Pokémon Go User Data-Driven Insights

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Introduction

Following the success of Pokémon Go, challenges were encountered in maintaining long-term engagement. In this study, RFM metrics, customer segmentation, lifecycle grids, and churn will be examined using Pokémon data from Summer 2022. This information can be used to analyze trends in engagement and purchase patterns over time. By optimizing its strategies, Niantic will be able to maximize profits and engage users.

Profiling and Basetable Creation

As this game is part of the free game industry, we are measuring RFM in two ways. We decided to consider not only the monetary spending of each player but also the time spent on the game. Based on Perišić & Pahor, 2023 research: "We employ the RFM feature framework (in the free game industry) which extends the well-known RFM feature framework by incorporating lifetime, intensity, and reward features where the selected features capture player-game interaction and are game-independent" (Perišić & Pahor, 2023). As a common practice to understand customer value in this industry, and thanks to the possibility to "track not only the purchases, but also (...) how often would the customer visit the store and many other non-strictly transactional details" (Burelli, 2022), our first base table considers:

- Frequency: Number of sessions (Count of sessions ID)
- Recency: Most recent session date
- Monetary Value: Total game time

On the other hand, for players who do make purchases:

- Frequency: Number of transactions (Count of Transactions ID)
- Recency: Most recent transaction date
- Monetary Value: Total spending value

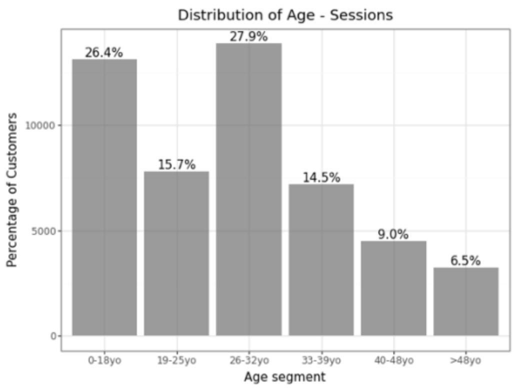
In total, there are 49.763 players, which are distributed as follows by customer type:

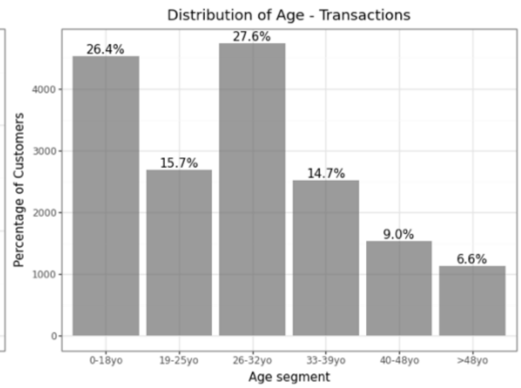
Table 1: Number of players by type in Summer

Customer Type	Number of players	% Total Players	Clients who purchase	% Purchase Players	% purchase over total	Avg Spend
0 - Walker	11,442	22.99%	3,106	18%	27.15%	$ 8.64
1 - Misc.	11,837	23.79%	2,812	16%	23.76%	$ 8.57
2 - Soc. Raider	13,521	27.17%	7,090	41%	52.44%	$ 15.14
3 - Catcher	12,963	26.05%	4,162	24%	32.11%	$ 9.66

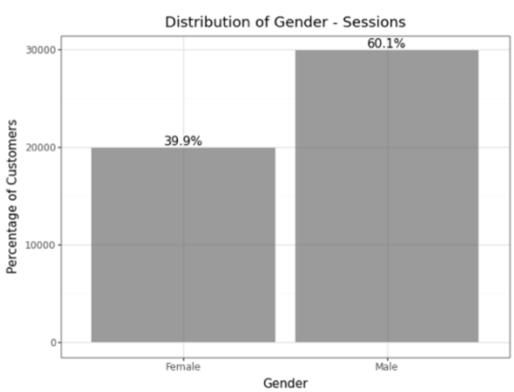
Total	**49,763**	**100.00%**	**17,170**	**100%**	**34.50%**	**$ 11.56**

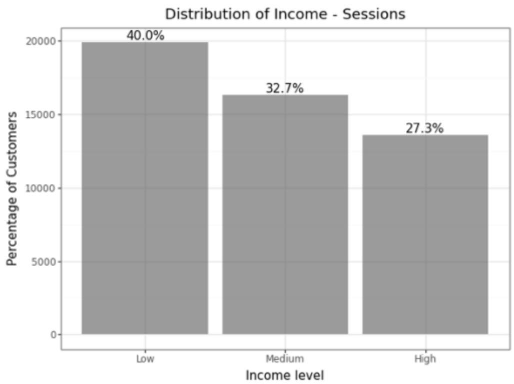
The average age is 28 years old, and the percentage of females rounds 40% and males 60%.

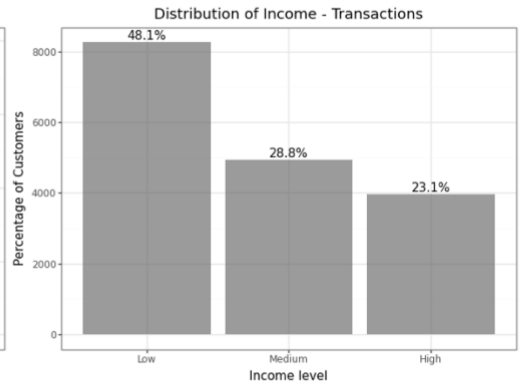




- The largest age group engaging with sessions and transactions is **26-32 years old** (~27.9% sessions, 27.6% transactions). This suggests that millennials are the primary audience.
- The **0-18 years old group** is the second most active segment (~26.4% for both sessions and transactions), indicating strong engagement among younger players.
- Engagement significantly drops among **older age groups (40+ years old)**, with the **>48 years old** category having the lowest participation (6.5% sessions, 6.6% transactions).
- The engagement pattern in transactions mirrors session behavior, indicating a consistent user base across activities.





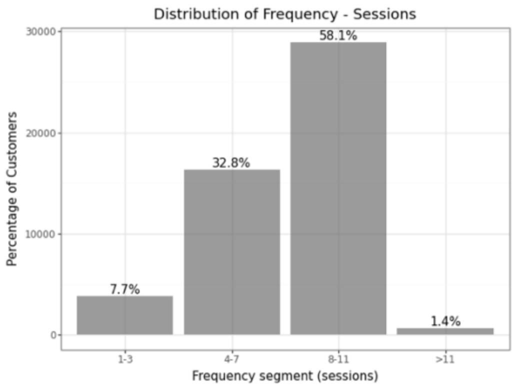


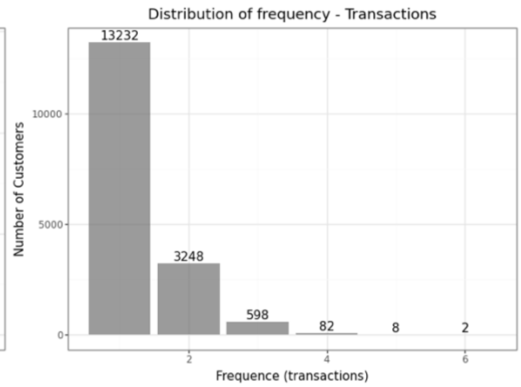
- Male users dominate Pokémon Go sessions and transactions, representing around 60%, whereas female users account for around 40%.
- Income distribution is fairly spread over all the players (sessions):
    - 40.0% of users belong to the lowest income group (0)
    - 32.7% in the mid-tier income group (1)
    - 27.3% in the highest income group (2)
- Almost half of the players who pay have a low income (48.1%).

Regarding engagement metrics:

Table 2: Game Statistics by Player Type

Customer Type	Avg Number of Sessions	Avg Social Actions	Avg Time Played Summer (min)	Avg Time per Session (min)	% who received Fall Bonus	Avg Years since Joined
0 - Walker	7.45	1.73	511.70	68.69	20%	2.3
1 - Miscellaneous	7.13	4.13	288.03	40.41	20%	2.0
2 - Social Raider	8.43	16.27	997.96	118.33	21%	1.3
3 - Catcher	7.38	0.65	199.95	27.11	20%	2.6
Total	**7.62**	**5.97**	**509.41**	**66.84**	**20%**	**2.0**





- **Sessions:**
    - 58.1% of players log in frequently (8-11 times)
    - 32.8% have moderate engagement (4-7 times)
    - 7.7% are low-engagement users (1-3 times)
    - Only 1.4% are highly active (>11 times)
- **Transactions:**
    - 77.1% of players make only one transaction
    - 18.9% make 2 transactions
    - Engagement significantly drops for higher transactions (>2), with <4% making 3 or more transactions.

CLV (Customer Lifetime Value)

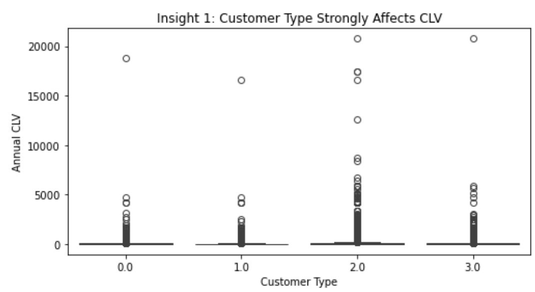
Assumptions and Justifications

1. **Forecast Period (T):** The analysis considers a forecast period of **3 years**. This is because mobile game player bases change rapidly, making predictions beyond three years **unreliable**. (Gupta & Lehmann, 2003)
2. **Retention Rate (r):** The retention rate varies by season:
    a. **Summer: 65%** (Higher engagement during summer)
    b. **Fall: 50%** (Moderate retention)
    c. **Long-term: 40%** (Churn increases over time) (Reinartz & Kumar, 2003)
    d. This reflects **seasonality**, where player engagement is **higher in summer** but **decreases in fall and winter**.
3. **Discount Rate (d):** A **12% discount rate** is used to account for the **uncertainty** in mobile gaming revenue. Since the industry is volatile, a higher discount rate is applied to future revenue projections. (Berger & Nasr, 1998)

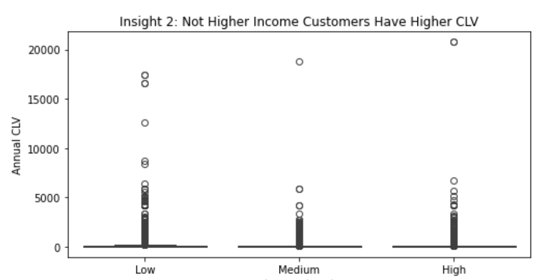
4. **Acquisition Cost (AC):** The cost of acquiring a new player is estimated at **$5 per customer**. This includes marketing efforts like promotions and incentives, such as the **fall bonus**, to attract and retain players. (Blattberg, Getz, & Thomas, 2001)
5. **Profit Margin (m):** Profit margins **vary by player segment**: (Rust, Lemon, & Zeithaml, 2004)
6. **Revenue per Customer (m):** Revenue is **based on player behavior**:
   a. **High spenders drive CLV**.
   b. Understanding customer segments is crucial to maximizing lifetime value.

Final Insights on CLV Drivers

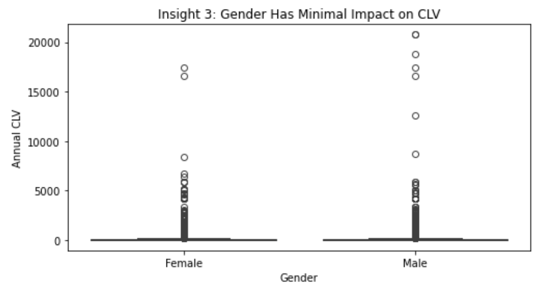
- The **average CLV is $6.72**, indicating that customers contribute this value over their lifetime.



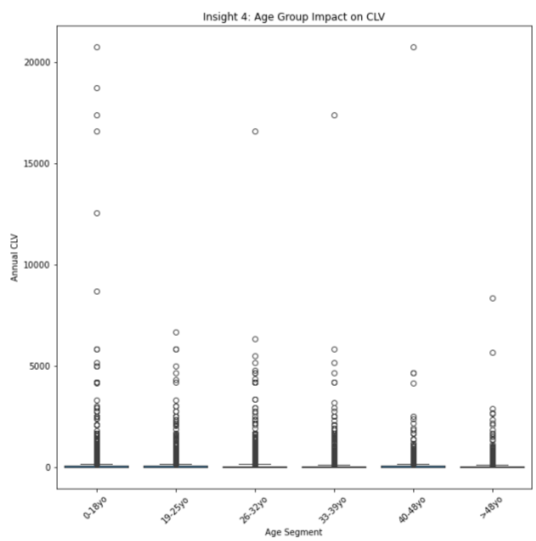
1. **Customer Type Strongly Affects CLV**
   a. Social raiders have **significantly higher CLV**.
   b. **Action:** Implement **targeted retention strategies** for social raiders.



2. **Lower Income Customers Have Higher CLV**
   a. Customers with **lower income** tend to have greater CLV.
   b. **Action:** Introduce **premium offerings** and personalized incentives for low-income segments.



3. **Gender Has Minimal Impact on CLV**
    a. No strong correlation between **gender and CLV** was found.
    b. **Action:** Gender-targeted marketing may **not be necessary** for increasing CLV.

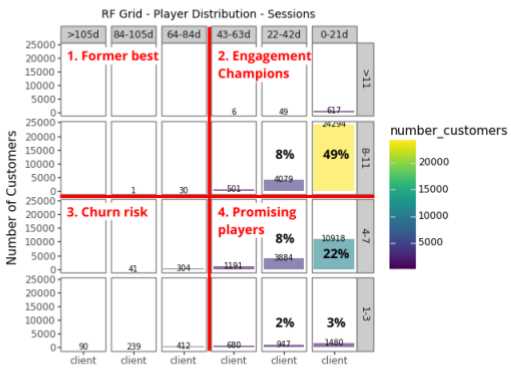


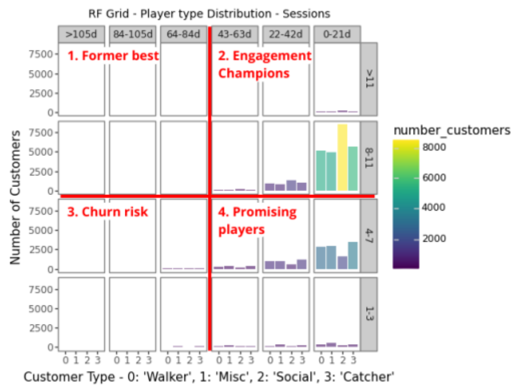
4. **Mid-Aged Groups (26-39yo) Have Higher CLV**
    a. Customers in the **26-39-year-old range exhibit the highest CLV**.
    b. **Action:** Prioritize marketing and retention efforts toward this **age group**.

Lifecycle grids:

After understanding the CLV, lifecycle grids were used to understand customers through their engagement and to evaluate the marketing strategies that each segment needs. Understanding the stages in the lifecycle of each customer would help implement a marketing strategy that's not only based on what the customer enjoys (walking, socializing, catching), but also based on where the customer is in the lifecycle grid.

As value can be measured in sessions (regarding engagement) and in spending (regarding transactions), the two types of grids were created and analyzed. At the end, the objective is to have a full picture of the segments, and the opportunities and tactics required.





From these, four segments were identified:

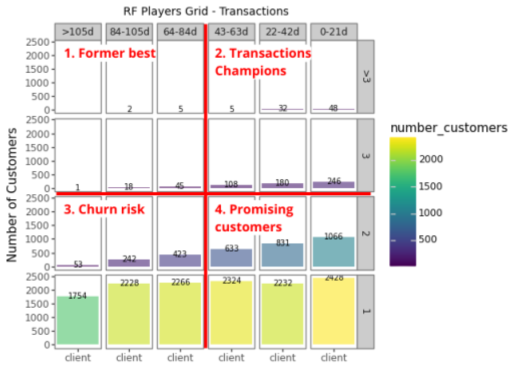
- Quadrant 1: Former Best Players:
  - Played frequently in the past (high frequency) but then stopped.
  - These players were loyal but are no longer engaged in the game.

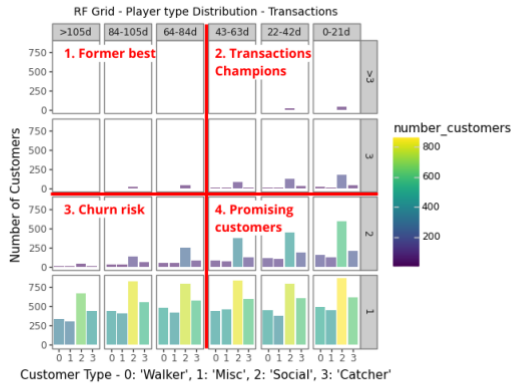
- Quadrant 2: Engagement Champions
  - These players are considered the most engaged players with high frequency and recent logins.
  - They are the most active ones.

- Quadrant 3: Churn Risk Players:
  - They used to play a lot in the past, but now they are slowly disengaging.
  - It is possible that they were engaged in the past, but they are not as active now, which could lead them to become Churn Risk players.

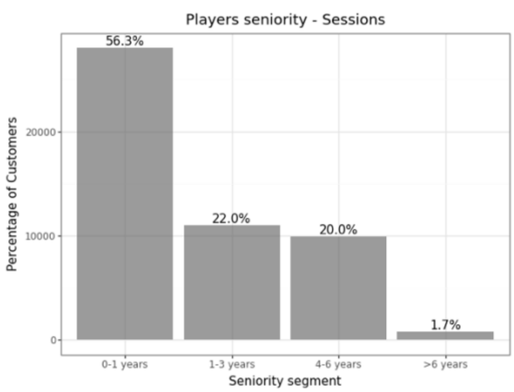
- Quadrant 4: Promising players:
  - These are our recently acquired players with low frequency.
  - If not highly engaged, they might consider dropping out early.

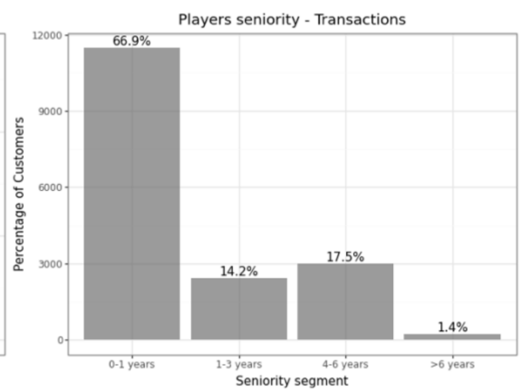
Champions represent 59% of all the players, this shows the hype with the game. Still, promising players are 38% of total players which indicates the game continues to attract players and maintain an active player base. The challenge is to retain both in the long term.

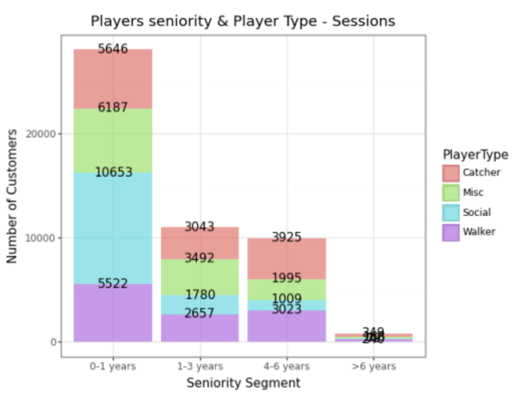


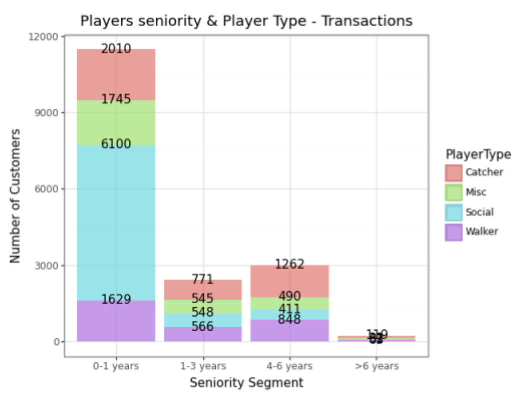


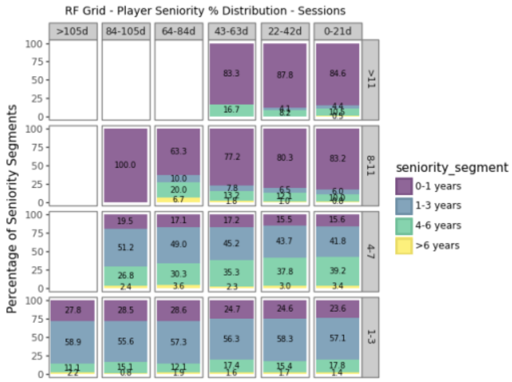
Regarding value measured by transactions, there is a relevant volume in the 3rd quadrant. This means there are customers willing to pay that only made a few transactions. Lastly, since most transactions only occur once, this may indicate that players are not seeing enough value from spending money, thus they'd rather enjoy the game for free.

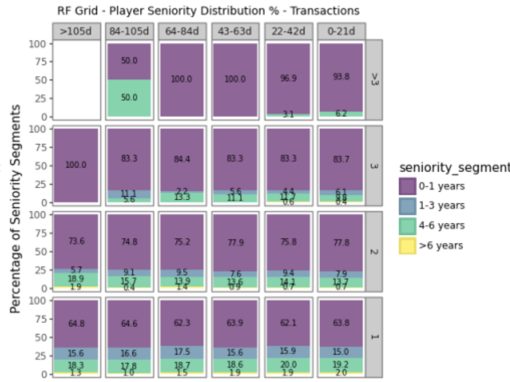








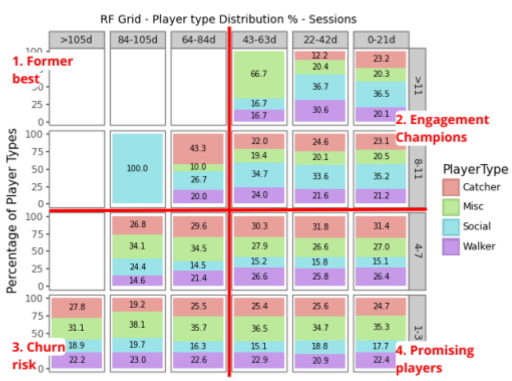


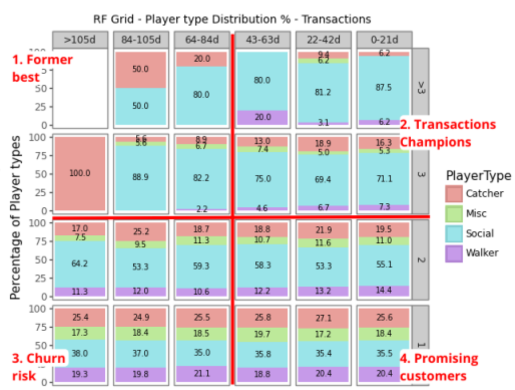


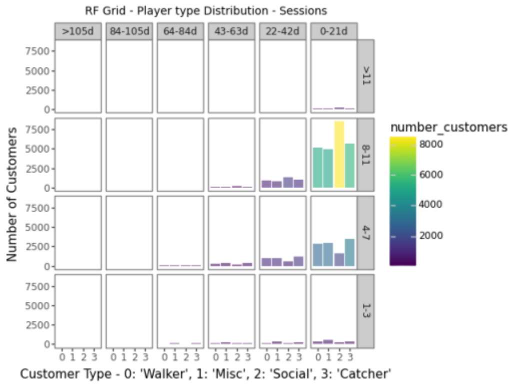
Players' seniority was measured using their registration date. According to the analysis, new players (0-1 years, purple) are the most active, which indicates the highest level of engagement. Over time, engagement seems to decrease, as evidenced by the lower proportion of players who have been playing for a longer time in the high-activity segment. New players are extremely engaged but may lose interest over time.

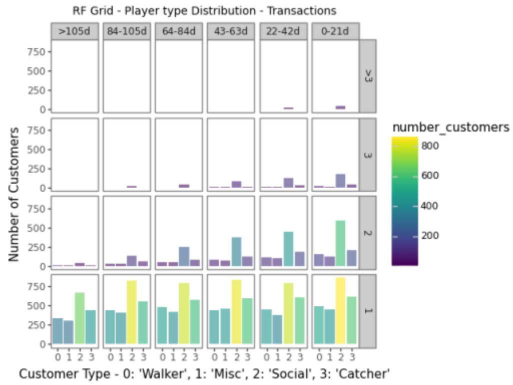
New players are more likely to make purchases, and to purchase again, which really shows how addictive and entertaining the game can be in the first year. While older players (>6 years old, yellow) rarely engage in purchases, it is suggested that they have no interest in buying in-game items or they just don't see any value in doing it.

Finally, we integrated Niantic's standard segments into the lifecycle grids.



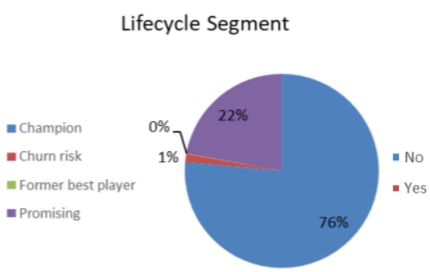


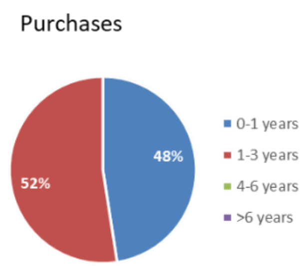


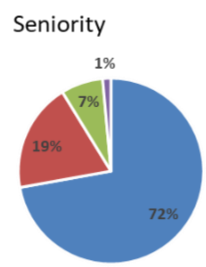


From this, we broke down each player type to understand their logic.

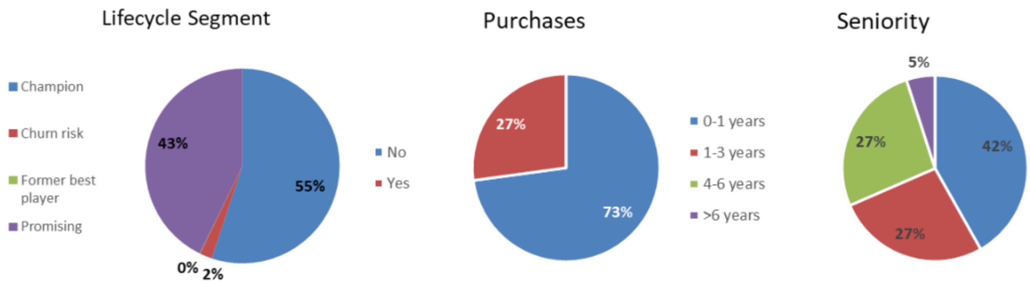
- **Socials:**
  The most engaged and top-spending players, mostly composed of champions. Based on that, they are an ideal target for premium purchases and special events. The opportunity is to retain them and grow the in-game purchases. They are likely to spend money on raid passes to play with their friends. What's important to notice is also that the majority (72%) of them have played the game for less than a year.



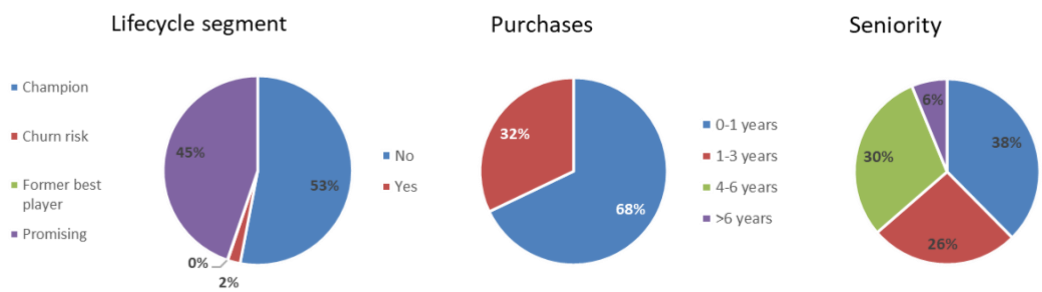




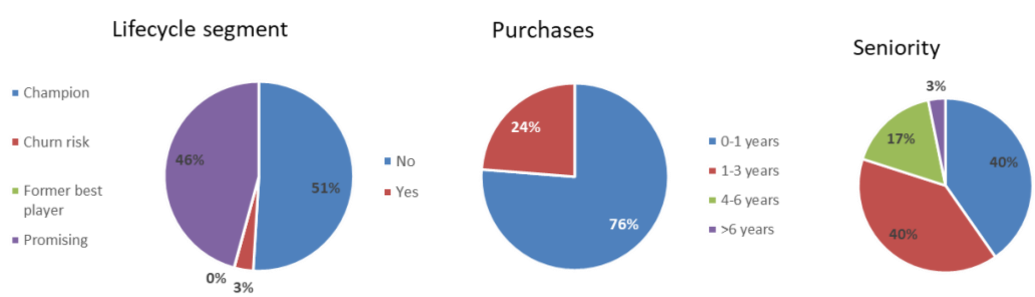
- **Walkers:**
  Here there are both new players in the hype (champions) but also promising (established). They have a moderate session time. This group does not show as much willingness to spend, with 72% of them not having made any transactions. This makes sense as they do not need to pay to enjoy what they like from the game. Nevertheless, 58% of them are established, with more than a year of seniority, showing that they can stay in the long run.



- **Catchers:**
  They are mainly champions and promising players. This is the most senior segment with 62% of the players having played for more than a year so it's key to continue developing their interest in the game. Most of them do not make transactions showing that their interest in the game does not need investments.



- **Miscellaneous:**
  They are the hardest player type to analyze as they show interest in all the aspects of the game, and they still hardly make transactions. Still a very important segment of players as a lot have played for a long time showing their loyalty.



Churn Analysis

Churn or churn ratio are the customers that stopped using a product or service and abandon the company. There is not a single business that doesn't have any churns, customers often move from business to business but in general it is good to know how frequently customers are leaving a business and how many customers are leaving. In this case, churn is defined as the players that played and paid in summer but stop paying in the fall period. The main idea behind this is to analyze this number as well as the demographics behind it, and the principal reasons or factors that affect or influence the churning to implement strategies to reduce the churning in any period.

After identifying the customers who churned during the fall period (the ones who played and paid in summer but did not pay in fall), descriptive statistics were conducted to uncover key characteristics of these users. A total of **5,172 churners** were identified, resulting in a **churn rate of 30.12%**. To determine the most relevant attributes, a t-test was performed, comparing their characteristics against the overall sample average. This approach helped highlight meaningful differences while excluding variables like gender and age, which showed no significant variation.

The most important characteristics of churned users are:

Less loyal and less engaged players

- They have been playing for fewer days (444 days vs. 578 days for non-churners)
- They have caught fewer Pokémon (134 vs. 150) and visit fewer PokéStops (117 vs. 125)

More Social but Less Retained

- Churners engage in more raids (6.27 vs. 4.53) and have higher social activity (10.5 vs. 7.5)
- Social players are more prone to churning

Impact of fall bonus

- Fewer churners received the Fall Bonus (16% vs. 22%), indicating that receiving incentives may have helped retain players.

Then, since the entire analysis is based on a defined customer type segmentation, the churn rate for each customer type was calculated. Additionally, the relevant characteristics were identified.

Customer Type	Walkers		Miscellaneous players		Social Raiders		Catchers	
	Churners	Non-churners	Churners	Non-churners	Churners	Non-churners	Churners	Non-churners
Value (total duration)	**572**	**573**	**329**	**351**	**1,080**	**1,086**	**225**	**222**
Fall Bonus	**16%**	**22%**	**19%**	**20%**	**16%**	**24%**	**16%**	**20%**
Days Joined	**682**	**728**	**501**	**567**	**284**	**326**	**708**	**805**
Churn	**23%**	**77%**	**25%**	**75%**	**40%**	**60%**	**22%**	**78%**

Social Raiders have the highest churning rate

- Social raiders have the highest churn rate at **40%**, significantly higher than other customer types, which suggests a seasonal engagement. In summer they have more time to spend time and play with their friends. So, it's important to focus on a way to keep this group motivated and remain in the game.

Walkers and catchers are more loyal

- Walkers and catchers show lower churn rates (23% and 22%, respectively), indicating a more stable, long-term engagement with the game.

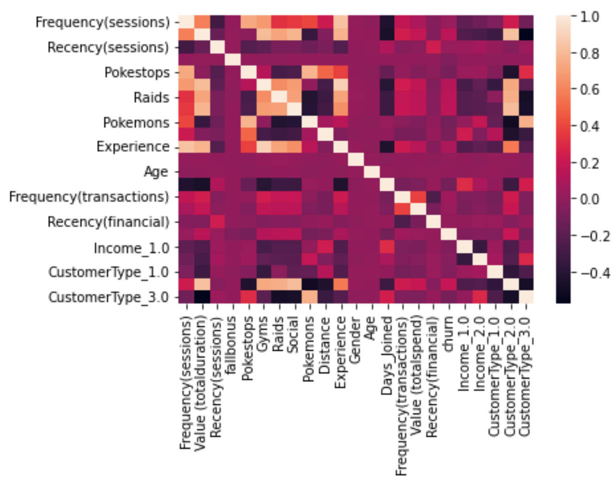
Also, the insights extracted from the previous analysis were validated, as the fall bonus seems to impact churn in every customer type. Additionally, the longer a player has been registered in the game (or the more days since they joined), the stronger their connection with the game, making them less likely to churn.

On the other hand, in the case of miscellaneous players, there are other important factors that may affect churn, such as the total session duration, which is usually lower for churners on average.

After performing the descriptive statistics, the next step was to build a model to predict churn. In this case, the data was first split into train and test sets, using stratification based on the churn, as the data is unbalanced.

Split the data into test and train to avoid overfitting the model with the same data. After that proceeded to compute the correlation matrix of the numerical independent variables to not consider them all in the model and avoid multicollinearity. If there were pairs of variables with high correlation between them, then there had to be a decision to keep the most representative variable of each pair.

Below is the resulting correlation matrix for the model. As it can be seen from the legend, light colors represent high correlation while dark colors represent low correlation. Frequency(sessions) and recency in sessions have high correlation between them, Pokemons and experience also, Frequency(transactions) and recency(transactions) do too and pokestops and raids are the final pair with high correlation. If we were to keep only half of the variables, we would keep Frequency(sessions), pokemons, Frequency(transactions) and pokestops. For the project these are the ones that make the most sense considering the scope of the project if to see the impact of the game on people and the number of churns.



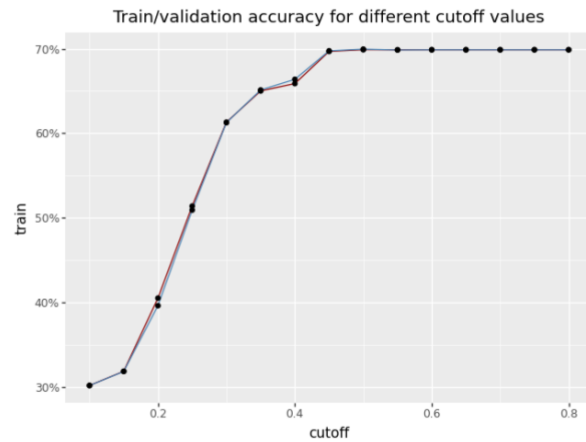
In the end, it was decided to use a bidirectional stepwise method for choosing the independent variables that are most significant when it comes down to predicting if a customer will churn or not. The way the method works is through 4 easy steps. First, decide whether starting with an empty model filling it in with the variables (forward) or with a complete model removing variables in each step(backwards), then use the forward step to add variables one by one and checking if the model improved based on a metric like the p-value or Akaike model criterion. After adding each variable to the model, it needs to be checked if the addition of the variable affected the existing variables by becoming significant or insignificant, in the case are insignificant remove them. This is an iterative process that needs to be done until the metrics don't vary that much.

After choosing the significant variables, a logistic model was used to determine if the selected variables together could predict if a person would churn or not. In the next there can be seen:

```
'Recency(sessions)']
                           Logit Regression Results
==============================================================================
Dep. Variable:                  churn   No. Observations:                12019
Model:                          Logit   Df Residuals:                    12013
Method:                           MLE   Df Model:                            5
Date:                Mon, 24 Feb 2025   Pseudo R-squ.:                 0.03575
Time:                        17:40:00   Log-Likelihood:                -7091.1
converged:                       True   LL-Null:                       -7354.1
Covariance Type:            nonrobust   LLR p-value:                2.105e-111
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
intercept            -0.6100      0.121     -5.029      0.000      -0.848      -0.372
CustomerType_2.0      0.6172      0.051     12.088      0.000       0.517       0.717
fallbonus            -0.3879      0.053     -7.306      0.000      -0.492      -0.284
Days_Joined          -0.0003   4.24e-05     -7.182      0.000      -0.000      -0.000
Pokestops            -0.0029      0.001     -3.996      0.000      -0.004      -0.001
Recency(sessions)     0.0044      0.002      2.818      0.005       0.001       0.008
=====================================================================================
```

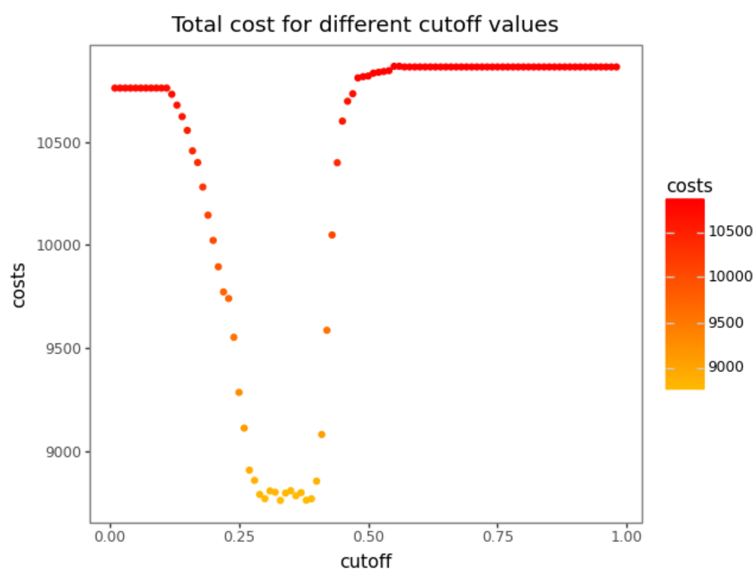
Img. Logistic regression results.

Based on the results of the logistic regression model displayed above the variables that were included in the final model can be seen. customerType_2.0 are the social rider players, Fallbonus is whether they received the bonus or not, days_joined are the days since they started playing the game, pokestops are the number of pokestops visited by each player and recency(sessions) is how long ago they stopped playing. When analyzing the results of the model, the p-value can tell us if the inclusion of a certain variable was significant in the model when it comes down to predicting the churn of a player. P-values should be lower than 5% for most studies but in this case the variables are significant also for a threshold of 1%, this means it can be said with certainty that there's less than 1% chance that the values found are random. Now when it comes down to seeing which variables affect the model in a positive or negative way, all the negative coefficients reduce the chance of a person churning while the positive coefficients induce higher churning probabilities. Only customerType_2.0 and recency(sessions) increase the likelihood of someone churning and fallbonus, days_joined and pokestops reduce it. It's important to focus on all the variables specially the ones that can be changed, in the case of custometype2 is something part of the game so there should be activities and rewards focused on these types of players which apparently are not being satisfied, regarding the recency there have to be implemented some strategies to avoid players for not playing recently, analyze the times that the joined the game, the activities they completed and the events and pokemon that were present during their session, this can give an idea on why they haven't played recently.



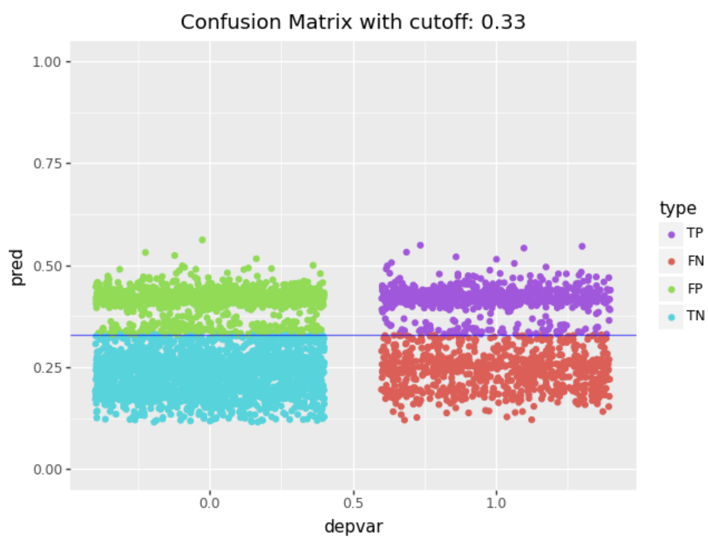
Img. Accuracy vs cutoff.

The graph above shows the relationship between accuracy and cutoff. In this case is how to find the best accuracy for the model according to a cutoff(probability) of a customer being classified as a churner or not churner. Between 0.1-0.3 the value for accuracy is low but gradually increases until it reaches a value between 0.35-0.46 where the accuracy is at its highest and then for values above 0.7 the accuracy doesn't change which suggests that higher values don't improve the results for the model.



Img. Cost vs cutoff values.

The second approach to find the optimal cutoff with precision and recall was one using the costs of players. FN (players that are churners, but the model classifies them as non-churners) were estimated using the average CLV of players paying in summer. Meanwhile, the FP (incorrectly predicting and non-churner player as a churner) were estimated using the minimum coin package a player can be which is $2.99. The minimum price package was used for the FP because this way the costs are not being overestimated in reality many of the people that churn in a business don't have high spendings; Additionally this way a company can use their resources in a conscious way to not overspend and give extra things(money) to customers that aren't worth it. The total cost that can be seen on the Y-axis was computed using a formula that considers the ratio of FN-FP with its price. Cutoff values between 0.27-0.38, the smallest value can be found; this helps minimize costs and spend money on excess.



Img. Confusion matrix categories proportion.

	Predicted 0	Predicted 1
Actual 0	2532	1067
Actual 1	796	756

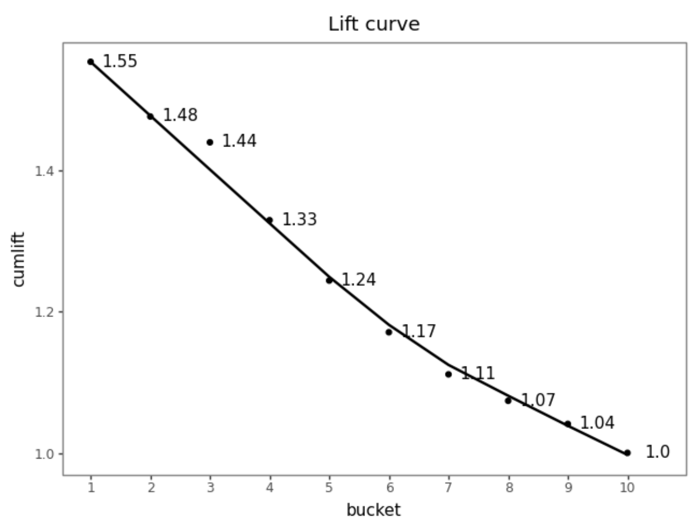
- **Percentage of churn in the training dataset:** 30.12%
- **Percentage of churn in the test dataset:** 30.13%

Model Performance metrics:

- **Accuracy Score:** 63.83%

- **ROC AUC Score:** 61.71%
- **Precision Score:** 41.47%
- **Sensitivity (Recall):** 48.71%
- **Specificity:** 70.35%
- **F1:** 44.22%

The most important metrics for the project are Precision and Sensitivity. The objective of the project is to identify if predicted churners churned and how many of the actual churners were correctly identified. 41.47% were predicted as churns and they churned and 48.71% of actual churns were identified. This is important because this way a company can analyze and act before people become churners without investing extra resources on people that are faithful customers.



Img. Lift Curve.

The lift curve shows the performance of a predictive model by comparing the results of a particular model and random guessing. Y-axis represents the ratio of predicting correctly the churns and X-axis represents predictions in different groups. The model performs good but not great because in the first “try” the logistic model predicted better a churn than just choosing a randomly. The values decrease gradually until the last group of predictions were the same as just choosing random values and picking the churns.

Conclusion/Recommendations

Key learnings summary:

- Main age groups: 0-18yo & 26-32yo
- 60% Male players & payers
- Half of the players who pay have a low income -> to be kept in mind when setting prices.
- Players are the most engaged during their first year of playing: it is a key timing to make them stay longer.
- Players are also more likely to pay during their first year of playing: the features need to make them feel like it was worth it.
- A lot of players make one purchase but don't do it again: this also needs to be addressed.
- Social players are the most active & spend the most, but they are also much more prone to churning.
- Other player types pay less but are more loyal.
- Fall bonus had a positive impact leading to less churn.

Understanding Pokémon GO players' engagement reveals key differences in actions, involvement, and spending habits across player types. While the player type tells us the favorite activity of the player, the lifecycle segment guides us in which strategy to implement and the target KPI we should look forward to improving with selected tactics.

When analyzing player churn, it becomes clear only a few variables impact the prediction. The focus should be on variables tied to engagement. For example, custometype2 is part of the game so there should be activities and rewards designed to satisfy these players. Recency is another important factor; strategies should focus on encouraging players to make players want to return to the game and play before it's too late. This involves analyzing metrics like time spent during the session, time of the day the session was played, what activities they completed and which events they were part of and what pokemons they were able to catch. Understanding these patterns can be beneficial to triggering specific emotions and reactions in players, making them susceptible to coming back to the game. On the other hand, variables like Fallbonus, days_joined and pokestops reduce churn rates. Therefore, it's important to continue offering top quality service when it comes down to variables like these.

The implementation of CRM strategies will allow Niantic to maintain top players, increase spending, and actively re-engage players at risk of churn. Personalized tactics are recommended and can be triggered according to appendix 1. In general, there are two main strategies that Niantic should follow:

1. Retention: for new and established players to keep them engaged. This must be focused according to the preferred activity of the player inside the game.
2. Growth/Development: for players willing to spend it is key to improving the added value of in-game purchases, also increasing third party activities to promote external monetization.

Here are our first, easiest recommendations to put in place, one free and one paid for each customer types (except miscellaneous, who can be attracted to any of these new features):

- **Trainer Support (*Volkner*):** Reminder to keep entertaining the different types of players. Rotate the campaigns to keep the game interesting for everyone.
- **Social players (*Raidchu*):**
    - ***Free:*** Promote social interactions by establishing objectives that can only be achieved as a group. Gives items.
    - ***Paid:*** Organizing online raids for players who do not have the time to meet in person but would still like to engage in social events. It would require a 'raid pass' (to be purchased).
- **Walker players (*Walktortle*):**
    - ***Free:*** Set high-distance goals every day (moderately high), this will encourage walkers to participate. Gives items.

- *Paid:* Organize walks using special itineraries that players must follow to win prizes. It would require a ‘city pass’ (to be purchased).

- **Catcher players (*Catcherpie*):**
  - ***Free:*** Set a weekly catching target so players will be motivated to play. Gives items.
  - ***Paid:*** Create Mega incense to attract customers in the player’s area without moving, aligned with the game’s collecting-based gameplay. It would be purchased through the store.

Below are more advanced recommendations to improve player retention, boost engagement, and increase revenue in the long term:

Lifecycle segment	**Marketing Strategy**	**KPI**	**Tactics (for Miscellaneous, apply all)**	**Business impacts**
Champions	Retention	Maintain frequency	<u>*All:*</u> Send a monthly reward to players who managed to be in the Champions segment, with a little congratulation text such as ‘‘Congratulations! You placed among the top players/buyers this month, here’s a reward for you’’ Create a monthly ranking with top10 players in the country - VIP reward Provide personalized support to the VIP players to make them feel valued. Implement a premium pass system allowing players to earn more rewards based on their progress and with more daily objectives <u>*Socials/Catchers/Walkers:*</u> Implement congratulation messages such as ‘Congratulations! You placed among the top raid winners/top catchers/top distances this month, here’s a reward for you’	Avoid disengagement and develop long term players. Recognize the players' value and show them we appreciate so they keep playing with pleasure.
Champions & Promising	Growth / Development (up sell)	Increase in-game and external monetization	<u>*All:*</u> Implement a one-time discount for players who have been playing for six months but have never purchased anything. Can be applied in the whole shop to make sure all player types	Convert highly engaged players into repeat spenders (building habits of spending through loyalty incentives).

			find something to buy (raid passes, city passes, incenses etc.). Introducing a loyalty program for players to receive free bundles after every 3 purchases. *Socials:* Implement a ranking among friends, establish a monthly recognition for the best achievements by player Introduce a clan system where groups of players can feel more connected and can battle against other players in completing challenges to gain bonus points and XP. *Catchers:* Unlock exclusive in-game items (e.g., Incubators, Lucky Eggs) **for free** after catching special pokemons. *Walkers:* Implement a daily target system allowing players to earn more rewards based on the places visited and with more daily objectives Establish partnerships with restaurants, coffee shops, and activity centers to offer exclusive in-game rewards for players who go there.	Keep the game entertaining to make sure they keep playing in the long run.
Promising	Growth / Development (up sell)	Up sell and first purchases	*All:* New Player Streak Challenge: Reward players who play for 7 days straight with a discounted bundle Seasonal bonuses so they can also enjoy free stuff. *Socials:* Introduce group-exclusive discounts: If friends in a Raid Lobby purchase a Remote Raid Pass, everyone gets a small bonus (e.g., free Potions to heal their pokemons after battles)	Encouraging first purchases with low-cost entry offers. Leveraging their playstyle to offer tailored discounts (social, catching, walking) Convince them to play more and for a long time.

			If a social player invites a friend to a Raid, they receive a discounted Raid Pass. *Catchers:* Offer "My First Bundles" with a mix of PokéBalls, Incense, and Lucky Eggs at a low price ($0.99) *Walkers:* Special Adventure Pack during Community Day, targeting Walkers & Catchers (discounted Incubators & Lures). Bonus items for walking milestones that unlock a discount on Incubators & Incense. "Trainer, your adventure is just beginning! Your next purchase comes with a 20% bonus!"	
Churn risk	Selective win back	Recover frequency	*All:* Re-engagement Through Nostalgia & Personalization: Personalized “Special Gift for Returning Trainers: A Raid Pass & Lure Module just for you!” Targeted Email: “What You’ve Missed” → Show big updates since they quit. *Socials:* “Come Back with a Friend” Bonus: If a returning player teams up with an active friend, they both get a free Raid Pass or increased trading range *Catchers*: Give them a bundle of Poké Balls and show nearby Pokémon they haven't caught	Show them updates in the game that they might like so they come back. Leverage their likings to lure them back in the game.
Former best player	Win back	Recover frequency	*All:* Send them a friendly message & reward: ‘You were among the top X% players, come back and reclaim your spot! Here’s a little booster for you, to thank you and help you get back into the game!’	Show them we recognize their value & we want them back.

With these segmented engagement strategies, Niantic can substantially increase daily active users, greatly improve retention, as well as create much more engaging, plus exceptionally dynamic in-game experience. Business partnerships, CRM-driven loyalty programs, and player-specific incentives will increase and sustain long-term engagement, maximizing profits.

Appendix

Appendix 1: Example of individual guide for personalized activation

Link to the sheet:

https://docs.google.com/spreadsheets/d/1KiXCqwSyqSTSxj9JocVrWb6SZIsILpR5/edit?usp=sharing&ouid=105985096361933459121&rtpof=true&sd=true

Customer	PlayerTyp	Lifecycle grid Segme	Lifecyle stage	Marketing strate	Objective 1	Objective 2
1	Social	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
2	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
3	Misc	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
4	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
5	Misc	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
6	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
7	Social	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
8	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
9	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
10	Misc	Churn risk	Attrition	Selective win back	Recover frequency	Purchase or participation in monetized event
11	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
12	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
13	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
14	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
15	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
16	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
17	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
18	Walker	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
19	Misc	Champion	Attraction	Retention	Maintain frequency	Increase purchases
20	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
21	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
22	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
23	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
24	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
25	Walker	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
26	Walker	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
27	Misc	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
28	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
29	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
30	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
31	Social	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
32	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
33	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
34	Misc	Champion	Attraction	Retention	Maintain frequency	Increase purchases
35	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
36	Social	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
37	Walker	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
38	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
39	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
40	Misc	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
41	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
42	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
43	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
44	Walker	Champion	Attraction	Retention	Maintain frequency	Increase purchases
45	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases
46	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
47	Catcher	Champion	Attraction	Retention	Maintain frequency	Increase purchases
48	Catcher	Promising	Growth/Retention	Development	Increase frequency	Up sell or 3rd party monetization
49	Social	Champion	Attraction	Retention	Maintain frequency	Increase purchases

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