4
200
440
147
Unlocks left
In these boxes
100
100
2
16
2
100
100
Continue

Problems?

Randomness as a game balancing technique

- Games of chance: Rewards are always unpredictable
- Games of skill: Rewards are unpredictable when skills and challenge are perfectly balanced (e.g., player and opponent skills matched)
- Perfect balancing is hard => add randomness to allow occasional success even if the challenge is too high
- Rule of thumb: combining skill-based and randomness-based rewards can make a game enjoyable for a wider audience with varying skill levels


Candy Crush
SAGA
Play Now

Clash Royale and randomness/unpredictability

- Explicit randomness of lootbox/chest contents
- Implicit unpreditability of battles due to matchmaking

Soulslike design pattern: breadcrumb with unknown/unpredictable items

Next topic – but first a quick poll

Problem 1: You have been given $1000. You are now asked to choose one of:

50% chance to win $1000 OR get $500 for sure.

Problem 2: You have been given \$2000. You are now asked to choose one of:

50% chance to lose \$1000 OR lose \$500 for sure.

Loss aversion (Prospect Theory): losses loom larger than gains in our decision making

Problem 1: You have been given $1000. You are now asked to choose one of:

50% chance to win $1000 OR get $500 for sure.

Problem 2: You have been given $2000. You are now asked to choose one of:

50% chance to lose $1000 OR lose $500 for sure.

Problems are equal in terms of outcomes, on average, but people choose the sure thing in 1 and gamble in 2 to avoid the sure loss.

Related: Endowment effect

- Perceived value of object is higher if we already own it
- Dark pattern: Frame paying as avoiding losing something. E.g., instead of getting loot as level completion reward, the player wins loot already during a level, and if they die, they have to either lose the loot or pay to keep it.

More on dark patterns

http://www.fdg2013.org/program/papers/paper06_zagal_etal.pdf

Dark Patterns in the Design of Games

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ABSTRACT

Game designers are typically regarded as advocates for players. However, a game creator's interests may not align with the players'. We examine some of the ways in which those opposed interests can manifest in a game's design. In particular, we examine those elements of a game's design whose purpose can be argued as questionable and perhaps even unethical. Building upon earlier work in design patterns, we call these abstracted elements Dark Game Design Patterns. In this paper, we develop the concept of dark design patterns in games, present examples of such patterns, explore some of the subtleties involved in identifying them, and provide questions that can be asked to help guide in the specification and identification of future Dark Patterns. Our goal is not to criticize creators but rather to contribute to an ongoing discussion regarding the values in games and the role that designers and creators have in this process.

Categories and Subject Descriptors

K.8.0 [**Computing Millieux**]: Personal Computing – *games*.

General Terms

Design, Human Factors

Keywords

Design patterns, video games, ethics, game design, dark patterns

1. INTRODUCTION

When writing about game design, authors often stress the focal role of the player using terms like 'player-centered' or 'play-centric' (e.g. [4; 20; 45]). Player-centric design is defined such that "a game's primary function is to entertain the player, and it is the designer's obligation to create a game that does so" [4]. Others note that "[t]he role of the game designer is, first and foremost, to be an advocate for the player" [20, p. 2]. The implication is that most of the work done by the designer is for the benefit of the player or as a dialogue between designer and player (e.g. responding to player demands for features, increased challenge, etc.). However, the game developers and player's interests are sometimes at odds.

In this article, we examine some of the ways in which opposed interests are manifested in a game's design. More specifically, we examine those elements of a game's design whose purpose can be argued as questionable, against a player's best interests, and perhaps even unethical. Rather than focus on particular games, we identify common design elements and implementations we have identified across several games. Our focus is on gameplay, meaning that we look at systemic properties of games – and how players interact with them – rather than thematic or representational issues (e.g. racist depictions of non-player characters). Building upon earlier work in design patterns, we call these abstracted elements Dark Game Design Patterns.

In addition to defining what a Dark Game Design Pattern is, we will discuss some of the challenges in identifying these patterns as well as the related notion of Anti-Patterns. Our analysis includes examples from contemporary games and questions that can be asked to help articulate and identify future Dark Patterns. Our goal is not to criticize game designers or developers but rather to contribute to an ongoing discussion regarding the values in games and the role that designers and creators have in this process.

1.1 Game Design Patterns

It has been almost twenty years since the first voices were raised regarding the lack of a critical language for analyzing and talking about game design [17]. Scholars and practitioners have since answered that call by proposing ways of understanding games, classifying them, deconstructing them, and more. For instance, Church argued for a set of "formal abstract design tools" [15], Hunicke and colleagues presented a framework for understanding games and bridging the gap "between game design and development, game criticism, and technical game research" [23], and Zagal et al. created an ontology "for describing, analyzing and studying games, by defining a hierarchy of concepts abstracted from an analysis of many specific games" [49]. In 2002, inspired by earlier work in architecture [6], Kreimeier proposed using game design patterns as a way to formalize and codify knowledge about game design [29]. This idea was broadened by Björk and Holopainen, who developed a collection of nearly 300 gameplay patterns [10]. These patterns differ from the original structure in architecture by replacing problem-solution pairs with cause and consequences categories that describe possibilities for the instantiation of a pattern and the potential consequences that pattern may have in a game's design. The reasons for this change were: to support the design and analysis of games, and to allow designers to use the presence or absence of gameplay design patterns as design goals. The design pattern idea has since been applied in other areas of gameplay design including non-player characters [30], 'Ville games [31], and level design [22; 36].

While this indicates that design patterns can be used to talk about specific gameplay features of a game's design, it does not necessarily make them useful for identifying problematic or

Citation info:
Zagal, J. P., Bjork, S., Lewis, C. (2013) "Dark Patterns in the Design of Games", Foundations of Digital Games Conference, FDG 2013, May 14-17, Chania, Greece
http://www.fdg2013.org/program/papers/paper06_zagal_etal.pdf


4m 45s
5
160
20
Unlocks left
You found several loot crates during the mission. Open them.


2m 25s
4
100
340
147
Unlocks left
100
In these boxes
100
2
The golden crate is still out there.


6
1087
690
94
Get 3 more
FREE!
Watch video
25
In these boxes
2
90
90
Continue

Computational rationality and loss aversion

Evolutionary explanations exist

On the Evolutionary Origin of Prospect Theory Preferences

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James H. Fowler University of California, San Diego
Oleg Smirnov State University of New York at Stony Brook

Prospect theory scholars have identified important human decision-making biases, but they have been conspicuously silent on the question of the origin of these biases. Here we create a model that shows preferences consistent with prospect theory may have an origin in evolutionary psychology. Specifically, we derive a model from risk-sensitive optimal foraging theory to generate an explanation for the origin and function of context-dependent risk aversion and risk-seeking behavior. Although this model suggests that human cognitive architecture evolved to solve particular adaptive problems related to finding sufficient food resources to survive, we argue that this same architecture persists and is utilized in other survival-related decisions that are critical to understanding political outcomes. In particular, we identify important departures from standard results when we incorporate prospect theory into theories of spatial voting and legislator behavior, international bargaining and conflict, and economic development and reform.

Prospect theory has become one of the most influential behavioral theories of choice in the wider social sciences, particularly in psychology and economics (Kahneman, Slovic, and Tversky 1982; Kahneman and Tversky 1979). It has also been applied to issues in political science (Druckman 2001; Lau and Redlawsk 2001; McDermott 2004; Mercer, 2005; Quattrone and Tversky 1988); in particular, in the areas of international relations (Berejikian 1997, 2002; Faber 1990; Jervis 1994, 2004; Levy 1994, 1997; McDermott 1998), international political economy (Elms 2004), comparative politics (Weyland 1996, 1998), American politics (Patty 2006), and public policy (McDaniel and Sistrunk 1991). As a model explaining decision making under conditions of risk, prospect theory provides an elegant description of the relationship between environmental contingency in the form of gains and losses and individual risk propensity. In short, those faced with gains tend to be risk averse, while those confronting losses become much more risk seeking. Prospect theory developed in explicit opposition to more normative models of rational choice, such as subjective expected utility theory.

Historically, prospect theory also evolved in reaction to earlier behavioral models exemplified by figures such as B.F. Skinner (1952) who wholly disregarded the importance of cognitive processing in human action. As such, prospect theory can be understood as representing the apex of the cognitive revolution in psychology and social sciences in general (Simon 1985). This historical development of prospect theory as a significant departure from behavioral into cognitive explanations for decision making is interesting because, as Mercer notes; "The dominant explanation for political scientists' tepid response focuses on the theoretical problems with extending a theory devised in the lab to explain political decisions in the field. . . .It suggests that prospect theory's failure to ignite the imagination of more political scientists probably results from their aversion to behavioral assumptions and not from problems unique to prospect theory" (2005, 1). And, indeed, more recent work in decision making within cognitive neuroscience has also begun to incorporate emotion and motivation into cognitively oriented theories of choice. Similar research trends can be observed in economics as well (Andreoni 1990; Bolton and Ockenfels 2000; Dawes et al. 2007; Fehr and Schmidt 1999; Rabin 1993, 2002).

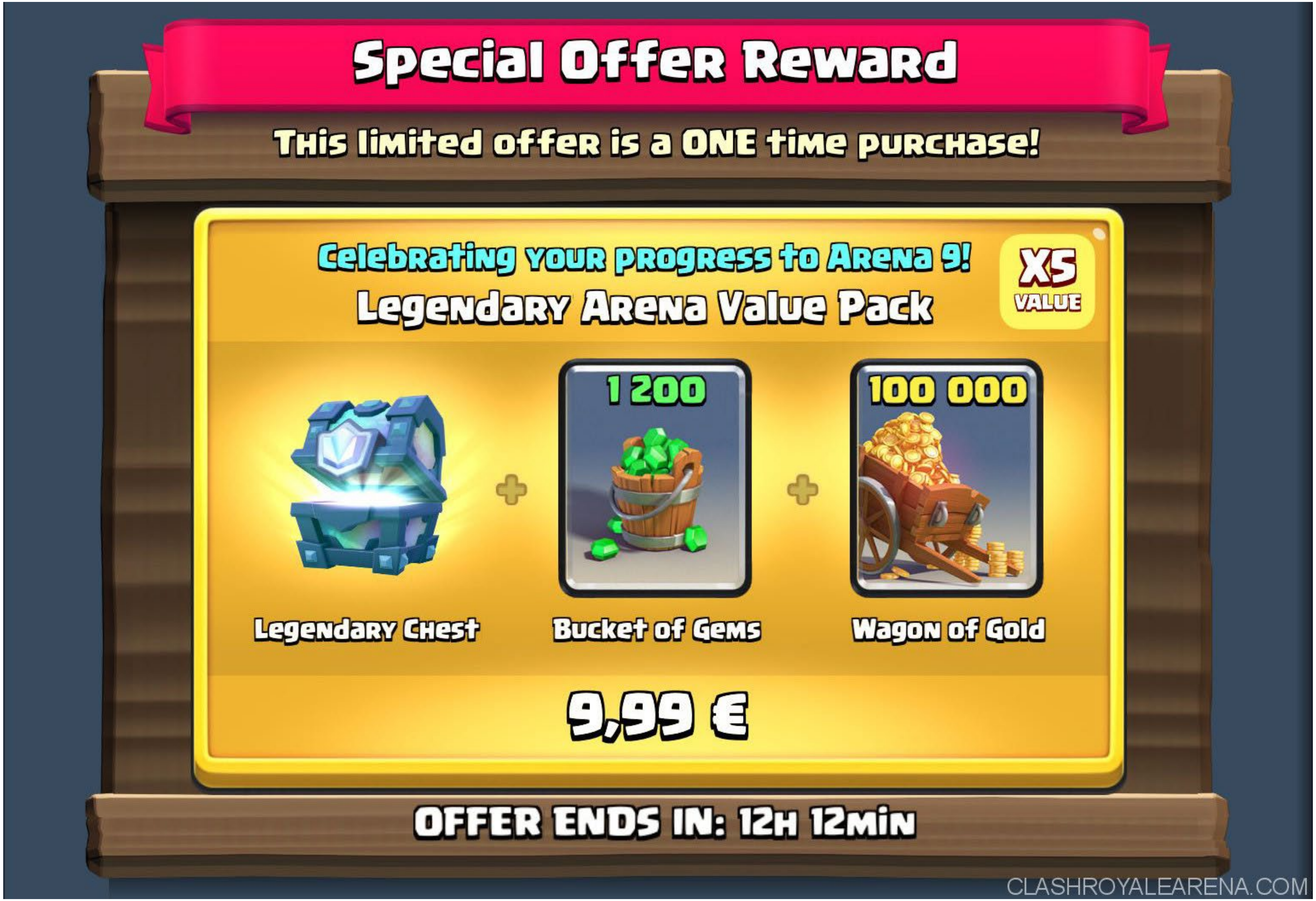
Models derived from risk-sensitive optimal foraging theory offer an opportunity to generate an

The Journal of Politics, Vol. 70, No. 2, April 2008, Pp. 335–350 doi:10.1017/S0022381608080341

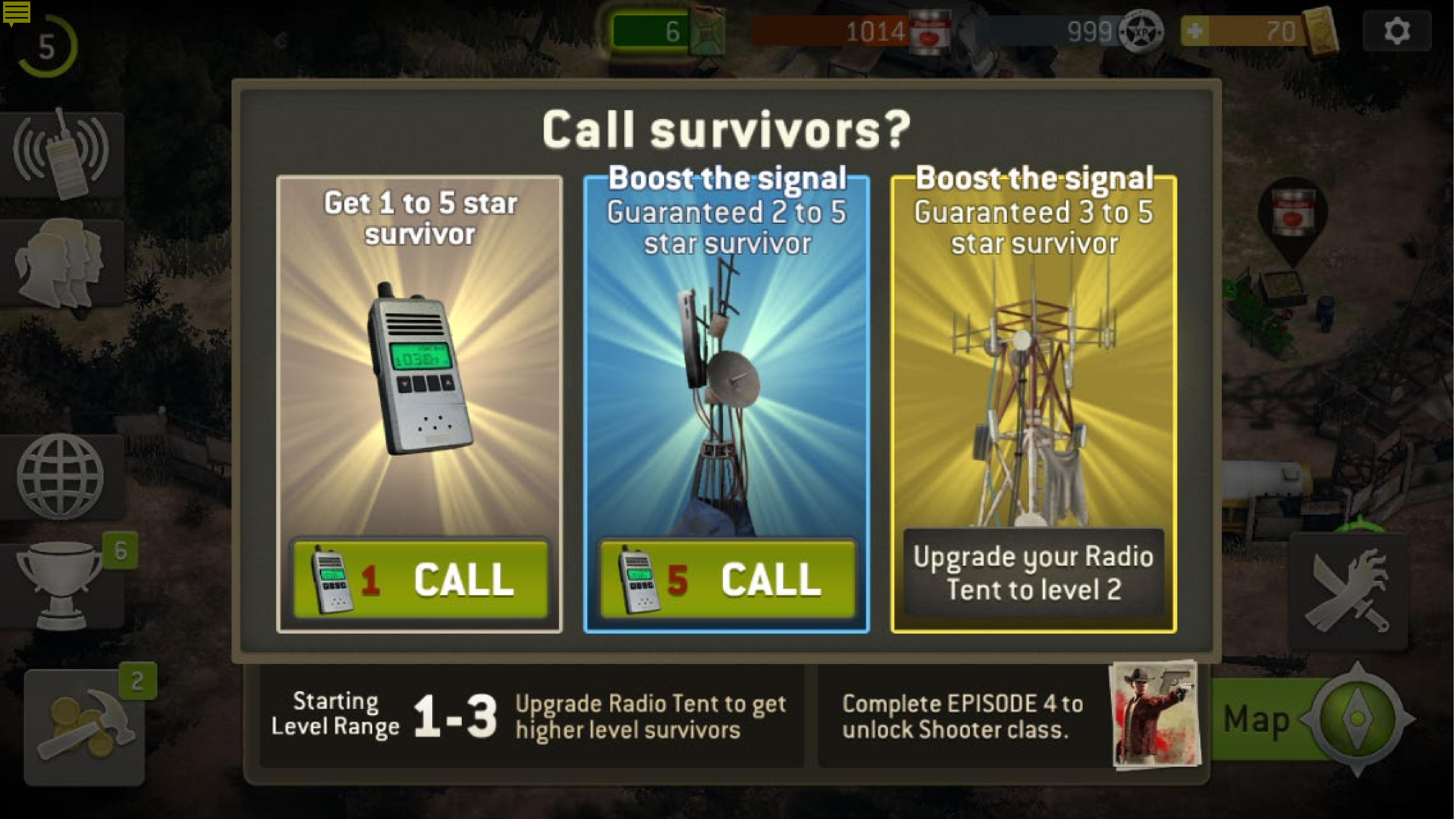
ISSN 0022-3816

Artificial scarcity

- Adding artificial scarcity or urgency increases desirability & sales
  - Limited time sales (e.g., Steam sales of computer games)
  - Limited edition books etc.
  - Limited art prints
  - Rarity of game items / characters
- Goal: make the customer buy quickly without thinking too much about it (i.e., without engaging System 2)
- One explanation: A form of loss-aversion – avoid losing the special opportunity to buy


Special Offer Reward
This limited offer is a ONE time purchase!
Celebrating your progress to Arena 9!
Legendary Arena Value Pack
X5 VALUE
1 200
100 000
Legendary Chest
Bucket of Gems
Wagon of Gold
9,99 €
OFFER ENDS IN: 12h 12min
CLASHROYALEARENA.COM

4
6
1314
999
83
Carol Wolf bundle
BUNDLE
1200
Gold!
Carol's Blade
New Outfit
Carol, Wolf
Offer ends in 1d 18h
€7,99 BUY
5
Map


5
6
1014
999
70
Call survivors?
Get 1 to 5 star survivor
1 CALL
Boost the signal
Guaranteed 2 to 5 star survivor
5 CALL
Boost the signal
Guaranteed 3 to 5 star survivor
Upgrade your Radio Tent to level 2
Starting Level Range 1-3
Upgrade Radio Tent to get higher level survivors
Complete EPISODE 4 to unlock Shooter class.
Map

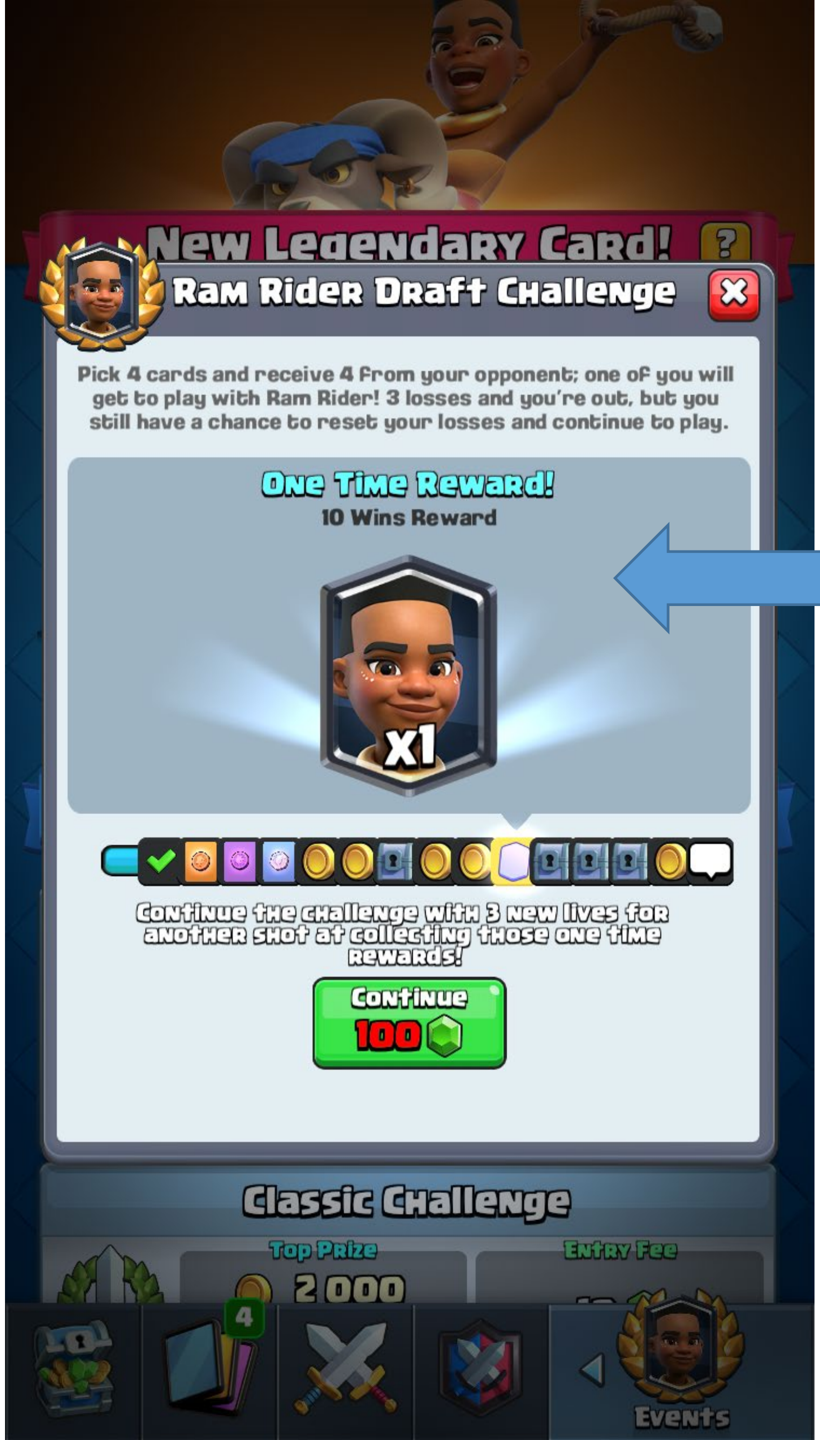
Sunk cost fallacy

- When making an investment, people tend to throw good money after bad. ”Oh I’ve lost quite a bit but maybe my luck will turn if I give it one more go”
- Rationally, we should only consider the expected return of future investment, not the already sunk cost
- Can be explained through loss aversion and gambler’s fallacy
- Implication for games: People are willing to invest more time in games they have paid for, even if some other game might provide more value
- Exploiting commitment: Pay to continue –mechanics (e.g., Candy Crush boosters offered after player has invested time in a difficult level but failed)

Sunk cost fallacy in Clash Royale

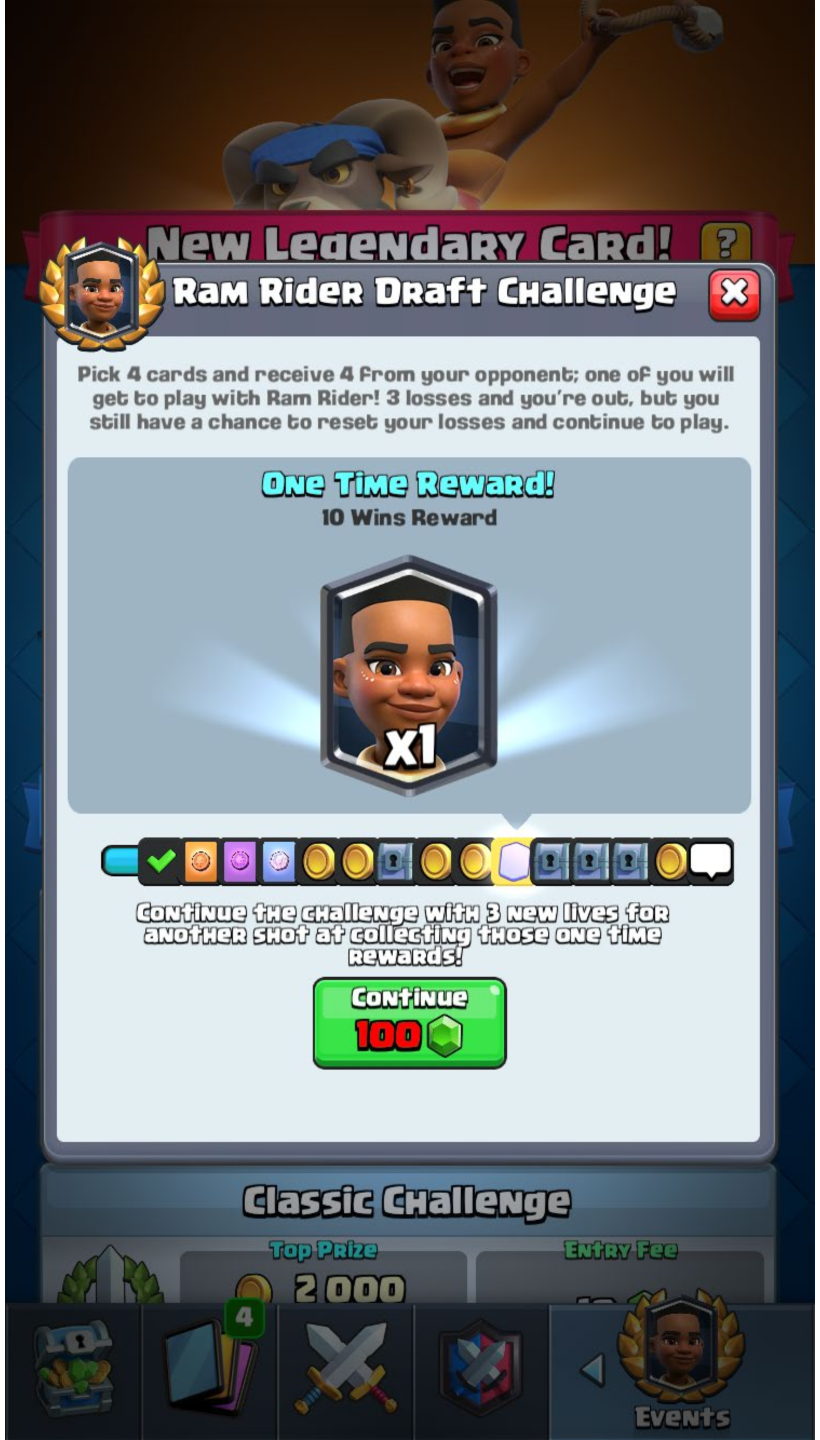
- This screen was presented after I failed the Ram Rider Draft challenge
- Decision: Pay 100 gems or lose any progress
- Design also utilizes: Artificial scarcity, anticipation of reward, affect-rich choice

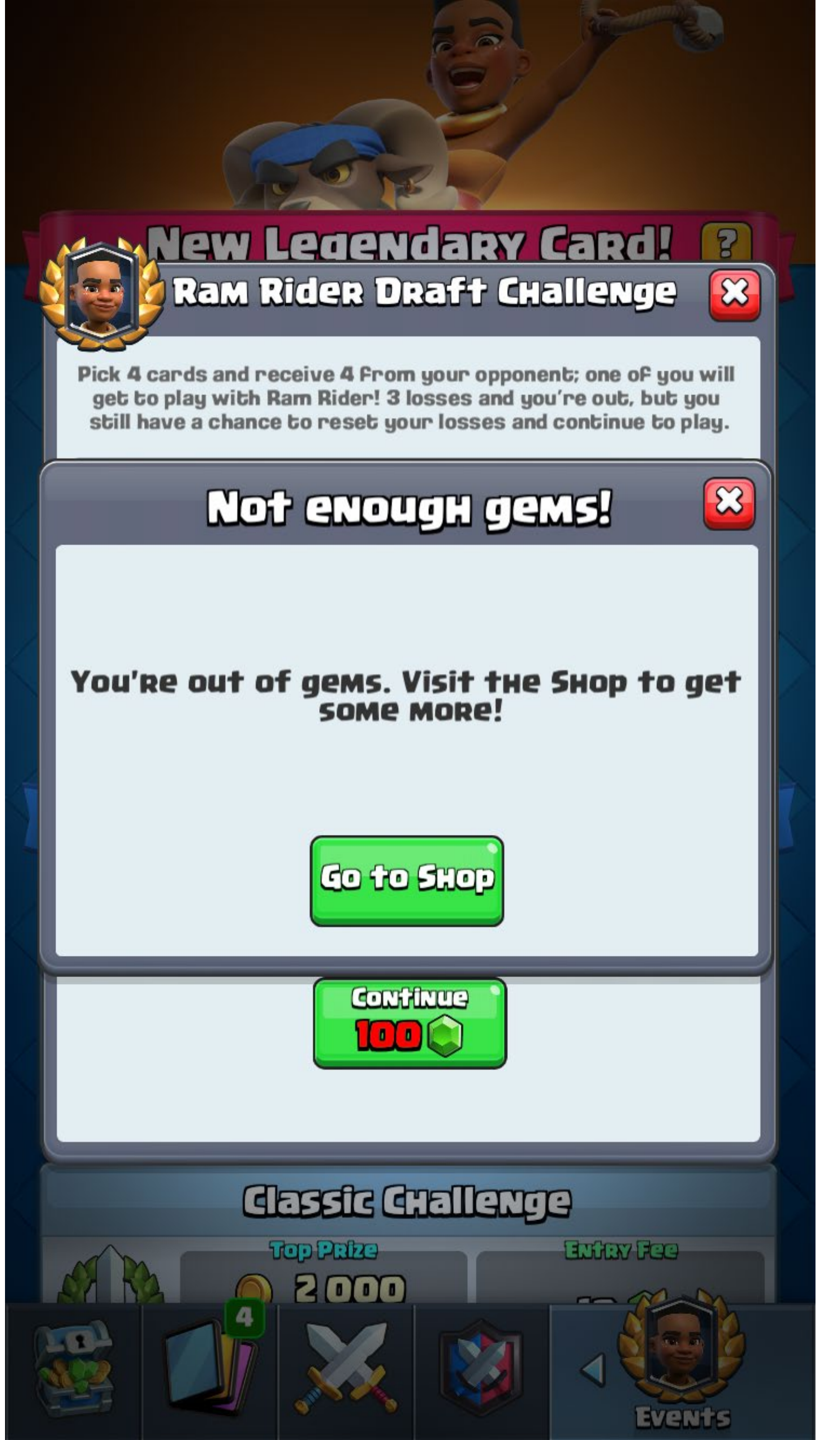
(Paying might also be rational, depending on details…)



Heighten the anticipation & scarcity


New Legendary Card!
Ram Rider Draft Challenge
Ends in: 2d 15h
Your Progress
1
Wins
Losses
Continue
100
Unlock Ram Rider and an exclusive emote!
Challenges
Grand Challenge
Top Prize
22 000
1 100
Entry Fee
100
Classic Challenge
Top Prize
2 000
Entry Fee
4
Events


New Legendary Card!
Ram Rider Draft Challenge
Pick 4 cards and receive 4 from your opponent; one of you will get to play with Ram Rider! 3 losses and you're out, but you still have a chance to reset your losses and continue to play.
One Time Reward!
10 Wins Reward
x1
Continue the challenge with 3 new lives for another shot at collecting those one time rewards!
Continue
100
Classic Challenge
Top Prize
2 000
Entry Fee
4
Events

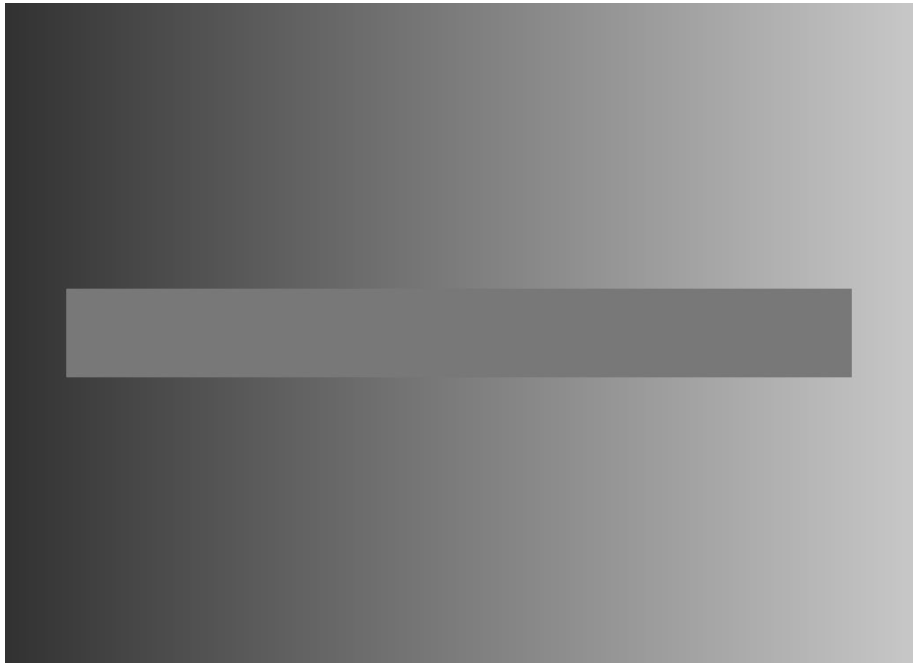

New Legendary Card!
Ram Rider Draft Challenge
Pick 4 cards and receive 4 from your opponent; one of you will get to play with Ram Rider! 3 losses and you're out, but you still have a chance to reset your losses and continue to play.
Not enough gems!
You're out of gems. Visit the Shop to get some more!
Go to Shop
Continue
100
Classic Challenge
Top Prize
2 000
Entry Fee
4
Events

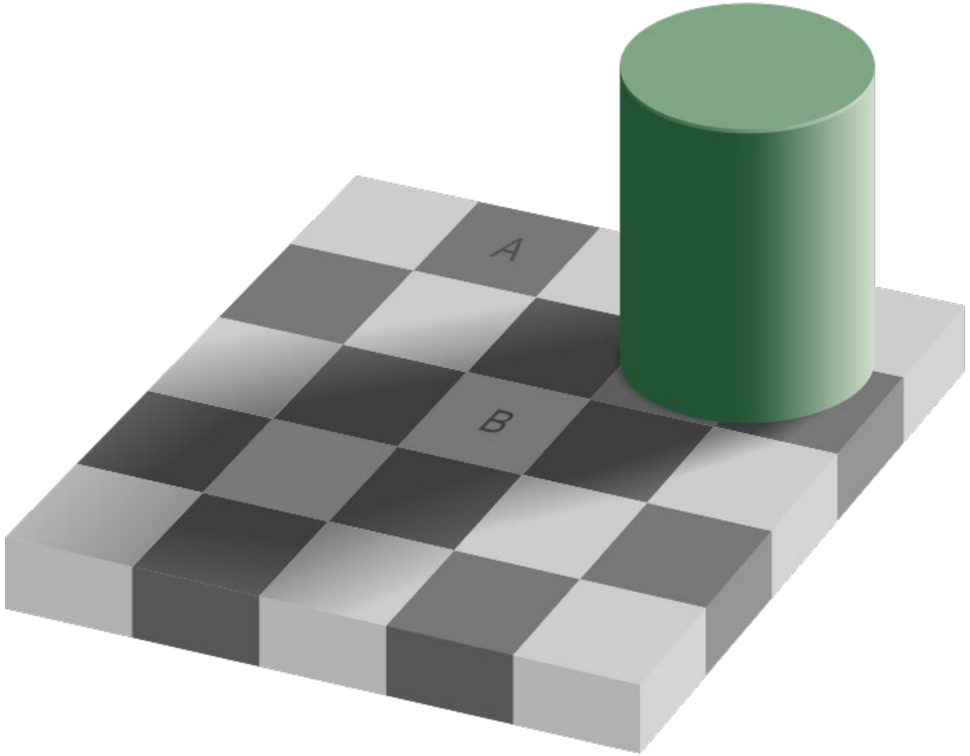
Design principles and implications

- Core reward design principles (anticipation and discounting of rewards)
- Avoiding thinking (System 1 vs. System 2, cognitive biases affecting reward evaluation)
- **Perception and attention (contrast, Halo effect, confirmation bias)**
- Memory (storing and retrieving information)
- Social (effect of other people)

Contrast principle (perception is adaptive and relative)

- Perception and judgements are always relative and adaptive
- A light seems brighter in the dark. We don't notice our own smell.
- Figures: The horizontal bar and the A and B squares are of same color, but their perception is affected by the surroundings





Rewards of others affect how we perceive our own rewards

https://www.youtube.com/watch?v=meiU6TxysCg

Two Monkeys Were Paid Unequally: Excerpt from Frans de Waal's TED Talk

Contrast in sales

- The trick of three product versions:
    1. Cheap & clearly low value
    2. Cheap
    3. Expensive and only a bit higher value
- The middle one is perceived as having both high value and low price. The user feels smart selecting that one even if the others were not even designed to be purchased.
- Men pay more for accessories if purchasing them after purchasing a suit.


4
6
1314
999
83
BEST VALUE
Carol Wolf bundle
1200
€7,99
Fresh Survivor Bundle
€2,99
Pile of Gold
500
€4,99
Pocketful of Gold
1200
€9,99
Plenty of Gold
2500
€19,99
Buildings
Gold

Computational rationality and contrast

- Our environment is highly variable and adaptive perception is probably necessary for survival
- We often have incomplete information to judge the true value of objects => the most rational thing we can do is to make relative judgements based on the information we're given

Integration of multiple information sources

- In presence of incomplete, uncertain and noisy information, it is optimal/rational to combine multiple information sources
- We integrate information across multiple senses, and combine new information with prior beliefs
  - Limitations: attention, working memory
- Effects:
  - McGurk illusion
  - Halo effect
  - Anchoring
  - Confirmation bias
  - Commitment & consistency

#bbc #illusion

Try this bizarre audio illusion! 👁👂😮 - BBC

https://www.youtube.com/watch?v=G-lN8vWm3m0

Halo effect

- Some qualities of a person or product may be irrationally dominant (possible reason: our attention may be selective)
- Attribute A affects the perception/judgement of attribute B
- Handsome people have higher salaries and get more votes in elections
- Game design: better to invest resources in making some aspect of the game really stand out.
- Conversely, if some part of the game is really broken, the whole game can be perceived as low quality.

Anchoring and confirmation bias

- Our perception is affected by prior information
- Price estimates of houses affected by asking price (the ”anchor”)
- Number of pebbles in a jar: the mean of people’s guesses is surprisingly accurate, but only if they guess without knowing what others guessed (no anchoring)
- Confirmation bias: We trust information that matches our prior beliefs


Rate Your Experience
X
Enjoying Dungeon Keeper?
5-Star ratings from you help us provide free updates!
How would you rate Dungeon Keeper?
1-4 Stars
5 Stars

The importance of first impressions

Alan: Intelligent, industrious, impulsive, critical, stubborn, envious.

vs.

Bill: Envious, stubborn, critical, impulsive, industrious, intelligent.

Design implications

- Importance of first impressions, in both pitching and designing a game.
- Optimizing the first few minutes of gameplay/onboarding is of utmost importance, especially in free games where there’s no sunk cost to keep the player from quitting.
- Loading time, menu flow, tutorial…
- Can’t raise the price of a game (or virtual goods) after launch, can only lower it. Thus, rather set a too high than too low initial price.

Commitment & consistency

- Our actions may change our self-concept, how we perceive ourselves
- If you’ve paid at least once, you’re more likely to pay again
  - Conversion rate: how many players ”convert” to paying customers
  - F2P design implication: There should be at least one **no-brainer first purchase** that one is insane not to make (e.g., due to contrast effect)


4
6
1095
810
83
Fresh Survivor
BUNDLE
400 Gold!
1 Survivor slot
Legendary Weapon Scout
5 Phones!
Full supplies
€2,99 BUY
4
Map

Perception recap

- Perception is **adaptive and relative**, affected by **spatial and temporal context**
- Contrast in sales: 3 product variants
- Subjective perception of time: It is possible to manipulate how close one feels to achieving a goal or reward
- Halo effect: a single feature may bias the overall perception of a game, for both good and bad
- Anchoring & confirmation bias => Importance of first impressions (game pitching, onboarding of players)

Design principles and implications

- Core reward design principles (anticipation and discounting of rewards)
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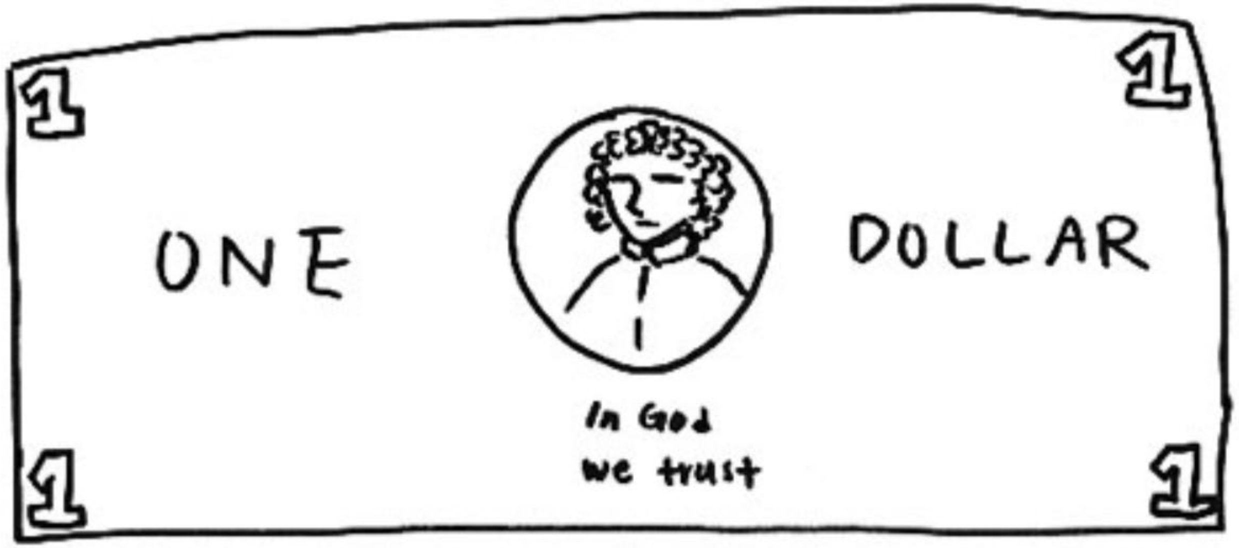
- **Memory (storing and retrieving information)**
- Social (effect of other people)


1
1
ONE
DOLLAR
In God
we trust
1
1


FEDERAL RESERVE NOTE
THE UNITED STATES OF AMERICA
THIS NOTE IS LEGAL
TENDER FOR ALL DEBTS,
PUBLIC AND PRIVATE
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WASHINGTON, D.C.
ONE
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SERIES
2013
ONE DOLLAR

Memory = tool for predicting the future

We remember things relevant to predicting: Memories form at the most surprising moments we experience.

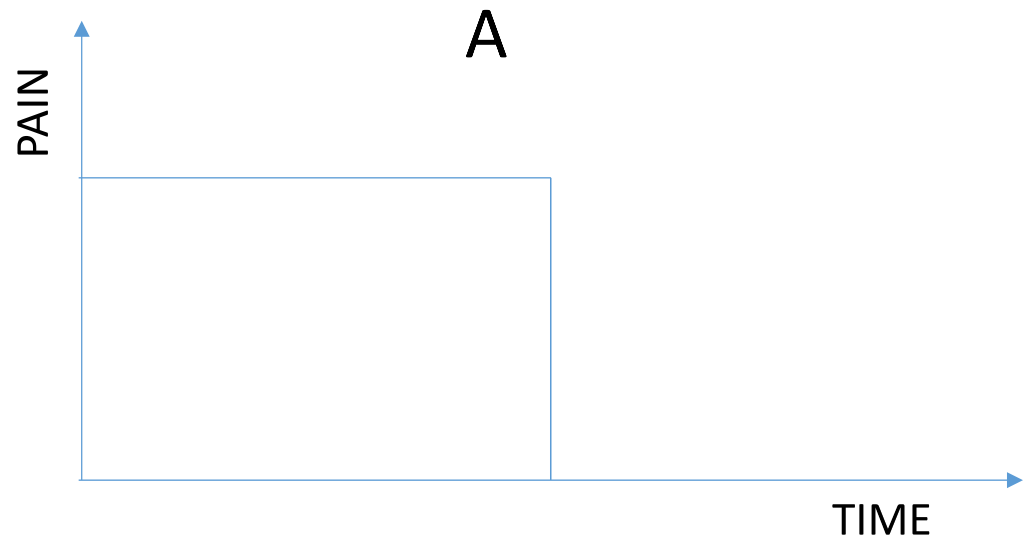
=> Novelty and/or unpredictability are important for memorable games

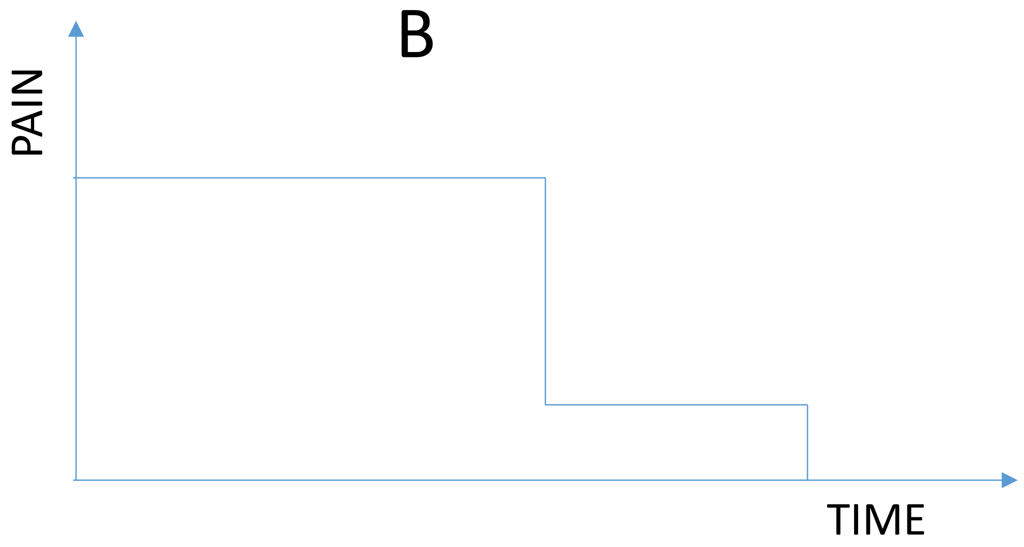
Charan Ranganath: Human Memory, Imagination, Deja Vu, and False Memories | Lex Fridman Podcast #430

https://www.youtube.com/watch?v=4iuepdI3wCU

Peak-end-rule

- Our memory of pain, fun etc. roughly equals the mean of the peak and end
- If experience A has 50 seconds of intense pain and experience B has 50 seconds of intense pain followed by mild pain, people want to repeat B although there is more total pain



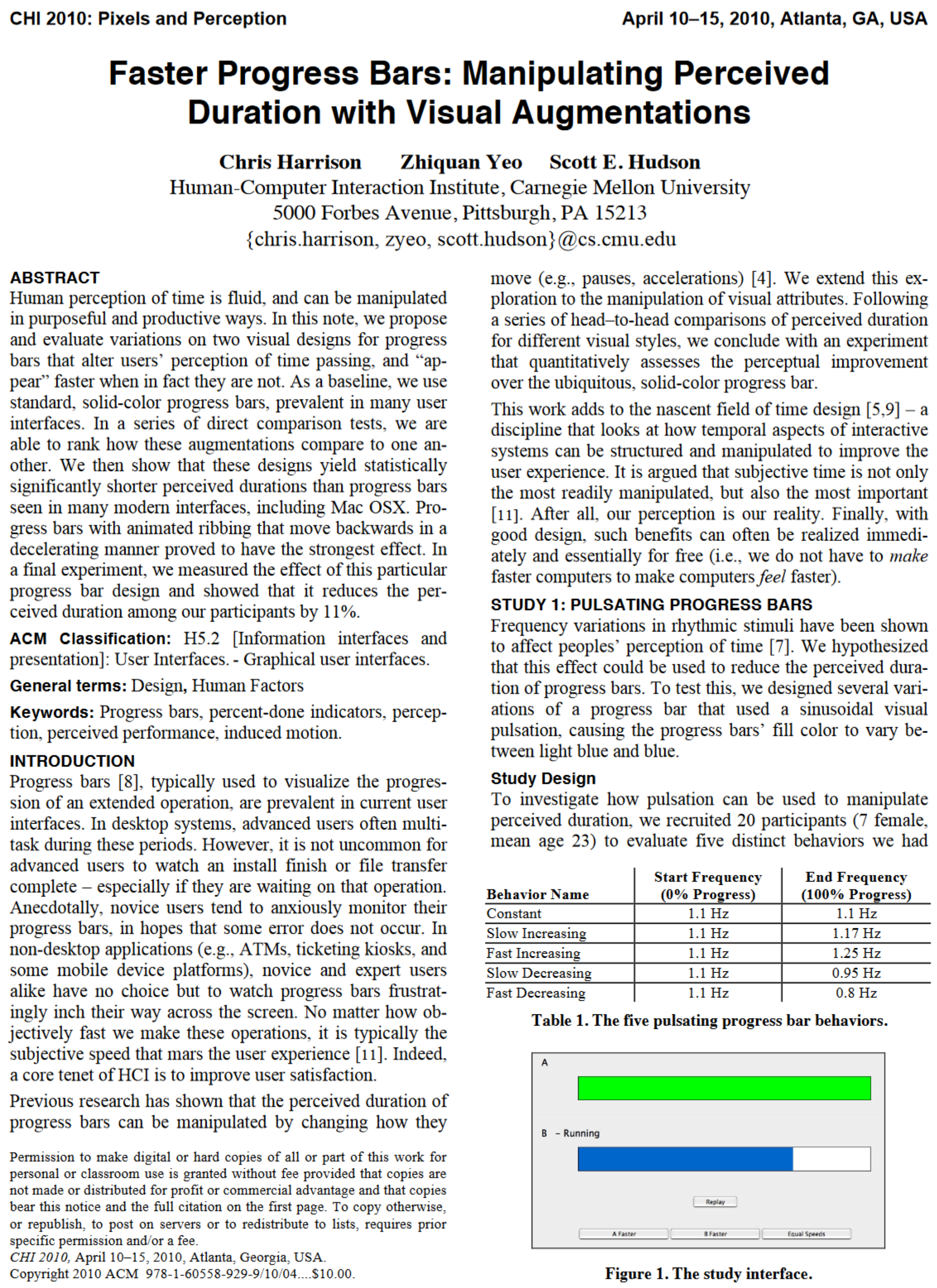


Peak-end-rule

- Implication in game design: to make the player come back, every play session should be structured to have an engaging end and at least some peak moment
  - Can you predict when the session is going to end, e.g., average length?
- Also related to randomness: adding randomness adds peaks and thus boosts the remembered experience, even if the mean remains unchanged.
- Development resource allocation: for the remembered experience, the peak(s) and end matter most, which one should consider when prioritizing.

Peak-end-rule in user interfaces

- Progress bars feel better if progress accelerates towards the end.
- Conversely, it leaves a bad memory if the bar gets stuck at 95%



CHI 2010: Pixels and Perception April 10–15, 2010, Atlanta, GA, USA

Faster Progress Bars: Manipulating Perceived Duration with Visual Augmentations

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ABSTRACT
Human perception of time is fluid, and can be manipulated in purposeful and productive ways. In this note, we propose and evaluate variations on two visual designs for progress bars that alter users' perception of time passing, and "appear" faster when in fact they are not. As a baseline, we use standard, solid-color progress bars, prevalent in many user interfaces. In a series of direct comparison tests, we are able to rank how these augmentations compare to one another. We then show that these designs yield statistically significantly shorter perceived durations than progress bars seen in many modern interfaces, including Mac OSX. Progress bars with animated ribbing that move backwards in a decelerating manner proved to have the strongest effect. In a final experiment, we measured the effect of this particular progress bar design and showed that it reduces the perceived duration among our participants by 11%.

ACM Classification: H5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

General terms: Design, Human Factors

Keywords: Progress bars, percent-done indicators, perception, perceived performance, induced motion.

INTRODUCTION
Progress bars [8], typically used to visualize the progression of an extended operation, are prevalent in current user interfaces. In desktop systems, advanced users often multitask during these periods. However, it is not uncommon for advanced users to watch an install finish or file transfer complete – especially if they are waiting on that operation. Anecdotally, novice users tend to anxiously monitor their progress bars, in hopes that some error does not occur. In non-desktop applications (e.g., ATMs, ticketing kiosks, and some mobile device platforms), novice and expert users alike have no choice but to watch progress bars frustratingly inch their way across the screen. No matter how objectively fast we make these operations, it is typically the subjective speed that mars the user experience [11]. Indeed, a core tenet of HCI is to improve user satisfaction.

Previous research has shown that the perceived duration of progress bars can be manipulated by changing how they move (e.g., pauses, accelerations) [4]. We extend this exploration to the manipulation of visual attributes. Following a series of head–to-head comparisons of perceived duration for different visual styles, we conclude with an experiment that quantitatively assesses the perceptual improvement over the ubiquitous, solid-color progress bar.

This work adds to the nascent field of time design [5,9] – a discipline that looks at how temporal aspects of interactive systems can be structured and manipulated to improve the user experience. It is argued that subjective time is not only the most readily manipulated, but also the most important [11]. After all, our perception is our reality. Finally, with good design, such benefits can often be realized immediately and essentially for free (i.e., we do not have to *make* faster computers to make computers *feel* faster).

STUDY 1: PULSATING PROGRESS BARS
Frequency variations in rhythmic stimuli have been shown to affect peoples' perception of time [7]. We hypothesized that this effect could be used to reduce the perceived duration of progress bars. To test this, we designed several variations of a progress bar that used a sinusoidal visual pulsation, causing the progress bars' fill color to vary between light blue and blue.

Study Design
To investigate how pulsation can be used to manipulate perceived duration, we recruited 20 participants (7 female, mean age 23) to evaluate five distinct behaviors we had

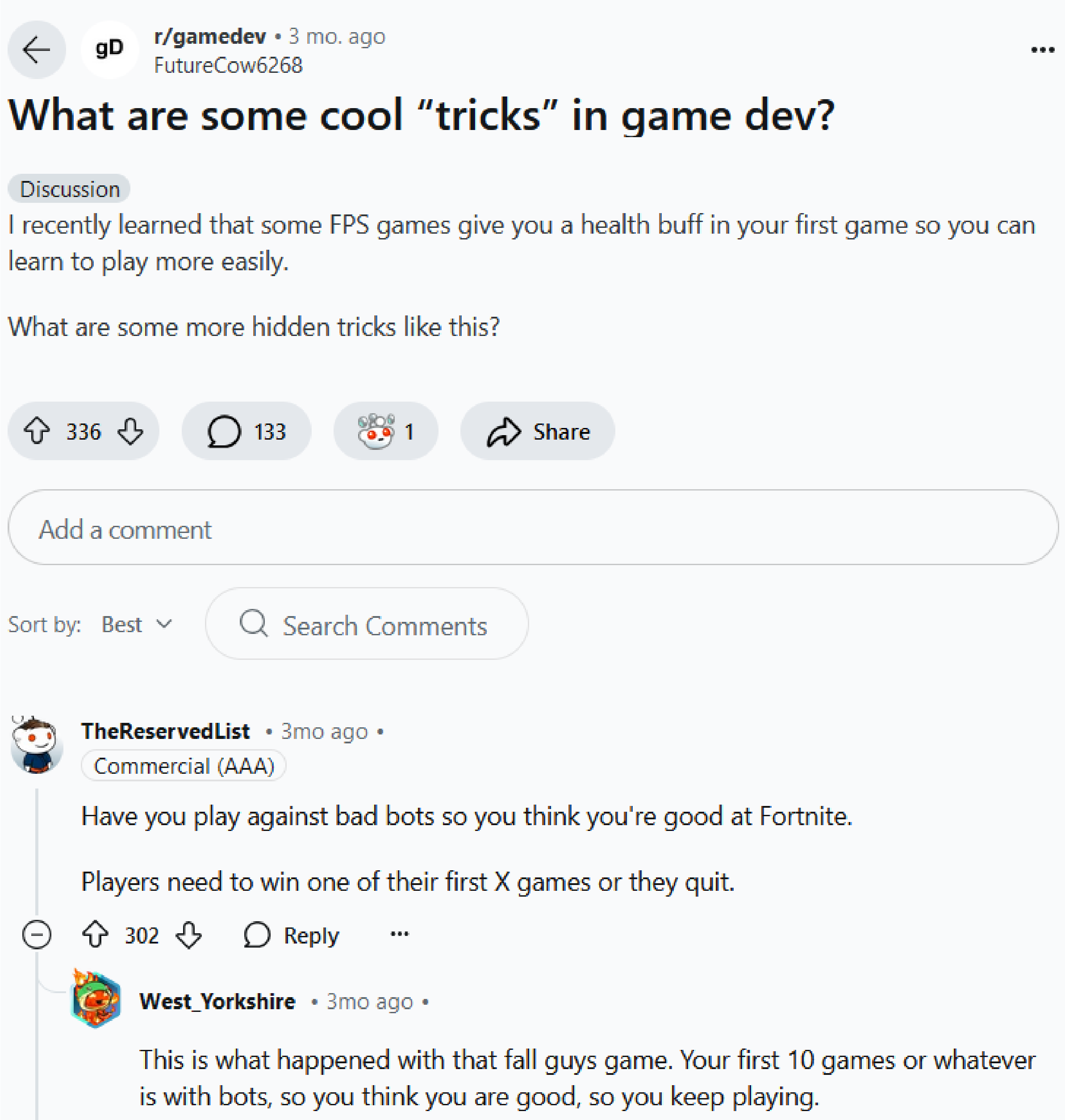
Behavior Name	Start Frequency (0% Progress)	End Frequency (100% Progress)
Constant	1.1 Hz	1.1 Hz
Slow Increasing	1.1 Hz	1.17 Hz
Fast Increasing	1.1 Hz	1.25 Hz
Slow Decreasing	1.1 Hz	0.95 Hz
Fast Decreasing	1.1 Hz	0.8 Hz

Table 1. The five pulsating progress bar behaviors.

Figure 1. The study interface.

How to add memorable moments?

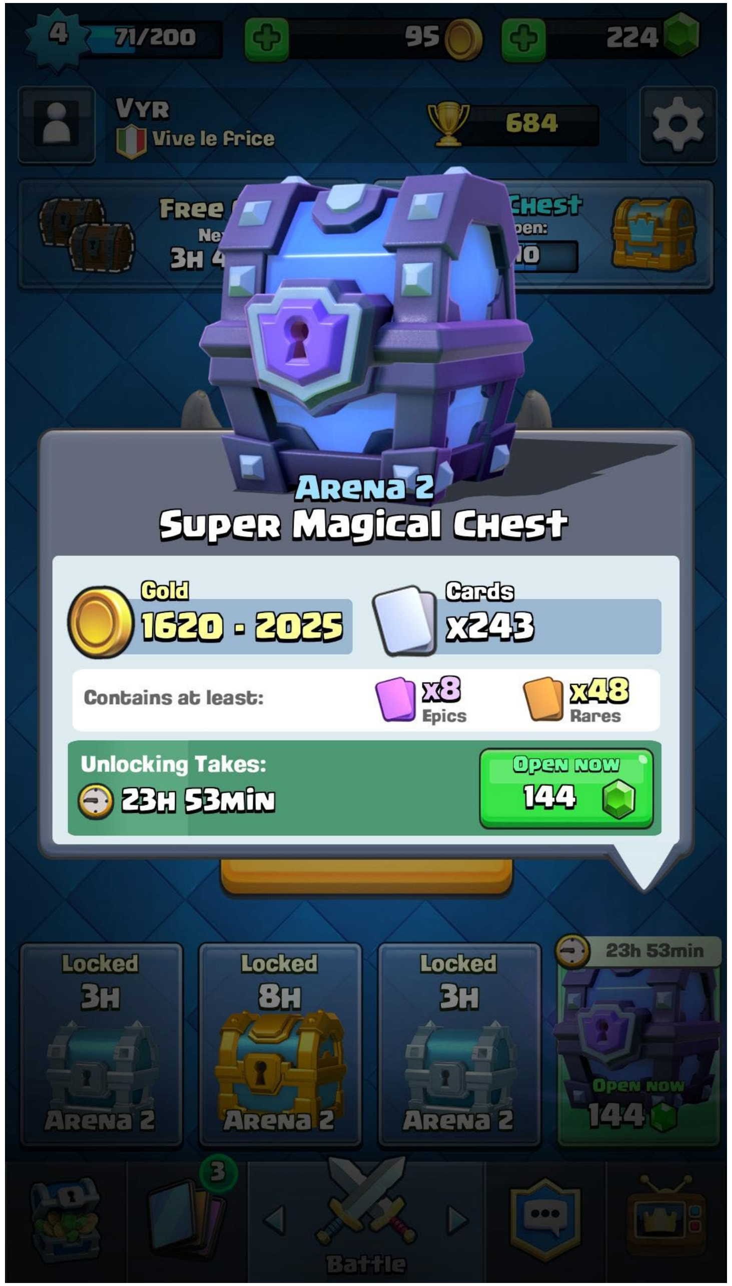
"I worked on a game a while back where the last bullet in your magazine always did double damage to increase the frequency of those **"oh shit I got him with the last bullet!" moments**



https://www.reddit.com/r/gamedev/comments/1eif299/what_are_some_cool_tricks_in_game_dev/

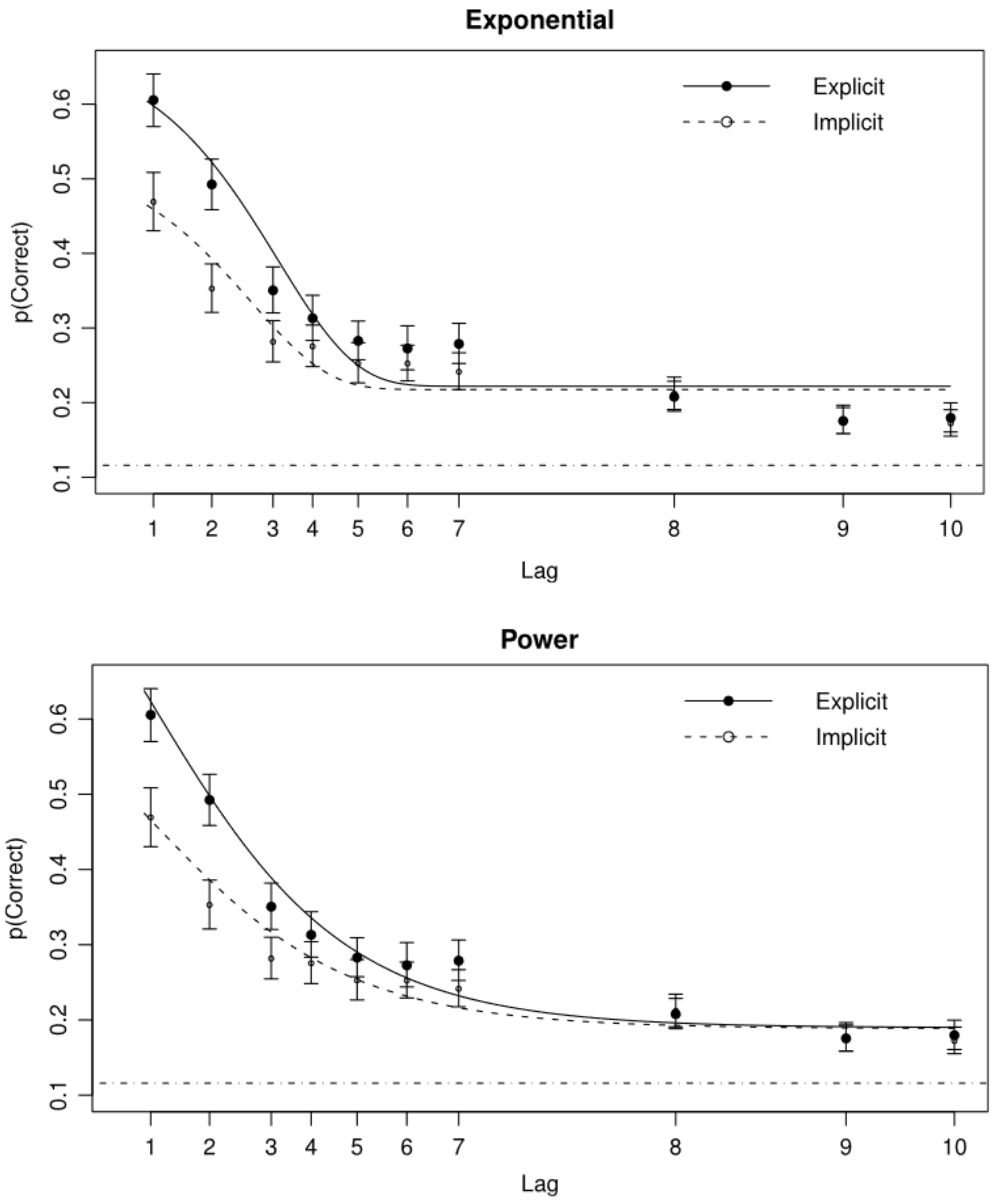
How to add memorable moments?

- In Clash Royale, very tight/improbable wins (right before time ends or winning when one’s King has only a few HP left) seem to be rewarded with more rare chests
- Can be interpreted as the designers boosting the game’s natural peak moments, making them even more memorable



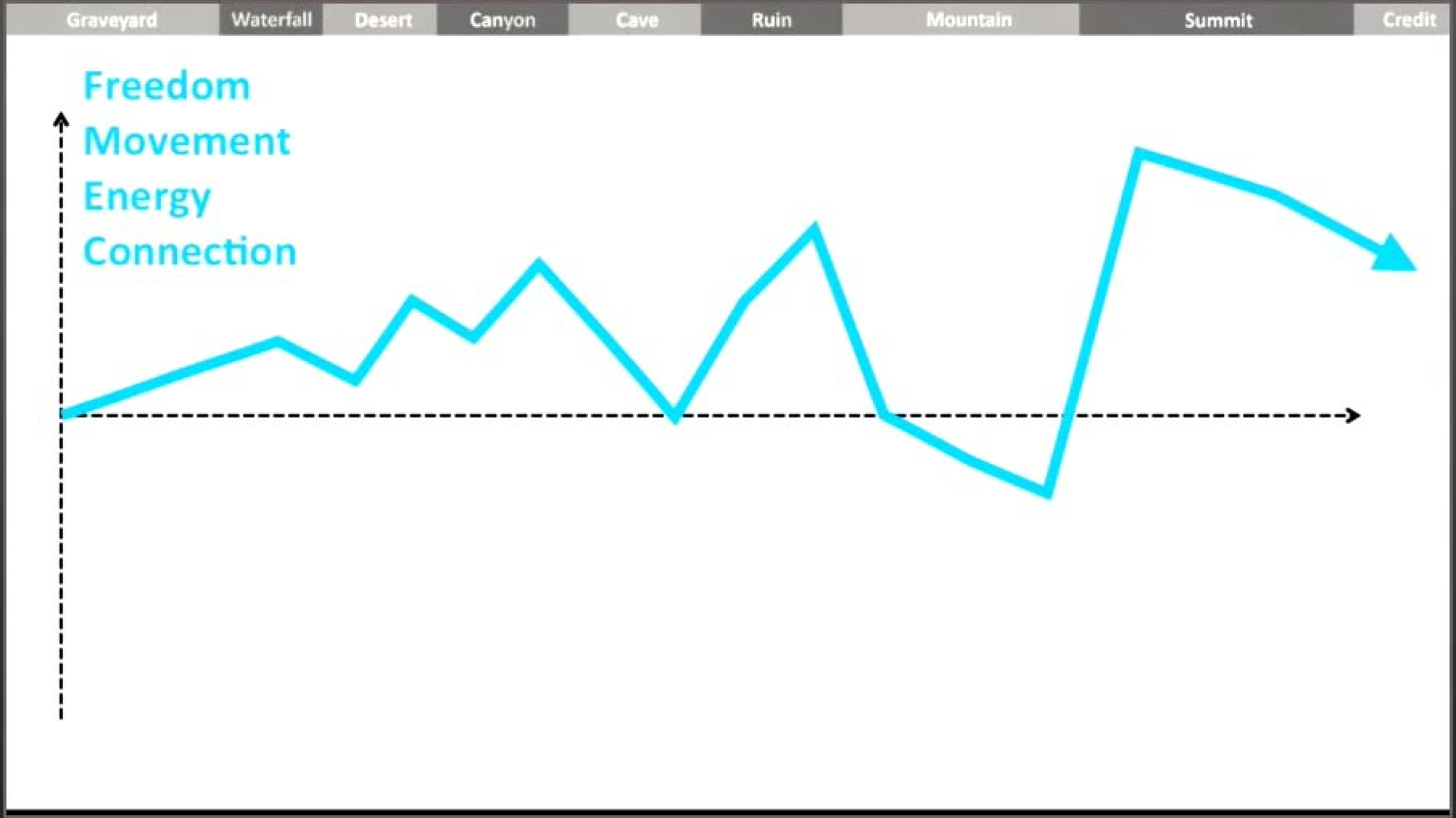
Beyond peak-end rule

- The rule seems too simplistic, and goes against more general memory research (e.g., forgetting curves)
- My hypothesis: What we remember is a function of time (most recent memories are strongest, hence the importance of the end) and other factors such as contrast and novelty/unpredictability (which amplifies surprising peaks)

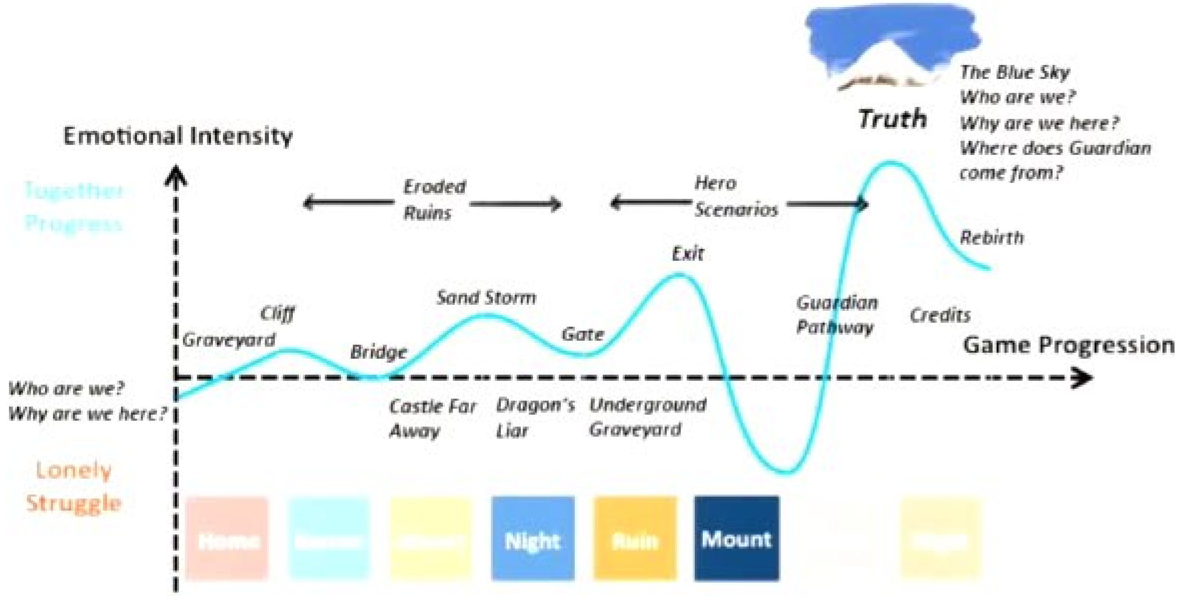


Forgetting curve fits from Averell & Heathcote 2011.

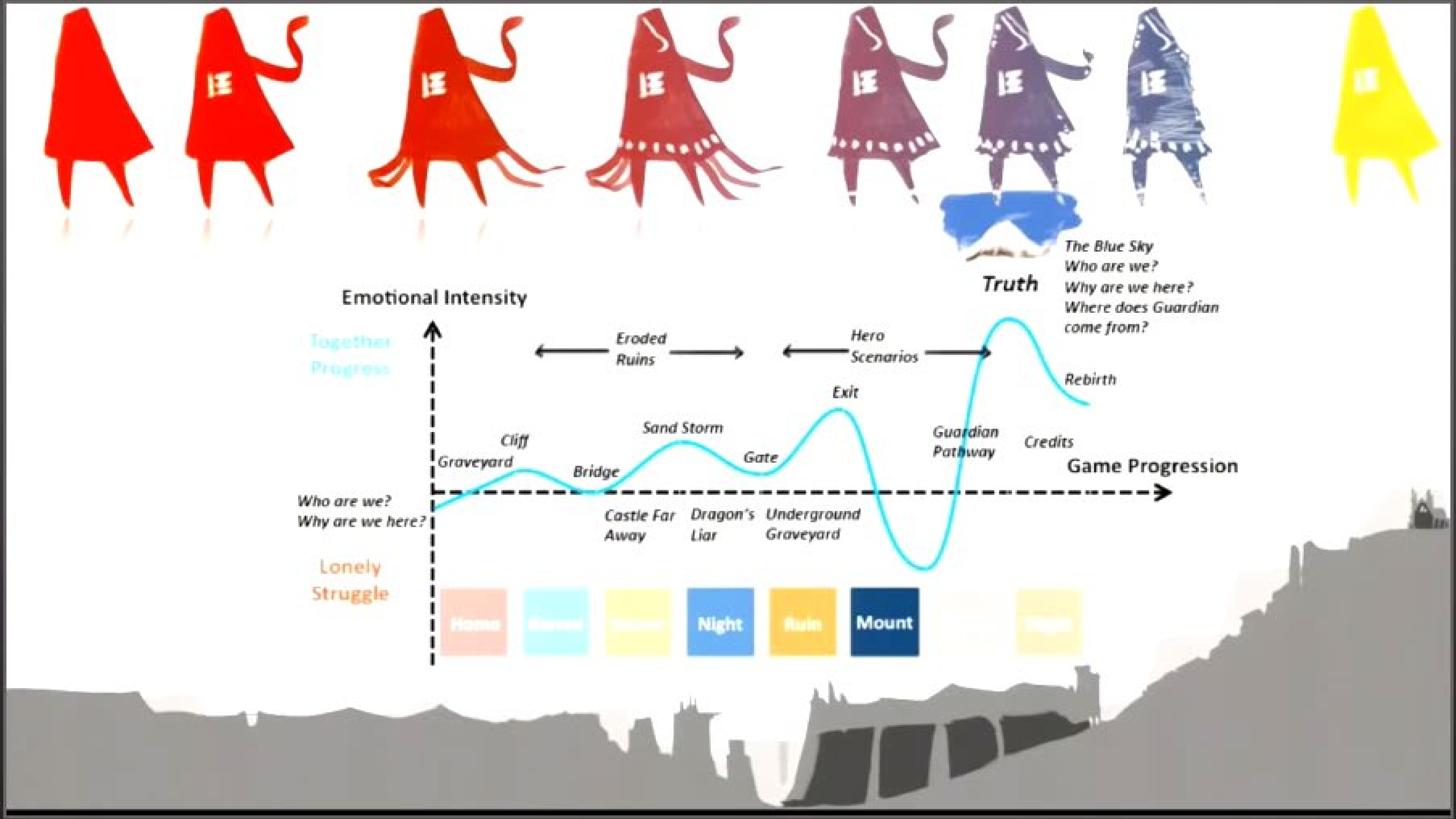
Peak-end rule and drama



"Catharsis, a sudden emotional breakdown or climax that constitutes ... any overwhelming change in emotion that results in renewal, restoration, and revitalization."



Emotional Intensity
Together
Progress
Lonely
Struggle
Game Progression
Who are we?
Why are we here?
Graveyard
Cliff
Bridge
Sand Storm
Gate
Exit
Eroded
Ruins
Hero
Scenarios
Castle Far
Away
Dragon's
Liar
Underground
Graveyard
Guardian
Pathway
Credits
Truth
The Blue Sky
Who are we?
Why are we here?
Where does Guardian
come from?
Rebirth
Home
Night
Ruin
Mount


The Blue Sky
Who are we?
Why are we here?
Where does Guardian come from?
Truth
Emotional Intensity
Together Progress
Eroded Ruins
Hero Scenarios
Rebirth
Exit
Sand Storm
Cliff
Graveyard
Bridge
Gate
Guardian Pathway
Credits
Game Progression
Who are we?
Why are we here?
Castle Far Away
Dragon's Liar
Underground Graveyard
Lonely Struggle
Night
Ruin
Mount

Design principles and implications

- Core reward design principles (anticipation and discounting of rewards)
- Avoiding thinking (System 1 vs. System 2, cognitive biases affecting reward evaluation)
- Perception and attention (contrast, Halo effect, confirmation bias)
- Memory (storing and retrieving information)
- **Social (effect of other people)**

Social proof

- The oldest sales trick, ”Finland’s most popular car”, ”Already 10 Million downloads” etc.
- Highlighting most frequently purchased items or ”people who bought X also bought...”
- The effect is stronger with closer social ties
  - Facebook shows ”Friend X likes Y” ads
  - ”90% of your facebook friends purchased Y” in IAPs?
- Base building games: players can see the bases of other players, what they’ve bought or achieved.


4
6
1314
999
83
Carol Wolf bundle
BUNDLE
1200
Gold!
Carol's Blade
New Outfit
Carol, Wolf
Offer ends in 1d 18h
€7,99 BUY
5
Map

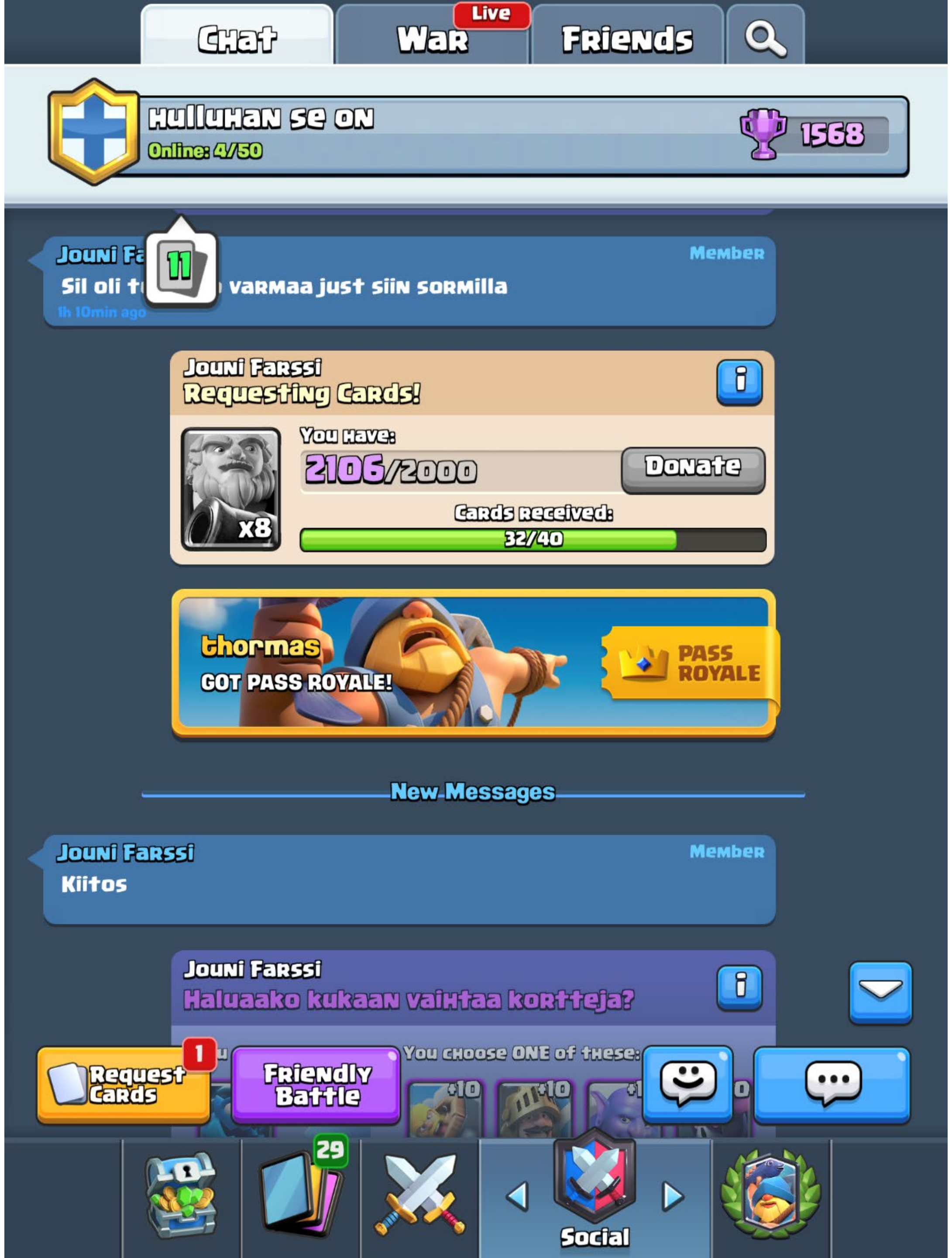

The weight is over.
Finally, smoother, softer, satiny style in half the time.
Living proof.
style | lab™
satin
hair serum
no oils or silicones
superior smoothing
frizz eliminating
shine creating
SEPHORA
You are the
Living proof.®

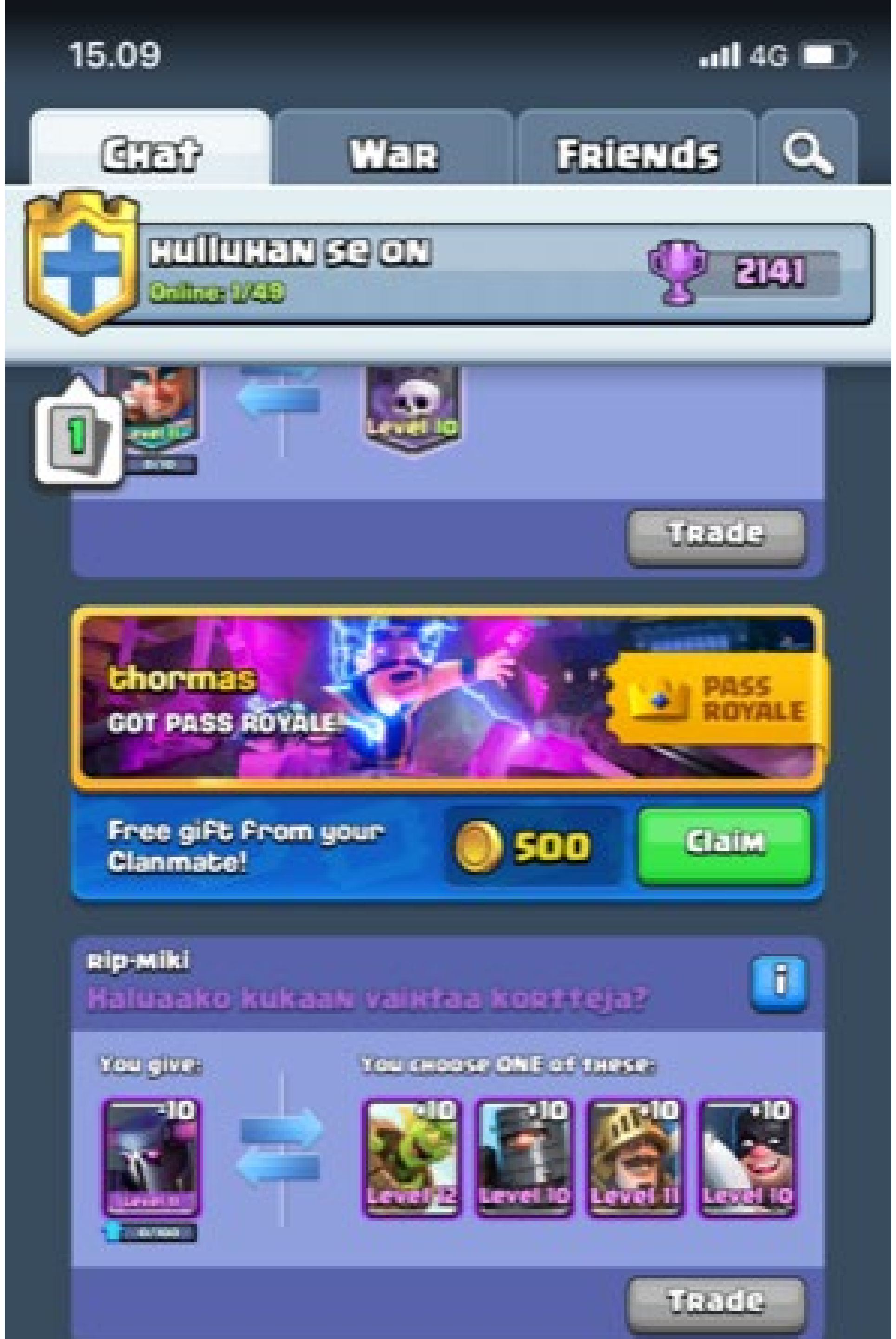
Computational rationality and social proof

- An instance of integrating multiple information sources – mitigating one’s own cognitive limitations by offloading some of the computation to others
- Rational if assuming reliability of others => makes sense that strength of experienced social connection affects the effect

Reciprocity (reciprocal altruism)

- Tendency to return favors (sharing of rewards/utility, on average over a long enough time span)
- Sales and marketing: free samples.
- Games: gifting behaviors can be used to drive monetization


Chat
Live
War
Friends
Hulluhan se on
Online: 4/50
1568
Jouni Fa
Member
Sil oli t
varmaa just siin sormilla
1h 10min ago
11
Jouni Farssi
Requesting Cards!
You have:
2106/2000
Donate
x8
Cards received:
32/40
thormas
GOT PASS ROYALE!
PASS ROYALE
New Messages
Jouni Farssi
Member
Kiitos
Jouni Farssi
Haluaako kukaan vaihtaa kortteja?
You choose ONE of these:
Request Cards
1
Friendly Battle
29
Social


15.09
4G
Chat
War
Friends
HULLUHAN SE ON
Online: 1/49
2141
Trade
thormas
GOT PASS ROYALE!
PASS ROYALE
Free gift from your Clanmate!
500
Claim
Rip-Miki
Haluaako kukaan vaihtaa kortteja?
You give:
You choose ONE of these:
Level 12
Level 10
Level 11
Level 10
Trade

Computational rationality and reciprocity

- Reciprocating can be rational in a social environment, in the long term
- Both learned (upbringing, religion…) and innate
  - Considerable amount of literature on the evolutionary basis

Chapter 4

Reciprocal altruism: 30 years later

Robert Trivers

https://link.springer.com/chapter/10.1007/3-540-28277-7_4

"Two are better than one; because they have a good reward for their labour. For if they fall, the one will lift up the other: but woe to him that is alone when he falleth; for he hath not another to help him up. Again, if two lie together, then they have heat: but how can one be warm alone? And if one prevails against him, two shall withstand him; and a three-fold cord is not easily broken." (Ecclesiastes 4, 9–12; King James Version).

4.1 Introduction

A little over 30 years ago, I had the good fortune of publishing my first scientific paper on reciprocal altruism, a subject that had not yet been addressed from an evolutionary standpoint. Hamilton's (1964) great work on kinship and altruism made it clear that in humans there existed a major form of altruism that could not be explained by kinship. Its elaboration was responsible for the complex economic systems in which we now live and its regulation could plausibly be explained by a system of interconnected human emotions, including feelings of friendship, gratitude, sympathy, guilt, moralistic aggression, a sense of justice and (I would now add) forgiveness.

I brought no great talents to this enterprise, beyond a willingness to take the evolutionary problem seriously and to model evolutionary logic on easily inferred psychological facts regarding our own behavior (for a description of how the paper was written, see Trivers 2002). The paper was certainly timely. My 600 reprints were quickly exhausted and the evolutionary idea was off and running. There now exists a very large literature on the subject and many subareas have advanced far beyond my original paper.

The purpose of the present paper is to provide a personal review of some major developments since my paper. These include the Prisoner's Dilemma (PD) as a model for reciprocal altruism, other models and third-party observer effects. I concentrate on the human sense of justice and the selective forces likely to have molded it. In the process, I discuss recent empirical work (using economic games) that bears on our sense of fairness and what seems to me the most plausible way to interpret these results. I neglect many important topics, for example, discrimination against cheaters in symbioses (see Sachs et al. 2004).

Reciprocity in games

- Social games: gifts were popular on facebook but fell out of fashion.
- Can virtual characters or game creators trigger social reciprocation in players?

Reciprocity in games

- Social games: gifts were popular on fb but fell out of fashion.
- Can virtual characters or game creators trigger social reciprocation in players?
- Waifu/husbando characters, maybe (I don’t have experience myself)
- Some games try to solicit reviews by making the player feel that the team has struggled to make a great game for the player’s benefit, and the player can give back by giving a 5-star review.
- Youtubers/influencers getting free games and in-game items, probably biases their reviews and videos
- Active redditors who have contributed to the community are likely to get more views on their game trailers

Recap time…

Summary

- There are multiple psychological principles that a designer should know.
- They are not a silver bullet, but a foundation that should feel natural, same as proper use of colors, UI design principles etc.
- At the same time, there are also false positive results. If there is only a single study about an effect or principle, take it with a grain of salt.
- Especially important: understand how human **perception,attention, information processing** and **memory** all have features and limitations that affect behavior, and how social interaction also contributes.
- Two systems theory: interplay of instinctive/fast and analytic/slow, and our tendency to avoid the latter.

Reward design checklist

- Rewards are a key tool for motivating players => Reward all desired behavior
  - Reward for winning or reaching goals (WDNML: loot boxes)
  - Reward for playing (failing to reach the goals, trying again) (WDNML rewards for failing: XP from killed walkers, timers that complete while playing)
  - Reward for coming back the next day (WDNML: upgrade timers, XP & can producers, random walkers)
  - Reward long-term retention (WDNML: episodic structure and episode rewards, character leveling, episodes too long to be completed in a single session. Also: achievements/trophies)
- Rewards motivate more when closer (breadcrumbing, endowed progress effect, other possible manipulations of perceived time-to-reward)
- Build anticipation – don’t assume your players are prescient (WDNML: announcing episode completion rewards in the beginning of episode)

Other common and well-established behavioral game design principles

- Random/unpredictable rewards (Loot boxes, combine skill-based and random play, balance skills and challenges)
- Peak-end-rule (provide a satisfying ending and one or more peak moments that are memorable and that your players want to talk about and share)
- Contrast effect (microtransaction pricing)
- Social proof (microtransaction advertising, seeing what other players have purchased or invested in)
- Artificial scarcity (limited offers, rarities of items)
- Going with the default (frame the desired player action as the default)
- Halo effect (Something really unique/cool/terrible can dominate the perception of an otherwise average game)
- Reciprocity (gifting mechanics can increase engagement, virality, and monetization)

Somewhat less common, still worth knowing

- Loss aversion (framing paying as avoiding losing something the player has already earned)
- Sunk cost fallacy (e.g., people invest more in games they've paid for, "pay to continue" after investing a lot of time on a level and failing)
- Commitment & consistency (Importance of no-brainer first purchase)
- Anchoring (Much easier to drop the price of one's game than to raise it)

Exercise: improve your rewards and behavioral game design!

Think about a game you are making: What is rewarding/satisfying for the player? Can you improve the reward design or employ behavioral game design to make the game more engaging?

Remember to avoid abusing the principles – what's really best for you and your players?

Report your findings using Google Slides or Powerpoint (submit as a .pdf via MyCourses, before next week's Monday session):

1. A brief summary of your game, with a screenshot if possible
2. The game's current reward design
3. How would you improve it considering the reward design and behavioral game design checklists from the previous slides? **(Add 1 slide per principle)**

Extra material

Evolutionary basis for random rewards

- We didn't evolve in the presence of slot machines and other forms of artificial randomness!
- Gambler's fallacy: "I've lost so many times now that I'll win next time"

NBER Working Paper #3769
July 1991

THE "GAMBLER'S FALLACY" IN LOTTERY PLAY

ABSTRACT

The "gambler's fallacy" is the belief that the probability of an event is lowered when that event has recently occurred, even though the probability of the event is objectively known to be independent from one trial to the next. This paper provides evidence on the time pattern of lottery participation to see whether actual behavior is consistent with this fallacy. Using data from the Maryland daily numbers game, we find a clear and consistent tendency for the amount of money bet on a particular number to fall sharply immediately after it is drawn, and then gradually to recover to its former level over the course of several months. This pattern is consistent with the hypothesis that lottery players are in fact subject to the gambler's fallacy.

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Durham, NC 27706

https://www.nber.org/system/files/working_papers/w3769/w3769.pdf

Evolutionary basis for random rewards

Optimism bias:

- We underrate our chances of getting divorced, being in a car accident etc.
- We overestimate our job market success, our children's talent etc.

https://www.cell.com/current-biology/pdf/S0960-9822(11)01191-2.pdf

Primer

The optimism bias

Tali Sharot

The ability to anticipate is a hallmark of cognition. Inferences about what will occur in the future are critical to decision making, enabling us to prepare our actions so as to avoid harm and gain reward. Given the importance of these future projections, one might expect the brain to possess accurate, unbiased foresight. Humans, however, exhibit a pervasive and surprising bias: when it comes to predicting what will happen to us tomorrow, next week, or fifty years from now, we overestimate the likelihood of positive events, and underestimate the likelihood of negative events. For example, we underrate our chances of getting divorced, being in a car accident, or suffering from cancer. We also expect to live longer than objective measures would warrant, overestimate our success in the job market, and believe that our children will be especially talented. This phenomenon is known as the optimism bias, and it is one of the most consistent, prevalent, and robust biases documented in psychology and behavioral economics.

The optimism bias is defined as the difference between a person's expectation and the outcome that follows. If expectations are better than reality, the bias is optimistic; if reality is better than expected, the bias is pessimistic. The extent of the optimism bias is thus measured empirically by recording an individual's expectations before an event unfolds and contrasting those with the outcomes that transpire. This methodology reveals, for instance, that students expect to receive higher starting salaries and more job offers than they end up getting. People tend to underestimate how long a project will take to complete and how much it will cost. Most of us predict deriving greater pleasure from a vacation than we subsequently do, and we anticipate encountering more positive events in an upcoming month (such as receiving a gift or enjoying a movie) than we end up experiencing (Figure 1A). Across many different

Sharot, Tali. "The optimism bias." *Current biology* 21.23 (2011): R941-R945.

Evolutionary basis for random rewards

LETTER

https://www.nature.com/articles/nature10384

doi:10.1038/nature10384

The evolution of overconfidence

Dominic D. P. Johnson[1] & James H. Fowler[2]

Confidence is an essential ingredient of success in a wide range of domains ranging from job performance and mental health to sports, business and combat[1–4]. Some authors have suggested that not just confidence but overconfidence—believing you are better than you are in reality—is advantageous because it serves to increase ambition, morale, resolve, persistence or the credibility of bluffing, generating a self-fulfilling prophecy in which exaggerated confidence actually increases the probability of success[3–8]. However, overconfidence also leads to faulty assessments, unrealistic expectations and hazardous decisions, so it remains a puzzle how such a false belief could evolve or remain stable in a population of competing strategies that include accurate, unbiased beliefs. Here we present an evolutionary model showing that, counterintuitively, overconfidence maximizes individual fitness and populations tend to become overconfident, as long as benefits from contested resources are sufficiently large compared with the cost of competition. In contrast, unbiased strategies are only stable under limited conditions. The fact that overconfident populations are evolutionarily stable in a wide range of environments may help to explain why overconfidence remains prevalent today, even if it contributes to hubris, market bubbles, financial collapses, policy failures, disasters and costly wars[9–13].

Humans show many psychological biases, but one of the most consistent, powerful and widespread is overconfidence. Most people show a bias towards exaggerated personal qualities and capabilities, an illusion of control over events, and invulnerability to risk (three phenomena collectively known as 'positive illusions')[2–4,14]. Overconfidence amounts to an 'error' of judgement or decision-making, because it leads to overestimating one's capabilities and/or underestimating an opponent, the difficulty of a task, or possible risks. It is therefore no surprise that overconfidence has been blamed throughout history for high-profile disasters such as the First World War, the Vietnam war, the war in Iraq, the 2008 financial crisis and the ill-preparedness for environmental phenomena such as Hurricane Katrina and climate change[9,12,13,15,16].

maximizing benefits over costs, especially under conditions of competition, uncertainty and asymmetric costs of different types of error[8,18–21]. Whereas economists tend to posit the notion of human brains as general-purpose utility maximizing machines that evaluate the costs, benefits and probabilities of different options on a case-by-case basis, natural selection may have favoured the development of simple heuristic biases (such as overconfidence) in a given domain because they were more economical, available or faster.

Here we present a model showing that, under plausible conditions for the value of rewards, the cost of conflict, and uncertainty about the capability of competitors, there can be material rewards for holding incorrect beliefs about one's own capability. These adaptive advantages of overconfidence may explain its emergence and spread in humans, other animals or indeed any interacting entities, whether by a process of trial and error, imitation, learning or selection. The situation we model—a competition for resources—is simple but general, thereby capturing the essence of a broad range of competitive interactions including animal conflict, strategic decision-making, market competition, litigation, finance and war.

Suppose a resource r is available to an individual that claims it, and there are two individuals, i and j. These individuals each have initial 'capability' θ_i and θ_j that determine whether or not they would win a conflict over the resource. Without loss of generality, we assume that θ is distributed in the population according to a symmetric stable probability density[22] with cumulative distribution Φ, a mean of 0, and a variance of 0.5. The initial advantage to individual i is $a = \theta_i - \theta_j$, and assumptions about the distribution of θ imply that the probability density of a has a cumulative distribution Φ, a mean of 0, and unit variance (see Supplementary Information for the full model).

If neither individual claims the resource, no fitness is gained. If only one makes a claim, then the claimant acquires the resource and gains fitness r and the other individual gains nothing. If both claim the resource, then both pay a cost c as a result of the conflict between them, but the individual with the higher initial capability will win the conflict, acquiring the resource and obtaining fitness r. This means there are only

Evolutionary basis for random rewards

- Probability neglect: We tend to over/underestimate very small probabilities
- Affect-rich choices: Perceived value of rare win (highly emotional, exciting!) might be much higher than the perceived cost of playing one more time (no emotion)

JOURNAL OF
BEHAVIORAL DECISION MAKING

Research Article | Full Access

How Affect Shapes Risky Choice: Distorted Probability Weighting Versus Probability Neglect

Renata S. Suter, Thorsten Pachur, Ralph Hertwig

First published: 01 July 2015 | https://doi.org/10.1002/bdm.1888 | Citations: 41

SECTIONS PDF TOOLS SHARE

Abstract

People's choices between prospects with relatively affect-rich outcomes (e.g., medical side effects) can diverge markedly from their choices between prospects with relatively affect-poor outcomes (e.g., monetary losses). We investigate the cognitive mechanisms underlying this “affect gap” in risky choice. One possibility is that affect-rich prospects give rise to more distortion in probability weighting. Another is that they lead to the neglect of probabilities. To pit these two possibilities against each other, we fitted cumulative prospect theory (CPT) to the choices of individual participants, separately for choices between options with affect-rich outcomes (adverse medical side effects) and options with affect-poor outcomes (monetary losses); additionally, we tested a simple model of probability neglect, the minimax rule. The results indicated a qualitative difference in cognitive mechanisms between the affect-rich and affect-poor problems. Specifically, in affect-poor problems, the large majority of participants were best described by CPT; in affect-rich problems, the proportion of participants best described by the minimax rule was substantially higher. The affect gap persisted even when affect-rich outcomes were supplemented by numerical information, thus providing no support for the thesis that choices in affect-rich and affect-poor problems diverge because the information provided in the former is nonnumerical. Our findings suggest that the traditional expectation-based framework for modeling risky decision making may not readily generalize to affect-rich choices. Copyright © 2015 John Wiley & Sons, Ltd.

https://pure.mpg.de/rest/items/item_2350314/component/file_2350905/content

Computational rationality and loss aversion

ELSEVIER

Journal of Economic Dynamics and Control

Volume 37, Issue 1, January 2013, Pages 18-31

Bounded rationality as a source of loss aversion and optimism: A study of psychological adaptation under incomplete information

Jing Yao [a], Duan Li [b]

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https://doi.org/10.1016/j.jedc.2012.07.002

Abstract

We develop a formal model to investigate the implications of bounded rationality for the origin and structure of loss aversion and optimism in marketplaces. Based on Simon's original description, we explicitly model bounded rationality as a decision mechanism that captures incomplete information, psychological adaptation, and rational behavior. We find that the endogenous loss aversion and optimism emerge when the degree of information incompleteness reaches a certain threshold, and both grow to be more prominent when information becomes sparser. Our results highlight that the psychological biases could be expected to take advantage of perceived information incompleteness in terms of value creation.

Computational rationality and loss aversion

ELSEVIER

Evolution and Human Behavior

Volume 41, Issue 1, January 2020, Pages 87-95

The evolution of the endowment effect

Justin Bruner [a], Frank Calegari [b], Toby Handfield [c]

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https://doi.org/10.1016/j.evolhumbehav.2019.10.004 Get rights and content

Abstract

People often value an item more when they own it than when it is available for purchase, and consequently are relatively reluctant to trade. This is the “endowment effect”, which has been widely documented in human populations and also in some non-human species. This paper develops a simple model in which it is adaptive to have a bias against trade, potentially explaining the basis of the endowment effect. The bias against trade arises from the strategic nature of trade in a moderately competitive environment: the interest of a potential trading partner in making the exchange is evidence that the decision maker already has the more valuable object. The model predicts that an endowment effect is promoted by large uncertainty about the fitness value of items, and also by conditions in which there are on average small gains to be had from trade. Because the model employs a simple bounded rationality heuristic for trade, it explains how the endowment effect could arise in species that lack theory of mind and related strategic reasoning abilities. The model also suggests an explanation for why endowment effects are so rarely observed in biological markets that exist between species. Because the trading classes have very different fitness functions, there is negligible competition across those classes. Consequently, there are substantial mutual gains to trade, so our model predicts there is unlikely to be adaptive pressure for an endowment effect.

Computational rationality and loss aversion

Wishful Thinking, Prudent Behavior: The Evolutionary Origin of Optimism, Loss Aversion and Disappointment Aversion

26 Pages • Posted: 31 Jan 2018

Chris Dawson
University of Bath

David de Meza
London School of Economics Department of Management

Date Written: January 24, 2018

Abstract

Optimism, the tendency to overestimate the likelihood of positive events, is one of the most established psychological "biases". So too are the apparently counteracting phenomena of loss and disappointment aversion. We propose an evolutionary based reconciliation of these seemingly conflicting biases and test it by looking at gender differences in their prevalence. The starting point is the theory advanced by Robert Trivers that optimism has evolved to more effectively persuade or deceive others. A side effect of optimism is mistaken own decisions and excessively rash behavior. Loss aversion does not affect optimistic beliefs but curtails the inclination to act on them. Disappointment aversion also induces prudence, partly through lowering optimism, a characteristic less useful to women. We find that men are more optimistic than women, both sexes are equally loss averse and women are more disappointment averse than men. This is consistent with gender-specific evolutionary adaptations.

Keywords: Gender; Optimism; Loss Aversion; Disappointment Aversion; Dread Aversion

JEL Classification: D03

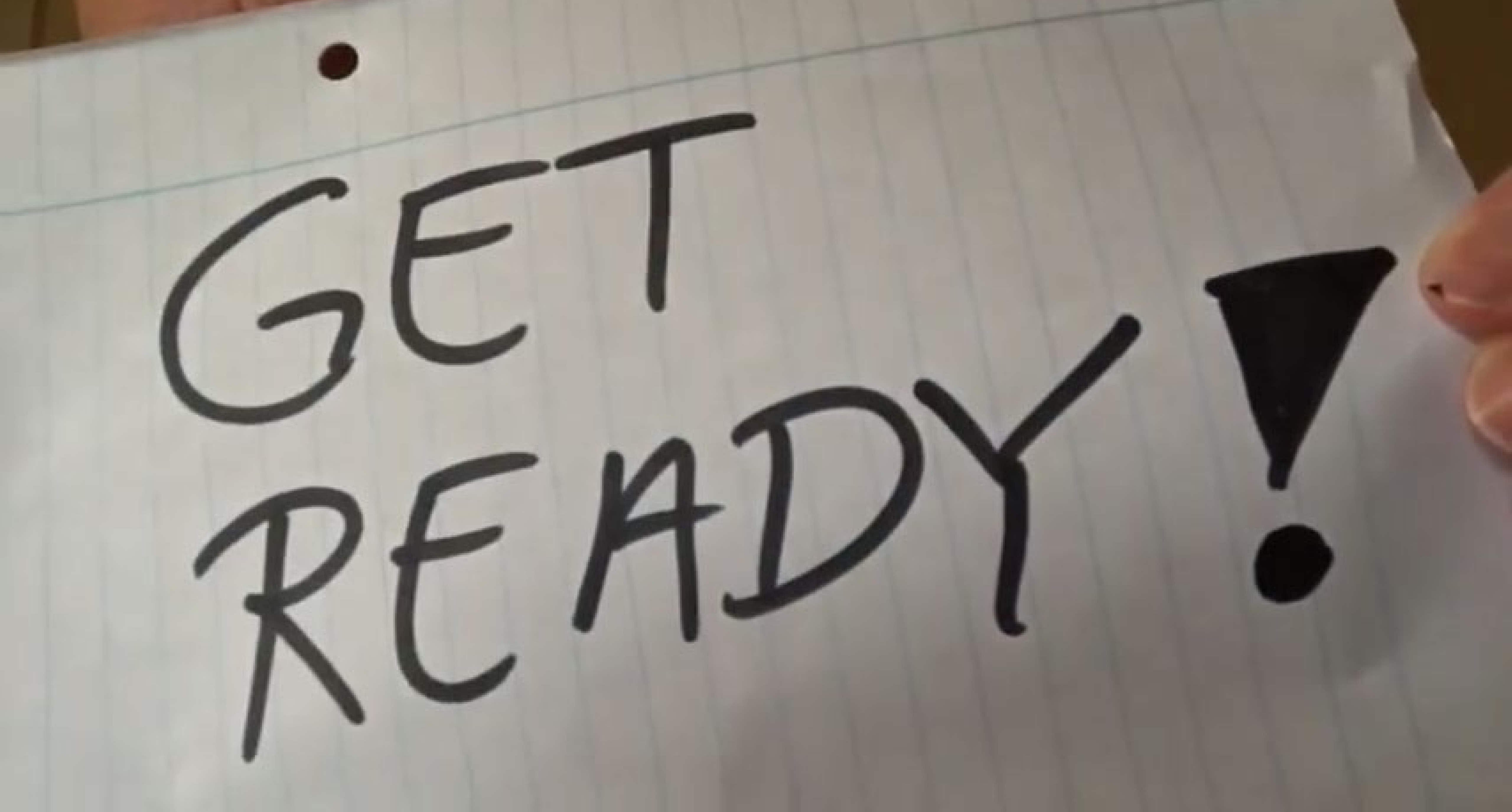
Suggested Citation:

Dawson, Chris and de Meza, David Emmanuel, Wishful Thinking, Prudent Behavior: The Evolutionary Origin of Optimism, Loss Aversion and Disappointment Aversion (January 24, 2018). Available at SSRN: https://ssrn.com/abstract=3108432 or http://dx.doi.org/10.2139/ssrn.3108432

Exploiting System 1 outside games

- Martial arts: probing and then exploiting the opponent's automatic (i.e., predictable) behaviors
- Politics: designing campaigns and advertising to trigger strong emotions that make people behave without thinking
- Magic tricks
- Sales and marketing

We’re constantly being manipulated by our media environment https://www.youtube.com/watch?v=66s8hPGzccY



Explanations?

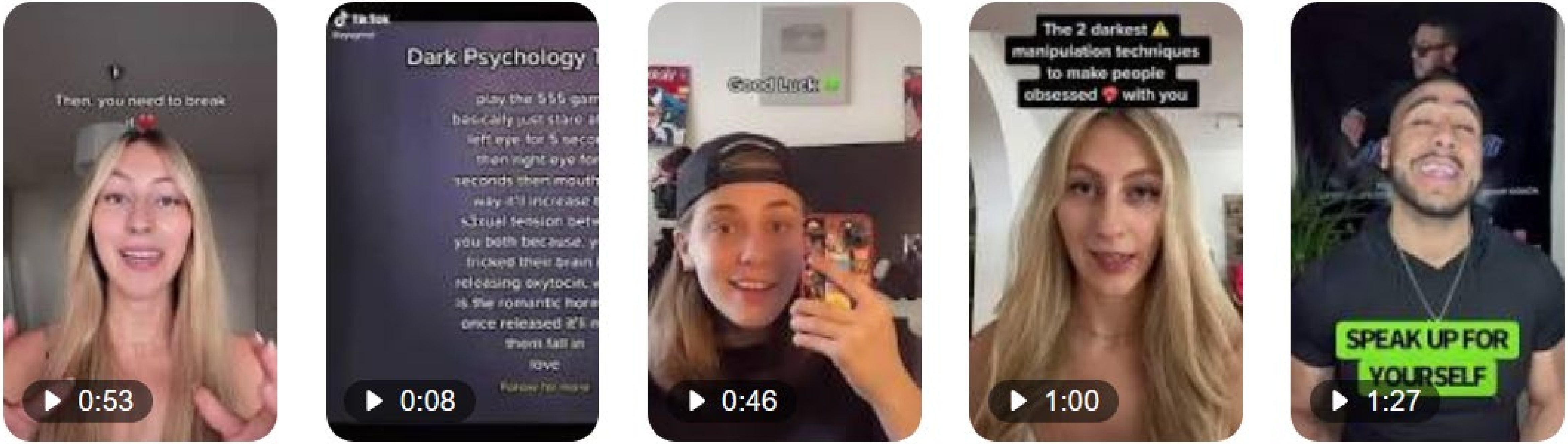
- 11-4=7, 12-5=7, and the last arithmetic operation before the final question was a subtraction
- 7 is close to the mean of the range 5…12
- 7 is the only number not shown (might work for those that try to come up with something unexpected)
- Odd numbers are perceived as slightly more random
- 7 is simply a common number people think of

The real psychological trick?

- Asking for the shares from those who ”fell” for it
- Maximizes perceived success rate
- Maximizes virality

https://www.tiktok.com › Discover

psychological manipulation tips | TikTok Search



17 Sept 2022 — Discover short videos related to **psychological manipulation** tips on **TikTok**. Explore the latest videos from hashtags: ...

Popular TikTok genre: False claims about psychological manipulation

Unbelievable findings are sometimes just that.

- Social psychology is undergoing a replicability crisis
- Some papers present findings based on too few participants and questionable research practices (QRP:s)
- Does not replicate: Forced smile (pen in mouth) makes you positive, Power posing affects hormones, Elderly priming, many other priming studies.
- Still, many classic effects such as anchoring and loss aversion do seem to replicate

https://replicationindex.com/category/pen-in-mouth-paradigm/

“I placed too much faith in underpowered studies:” Nobel Prize winner admits mistakes

Although it’s the right thing to do, it’s never easy to admit error — particularly when you’re an extremely high-profile scientist whose work is being dissected publicly. So while it’s not a retraction, we thought this was worth noting: A Nobel Prize-winning researcher has admitted on a blog that he relied on weak studies in a chapter of his bestselling book.

Daniel Kahneman

https://retractionwatch.com/2017/02/20/placed-much-faith-underpowered-studies-nobel-prize-winner-admits-mistakes/

Psychological Science
Volume 22, Issue 11, November 2011, Pages 1359-1366

https://doi.org/10.1177/0956797611417632

General Article

False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant

Joseph P. Simmons[1], **Leif D. Nelson**[2], **and Uri Simonsohn**[1]

Abstract

In this article, we accomplish two things. First, we show that despite empirical psychologists' nominal endorsement of a low rate of false-positive findings (≤ .05), flexibility in data collection, analysis, and reporting dramatically increases actual false-positive rates. In many cases, a researcher is more likely to falsely find evidence that an effect exists than to correctly find evidence that it does not. We present computer simulations and a pair of actual experiments that demonstrate how unacceptably easy it is to accumulate (and report) statistically significant evidence for a false hypothesis. Second, we suggest a simple, low-cost, and straightforwardly effective disclosure-based solution to this problem. The solution involves six concrete requirements for authors and four guidelines for reviewers, all of which impose a minimal burden on the publication process.

Keywords

methodology, motivated reasoning, publication, disclosure

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https://journals.sagepub.com/doi/full/10.1177/0956797611417632

Statistical Significance Testing at CHI PLAY: Challenges and Opportunities for More Transparency

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ABSTRACT

Statistical Significance Testing – or Null Hypothesis Significance Testing (NHST) – is common to quantitative CHI PLAY research. Drawing from recent work in HCI and psychology promoting transparent statistics and the reduction of questionable research practices, we systematically review the reporting quality of 119 CHI PLAY papers using NHST (data and analysis plan at OSF.io). We find that over half of these papers employ NHST without specific statistical hypotheses or research questions, which may risk the proliferation of false positive findings. Moreover, we observe inconsistencies in the reporting of sample sizes and statistical tests. These issues reflect fundamental incompatibilities between NHST and the frequently exploratory work common to CHI PLAY. We discuss the complementary roles of exploratory and confirmatory research, and provide a template for more transparent research and reporting practices.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in HCI*.

data to produce new insights regarding player-computer interaction [179]. Often, data analysis proceeds by way of p values (e.g., as computed via t-test or ANOVA), which are used to understand whether trends in data represent real effects, or merely noise. This is commonly called *Null Hypothesis Significance Testing* (NHST).

However, NHST methods have become increasingly subject to critique. False positive results, whereby noise is misidentified as a real effect, can easily occur as a result of common practices performed during analysis [79, 154]. These *Questionable Research Practices* [177, QRPs] threaten the legitimacy of statistical significance and therefore complicate interpretation of published research findings [79, 154]. QRPs are facilitated by a publishing climate biased towards statistically significant results[1], leaving non-significant research findings in the file drawer [33, 49, 131, 170].

A growing number of HCI scholars have consequently called for greater consideration of the quality of NHST analyses, and statistical reporting more broadly [26, 27, 48, 75, 88]. However, the extent to which these issues affect HCI research on games and play – and CHI PLAY in particular – is yet to be determined.

Yet CHI PLAY arguably has much to gain from other fields where

https://acris.aalto.fi/ws/portalfiles/portal/44527123/NHST_at_CHI_PLAY_CameraReady.pdf

Books:

Kahneman 2011: Thinking, fast and slow (but, see also: https://retractionwatch.com/2017/02/20/placed-much-faith-underpowered-studies-nobel-prize-winner-admits-mistakes/)

Cialdini 2006: Influence – The psychology of persuasion, revised edition

Research papers and reports:

UTA Free2Play Research Project Final Report: http://tampub.uta.fi/handle/10024/98584

Hamari 2011: Perspectives from behavioral economics to analyzing game design patterns: loss aversion in social games

Butler 2014: Game design through the lens of behavioral economics

Lewis et al. 2012: Motivational Game Design Patterns of 'Ville Games

Video:

South Park episode: Freemium isn't free

Web:

http://www.psychologyofgames.com

http://www.gamasutra.com/view/feature/172409/10_years_of_behavioral_game_design_.php

https://en.wikipedia.org/wiki/List_of_cognitive_biases

https://www.youtube.com/watch?v=xNjI03CGkb4 (Let's go Whaling talk – informative if not ethical)

Exercise: in groups, pick a game & analyze

- What psychological principles are utilized?
  - Add screenshots (or series of them) to illustrate the principles.
- Focus on the most common principles to avoid overinterpretation:
  - Building anticipation of rewards
  - Providing short and long term rewards (breadcrumbing, daily login rewards…)
  - Providing random rewards
  - Contrast effect (e.g., in-game shop)
  - Loss aversion, especially in form of artificial scarcity
  - Framing desired player action as the default choice
  - Social proof (e.g., in advertising microtransactions)
  - Using social reciprocation to elicit gifting or other desired player behaviors
- What principles could be utilized better? Can you improve the reward design?
- Collect the results in a shared Google Slides