Folk Models of Loot Boxes in Video Games

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Regulations require video games to provide transparency regarding loot box odds to keep players informed, leading many games to disclose probabilities in various ways; yet, the extent of players' comprehension of loot box mechanics remains unclear. We performed a content analysis on 80 online posts to understand players' perceptions of loot box odds in two popular video games (*Genshin Impact* and *Honkai: Star Rail*). We then conducted semi-structured interviews with 24 players to explore the causes of these folk models across more games. Utilizing a bottom-up open coding approach, we created a taxonomy of folk models players have about loot boxes. We found that participants generally possessed inaccurate mental models of how loot boxes work, and they wanted game companies to enhance loot box transparency in three areas of probability disclosures: granularity, longitude, and scope.

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

Additional Key Words and Phrases: loot box; video game; folk model; transparency; design; regulation; player experience

ACM Reference Format:
Jinhe Wen, Zhongyang Zhang, Tuan M. Tran, Lianrui Mu, Tauhidur Rahman, and Haojian Jin. 2024. Folk Models of Loot Boxes in Video Games. *Proc. ACM Hum.-Comput. Interact.* 8, CHI PLAY, Article 307 (October 2024), 23 pages. https://doi.org/10.1145/3677072

1 Introduction

In video games, loot boxes are digital containers for a random mix of in-game assets like weapons, cosmetic skins, or other rewards [74, 90, 91], which "can be purchased using real-world currency, purchased using virtual in-game currency, offered as free rewards, or offered in some combination thereof"[1] [48, 58]. In 2020, the video game industry generated 15 billion dollars through loot box mechanics [8]. Public media have reported numerous instances of loot box high spending: A *FIFA* [G2] player spent over US$10,000 in a mere two years [93]. In another incident, four children

[1]While there are multiple definitions of loot boxes, we appropriate Kao's and Macey's definitions, which consider free digital containers part of in-game loot boxes [48, 58]. Players often have to obtain these containers through in-game efforts (e.g., repetitive grinding [94]), which may lead to potential regulation needs [37].

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ACM 2573-0142/2024/10-ART307
https://doi.org/10.1145/3677072

used up nearly US$715 of their father's money without his knowledge in just three weeks and still did not obtain the rare item they were after [50].

The psychological similarities between loot boxes and gambling have prompted governments and platforms to implement probability disclosure regulations [15, 22, 38, 54, 56]. For example, since May 2017, the People's Republic of China (PRC) has mandated that video game companies reveal the chances of acquiring randomized rewards from loot boxes. Similarly, Apple demands that all games on the iOS platform worldwide disclose the odds of loot boxes [41]. Previous studies have investigated the suboptimal compliance with disclosure regulations [89, 91] and the ineffectiveness of current loot box warning labels [33, 87].

Yet, a less studied aspect is how players comprehend loot box mechanics in the wild. Existing regulations often give game companies broad latitude in their disclosure methods. Game companies can display the odds either on the in-game loot box purchasing interface or on the external game's official website [60]. There aren't specific guidelines regarding the font size, symbols, or terminology for loot box disclosures, the positioning of such disclosures on websites, or how these odds are presented to the player, whether numerically or visually [91]. Consequently, our understanding of how players form their perceptions [65] after encountering various disclosures is limited.

This paper studies the existence and causes of game players' folk models of loot boxes in video games. *Folk models* refer to mental models that might not align with actual real-world phenomena but are widely used by people in practice [21, 44]. It's widely recognized that users frequently rely on these misconstrued folk models, especially in technology-related settings [84, 92]. One prevalent folk model in our findings is the *Beginners' Luck*, where many players believe that companies tweak the odds in favor of newcomers to keep them engaged [73]. Through examining these folk models, our objective is to gain insights into the current perceptions players have about loot boxes, and explore potential opportunities to help policymakers refine regulations and help game developers enhance their disclosure methods.

We conducted the study in two stages. First, we identified ten publicly available videos illustrating different tricks for interacting with loot boxes in two popular games: *Genshin Impact* [G6] and *Honkai: Star Rail* [G7]. We collected 80 public discussion posts under these videos, which often act as hubs for players to share and discuss loot box techniques. Using a bottom-up open coding approach, we identified a set of initial folk models in these two games. Second, we conducted semi-structured interviews with 24 players, spanning 30 different games, to validate the list of folk models and explore participants' in-depth understanding of these folk models. During each interview, we asked participants to nominate and validate strategies they employ when interacting with loot boxes and provide insights into the genesis of these tactics, their perceived efficacy, the influence these models have on their decision-making, and the types of transparency they desire.

Our research allowed us to answer the following research questions:

RQ 1: What kinds of folk models do players have towards loot box mechanisms? Our results suggest that all players have some misconceptions about loot box mechanics. We identified 15 prevalent folk models, categorized under four categories: player discrimination models (e.g., *Beginners' Luck*), context-based models (e.g., *Lucky Moments*), activity-based models (e.g., *Companies Will Listen to My Wishes*), and longitudinal models (e.g., *Pity Timers*). These folk models influence our interviewees' behaviors within games differently, depending on the particular contexts of the games (see discussions in Section 6.1).

RQ 2: What are the causes of these folk models? Participants develop folk models by synthesizing information from various sources, which can be grouped into three primary categories: (1) Assumptions based on business models (e.g., companies want to retain new players), (2) Empirical experiences (e.g., participants have a lucky streak experience), and (3) Superstitious beliefs (e.g., playing specific music).

RQ 3: What types of transparency do players want? Participants hope that companies can offer more fine-grained probability information, such as the odds for individual items instead of a collective average for a class of items, expand the coverage of disclosures, such as disclosing the odds for items obtained for free, and be transparent about their future plans, such as whether they will release another more powerful item.

Our main contribution is an in-depth investigation into players' perceptions of loot box probabilities in video games. We identified 15 folk models of loot boxes categorized under four categories, delved into the root causes of these perceptions, and highlighted the level of transparency players seek. These findings could inform game developers to design future disclosure methods and for policymakers to craft regulation guidelines, creating a healthier environment for gamers.

2 Background

Loot Boxes. We adapt the definitions from Kao [48] and Macey [58] to characterize loot boxes.

(1) *Container:* A loot box should appear as a staged container, such as scratch cards, card packs, or prize wheels [90, 91]. Conversely, a playing experience that generates continuous rewards does not qualify as a loot box.
(2) *Randomness:* The output from opening a loot box should be non-deterministic. In contrast, an item promotion bundle, in which the specific items and their quantities per bundle are disclosed in advance, is not considered a loot box.
(3) *Reward:* Loot boxes must give a reward upon opening rather than penalties. For example, random teammate matching is not considered a loot box.

Folk Models & Mental Models. In "The Design of Everyday Things," Norman defines *mental models* as conceptual models that users use to explain and predict how devices behave in different scenarios [65]. In the context of loot boxes, developers disclose the internal implementation of the loot box to players through simplified user interfaces (i.e., odd disclosure). Players then form a mental model about the loot box based on the interfaces and external factors that developers do not control, such as their prior experiences, news reports, and anecdotes from friends.

Users' mental models vary from person to person. It is widely recognized that in technological settings, users frequently rely on inaccurate mental models [84]. In contrast, *folk models* are mental models that are not necessarily accurate but are **shared among users** [21, 84]. Understanding players' folk models of loot boxes can help us understand the limitations of existing probability disclosure practices.

3 Related Work

We have organized related studies into three categories: regulations and implementations of loot box disclosures, folk models in computer systems, and psychology for money-related activities.

3.1 Regulations and Implementations of Loot Box Disclosures

The similarities between loot boxes and gambling have prompted policymakers to regulate loot boxes through various approaches [11, 24, 51, 60, 66, 68, 81, 82], such as classification and warning labels [24, 66, 68], restrictions on purchases using real money [11, 60], and restrictions on transfers between players and real-life currency conversion [81]. Beyond that, some regulatory bodies require the disclosure of loot box odds [18–20, 60, 78].

Current regulations on loot box disclosures cover various aspects, including disclosure granularity (e.g., Taiwan [19, 20], South Korea [78]), reliability (e.g., UK [18]), and positioning (e.g, PRC [60], Taiwan [20]). In Taiwan and South Korea, companies must disclose the probability of obtaining each specific item [19]. This means that disclosure based on an item's rarity or quality category is no longer compliant [88]. Besides, the UK's Committee of Advertising Practice (the organization responsible for advertising rules) has warned game companies against misleading users about their chances of winning [18].

However, existing regulations fail to provide an industry-wide, uniform social norm regarding loot box disclosures, giving companies broad latitude in their disclosure methods [63, 87, 89, 91]. In the PRC, game companies should display the loot box odds either on the in-game loot box purchasing interface or on the game's official website [60], but there aren't specific guidelines regarding font size, symbols, terminology to signify in-game disclosure; the placement of disclosure on website; or how these odds should be conveyed to players, whether numerically or visually [91]. This results in diverse and incomplete disclosures by companies. For example, Xiao et al. identified six in-game disclosure formats (e.g., odds appearing after tapping a symbol) and five website-based approaches (e.g., disclosure notifications listed chronologically alongside other news posts) in the PRC [91]. In the UK, there are instances where disclosed percentages do not sum to 100% or appear as a range (e.g., '45%–70%') instead of a precise value [89].

Furthermore, players may develop varying perceptions in response to diverse and incomplete disclosures, even if the disclosed mechanisms are equivalent [63], and we currently have a limited understanding of how players form these perceptions [65]. Our research intends to fill this gap by studying users' folk models of loot box mechanisms.

3.2 Folk Models in Computer Systems

Building on the mental model approach [32, 45, 46], we aim to examine players' comprehension of loot box mechanics. Existing literature has utilized mental models to explain people's reasoning and decision-making processes across various fields, including language, music, and technical systems [32, 46, 49]. For example, users' mental models of a thermostat's mechanism influence their operational behaviors in home heat control [49].

The mental model approach has been a cornerstone of research when probing people's comprehension of various systems, as evident in numerous studies [10, 39, 40, 43, 71, 72, 77, 79, 80, 84, 85, 92]. For instance, Thatcher and Greyling employed this approach to investigate people's ideas about the Internet, unveiling mental models like the belief that the Internet functions as a central database [80].

However, a lack of deep understanding of system mechanisms (i.e., transparency) can lead to oversights and ill-informed decisions. Wash uses the term *folk models* to denote mental models that might not align with reality but are shared by people in practice [21, 84]. He identified eight folk models in home computer security and illustrated the influence of these models on untrained computer users, leading them to overlook expert security advice and make questionable decisions [84]. Yao et al. identified four folk models explaining how Online Behavioral Advertising (OBA) works and demonstrated how these models are either incomplete or inaccurate in representing typical OBA practices [92]. Zou et al. studied consumers' folk models regarding credit bureaus, and found that these wrong mental models become significant barriers to taking protective measures [98].

Our study builds on the lessons learned from the studies mentioned above but focuses on the emerging topic of loot boxes. Loot boxes have caused significant financial losses and addictions [8, 28, 50, 93], so it is important to understand game players' folk models of how loot box mechanisms work (RQ 1), investigate why they think this way (RQ 2), and gain deeper insights into their preferences and expectations (RQ 3). We aim to offer advice to game developers on how to better meet users' needs for transparency in loot box design.

3.3 Psychology for Money-related Activities (Gambling and In-game Purchases)

Current literature has suggested significant psychological similarities between loot boxes and gambling [15, 16, 22, 36, 62, 96, 97]. For instance, superstitions, which are cause-and-effect misconceptions associated with gambling behavior [12, 23, 47], are incorporated into loot box design. *Overwatch* [G1] creates anticipation by emitting a glow from a loot box's cracks before players open it. This design misleads players into superstitions of attributing the quality of drops to random variations in the animations [62]. Reflecting on behaviors, players at higher risk of problem gambling tend to spend more on loot box purchases, particularly as their income increases [34].

Existing research has extensively studied how players experience and make sense of various in-game microtransactions [25, 35, 42, 64, 69, 75, 76, 86]. Wohn's analysis of players' purchase log data revealed that virtual item exchanges and the number of social connections increase spending behaviors, with high spenders favoring cosmetic purchases and low spenders buying only essential items [86]. Additionally, researchers have examined some players' unwillingness to spend money [75, 76, 95]. These findings align well with Fogg's theory [26], indicating that a user's purchase behavior occurs only when three elements converge simultaneously: motivation (e.g., limited-time offers), ability (e.g., income), and an external prompt (e.g., promotion events) [26].

Players' attitudes toward in-game purchases also vary. Gibson et al. noted that some players feel obligated to continue playing after making purchases, while others feel regretful or cheated [35]. Nielsen observed players' frustration with microtransactions, which distort the nature of gameplay by prioritizing spending over player experience or skills [64]. Similarly, Petrovskaya et al. highlighted that, in the context of monetization-driven design, users significantly desire fairness, transparency, and an undegraded user experience [69].

Moreover, in an unpredictable game environment, a player's perception of uncertainty can heavily influence their decision-making [27, 53]. This means that the uncertainty surrounding loot boxes may lead to players' inaccurate perceptions. Consequently, our study focuses on understanding how users comprehend the mechanisms behind the loot boxes they have encountered.

4 Method

We conducted the study in two stages. First, we collected 80 online discussion posts about loot boxes, and then created a taxonomy of folk models. Second, we interviewed 24 video game players to validate these folk models, investigate why they developed these models, and explore the transparency they want in future loot box designs.

4.1 Online Discussion Analysis

Data Collection. We started from *Genshin Impact* [G6] and *Honkai: Star Rail* [G7], two popular games [61] with well-known loot box mechanics. We found that a few expert players have created popular videos to explain how loot boxes work in different games, and the comment sections often become hubs for players to share and discuss their experiences of interacting with loot boxes. We then selected popular videos on loot box strategies in these games, each with over 1,000 comments and over 400,000 views on Bilibili [7], a video-sharing platform with substantial content within the gaming community.

In the comment sections of these videos, we reviewed discussion posts where players describe how they interact with loot boxes. To uncover players' folk models about loot box mechanisms, we focused on posts where commenters express their subjective perceptions about loot boxes, particularly those not officially confirmed in the game companies' disclosures. To ensure each post in our collection was also recognized by other players, we only included posts that received more than five ‘likes.’ After observing saturation with similar posts, we ended data collection at the tenth video we selected. This led to a final selection of 80 posts.

Coding Process. Two authors performed a content analysis [52] through an open coding process on the 80 posts. First, we compiled all the data into a document and collaboratively coded 10 posts to create an initial code book of folk models in loot boxes.

Next, the two coders independently coded all posts with the code book. If we encountered new folk models which are not covered by the existing code book, we added new codes accordingly. Once finished, the two coders reached out to the producer of a loot box strategy video we selected, to discuss and refine the codes. For instance, codes *“Some IDs are always lucky”* and *“The random seeds of rates are linked to the user’s ID”* were merged into a single code named *“Lucky IDs.”* This refinement resulted in an updated code book containing 15 unique codes. Using the revised code book, the two coders re-coded all posts again and achieved a final inter-coder agreement [83] of 85.3%.

Then, the coders wrote the 15 codes on post-it notes and used them to create an affinity diagram, grouping these codes into four high-level categories: player discrimination, context-based, activity-based, and longitudinal folk models. These 15 codes correspond to the taxonomy of 15 folk models shown in Table 2. Finally, we reviewed the associated posts to ensure their coherence with each high-level category. Based on this review, we adjusted any codes (folk models) that were inappropriately grouped, as well as the affinity diagram itself.

4.2 Semi-structured Interviews

We developed a taxonomy of 15 folk models in loot boxes by analyzing the online discussions around two popular games. However, it remains unclear whether these models also occur in more games. Furthermore, the posts did not clarify why users developed these folk models (RQ 2) and their expectations regarding the transparency of loot boxes (RQ 3). We conducted IRB-approved, semi-structured interviews with 24 game players to address these questions.

4.2.1 Protocol. Our interviews included following parts:

Gaming Status Questions. We began our interviews with questions about participants’ demographics such as gender, location, and occupation. Following that, we delved into their gaming habits, asking about their most frequently played games featuring loot boxes, the devices they used for each game (e.g., Mobile, PC, PlayStation, etc.), their weekly play duration per game, financial expenditure on each game, and whether they had opened loot boxes in the games they mentioned.

Loot Box Tricks Nomination. To avoid priming, we omitted the specialized term ‘folk model,’ when conducting interviews. Instead, we asked participants to nominate ‘tricks’ that they were aware of for improving their loot box outcomes. We used the term ‘trick’ because players commonly use it to share their experiences in forums. Previous research has also employed this term [31, 43, 55] in soliciting users’ special strategies. One concern is that ‘trick’ may have a potentially negative connotation. We found that players use this term to describe a variety of game experiences, both positive and negative [1–3, 6].

For each ‘trick,’ we asked following questions:

(1) How did you know this trick? How does it work?
(2) Were your in-game behaviors influenced by this trick? Why?
(3) Did game companies officially disclose relevant information about this trick?

Loot Box Scenarios Review. We crafted scenario descriptions based on the 15 folk models identified by analyzing online discussions. We showed each participant the scenarios in a random order, excluding scenarios for folk models they had previously nominated. For instance, we framed the scenario of *Lucky Boomerang Players* as follows: *"You were actively playing a game but paused for a long period, spanning several days or months. Now that you've returned, you are luckier than others in winning loot box lotteries."* We then asked participants whether they had experienced each scenario in their loot box engagement that game companies had not confirmed in their disclosures. If participants agreed with the scenario, we asked them how they learned about it, how it worked, whether their in-game behaviors were influenced by it, and why. Since participants often spent different amounts of time on scenarios, they reviewed 3-10 scenarios in one interview session. The scenarios were randomly selected to ensure a wide coverage.

Loot Box Transparency Feedback. To understand participants' desired transparency, we asked them to describe if they wanted the game developers to disclose any additional information about loot boxes.

4.2.2 Pilot Studies. We carried out preliminary studies with the initial four participants, following the procedure of 'Gaming Status Questions,' 'Loot Box Tricks Nomination,' and 'Loot Box Transparency Feedback' detailed in Section 4.2.1. Initially, in the 'Loot Box Scenarios Review' process, we only provided the names of each folk model for their review, without any explanations. This method resulted in confusion, as all participants sought further clarification. To remedy this, we created detailed scenarios for each model to improve comprehension. This adjustment facilitated a better understanding of our questions among later participants.

4.2.3 Interview Analysis. With the participants' consent, we recorded all interviews and subsequently transcribed them. Following this, the two lead authors performed a thematic analysis [14] on the transcribed data to discern patterns in the participants' responses. Our initial step involved repeatedly reading through the data to fully engage with its content. We then coded the transcriptions line by line to summarize and better understand the relevance of each line. Next, we organized the folk models mentioned during the 'Loot Box Tricks Nomination' and compared these to our previously identified taxonomy of 15 models from online discussions. Interestingly, the interviews did not reveal any new types of folk models, indicating that our taxonomy had reached saturation. This taxonomy of folk models will be reported in Table 2.

Following that, we delved into understanding why users developed each folk model and their expectations regarding the transparency of loot boxes. We conducted a more focused round of coding, grouping the initial codes into broader categories and themes. These final codes were then organized to create an affinity diagram, representing a hierarchical system of information across all the interviews. This process leads to the basis of our findings in Section 5.2 and Section 5.3. Additionally, we discovered that the impact of folk models on user behaviors varies. This will be discussed at the end of Section 5.1 and further explored in Section 6.1.

4.3 Participant Recruitment and Information

We recruited 24 participants through a snowball sampling strategy [13]. The authors initially reached out to potential participants from professional and alumni networks, as well as from an internet café. Subsequently, the authors contacted eligible references from the initial participant pool. To determine the eligibility of potential participants, we first provided a definition of loot boxes: "digital items that players can purchase or acquire, offering a random mix of in-game assets like weapons, cosmetic skins, or other rewards." This definition helped potential participants recall whether they have experiences interacting with loot boxes in the video games they have played. While recruiting participants, we sampled for diversity in the number of games containing loot boxes that participants have played, their expertise (i.e., the number of years they have played each game), their spending on these games, and their weekly playtime. Our final group comprised 13 participants from the US, 10 from China, and one from Germany. Among them, 3 participants

Table 1. Participants' information (P1-24, with P1-P4 designated as pilot study participants): their location, the number of games with loot boxes they have played, their average experience playing each game (in years), the average amount of money they have spent on each game (in US dollars, with conversions from other currencies made using the exchange rate applicable at the time of the interview), and their average weekly playtime for each game (in hours).

Participant	Location	#Games	Avg Experience	Avg Money Spending	Avg Weekly Playtime
P1	China	2	5.5	122.7	9.2
P2	China	3	4.0	46.7	4.8
P3	China	1	3.3	17.5	2.0
P4	Germany	2	2.5	490.0	30.0
P5	US	2	3.0	140.0	10.0
P6	US	2	3.0	200.0	6.5
P7	China	2	5.5	105.0	3.5
P8	China	4	3.2	142.5	14.8
P9	US	2	4.8	125.0	9.8
P10	China	2	0.2	17.5	7.3
P11	US	3	5.0	33.3	5.8
P12	China	1	0.5	91.0	4.5
P13	US	5	2.8	88.7	10.3
P14	US	2	2.0	35.0	12.5
P15	US	2	2.1	140.0	2.3
P16	China	4	1.3	126.0	13.3
P17	US	3	5.1	268.3	17.7
P18	US	3	0.1	70.0	6.3
P19	China	2	7.6	42.0	4.5
P20	China	4	1.0	16.3	8.3
P21	US	1	0.5	30.0	5.5
P22	US	4	3.8	3405.0	9.0
P23	US	3	2.8	6.7	18.0
P24	US	2	2.3	1750.0	5.5

(12.5%) identified as female, and the remaining identified as male. The majority were students (13 graduate and 10 undergraduate). The average interview duration was 59.2 minutes. Each participant received $15 as compensation, in the form of an online shopping gift card.

Participants exhibited diverse backgrounds in playing games featuring loot boxes. They cited 30 unique games in total, with *Genshin Impact* [G6] and *Honkai: Star Rails* [G7] each at 13.21% of their responses, *FIFA* [G2] at 9.43%, and *Honor of Kings* [G12] at 7.55%. 11 participants reported playing two loot box games, five played three, four played four, three played only one, and one played five. On average, these participants possess 3 years of experience, invest $312.9, and dedicate 9.2 hours weekly to each loot box game. Table 1 enumerates a breakdown of participants' information.

4.4 Research Ethics

Our study received approval from our institution's Institutional Review Board (IRB). Before starting the interviews, we asked participants to review and sign an informed consent form. We instructed participants to focus on their experiences and views and not reveal sensitive information throughout the interviews. All collected data was stored in a secure location only accessible to the research team and was anonymized during analysis and reporting results. We only collected participants' emails for sending US$15 compensation in the form of shopping gift cards. We deleted these emails upon the completion of the study.

5 Results

5.1 RQ 1: What kinds of folk models do users have towards loot box mechanisms?

We identified 15 folk models and clustered them into four categories: player discrimination, context-based, activity-based, and longitudinal models. Table 2 enumerates the taxonomy of these folk models, each accompanied by a representative example from either online posts we collected or from the interviews conducted.

Player Discrimination Models includes five folk models where gamers believe that game companies segment players into different groups, each with distinct odds. The most popular model in this category is *Lucky IDs*, where gamers believe that certain accounts naturally have better luck. For example, in an online post we collected, someone questioned whether a friend's account, which obtained two rare five-star items in 21 pulls, had been granted 'extra luck' in *Genshin Impact* [G6]. Conversely, this user ended up with only one unwanted five-star item after 77 attempts.

The second most popular folk model is *Lucky Casual Players*, which refers to players who invest less time and money in the game yet experience significant luck. For instance, one interviewee, P5, obtained her best two rewards when she had not made any microtransactions in *Ashes of the Kingdom* [G11].

Another prevalent model is *Beginner's Luck*, where players believe that game companies tweak the odds in favor of newcomers to keep them engaged. In *Yu-Gi-Oh! Master Duel* [G4], P7 obtained his best item on the day he registered for the game.

Additionally, players have observed that returning players, who had not logged into the game for an extended period, tend to have better luck with loot boxes upon their return (*Lucky Boomerang Players*). Moreover, those who purchase combinations of several loot box pulls often receive better rewards compared to those who only buy single pulls (*Lucky Combo Buyers*, as shown in Fig. 1).

Context-based Models comprises four folk models suggesting that loot box drop probabilities might be swayed by certain tangible factors or in-game contexts. The most popular one is *Lucky Moments*, which suggests that particular times or intervals may provide enhanced loot box drops. For instance, in an online post, a *Honkai: Star Rail* player pulled five golden cards at 12 am.

One of the other two widely shared folk models is *Lucky Locations*. Illustrated in Fig. 2 and Fig. 3, specific in-game spots would lead to superior loot rewards. According to *Demand-based Discrimination*, loot box rewards adjust based on user demand, making scarce items more difficult to obtain. In another post, the *Honkai: Star Rail* [G7] user expressed frustration over loot boxes frequently providing items they already possess, leading them to believe that *Demand-based Discrimination* certainly exists.

Additionally, the *Lucky Devices/Servers* model within this category speculates that various devices, operating systems, or platforms (e.g., Android vs. iOS) may influence the level of luck experienced in loot boxes.

Activity-based Models suggest that game developers might factor in players' unrelated actions to determine the loot outcomes. The *Companies Will Listen to My Wishes* model argues that a player's desire for a specific item could be detected through in-game chats, browsing history from stores, or trends in official forums (Fig. 4). For instance, in *Arknights* [G3], P19 observed that the outcome

Table 2. We identified 15 folk models of video game loot boxes and clustered them into four categories. Each folk model example is from online posts or interviews, with the corresponding game noted in square brackets. The last two columns show the frequency with which each folk model occurs in online posts and interview studies.

Player Discrimination Models	Examples *[Game Being Discussed]*	#Posts	#Studies
Beginners' Luck	"Here's what happened to my friends: Three new players got a gold card after 30 pulls, while other four regular players who have been playing since the last version of this game, needed 80 pulls. That's definitely discrimination." *[Honkai: Star Rail]*	6	12
Lucky Casual Players	"I pulled my best two rewards when I was a casual player who hadn't made any microtransactions in this game." *[Ashes of the Kingdom]*	18	6
Lucky Boomerang Players	"Over the past two years, I've taken breaks from the game and returned every few months. I've been pleasantly surprised by the loot box drops each time I reinstall it. Remarkably, I got a rare character with just five pulls, whereas it usually takes me 100 to 200 pulls." *[Honor of Kings]*	6	5
Lucky Combo Buyers	"The probability per pull is lower for single-pull. In other words, a ten-pull combo drops better items than 10 separate pulls or two sets of five-pull." *[Honor of Kings]*	2	11
Lucky IDs	"I've created 11 accounts, with some getting golden cards within 30 draws and others not pulling anything until they reach the game's guaranteed threshold." *[Honkai: Star Rail]*	24	9
Context-based Models	Examples *[Game Being Discussed]*	#Posts	#Studies
Lucky Devices/Servers	"Drop rates vary between accounts created on iOS, PC, Android, and others." *[Genshin Impact]*	1	2
Lucky Moments	"12 a.m. is magical; last month, I obtained five gold cards at that time." *[Honkai: Star Rail]*	5	11
Lucky Locations	"This game is set in the Three Kingdoms era of China, and visiting historically significant locations related to a character can improve your chances of obtaining their card. For example, if you aim to draw General Ma Chao's card, visiting Liangzhou, his domain, could increase your likelihood of success." *[Infinite Borders]*	1	11
Demand-based Discrimination	"I feel the storage inspection is 99% a reality. The box always 'randomly' picks out a character I already have, which is actually the worst outcome for me." *[Honkai: Star Rail]*	6	6
Activity-based Models	Examples *[Game Being Discussed]*	#Posts	#Studies
Companies Will Listen to My Wishes	"The outcome contradicts my intentions. In a pool of three special characters (A, B, C), I was aiming for A. Strangely, I deliberately checked profiles of B and C multiple times, and then drew A in one go." *[Arknights]*	8	2
Supernatural Influences	"The Chinese Yin-Yang theory guides ideal card pulls: your character's gestures, timing, orientation, and whether there's a river nearby. I learned this from a YouTuber, and this method consistently yields good results." *[Genshin Impact]*	2	9
Longitudinal Models	Examples *[Game Being Discussed]*	#Posts	#Studies
Deterministic Sequences	"When you click the lottery button, the system has already determined your prize. The spinning wheel in the animation may slow down near the jackpot but will eventually land on the lowest prize." *[Honor of Kings]*	15	9
Scratch Lotteries	"When the prize pool is freshly opened, your chances of winning what you want are higher due to simultaneous draws by many users, which act as 'padding' before reaching the jackpot threshold." *[Onmyoji]*	6	11
Pity Timers	"I believe I'll get what I want once my pities reach a certain threshold. So, even if I'm unlucky initially, I keep making pulls." *[Genshin Impact]*	16	10
Hot/Cold Hands	"I got Bronya, two Gepards, and a 5-star Light Cone in the first 90 pulls but nothing in the following 100 pulls. Looks like my luck has been used up." *[Honkai: Star Rail]*	14	12

Fig. 1. Players believe that those who purchase ten-pull combos would be luckier than those who only repeatedly choose one-pull. The interface demonstrates two options for loot box pulling: 'Wish × 1' (i.e., one-pull) and 'Wish × 10' (i.e., ten-pull combo). The lower part of the image shows the dropped rewards in a ten-pull combo, including two 5-star characters—a favorable outcome *[Genshin Impact [G6]]*.

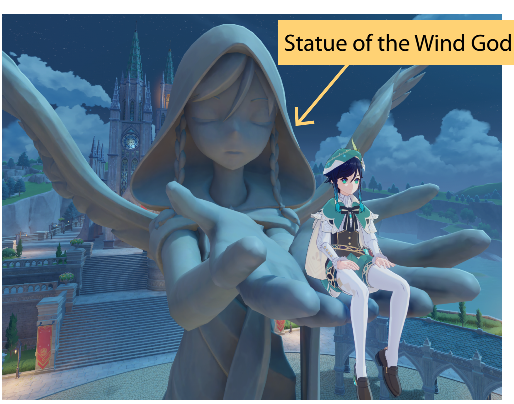

Fig. 2. Players pull loot boxes at the Statue of the Wind God, with the belief that the drop rate of Venti, a Wind God character, would be increased *[Genshin Impact [G6]]*.

Fig. 3. Players believe that in Liangzhou, where Ma Chao served as Governor, it is more likely to obtain this character from loot boxes *[Infinite Borders [G8]]*.

contradicted his 'intentions' revealed through in-game behaviors. In a loot box featuring three special characters (A, B, C), what he wanted was A. Despite this, he intentionally clicked on the profiles of B and C several times in the store, and then successfully obtained A in only one attempt.

Moreover, the *Supernatural Influences* model suggests that seemingly unrelated factors beyond the scope of loot boxes and even the game itself can influence the loot box outcomes as well. In *Genshin Impact* [G6], P16 applied the Chinese Yin-Yang theory to guide his card pulls. For example,

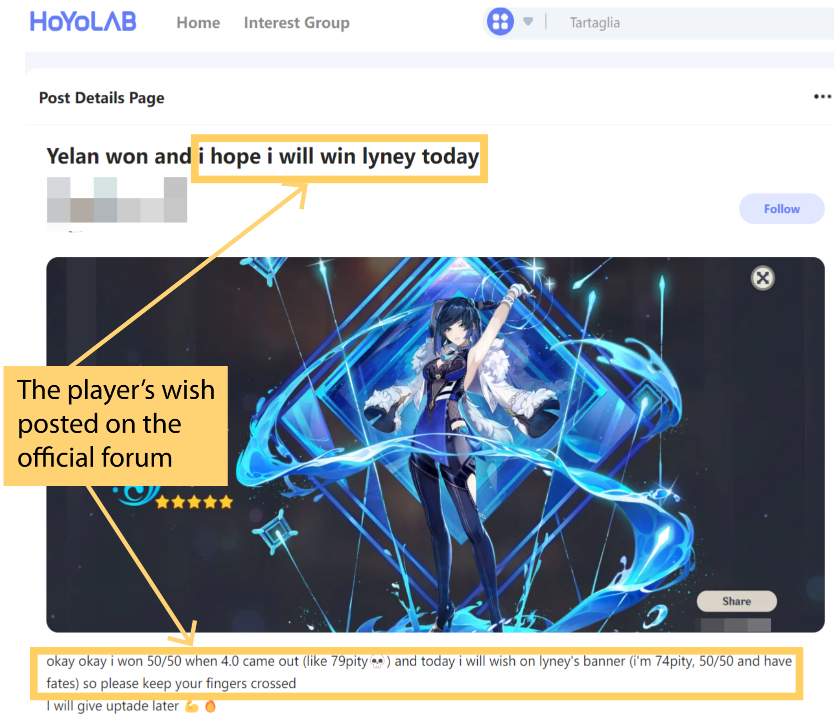

Fig. 4. A player posted on the official forum, hoping for an increased drop rate for the intended character *[Genshin Impact [G6]]*.

the character's gestures, orientation, and even the presence of a nearby river were believed to influence the outcome.

Longitudinal Models suggest how recent loot box openings are interconnected, revealing patterns over extended lottery sequences. The two most popular folk models are *Pity Timers* and *Hot/Cold Hands*. *Pity Timers* indicates that the game keeps tabs on each pity, ensuring a player receives the desired reward after a string of unfortunate loot box openings. In this context, a "desired item" is not just an arbitrary item within a rare category (such as a 4-star or 5-star item) but a specific item or subset of items which the player wants. In one of the online posts we collected, a player believed that reaching a certain threshold of pity would result in obtaining the desired item, motivating them to continue pulling boxes despite initial unlucky outcomes. *Hot/Cold Hands* suggests that each player may experience unique phases where their luck consistently swings between exceptionally good and bad, as illustrated in Fig. 5.

Another popular folk model in this category is *Deterministic Sequences* model, which suggests that reward sequences are predetermined when a lottery event is initiated. P3, an *Honor of Kings* [G12] player, mentioned that the outcome is predetermined by the system as soon as users click the lottery button. Although the spinning wheel animation may slow down near the jackpot, it will ultimately land on the lowest prize.

Additionally, the *Scratch Lotteries* model draws a parallel to scratch lotteries, where loot box rewards are distributed based on a fixed number of individuals, and the quantity of each reward type is limited and shared within the game world or specific loot boxes. For instance, P19 confirmed

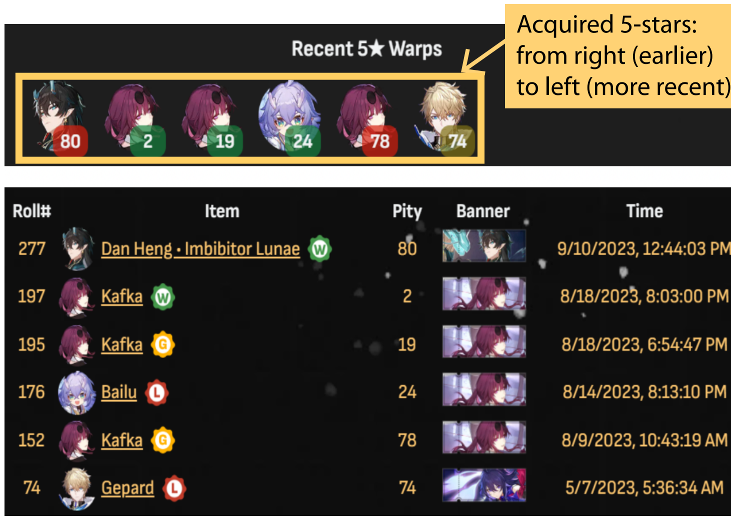

Fig. 5. In a player's loot box history, 74 initial pulls followed by 78 additional pulls secured the first two 5-star characters (cold hand). This was followed by a streak of three consecutive 5-stars with minimal attempts (hot hand), and then 80 additional pulls led to another 5-star (cold hand). In the upper part of the image, the acquired 5-star characters are displayed from right (earlier) to left (more recent), with Kafka appearing three times. The lower section illustrates cumulative pulls, 5-stars obtained, pities since the last 5-star, banner details, and drop times *[Honkai: Star Rail [G7]]*.

this folk model in the game *Onmyoji* [G9], where limited edition items could even be restored when the game server refreshes daily or weekly.

The impacts of folk models. All 24 participants recognized some folk models they have during the interview. However, we found that the influence of each folk model on their in-game behavior differed. Some participants aligned their behaviors to conform to the suggestions of the folk models. For instance, recognizing the advantages of *Lucky Boomerang Players*, P2 has *"taken breaks from the game and returned every few months"* over the past two years.

On the other hand, some participants demonstrated strong independence from these folk models, despite believing in them. For instance, P13 shared his perspective on *Lucky IDs*: *"My friends have opened new accounts and noticed they tend to be luckier with loot boxes than the older ones. However, I will not follow them; having one account is sufficient for me."*

Regarding the *Scratch Lotteries* model, P7 observed that in-game public announcements of someone winning a limited edition item encouraged many of his friends to gamble, often successfully. Yet, he opted out, stated, *"It just gives people a sense of missing out and leads them to spend more than anticipated."*

We will discuss why belief in folk models results in varying impacts on user behavior in Section 6.1.

5.2 RQ 2: What are the causes of these folk models?

By exploring why participants believe in the effectiveness of each folk model, we identified three underlying causes of folk models, as summarized in Table 3.

Assumptions based on Business Models. The belief that loot boxes are designed to enhance gaming companies' profits leads to eight folk models. For *Beginners' Luck*, nearly half of the

Table 3. Players develop folk models of loot boxes due to three main causes. The number of interviewees who attributed the folk model to each cause is indicated in brackets.

Cause	**Description**	**Related Folk Models** *(Amount of users developing the model due to this cause)*
Assumptions based on Business Models	The assumption that companies manipulate loot box odds to boost revenue.	Beginners' Luck *(10)*, Lucky Casual Players *(3)*, Lucky Boomerang Players *(5)*, Lucky IDs *(2)*, Lucky Devices/Servers *(1)*, Lucky Moments *(3)*, Demand-based Discrimination *(2)*, Companies Will Listen to My Wishes *(2)*
Empirical Experiences	Experiences from other games and insights from friends or online forums.	Lucky Combo Buyers *(3)*, Lucky Moments *(9)*, Deterministic Sequences *(4)*, Scratch Lotteries *(2)*, Pity Timers *(3)*, Hot/Cold Hands *(4)*
Superstitious Beliefs	Amusement-driven superstitions without logical explanation.	Lucky IDs *(1)*, Companies Will Listen to My Wishes *(1)*, Supernatural Influences *(5)*, Lucky Locations *(3)*, Lucky Moments *(2)*, Hot/Cold Hands *(1)*

interviewees (P1, P6, P7, P9-11, P15, P17-19) argued that companies aim to retain new players this way. P7 asserts: *"Receiving free pulls and obtaining favorable outcomes upon registering for a game significantly heightens my interest and motivation to investigate further."*

Similarly, *Lucky Boomerang Players* (P1-3, P19) and *Lucky Casual Players* (P6, P23, P24) are believed to enhance the gaming experiences of leisure players to keep them engaged. This also applies to *Lucky Moments*, with players believing that games intentionally set up leisure slots (e.g., 12 a.m. or p.m.) as magic moments to divert players to these times, easing the server's pressure during peak hours and decreasing the cost of technical maintenance (P2, P15, P18). Furthermore, P1 and P7 argue that games assign *Lucky IDs* to streamers to better advertise the game and attract players through live streams.

Empirical Experiences. Six models are adopted based on users' experiences from other games, as well as insights from friends or online forums. For instance, the observed benefits of ten consecutive draws in other games have led to the emergence of the *Lucky Combo Buyers* folk model, even in cases where it is not explicitly stated in the current game (P2, P8, P15). P2 said, *"In my previous games, I noticed that a ten-pull combo often yields better results than ten single pulls. Therefore, I choose to follow this approach in current games as well."*.

Similarly, in games with a fixed quantity of in-game items, P13 and P15 adopt models like *Scratch Lotteries*, operating under the assumption that if a specific rare item hasn't been won by a certain number of players, the next person to open a loot box is sure to obtain it. This belief is extended even to games without item quantity limits. For *Pity Timers*, P1, P4, and P16, influenced by social platforms, believe that continually drawing lower-level items increases the odds of obtaining higher-level items. This prompts them to test their luck in cost-free areas before attempting the actual draw. Moreover, nine participants (P7, P8, P10, P11, P13, P15, P16, P18, P19) have embraced *Lucky Moments*, influenced by their friends' experiences, and believe that drop rates fluctuate over time.

Superstitious Beliefs. Six models are associated with superstitious beliefs among players, leading to curious behaviors that lack a logical explanation. *Supernatural Influences* is the most representative of these; for instance, the belief that *"changing the person performing draws can yield* *different results"* prompted P5 to seek out "lucky" individuals for this task. There's also a practice of playing celebratory music like 'Good Luck Comes' when opening loot boxes. However, it's often viewed more as a ritual or amusement than a genuine belief in its effectiveness, as indicated by participants P9, P13, and P16. These superstitious actions add an intriguing layer to players' gaming experiences.

5.3 RQ 3: What types of transparency do players want?

At the end of our interviews, we asked participants to describe the additional information about loot boxes that game developers should offer. Through this analysis, we aim to provide advice to game developers on how to better meet users' needs for transparency in loot box design.

Fine-grained Transparency. Companies sometimes offer a combined likelihood for groups of items, without revealing the chance for each specific item [4, 9, 59]. For instance, on their official webpage 'Pack Probability in FIFA Ultimate Team' [9], *FIFA* [G2] announced, "The percentages that you see are the minimum probability of getting one or more players in the ratings range and item type (i.e., overall category) listed." Fig. 6 illustrates the probability breakdown for the 'Premium Gold Pack'—a featured 'loot box' in this game—where the probability disclosure is limited to the category level, omitting the probability of obtaining each specific item.

Yet, players often desire just one or two items within a group. Nine participants (P6, P7, P9, P10, P12, and P18-P21), representing 37.5% of the total 24, advocated for a detailed probability breakdown, calling for the odds of each item to be specified individually. For instance, P7 stated, *"Game companies should disclose more detailed probabilities if they really want us know something. Don't just tell me the categories."* Similarly, P19 commented, *"I need clear probabilities for each item, not just for a six-star category."*

Such transparency would allow players to better gauge their spending based on the true odds of acquiring their sought-after item. The prevailing method of presenting an aggregated probability can mislead players, causing them to spend money without a clear understanding of the actual costs.

Temporal Transparency. Many game developers capitalize on players' fear of missing out to boost in-game transactions [5, 57]. Four participants (P1, P16, P18, and P20) highlighted the need for temporal transparency. They noted that the chances of acquiring items often fluctuate, especially during the beginning and close of an in-game season. For instance, P1 described the 'Perpetual Motion' phenomenon in *FIFA* [G2], and expressed a wish for clear official teasers: *"Rates significantly increase before each game version expires, allowing players to trade lower-tier cards for top-tier ones. Yet, the lack of notifications about this is unfair to uninformed users. Official notifications and even teaser videos could be considered."*

If loot box mechanics are tied to seasonal variations, participants contend that companies should clearly disclose their upcoming schedules, like when players might have another opportunity to obtain their desired item from the loot box. P16 suggested, *"Companies should provide update timelines and content previews, such as new characters in upcoming loot boxes or skill animations, which could facilitate better user planning."*

Wider Transparency. As gaming companies start to disclose the odds for paid loot boxes, the probabilities for boxes earned through in-game tasks often remain hidden. For example, in *Pokémon Go* [G10], players can receive loot boxes for completing a 7-day streak of logins. Participant P18 expressed a desire for more transparency about these free loot boxes, saying: *"Please consider free-to-play users and reveal the odds of obtaining a specific item or box after weekly challenges. It would be helpful to know if I can get the item I want by completing my weekly tasks."*

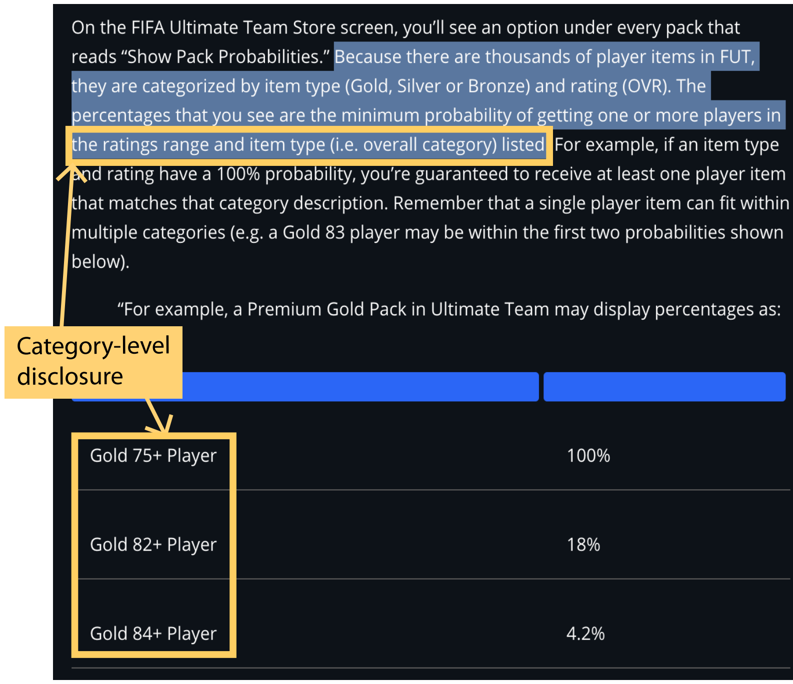

Fig. 6. The probability breakdown for the 'Premium Gold Pack'—a featured 'loot box' in *FIFA* [G2]. The disclosure is limited to the category level, omitting the probability of each specific item.

6 Discussion

6.1 Impacts of Folk Models on User Behaviors

Our study found that the impact of folk models on user behaviors differs. Similar to player experience with in-game purchases [25, 35, 42, 64, 69, 75, 75, 76, 76, 86, 95] we discussed in Section 2, this variation can potentially be understood with the Fogg Behavior Model [26], which posits that for a behavior to manifest, *Motivation*, *Ability*, and a *Prompt* (i.e, a trigger telling people to perform the behavior) must align simultaneously. Below, we discuss these factors in the context of loot boxes.

Practicing folk models can be costly. Additional time and financial investment constrains the user's *Ability* [26] to practice folk models. For instance, P4 avoided the *Lucky Devices/Servers* model, believing that creating a new account on a 'lucky' server for better drop rates wasn't worth the extra time and money. This also applies to P24's attitude towards *Lucky IDs*. P1 also highlighted *Supernatural Influences* in *FIFA* [G2]: *"Spending money on card packs yields better rewards than using points earned through challenges, but not everyone can afford it."*

The scope of folk models may be limited. A player's *Motivation* [26] fluctuates when their status does not align with the group to which a folk model applies. P1 and P4 observed that some *Lucky IDs* are reserved for streamers or professional players, having no impact on regular players like themselves. Furthermore, the time frame of folk models is also significant. P7 noted that *Beginners' Luck* provides only temporary encouragement to new players, with its influence fading over time, a sentiment echoed by P14 regarding *Lucky Boomerang Players*.

Players tend to adopt models that complement their habits and routines. If the *Prompt* [26] suggested by the folk model requires minimal extra physical and mental effort, as well as low monetary and time investments compared to players' current gaming styles, their *Ability* [26] to take action would be greater. P2 and P18 often purchase ten-pull combos just to accelerate their in-game progress, even without bonuses, aligning with the *Lucky Combo Buyers* model. P5 enjoys pulling loot boxes at *Lucky Locations*, finding it enhances the gaming experience without extra investment. Meanwhile, P5 follows *Supernatural Influences*, reasoning: *"There's nothing to lose with my current poor luck, so why not try one or two attempts that might work?"* Additionally, *Deterministic Sequences* motivates P23 to plan future box purchases better. Due to his daytime work routine, P15 only tries *Lucky Moments* at midnight.

6.2 Connecting Our Findings to Regulations

Our findings in Section 5.3 align with some early regulation policies on loot box disclosures that focus on disclosure granularity [19, 20, 78], positioning [20, 60], and reliability [18]. Further, our results also lead to a few concrete suggestions for future policies.

Alignment between our findings and regulations. Item-specific disclosure requirements in Taiwan [19, 20] and South Korea [78] mandate companies to disclose the probability of obtaining each specific item. This aligns well with our participants' desire for *Fine-grained Transparency*. The regulation from the UK [18] also aligns with *Temporal Transparency*, requiring game companies not to mislead players by implying that an item is 'only available' for a specific time if it will later be made available again or more generally.

However, there exist no notable regulations that address players' expectations for *Wider Transparency*. Below we provide guidance for policymakers to consider users' perspectives into future regulations.

Classification & warning label. Australia (2022), the European Union (2018), and the United States (2020) have all opted for a classification system with warning labels, respectively with the ACB, PEGI, and ESRB rating systems [24, 66, 68]. The effectiveness of this policy has been brought into question by researchers [17, 33]. For instance, *Genshin Impact* [G6], correctly labeled by the PEGI system, even failed to be labeled accurately by the ESRB system [30]. To avoid ambiguity in labeling, policymakers could enhance the granularity of game labels by incorporating the desired transparency identified in our findings. For instance, they could specify whether the game discloses loot box probabilities in item-level.

Restriction on direct purchases. PRC (2016) and Belgium (2018) have ruled that any loot boxes that are purchasable with real currencies would be considered gambling, and have to comply with stricter regulations [11, 29]. Blizzard Entertainment, the creator of *Overwatch* [G1], have found ways around this restriction. Blizzard announced the ability to purchase in-game currency and bonus gift loot boxes will be included [29]. Beyond this, regulations should also cover free loot boxes that include rewards with real-money values to ensure these boxes are also subject to strict disclosure, similar to those purchased with real money. This approach could help fulfill players' desire for *Wider Transparency*.

Restriction on items transfer between players and real-life currency conversion. In 2018, the Netherlands ruled that loot boxes that can be evaluated with real-world currencies shall legally be considered gambling [81]. This decision was heavily opposed by Electronic Arts (EA), whose *FIFA* [G2] sports games fit this description. After appealing to the highest administrative court in the Netherlands, the court ruled in EA's favor in March 2023 [70]. This has set a precedent for other similar loot box mechanics to be considered legal in the Netherlands. Future regulations on disclosure could be enhanced and made fine-grained and adaptive to various loot boxes to achieve effective disclosure regulation.

6.3 Beyond Transparency

While focusing on understanding the transparency requirement for loot boxes, we also observed two other requirements that the participants desired, which could inform future loot box design.

Fair gaming. P5 and P16 understood that disclosing specific drop rates might be challenging without reservation; however, they emphasized their desire for fairness. P16 noted, *"Even if the drop rate is low and hard to disclose, it should be fair among users and not be influenced by other factors [they don't know]. It's important to maintain a fair game environment."*

Understandable mechanism. A common belief among our interviewees is that games, such as *Genshin Impact* [G6], employ a confluence of various loot box mechanisms—namely, *Pity Timer*, *Lucky Moments*, and *Scratch Lotteries*—leading to a system that they perceive as overly intricate and potentially unfair. This complexity poses a particular challenge for casual players, who may find it difficult to understand these mechanisms and accurately estimate the true cost of obtaining desired items. The complexity is such that one participant in our study, who runs a professional loot box consultancy, offers services to assist players in navigating these systems for optimal outcomes.

Moreover, participants P5, P13, P15, and P16 emphasized the need for transparency and equality in these systems. They advocate for a straightforward approach where the probability of acquiring any given item should be consistent and equal for all players, adhering to a principle of independent and identical distribution. This suggestion points towards a desire for a more transparent and equitable loot box system, where chances are not obscured by complex mechanisms and are the same for every player at any given time.

6.4 The Negative Implications of Loot Box Transparency

Conversely, unlike the three kinds of desired transparency, P11 and P24 present a notable argument for the benefits of maintaining limited transparency. P11 suggested that the excitement from loot boxes is integral to the gaming experience and can even form the game's storyline, as observed in *Fate/Grand Order (FGO)* [G5]. Similarly, P24 posited that the risk of losing in a 50/50 chance scenario also enhances the game's appeal. Future work may examine these problems and develop a theory to help game designers balance playability and transparency.

6.5 Limitations and Future Work

We outline our study limitations and directions for future research. First, we did not include a particularly large sample, but we conducted studies in an iterative manner, including an online discussion analysis (N=80) and semi-structured interviews (N=24, including 4 pilot studies). In fact, we did not learn any new folk model types from interviews, suggesting theoretical saturation, for which we are confident our results are valid.

Second, our online data were from a Chinese platform, and 10 of our interviewees were from China. All the Mandarin data were analyzed by native Chinese-speaking researchers, and then translated into English. However, as is common with translations, nuances and cultural contexts may not have been completely captured. Additionally, 13 of the 30 games we studied were from China. For online data collection (Section 4.1), we chose two games with which we had prior experience to ensure the quality of data. This selection may lead to bias. Though our final results saturated, future studies could benefit from incorporating a broader cultural and game selection to examine folk models more comprehensively.

Third, our sample was predominantly male and mainly comprised students, with most participants hailing from either China (10) or the US (13). As Paul [67] emphasizes, further research could benefit from examining loot box experiences across varied demographic backgrounds.

Fourth, this qualitative research focused on exploring player's folk models of game loot boxes comprehensively, rather than evaluating their statistical representation in the broader population. For future work, we plan to conduct an extensive survey to investigate how folk models are correlated with various factors, such as age, occupation, financial and time investment, etc.

Additionally, if game companies consider our findings, they must ensure these insights are applied ethically. Our research provides information on how players appraise loot boxes, and it is crucial to use this knowledge responsibly to avoid exploiting players.

Finally, our online posts and interviews consist solely of self-reported data. To quantify the impact of folk models on user behavior, future studies could consider a large-scale analysis of behavior through log data.

7 Conclusion

Loot box mechanisms are becoming increasingly common in the video game industry. We analyzed 80 online posts and interviewed 24 video game players to investigate their perception on how loot boxes work. We identified fifteen folk models held by players, grouped into four categories: player discrimination models, context-based models, activity-based models, and longitudinal models. We also identified three key causes that contribute to the development of folk models and players' expectations in regard to the transparency of loot boxes. In addition, not every folk model impacts users' behaviors, and current regulations have not fully met users' needs. Future loot box designs and regulations should consider these folk models and user needs.

Acknowledgments

We extend our sincere gratitude to our study participants; their involvement was crucial to the success of this research. We also appreciate the valuable feedback provided by our anonymous reviewers.

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Received February 2024; revised June 2024; accepted July 2024