GAME MANAGEMENT

The Art and Science of Free to Play

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Managing Games
The Art and Science of Free to Play
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Version 1.0 - January 2026

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Cover and book layout: DTPerfect Book Design (dtperfect.com)

Chessboard position on front cover:
FEN: 5r1k/4N1pp/5p2/4N3/3R2K1/4q3/8/8 w - - 0 1

Paperback: 979-8-9941443-0-5
Hardcover: 979-8-9941443-1-2
eBook: 979-8-9941443-2-9

CHAPTER 2

Chasing the Mother Lode: Retention and Active Player Management

SUMMARY

Retention is the first of the three core pillars of product focus and analysis, and it is the clearest indicator that a player is enjoying the experience the game provides. While there are numerous ways to support retention, a game cannot trick a player into staying. Players ultimately stay because they are entertained. Furthermore, it is challenging to convert a player into a payer in a game in which they are not actively engaged, and a significant player base is necessary for the ultimate goal of product revenue.

The number of active players is one of the most consequential factors for a product's long-term success. Therefore, the team spends significant

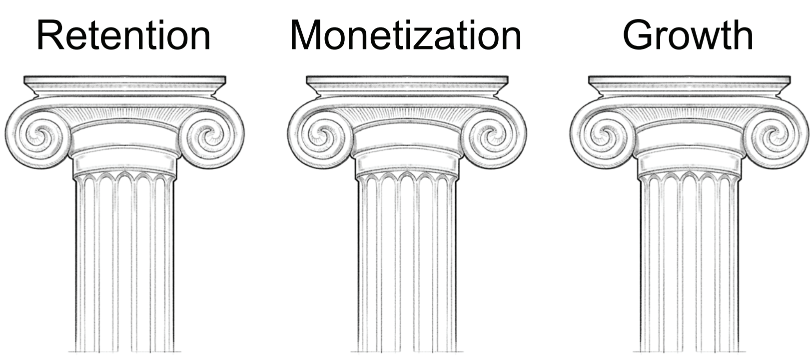

FIGURE 2.1 – Retention, Monetization, and Growth as the Three Primary Pillars of Product Focus and Analysis

effort maintaining and even growing the player base over time. Ultimately, if you cannot retain your players, your game will be less lively, you will soon have no one left to monetize (in a much shorter timeframe than you would like), and any new players you do acquire will leave in short order. Knowing how to analyze and influence retention is essential to managing the active player base.

This chapter begins with a conceptual framework for understanding what factors contribute to a product's active player base size. It then covers the rigorous set of metrics and visualizations that the team must regularly monitor. These metrics help inform player retention strategies and identify new features to enhance retention and engagement. Finally, the chapter describes various methods for creating models to predict the future size of your active player base and performing a sensitivity analysis to identify the specific factors that are most significant for maintaining and growing it.

ACTIVE USER THEORY

Active user theory describes the study and analysis of the fundamental components that influence and comprise the number of people who play the game with some frequency. In essence, it is simply a way to explain where the active player base comes from and what causes it to increase or decrease.

The Reachable Player Onion

The overall population of a game is often diverse, composed of players at many different levels of engagement and depths in the game. We call the players engaging with the game with some frequency the reachable players, and we group them by play frequency. Together, they form the Reachable Player Onion.

The ***Daily Active Users (DAU)*** are the innermost layer and are the number of unique players on a particular day. These players provide the revenue for the day and include the most highly engaged daily players. Thus, maximizing DAU is a significant focus.

The ***Weekly Active Users (WAU)*** form the middle layer and include all the most immediately reachable players. This group contains all the players actively engaging in the core loop, consisting of highly and moderately engaged players. The WAU is the total number of unique players within the past seven days, which is also the deduplicated DAU for each day within those seven days (individual players in each day's DAU are only counted no matter how many days they played during the seven day period). Players

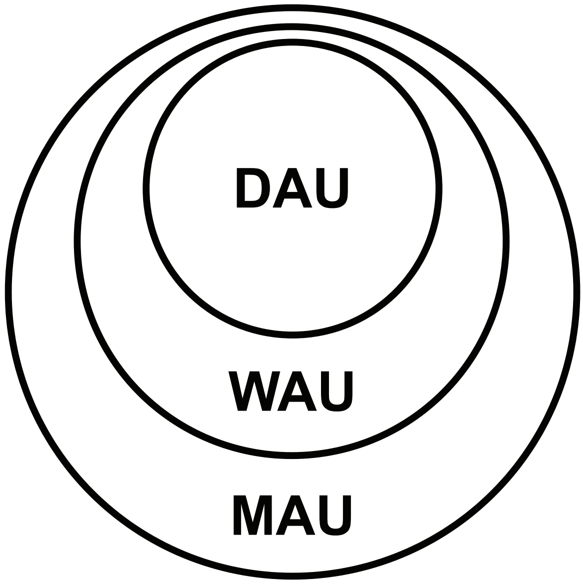

FIGURE 2.2 – The Reachable Player Onion

who have lapsed out of WAU have been absent from the game for seven or more days and are called **lapsed players** or **lapsers**.

The ***Monthly Active Users (MAU)*** form the outermost layer and are all the players your game messaging should still actively target. It includes all the highly and moderately engaged players and the players who play very infrequently or have recently lapsed. The MAU is the number of unique players within the past 30 days. Thus, MAU is a superset containing the deduplicated DAU of each day in those 30 days and the deduplicated WAU of each 7-day timeframe in those 30 days.

Players who have lapsed out of the MAU are considered to have quit the game and are, therefore, referred to as **churned users** or **quitters** because they have been absent for 30 or more days. They are no longer as likely to return as they have already ignored 30 days of messages targeted at reactivating them. However, you should never completely give up on them; just target them differently with lowered expectations.

Relating DAU to WAU: Weekly Engagement

DAU is the lifeblood of day-to-day operations, but its movement is significantly noisier than WAU and MAU due to various contributing factors on a given day. A game's DAU is often cyclical based on the day of the week, with weekends and holidays having a strong impact on expected DAU. On the other hand, the WAU includes the most immediately reachable players (the highly and moderately engaged player base) and is less subject to this cyclical variance, so we often use WAU instead of DAU as the basis for our analysis of the overall growth and decline of the game.

Therefore, we need a way to estimate DAU based on WAU. We do that using a metric called ***weekly engagement***, which is the ratio of daily to weekly players (also known as the DAU/WAU ratio). This ratio represents the percentage of weekly players who are playing on any particular day:

$$weekly\ engagement = \frac{DAU}{WAU}$$

If we rearrange the equation:

$$DAU = weekly\ engagement \cdot WAU$$

We see that one can increase the trajectory of DAU by increasing engagement, which means causing existing players to play more frequently each week, or by growing WAU, which means having more people play the game overall. While there can be some potential in improving weekly engagement if it is below competitor benchmarks, there is often more significant potential in increasing WAU. Nevertheless, games with a low weekly engagement metric (less than 50%) should prioritize addressing this issue, as it indicates that other engagement and retention indicators are likely also suffering.

Monthly engagement is also a valuable calculation and is called **stickiness** (also known as the DAU/MAU ratio):

$$monthly\ engagement = \frac{DAU}{MAU}$$

You will likely have significant retention issues if your stickiness is less than 10%. However, if your stickiness exceeds 30%, your product is considered compelling and even "addictive."

It is notable that if DAU is dropping significantly faster than WAU, it indicates that users are moving from higher engagement buckets to lower engagement buckets. These players have a greater overall risk of imminently lapsing and, therefore, need more compelling reasons to return more often in a given week. Consequently, when facing low engagement, seeking to inflect weekly engagement, or examining a significant change in weekly engagement, it is helpful to bucket the players into engagement buckets based on play frequency and track the players' movement between buckets.

TABLE 2.1 – Play Frequency of Players by Weekly Engagement Bucket

WEEKLY ENGAGEMENT BUCKET	PLAY FREQUENCY
New User	Less than 7 days since first run
Low	1–2 days per week
Medium	3–4 days per week
High	5–6 days per week
Regulars	7 days per week

Decomposing DAU: Weekly Engagement and Regularity

Building upon the weekly engagement concept, we can examine our DAU according to the number of times each player has played the game in the past seven days as an indicator of their weekly engagement.

Furthermore, we can identify the percentage of DAU who are highly engaged players. Players who have played all seven out of the past seven days are called ***regulars***. Therefore, ***regular DAU*** is the number of regulars in the game on any given day, and ***regularity*** is the percentage of DAU that comprises regulars who are thus playing on their seventh or more consecutive day. When we calculate regularity, we exclude new players (players whose first run was in the past seven days) from our DAU, as they have not yet had the chance to become regulars. Regulars represent the most engaged player base and the most likely to monetize. Regulars often drive a majority of revenue for games after their initial launch. Therefore, it is essential to monitor and maintain regular DAU as a quantity, and regularity as the share of DAU that consists of regulars.

The Leaky Bucket Model

A "leaky bucket" is a useful mental model for analyzing what contributes to and detracts from the number of active players. The leaky bucket has water pouring in from faucets; this water represents players entering the game. There is also water in the bucket, which represents the people who have played the game during the past seven days and are thus considered active players. However, holes in the bottom of the bucket are leaking water, representing players leaving the game.

This mental model makes it easy to understand the core principle: the determining factor that raises or lowers the water level in the bucket is whether the holes in the bottom of the bucket are leaking out water faster or slower than water is pouring into the bucket from the faucets. In other words, the change in the water level is equal to the difference between the amount of water pouring in and the amount of water leaking out. The goal is to patch the holes in the bucket while increasing the water flow from the faucets pouring into the bucket, to keep as much water in the bucket as long as possible.

Applying the leaky bucket model to the specifics of WAU, there are two faucets pouring water into the bucket and three holes leaking water out of the bucket. These represent the five control factors we have over WAU.

The two faucets providing inflow to the game for the week are new users and reactivated users. **New users** are new players who came into the game for the first time. New users are also commonly referred to as installs, but there is a distinct difference between someone who installs a game and someone who runs it for the first time to the point the system can give them a unique identifier. It is usually easier to track the latter in the product and product analytics. By contrast, the former is primarily available from

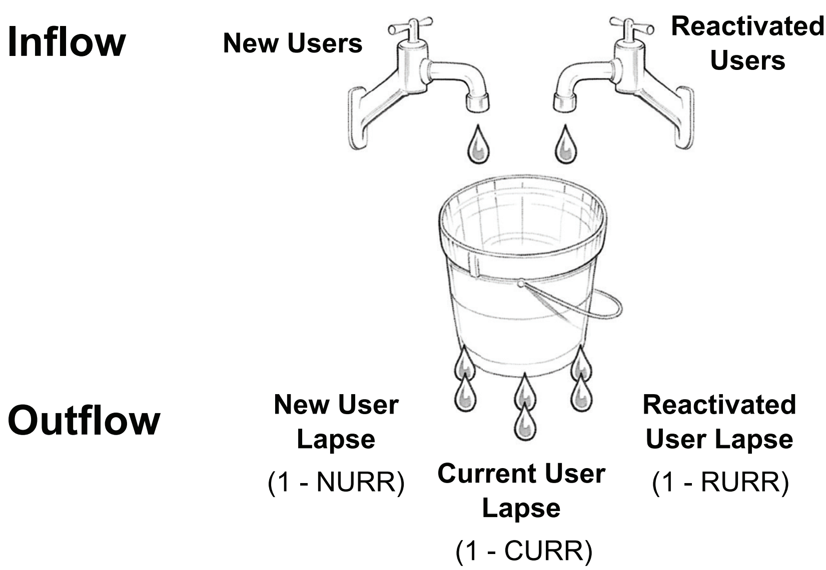

FIGURE 2.3 – The Leaky Bucket Mental Model

user acquisition campaign metrics. ***Reactivated users (reactivators or reacts)*** are formerly lapsed players with a 7-or-more day absence from the game but have returned to play the game once again. Often, when discussing reactivated users, we indicate the length of time of the lapse as n-day reactivators, meaning players who came back after an absence of greater than or equal to *n* days. Thus, 30-day reactivators are players who were also formerly churned players and decided to come back and try the game again after an absence of 30 or more days. Overall, many factors control the player inflow, including but not limited to marketing spend, exposure within social networks, organic factors, app updates, and app store featuring campaigns.

The three holes leaking water out of the bucket represent the three types of players lapsing. ***New user lapse*** is the number of players who played for the first time the prior week but did not continue to play the current week. ***Current user lapse*** is the number of players who played two weeks ago and the prior week but did not continue to play the current week. ***Reactivated user lapse*** is the number of players who played the prior week but not two weeks ago, and who did not continue to play the current week. In general practice, however, we look at these lapse rates as the complement of the probability that we retain each type of player, and call them the **weekly user return rates**. We will discuss these in more depth later in this chapter.

In summary, the WAU will decrease if the outflow is consistently larger than the inflow. Significant outflows will be an insurmountable obstacle no matter how many new and reactivated users come daily, as players will leave faster than they are replenished. Thus, maximizing the weekly user return rates is essential to minimizing the weekly player loss. This is done by utilizing distinct strategies and developing features to influence each one positively. Ultimately, the size of your active player base is a function of the number of players entering the game and the overall player retention, which indicates the number of players leaving the game.

Impact of Compound Weekly Declines

Keeping the active user count as high as possible, for as long as possible, is the goal. Often, especially in older games, there is a natural decline in active players over time. Nevertheless, it is critical to understand what it means for the product if you accept even the smallest consistent weekly decline compounded over a year.

TABLE 2.2 – Resulting Yearly Player Decline by Rate of Weekly Player Churn

RATE OF WEEKLY PLAYER CHURN	RESULTING YEARLY CHANGE IN ACTIVE USERS
−1.0%	−40.7%
−3.0%	−79.5%
−5.0%	−93.1%
X%	$= (1 + X)^{52} - 1$

As you can see, seemingly small weekly declines compound into significant yearly losses. Thus, your primary job should be to keep the number of players steady or growing weekly.

ACTIVE USER BASE ANALYSIS

Now that you have a basic understanding of the forces that influence the size of the active player base, we can look at the set of essential metrics that illuminate the current state of the player base and what is driving its changes. These metrics provide the framework for top-level analysis that, in many cases, provides direction for deeper investigations into underlying causes.

DAU Versus Projections Graph

Since DAU is the game's lifeblood, it is imperative to watch it regularly, if not daily. The DAU is generally reported as compared to the DAU the previous day (called day over day, abbreviated DoD or d/d), the same day the previous week (called week over week, abbreviated WoW or w/w), and the same day two weeks ago (called week over two weeks, abbreviated Wo2W or w/2w). We also report DAU as compared to the projected or quarterly target DAU. To that end, a line graph of actual versus projected DAU, such as Figure 2.4 with important events on the timeline marked, is essential to understand where you are versus goals.

Of course, DAU has numerous valuable sub-slices, such as DAU by device platform (iOS, Android, web, etc.) and DAU by geography (United States, Germany, Japan, Brazil, etc.). However, those slices are primarily

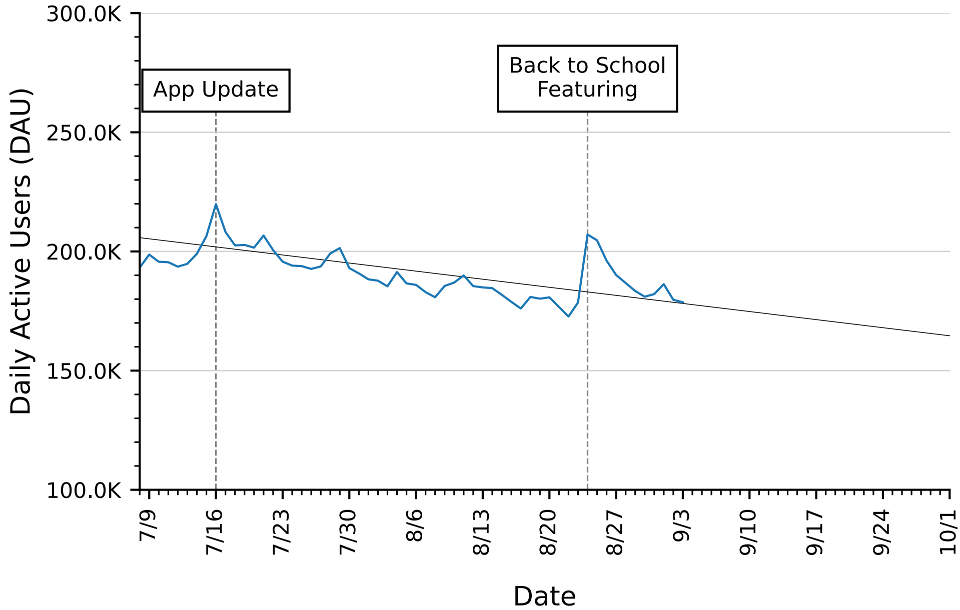

FIGURE 2.4 – Trending Daily Active Users

useful when doing a deeper dive to investigate specific issues rather than day-to-day player base management. Nevertheless, the common useful slices for this and most other reports in this book include install date range, platform (e.g., iOS vs Android), install type (organic vs paid), ad network (e.g., Facebook, Google Ads, ironSource, Unity Ads), and country code.

WAU Flow Graph

The WAU Flow graph shows the daily positive and negative forces influencing WAU, representing the most immediately reachable actively engaged players. Often, WAU is the preferred measure for calculating any weekly net loss in players, as a target for user acquisition activities to keep the player base steady. The graph for showing WAU is a stacked column graph, with the resulting daily net delta as a line graph. It is often advantageous to pair it with a WAU line graph so that the line graph contextualizes the WAU movements, and the WAU Flow beneath gives the underlying details.

The graph in Figure 2.5 shows WAU over time. Here, we can see the leaky bucket model in action. The two positive forces that comprise inflow

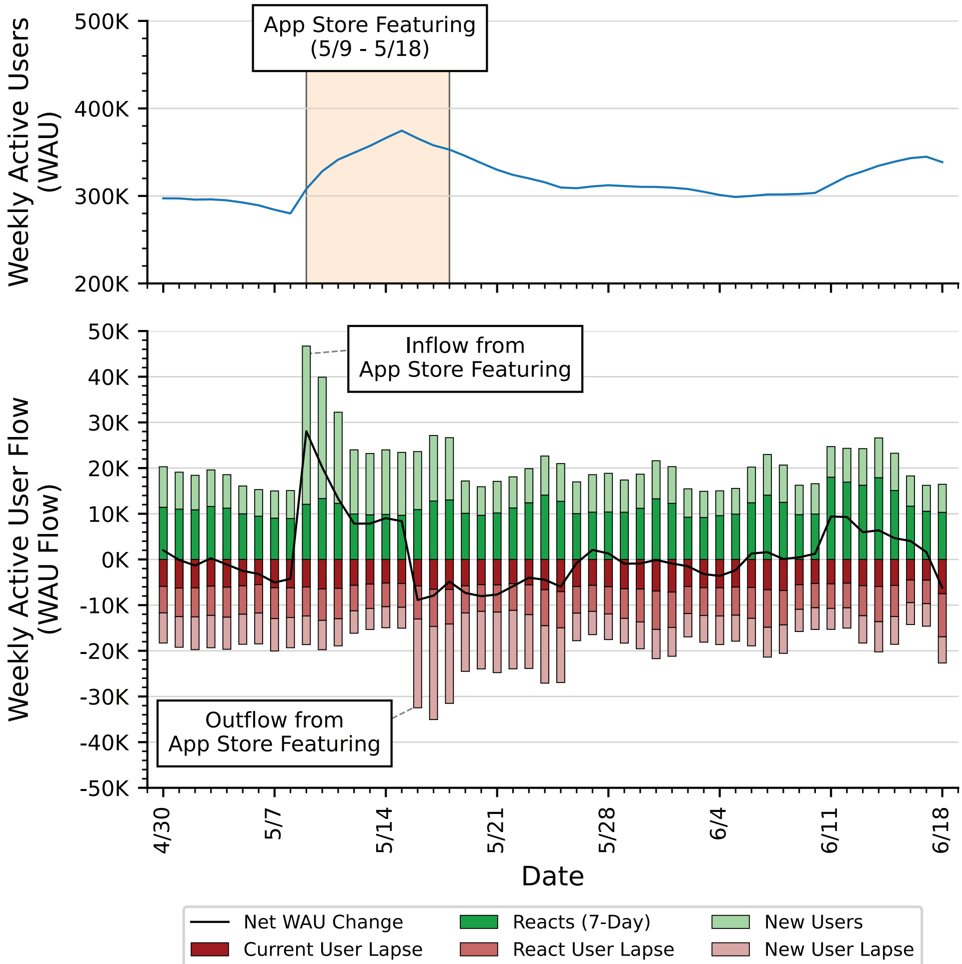

FIGURE 2.5 – Weekly Active User Flow

are reactivated users and new users, and the three negative forces that comprise outflow are lapsers from current users, reactivated users, and new users. The goal is to keep the inflows greater than the outflows so the black net WAU change line remains at or above the x-axis as much as possible (which means WAU is expanding) rather than below the x-axis (which means WAU is shrinking). While there are usually minor weekly cycles to the inflows and outflows, the root causes of significant changes to the inflow and outflow need to be identified and annotated.

Inflows are more straightforward to analyze for the root cause of changes because they represent players coming into the game from the outside. Further, if the platform can identify new users and reactivated users by channel (such as the ad network and campaign that sourced new users), we can narrow down the change to specific underlying causes on the source channel. Otherwise, it will require careful investigation to identify what external changes (new user or reactivation targeted marketing campaigns, app store featuring campaigns, new app updates or content releases, new viral features, etc.) are taking place that could be the root cause of the changes, supplemented with any external data available.

Outflows are more difficult to analyze. Not only do we need to analyze the channels for changes in effectiveness at bringing those players who are likely to be retained, but we also need to verify that the various retention rates for new, reactivated, and current users did not drop due to other internal reasons (lack of content, economic or systemic forces, new feature, etc.), which may require finding behavioral correlations in player data. Also of note is that a significant positive inflow is often accompanied by an increased outflow seven days later, as a portion of that inflow fails to retain and subsequently lapses at the 7-day mark.

MAU Flow Graph

The MAU Flow is useful for tracking the size of the total current player base of all active players, including the moderately to low-engaged players with whom the game is still actively communicating. Thus, the MAU Flow represents the totality of the game's current player base. The MAU Flow is similar to the WAU Flow but instead tracks the daily positive and negative forces on MAU. Therefore, the MAU Flow is shown as a stacked column graph for the inflows and outflows to MAU, with the net balance of the flows as a line graph. It can be paired with an MAU line graph for context. Due to the 30-day time horizon of MAU, the positive forces are new users and 30-day reactivators, and the only negative force is 30-day lapsers, as shown in Figure 2.6.

Like with the WAU Flow graph, the inflows are more straightforward because they are directly related to the channel that brought the person to (or back to) the product on that particular day. Similarly, the outflows are more difficult because the root cause of an increased outflow could be a channel losing effectiveness, a change in retention rates, or an inflow of players 30 days prior who are now lapsing back out.

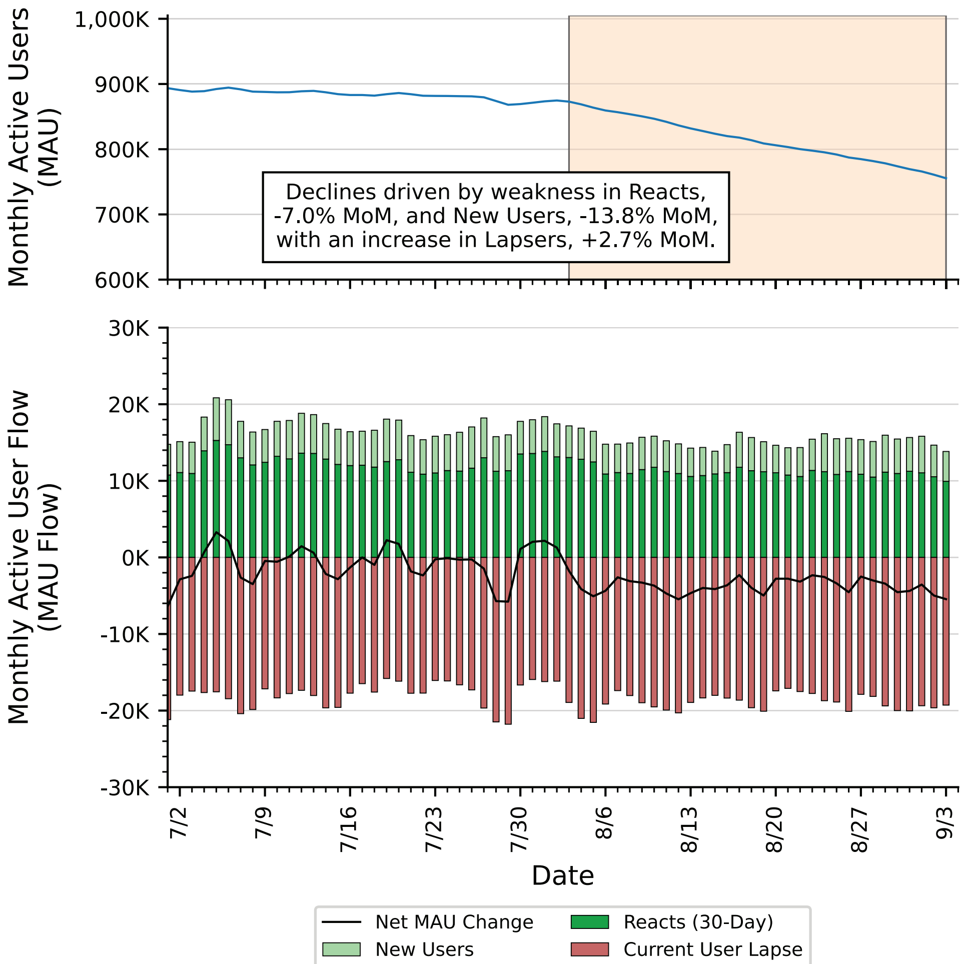

FIGURE 2.6 – Monthly Active User Flow

CHANNEL ACTIVE USER ANALYSIS

For products with multiple different access points driving player entry that can be tracked and attributed, it is beneficial to analyze DAU by the daily initial product entry channel. This ensures all access points are working to bring users into the product to the best of their abilities. It also aids in determining how the most recent release or platform changes have impacted or shifted those traffic patterns. While this section discusses channel active users, the same analysis works and is also useful for the new users by channel.

Note that channel active user analysis is not generally applicable to the current offering of free-to-play mobile games: they do not have multiple prevalent channels competing to bring players back to the game. This analysis is predominantly for web games and games on social media platforms, particularly where social posts, activity, and invites help drive active users each day. I included it here in case it becomes relevant on some platform once again.

Channel DAU

Monitoring the DAU each channel and sub-channel contributes is worthwhile if the platform allows for DAU channel attribution. While a user may enter the product through multiple sources in a day, each channel only gets credit for ***channel DAU*** when it is the first channel a player uses to enter for a given day. Depending on the platform, you may be limited to only a few channels, such as mobile push notifications or direct icon access—or an unrestricted plethora of categories, such as on a web platform where referral links track access from viral messages on social network platforms, platform app bookmarks and directories, marketing-driven emails and social media posts, and cross-promotions from other sibling products, among multitudes of others.

However, to effectively analyze channel DAU, you must investigate the overall number of daily unique channel users, also called unique clickers, regardless of the DAU the channel drives. We will use the ratio between channel DAU and the daily unique channel users to identify the difference between fundamental channel strength or weakness and cross-channel cannibalization.

Cross-Channel Cannibalization

For each channel, it is essential to determine what portion of a change in sourced DAU is due to underlying changes in the performance of the channel, and what portion is from cannibalization to or from another channel. Thus, we need to keep track of daily unique channel users and, to a lesser extent, total usage volume to determine the underlying stability or instability in the channels the players are utilizing, despite any change in the DAU each channel is contributing.

To this end, the ratio between the channel DAU and the number of unique channel users is the critical metric for cross-channel cannibalization. The ratio shows the proportion of players who enter the game for the first time each day through a particular channel. More importantly, when this ratio changes, we can look at the numerator and denominator of the ratio to determine the probable cause. If the number of unique channel users is relatively stable but channel DAU changes, cross-channel cannibalization to or from another channel is likely. However, if the channel DAU is stable, but the number of unique channel users changes, it indicates shifts in underlying channel engagement. Only when both the channel DAU and the number of unique channel users move together in the same direction is there likely to be an actual performance change in a channel.

The answer is not always as straightforward in real-world data because channel DAU and unique channel users will naturally fluctuate daily and weekly. The chart in Table 2.3 helps determine the primary and contributing factors driving a given movement in the ratio of channel DAU to unique channel users. However, frequently, the culprit is the volume and prevalence of viral social activity or platform changes impacting the prominence of the various channels.

Channel DAU or New User Walk

When the platform allows channel DAU attribution, a *DAU walk* is valuable for visualizing and summarizing the most significant contributors and

TABLE 2.3 – Deciphering Cross-Channel Cannibalization

RATIO CHANGE	NUMERATOR	DENOMINATOR	MEANING
Increase	Channel DAU up	Unique Channel Users stable	Gains due to cross-channel cannibalization
	Channel DAU stable	Unique Channel Users down	Less channel engagement
Decrease	Channel DAU down	Unique Channel Users stable	Loss due to cross-channel cannibalization
	Channel DAU stable	Unique Channel Users up	More channel engagement
Stable	Channel DAU up	Unique Channel Users up	Channel growth
	Channel DAU down	Unique Channel Users down	Channel decline

detractors to the week-over-week 7-day average DAU change. A similar graph works for attributable sources of new users.

In this type of graph, the leftmost column is the starting value, and the rightmost column is the new value. Between them are the deltas of the different contributing channels, which add or subtract to reach the overall net change. The graph orders the contributing channels from greatest positive to greatest negative. It annotates each with their percentage change, the numeric change they contributed, and any callout notations as to what underlying factors drove those changes from the specific channel analysis. The starting and ending values and the contributing channels are all based on 7-day averages. Generally, any channel that changes more than 3% in either direction deserves a callout.

The graph in Figure 2.7 shows that while new user attribution increased for TikTok, Google Ads, and Facebook, their strength was countered by weaknesses in three others: Organic, IronSource, and Unity Ads. The Unity Ads channel was weak due to the elevated cost of user acquisition. By contrast, IronSource was weak due to degrading performance in a particular type of ad creative, which warrants further investigation into whether it deserves a refresh. The overall net result is an unfortunate −1.2% WoW decrease in new users.

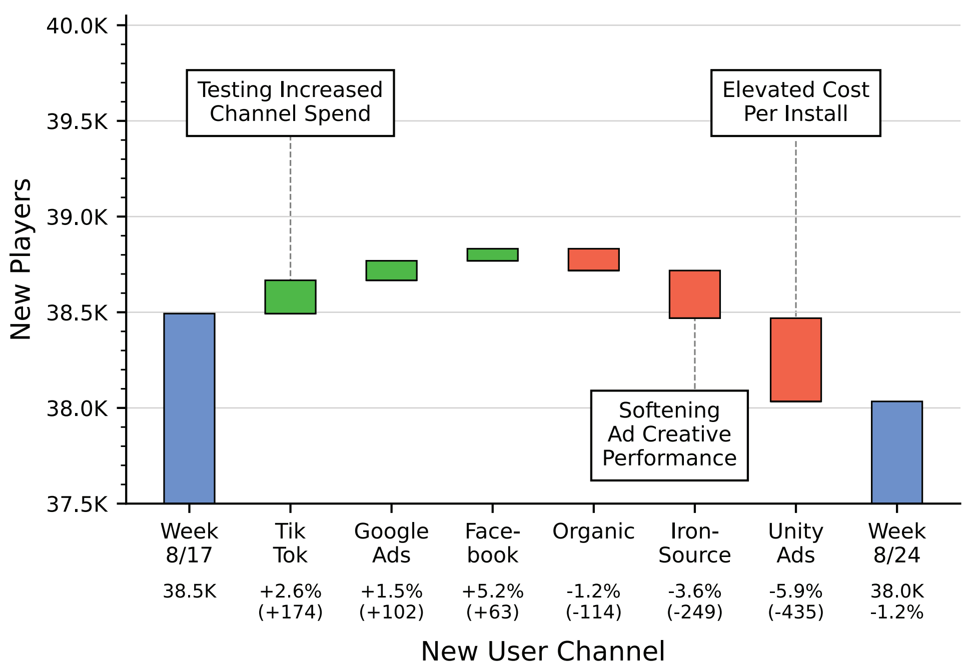

FIGURE 2.7 – Week-Over-Week New User Walk

USER RETENTION ANALYSIS

Thus far, we have primarily examined the number of active users at different temporal granularities, along with the positive forces bringing new users to the game and reactivating lapsed users. However, we must also more closely examine the rate at which those users subsequently lapse. Returning to the leaky bucket analogy, even an enormous faucet will do little to fill the player bucket if the holes in the bottom are significant. Moreover, large user-acquisition sources bringing in sizable quantities of new users with beneficial economics for the business rarely last indefinitely and are expensive to maintain, so user retention is critically important in preparation for increased user acquisition activity.

Daily Retention Rates

The daily retention rates are the most familiar player retention metrics. Daily retention rates are denoted as Day *n* Retention, Dn Retention, or DnR, and represent the proportion of users who were active exactly *n* days since their first run day. Thus, D0 retention is always 100% by definition since the player had to engage with the game to count as a new user on their first run day (day 0). Likewise, the retention on D7 (D7R) represents the proportion of people who first used the product seven days ago (D0) and who also used it on the seventh day (D7). The day *n* retention metric is primarily useful for investigating the retention of new users $n \leq \sim 30$ days from their first run, with some exceptions for benchmarking at specific longer checkpoints and for predicting player lifetime value. It is not a sufficient measure for longer-term retention. Dn Retention will be considered in more detail in Chapter 4, where we discuss early retention analysis as one of the underlying components of the lifetime value of a player.

Daily retention rates are a critical new-user retention metric for free-to-play games, both mobile and web, that seek to engage players multiple times a week. It is less commonly used for console and PC games, which rely more heavily on weekly retention, as those fit the play patterns for their users better.

Weekly User Return Rates

User acquisition analysis primarily examines retention in the new user experience from the standpoint of milestones and daily retention. However, a thorough retention analysis looks at retention for all users, not just new ones. Therefore, we use weekly retention to analyze players in three categories: new users, reactivated users, and current active users.

New users have recently started playing, and their first run was within the past few weeks. Reactivated users are those who recently returned to start playing again within the past few weeks after lapsing for a period. Reactivated users are similar to new users in some aspects, but they have prior experience with the game and, therefore, the game needs to re-engage them. Current active players are players who have been playing each week all along, with some recurrence. We group all current active players together, regardless of their player age, because players start looking similar at some point in their journey, despite the number of days since their first run. A player who has played consistently for 60 days looks and behaves similarly to a player who has played consistently for 360 days. Thus, we can treat them similarly.

To measure the retention of players in these three categories, we consider their likelihood of returning to play again the following week, which is called their ***weekly return rate***. The three weekly user return rates, new, reactivated, and current, are expressed positively as the complement of their corresponding lapse rates to indicate the weekly retention of players we need to maximize. They are defined as week-over-week retention rates so we can do active user modeling using WAU with all categories based on comparable temporal units. Collectively, these retention rates are called the weekly user return rates.

New User Return Rate (NURR). New User Return Rate (NURR) is how well the game retains new players week over week. Quantitatively, NURR calculates the proportion of people who returned to play between day *d* and day *d – 6* from all who played for the first time between day *d – 7* and day *d – 13*. A

	Past *d - 21+*	**Prior Week** *d - 14 to d - 20*	**Last Week** *d - 7 to d - 13*	**This Week** *d - 0 to d - 6*
NURR *New User Return Rate*			✔ First Run	✔ Played
RURR *Reactivated User Return Rate*	✔ Played	✘ Not Played	✔ Played	✔ Played
CURR *Current User Return Rate*		✔ Played	✔ Played	✔ Played

FIGURE 2.8 – Calculating Weekly User Return Rates

successful game should target NURR above 35%, though it will vary by platform, game genre, and state of user acquisition challenges in the industry.

Reactivated User Return Rate (RURR). Reactivated User Return Rate (RURR) is how well a game retains players week over week who return to the game after a break of 7 or more days. (This metrics is also sometimes known as *return user return* rate or even *resurrected user return rate*.) Quantitatively, RURR calculates the proportion of people who returned to play between day d and day $d - 6$ from all the people who returned to play between day $d - 7$ and day $d - 13$, and had played at some point in the past day $d - 21+$, but did not play between day $d - 14$ and day $d - 20$. A successful game should target RURR above 35%.

Current User Return Rate (CURR). Current User Return Rate (CURR) is how well a game retains current active players week over week. Quantitatively, it calculates the proportion of all players who returned to play between day d and day $d - 6$ from those who played between day $d - 14$ and day $d - 20$ and between day $d - 7$ and day $d - 13$.

CURR, in particular, often has the most significant impact on the long-term profitability and success of the product. If your game cannot retain current active players for the long term, the player acquisition and reacquisition costs will quickly overwhelm any revenue brought by your players. Healthy games that sustain their player base indefinitely often have CURR around 90% or greater. Any game with a CURR lower than 80% has severe long-term retention issues.

However, when investigating changes in the weekly user return rate metrics, such as in Figure 2.9, finding which stimulus was the root cause can be difficult since the underlying cause can be anywhere up to three weeks ago. Great care is needed to uncover the catalyst of the movement. For example, a decrease in the current user return rate could be due to an increase in poor quality new users three weeks ago, problems with shorter-term notifications that remind players to return the second week but fail to do so on the third, or a lack of good content the past week which was unable to retain players.

Daily Retention Rates Versus Weekly User Return Rates

We have discussed two different retention measures: daily retention rates (DnR) and weekly user return rates. Why use one over the other? Do we need two different ways to measure retention? The answer is yes, we need

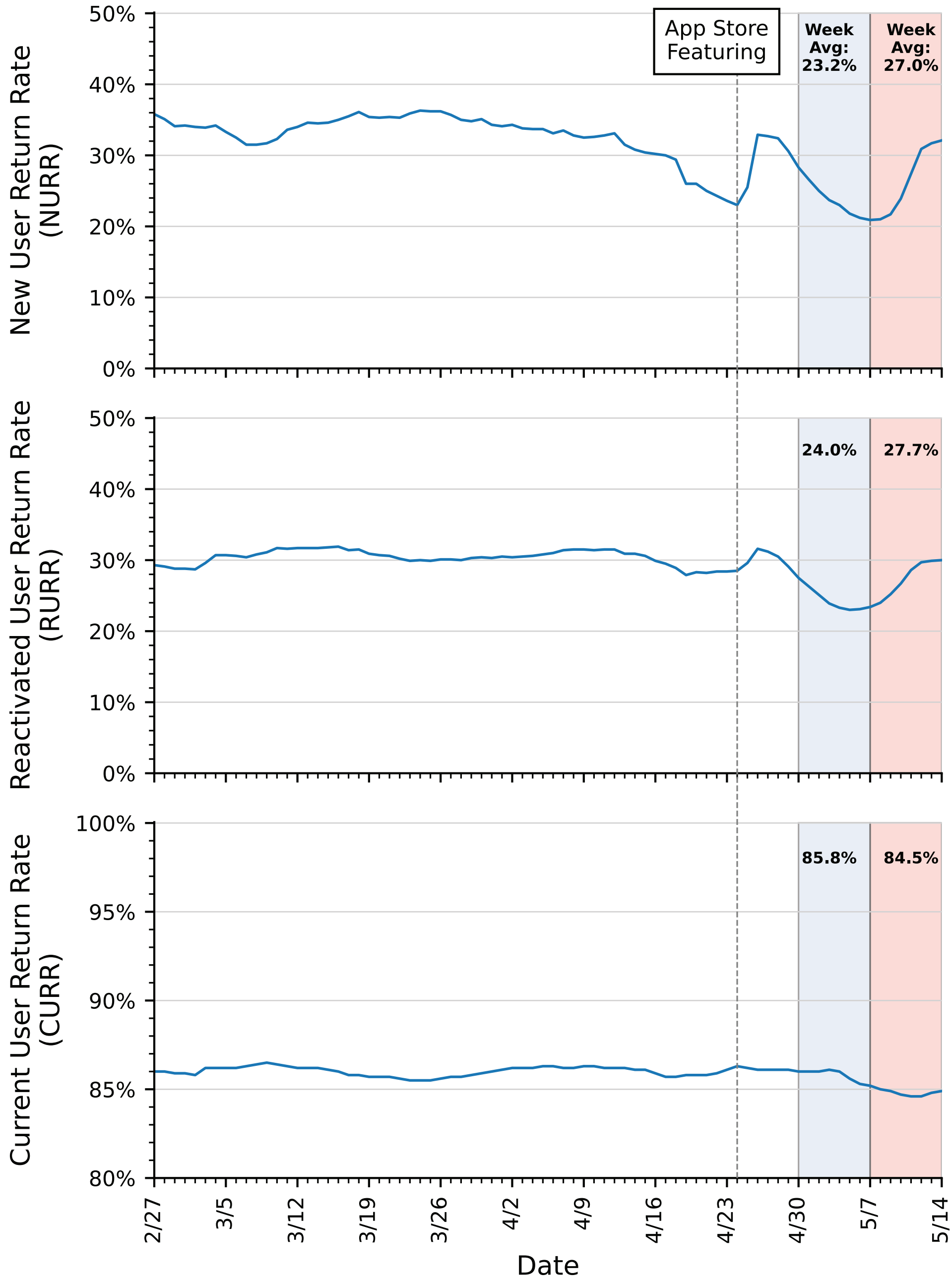

FIGURE 2.9 – Weekly User Return Rates

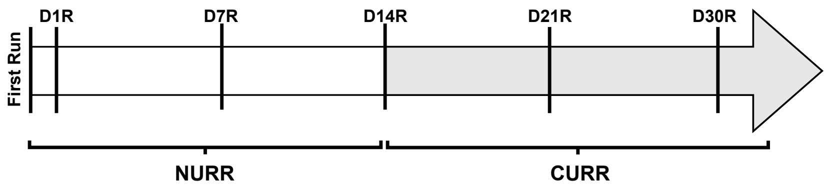

FIGURE 2.10 – Daily Retention Rates Versus Weekly User Return Rates

both. Daily retention rates and weekly user return rates are complementary. While NURR overlaps with much of the curve formed by the day *n* retention values, it does not provide the granularity that the day *n* retention metrics provide when attempting to pinpoint new player retention issues.

Likewise, day *n* retention rates lose their ability to provide insight beyond the first 30 days as the day *n* retention curve smooths out and players are too few and too distributed for statistically significant reads. However, current players who have played multiple weeks in a row and return players who return after a week or more of absence behave relatively similarly to one another despite their differing ages in days since their first run. Thus, CURR and RURR provide invaluable insight into those players that the day *n* retention cannot.

The day *n* retention metric focuses on the early game and is a predominant metric for new games that are fighting for survival before and during launch as they prove their business case and profitability. However, solely using day *n* retention often leads to decisions made only for new players, to the exclusion of the elder players who are key to profitable games that sustain operations for years. Therefore, for a mature and thriving game, the weekly user retention model is invaluable as it provides insight into the long-term business and reveals the inputs necessary to maintain and grow the player base.

OTHER ENGAGEMENT METRICS

Other secondary engagement metrics are essential to know for your product but have more limited day-to-day usefulness. Nevertheless, these metrics can be a valuable link to understanding the root cause of a trend in the top-level retention metrics. First, ***daily session length*** and ***daily minutes played*** indicate how much time players engage in your game. Low daily session length or minutes played can indicate low player engagement. More is often better, to a point. However, if the time spent grows too excessive, the game is likely limiting itself to those who have unlimited time to play and are willing to neglect the rest of their lives.

Similarly, the ***sessions per day*** metric indicates how many times players return to play the game each day. Games that do not stay top of mind enough to need multiple daily sessions tend to drop from a player's memory quickly and thus have retention issues. Likewise, we can examine player behavior by the number of ***core actions per day*** they perform, though this metric is less useful as a comparison to other games as a benchmark because each game is different. Nevertheless, these core actions should be integral to the core game loop and could be the number of battles, puzzle attempts, items crafted, etc., depending on the game. For example, a player who logs in just to collect the daily reward is not nearly as valuable as a player who more deeply engages with the game each day. Identifying players who are less engaged and likely to churn, and targeting features to increase their game engagement, can be beneficial.

All these other engagement metrics are helpful to examine, particularly when you compare the values for players when bucketed based on either weekly engagement or weekly total value of purchases. These engagement metrics are also valuable for progression modeling and simulation, in addition to their usefulness as secondary metrics that can provide insight into user engagement issues.

ACTIVE USER PROJECTIONS

Building accurate projections for the number of future active users and the expected revenue for the product is essential for the business. It is often prudent to build multiple projection models using different methodologies to verify the case for your projection. The more agreement there is between projections that use various methods, the greater confidence you can have in your forecasts.

Regression Model

A basic regression is often sufficient to project the number of active users, especially for established products. The trick is to try a few regression model formulas (linear, exponential, weekly decay, etc.) and pick the one that best fits the existing data and, thus, is most likely to predict future active user counts accurately. We can determine the regression model formula that best fits by comparing the R^2 coefficient of determination. However, we also must use common sense when looking at the data and projections to see if the trajectory for future projections matches the apparent trajectory of the data.

A linear regression model ($y = m \cdot x + b$) is often a reasonable starting place to form a projection, by projecting the WAU decline over a quarter and then using the weekly engagement ratio to determine daily DAU. In Excel, the functions SLOPE(), INTERSECT(), and RSQ() calculate *m*, *b*, and R^2, respectively.

Another similar frequently used model is an exponential WAU model ($y = s0 \cdot (1 + r)^x$), which projects WAU each week using a small average percentage change each week. In this model, s_0 is the current starting WAU and *r* is the percentage weekly change. The points between the projected value of WAU each week can then be filled in using linear regression.

Weekly User Return Rate Model

The weekly retention rate model is a more sophisticated model based on the key inputs from the leaky bucket model. It is built to use the weekly user return rates to project the weekly users using a combination of historical averages and comparable data. This model allows for more granular week-by-week control in a single model that can handle the launch and initial growth, and on through the content cadence and maintenance phases. One advantage of the retention rate model is that it allows for sensitivity analysis to show which of the five forces on WAU will have the most significant effect on the player base, which is invaluable in informing your feature strategy.

Assuming data or projections for week_t, we can project week_{t+1} as shown in Table 2.4. We use historical averages or comparables for the following metrics foundational to the model: new users, reactivated users, RURR, NURR, CURR, and weekly engagement.

ADDRESSING RETENTION ISSUES

Now that we have the frameworks for understanding our payer base and how to analyze it, the next task is addressing any retention issues. The particulars will vary depending on factors such as platform and game genre; however, the game needs to provide adequate reminders and motivations for players to return to play frequently, as well as address any places where players are lapsing from the game. We will discuss addressing early game player lapse issues in Chapter 4.

Reminders include external prompts that bring players back to the game. For example, mobile apps should utilize a sequence of strategic app notifications to notify users of noteworthy game events that may prompt

TABLE 2.4 – Weekly User Return Rate Model for Active User Projection

	$WEEK_{T+1}$
DAU_{t+1}	$= WAU_{t+1} \cdot \text{weekly engagement}$
WAU_{t+1}	$= \text{total returns}_{t+1} + \text{new users}_{t+1} + \text{reactivated users}_{t+1}$
$\text{total returns}_{t+1}$	$= \text{retained reactivated users}_{t+1} + \text{retained new users}_{t+1}$ $+ \text{retained current users}_{t+1}$
$\text{retained reactivated users}_{t+1}$	$= \text{reactivated users}_t \cdot RURR$
$\text{retained new users}_{t+1}$	$= \text{new users}_t \cdot NURR$
$\text{retained current users}_{t+1}$	$= \text{total returns}_t \cdot CURR$
new users_{t+1}	*Based on user acquisition plans or estimated from historical average data.* *This can be estimated as follows:* $\text{new users}_{t+1} = \text{average}\left(\frac{\text{weekly new users}}{WAU}\right) \cdot WAU_t$
$\text{reactivated users}_{t+1}$	*Based on reactivation marketing campaign plans or estimated from historical average data.* *This can be estimated as follows:* $\text{reactivated users}_{t+1} =$ $\text{average}\left(\frac{\text{weekly reactivated users}}{WAU}\right) \cdot WAU_t$
RURR	*Estimated from historical data*
NURR	*Estimated from historical data*
CURR	*Estimated from historical data*
weekly engagement	*Estimated from historical data*

them to return. They should also employ an extended sequence of reminders targeting lapsed players to return to the game. In a bygone era, these reminders were messages and posts from friends on their social media. In current mobile games, these are app notifications. No matter how games and platforms evolve in the future, games should seek to reach out to players regularly to invite them back to play each day and to return for their next session after.

The game design should also employ compelling intrinsic reasons for players to return to the game for their next session. Early in a game, these often include time-based callbacks such as refilled energy or completion of a building. These callbacks encourage players to return habitually for their next compelling session of progress. Later, these callbacks expand to include reasons such as limited-time LiveOps events with exclusive rewards that the player can chase, social gameplay and obligation, and competition, whether individual or team-based.

Additionally, the game should provide compelling short- and long-term goals for the player to pursue as motivation to engage regularly for many sessions, days, weeks, months, and even years. These shorter-term goals should allow players to make visible progress toward completing them each play session. However, some goals should be long-term, allowing the players to plan and strategize for how to best pursue and prioritize them over time. Both are invaluable to retaining players. These are important elements of the principles of good game balance, which we discuss further in Chapter 7.

CONCLUSION

This chapter discussed retention as a foundational pillar of free-to-play game success and explored how the size and health of a game's active user base directly impacts its long-term sustainability. We started by discussing the core player metrics, DAU, WAU, and MAU, as well as primary engagement metrics such as weekly engagement and regularity. We also utilized a "leaky bucket" as a mental framework for understanding the forces that impact the size of the player base. This led to an examination of various player retention metrics, such as Dn Retention, RURR, NURR, and CURR. Finally, we discussed a regression-based approach and a weekly user return rate-based model for developing accurate active user base projections for resource and strategy planning.

In the end, the active user base is the lifeblood of any product. If no one is playing the game, then no one remains to monetize. Thus, maintaining those users is essential to the long life of your product. It is best done by understanding the forces that influence the size of the user base and knowing how to diagnose any retention and engagement issues that arise.