AI-Driven Retention Improvement Case Study

Redesigning the First-Week Experience for a Music Streaming App

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Product & Data | Consumer App Retention | Activation Strategy

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****Assumptions & scope (please read)****
This case study is an assumption-driven product analysis that uses publicly-known industry heuristics and hypothetical baseline metrics. No internal or proprietary data was used. The numbers and cohort estimates included are illustrative and used to demonstrate product reasoning, experiment design, and prioritization.

Redesign first-week experience to increase Week-1 retention (assumed baseline 18% → target 28–30%) by improving onboarding personalization, activation flow, and Day-1 reactivation.

Improving Week-1 Retention for a Music Streaming App
A student product case study on onboarding, activation, and habit-building

Author: Mohith Pulavarthi
Role I'm Targeting: Product / APM roles
Project Type: Self-initiated case study (assumption-driven)
Timeline: ~1–2 weeks of part-time work
Tools: Notion (documentation), Figma (wireframes), Sheets/Excel (metrics thinking)

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1. Introduction & Problem Context

Over the last few years, I have spent a lot of time using music and video streaming apps. One pattern I noticed as a user is that I install many apps, try them once, and then never open them again. When I started exploring product management, I realized this behavior is exactly what hurts consumer apps the most: they pay to acquire users who simply do not come back after the first few days.

This case study is my attempt, as a student, to think like a Product Manager working on that problem.

I imagined I had joined the product team of a generic music streaming app (not tied to any specific company) and was asked a simple but important question:

How can we redesign the first-week experience so that more new users actually come back and become retained users?

Because I do not have access to real company data, I worked with **assumed baselines** that are reasonable for a streaming product: around **22% Day-1 retention**, **18% Week-1 retention**, and **25% activation rate** (users who perform at least one meaningful action like completing a play, liking, saving, or following). These numbers are taken from publicly-discussed industry ranges and used only for reasoning, not as real internal data.

The core business problem is straightforward:

- The app is acquiring new users,
- but **more than 70–80% of them stop using it within the first week**,

- which means a lot of marketing spend is wasted and the product never gets enough time to learn user preferences or build habits.

In this project, I focused on three specific parts of the early experience:

1. **The first session** – what a new user sees and does in the first few minutes after signup.
2. **The activation moment** – the first time a user does something meaningful (like completing a song, saving it, or following an artist).
3. **The first week** – whether the user actually comes back on Day-1 and a few more times in the first seven days.

My goal was not to design a perfect product, but to show structured product thinking as a student:

- understand the problem and user behavior
- map out where users drop off in the funnel
- identify the key drivers of retention
- propose a small set of high-impact product changes
- outline how I would test and execute these changes if I were on the team.

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2. How I Approached the Problem (Research Approach, Assumptions & Scope)

Since this is a self-initiated project done without access to real internal data, my first step was to define **a realistic problem boundary**, make **clear assumptions**, and set **simple rules for myself** so the case study feels grounded and not theoretical.

2.1 What I Started With

When I began, all I had was:

- my experience as a frequent user of streaming apps
- publicly discussed industry benchmarks
- my understanding of early retention challenges
- a few metrics ranges typical for consumer apps

There was no dataset, no product team, and no user interview resources. So my approach had to be structured and assumption-driven, but also practical enough to resemble how a junior PM would think.

The first decision was to **narrow the project**. I did not want to redesign the entire app or imagine complex algorithms. I wanted to focus only on the period where churn is the highest: the **first 7 days** of a new user's journey.

2.2 Assumptions I Made

To make the analysis consistent, I defined a set of working assumptions that guided the entire project. These were inspired by common patterns seen across streaming apps and were used only for reasoning:

- **Day-1 retention baseline**: ~22%
- **Week-1 retention baseline**: ~18%
- **Activation rate baseline**: ~25% (meaningful action: play completion, like, save, follow)
- **Largest drop-offs** happen before the first meaningful action.
- **Onboarding is mostly generic** and personalization usually starts after the first few interactions.
- **Signup → Homepage load:** ~70%
- **Homepage → First content click:** ~45%
- **First click → First play completed:** ~28–30%

These numbers are not meant to be accurate data—they simply help frame the funnel and create a believable context for decision-making.

2.3 What Was In Scope

I kept the project deliberately tight and focused:

In Scope

- First-session experience (first 5–10 minutes)
- New-user onboarding flows
- Activation moment design (first play, like, save, follow)
- Early personalization challenges
- Day-1 → Day-7 habit building
- A simple 12-week execution plan

- High-level A/B test strategy

Out of Scope

To make the project manageable, I excluded:

- long-term retention or subscription funnels
- advanced recommendation system architecture
- creator ecosystem features
- backend engineering design
- legal or policy constraints

As a student, focusing on everything at once would create noise. Limiting scope helped me think like a PM making trade-offs with limited time and resources.

2.4 How I Broke Down the Problem

To avoid getting lost in the complexity, I divided my work into three main questions:

1. **Where exactly are new users dropping off?**
   (This led me to map the first-session and first-week funnel.)
2. **What behaviors predict whether a new user will return?**
   (This pushed me to identify activation events and retention drivers.)
3. **Which product changes can realistically improve Week-1 retention?**
   (This guided the final solution set.)

This simple three-question model helped me stay focused and avoid over-designing the product.

2.5 How I Evaluated My Own Work

Since I wasn't working with a real PM team, I used my own criteria to judge whether my reasoning was meaningful:

- Does each insight connect directly to a point in the funnel?
- Does each proposed solution fix a real behavioral problem?
- Can the solution be built within ~12 weeks?
- Would this make sense if I were explaining it in a PM interview?

This forced me to avoid unrealistic ideas and stick to simple, high-impact solutions.

2.6 What I Wanted to Learn

As a student, this project was also a learning exercise. I wanted to understand:

- How early personalization affects user retention
- Why activation events are so critical
- How to spot the biggest drop-offs in a funnel
- How PMs prioritize features with limited data
- How to structure a case study that feels real and PM-like

This mindset shaped the entire direction of the project and kept it grounded.

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3. Understanding the User (Personas, Motivations, Pain Points & First-Session Behavior)

Before jumping into solutions, I wanted to understand what new users typically expect from a streaming app and why so many of them leave within the first few minutes. Since I didn't have access to real user interviews, **I relied on:**

- my own usage patterns,
- conversations with friends,
- common behaviors seen in streaming apps, and
- documented industry insights around early retention.

This helped me build a simple but realistic picture of new-user behavior.

3.1 Personas (Simplified & Practical)

Instead of creating too many personas, I focused on three broad types that capture most early behaviors. These are not fictional characters—they reflect real tendencies I've observed.

Persona 1: The Explorer (16–30 years)

This user opens the app out of curiosity.
They scroll, sample a few songs or videos, and decide very quickly whether the content feels relevant.

What they care about:

- fast, engaging content
- popular or trending items
- variety

Risk:
They drop off in 10–20 seconds if nothing clicks.

Persona 2: The Hobbyist (22–40 years)

Someone who already knows what they like—specific genres, artists, moods.

What they care about:

- personalization
- building playlists
- consistent recommendations

Risk:
If the app feels generic, they don't trust it and don't invest time.

Persona 3: The Power User (20–45 years)

These are long-session users: study playlists, workouts, travel modes.

What they care about:

- uninterrupted sessions
- reliability
- smooth playlists

Risk:
Low—they typically stay, but only if the app meets performance expectations.

3.2 What Motivates New Users

Across these personas, I noticed a few motivations that appear consistently:

- They want **something relevant, fast**.
- They want to discover **new content**, not irrelevant suggestions.
- They want to **build a small personal library** eventually.
- They want the app to feel **made for them**, not generic.
- They want the experience to be **simple**, especially in the first session.

If the app fails on these in the first few minutes, retention almost always suffers.

3.3 Pain Points (Why They Leave Early)

From both personal experience and common product patterns, new users tend to leave because:

1. Generic Homepage

The home feed often shows random or broad categories (Trending, Top Hits), which do not feel personalized yet.

2. Decision Overload

Too many carousels, too many genres, too many choices.
Users freeze instead of clicking.

3. Weak or Irrelevant First Play

If the first song/video doesn't match their taste, they skip instantly.
If they skip 3–4 times in a row, they assume the app doesn't understand them.

4. Empty Library Problem

New users start with zero playlists, zero creators followed, zero favorites.
This makes the app feel cold.

5. Poor Search Experience

Some users join with a specific song in mind.
If search is slow or results feel off, they churn immediately.

6. Early Ads, Permissions, or Prompts

Pop-ups can break momentum, especially in the first session.

These pain points guided how I later structured the funnel and designed the solutions.

3.4 First-Session Behavior Patterns (What Users Actually Do)

While thinking through the new-user journey, I noticed three common behavioral patterns (all of which I've personally done many times):

Pattern A: The Quick Sampler

Scrolls fast → opens 1–2 items → skips → leaves.
These users churn if they don't see something for them immediately.

Pattern B: The Direct Searcher

Opens the app → searches for one specific song/video → plays it → leaves.
This user may not explore anything else.

Pattern C: The Indecisive Drifter

Scrolls endlessly without choosing.
Too many options → cognitive overload → exit.

These patterns strongly influenced my thinking around activation and early personalization.

3.5 Why Understanding Users Mattered for My Case Study

This entire section shaped the rest of the project because it helped me answer three key questions:

1. **Why do users leave so quickly?**
2. **What moments define whether a user returns?**
3. **What parts of the first-session experience need redesigning?**

It became clear that the biggest impact would come from:

- fixing the first 20–30 seconds
- helping users reach a strong first play
- guiding them toward at least one meaningful action.

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4. Funnel Breakdown & Drop-Off Diagnosis

Once I had a basic understanding of user behavior, my next step was to map out the **new-user funnel**. Even though I did not have real product analytics, I relied on industry baselines and the assumption-driven funnel structure I outlined earlier. My goal was simple:

Find exactly where new users disappear and why.

Streaming apps typically lose most of their users before any meaningful interaction happens. When I looked at the assumed numbers, this pattern became very clear.

4.1 The Assumed New-User Funnel (What Happens to 100 New Signups)

Using the baseline metrics from industry patterns, I reconstructed a simplified funnel to understand the drop-offs:

Funnel Stage	Users Remaining	What Happens Here
App Install → Signup	100	Starting point
Signup → Homepage Load	~70	30% vanish due to friction or low intent

Homepage → First Content Click	~45	Many users see irrelevant or overwhelming content
First Click → First Play Completion	~28	If first play isn't relevant, users skip and leave
First Play → Activation Event	~25	Only a small group performs a meaningful action
Activated Users → Day-1 Return	~22	No strong trigger to come back
Day-1 Users → Week-1 Retained	~18	Habit never forms

This funnel was the turning point of my project because it showed something very important:

From this funnel, the most important drop-offs are:

- **Signup → Homepage:** 30% users drop immediately
- **Homepage → First-play completion:** only ~28% finish even a single track
- **Activation:** only ~25% perform a meaningful action
- **Day-1 return:** stabilizes around ~22%
- **Week-1 retention:** drops to ~18%

Most retention problems occur before the user even forms an opinion about the product.

4.2 Where the Biggest Drop-Offs Happen (The Three Critical Cracks)

After plotting the funnel, I highlighted the three biggest leaks. These are the moments that heavily affect retention and therefore require the strongest product intervention.

1. The Cold Start Drop-Off (Signup → Homepage)

Roughly 30% of new users never make it past the first screen after signup.

Why?

- slow load
- generic homepage
- confusing layout
- too many categories
- no clear start here

This told me that **personalization cannot start after the first play—it has to start before the user even sees the homepage**.

2. The First-Play Drop-Off (Homepage → First Play Completion)

Only ~28% of users complete even one full song or video.
This is a massive problem, because:

- completion signals interest
- completion feeds the recommendation algorithm
- completion is strongly correlated with Day-1 return

If the first play is irrelevant, everything after that becomes harder.

This is where activation either happens or dies.

3. The Activation Drop-Off (First Play → Meaningful Action)

Even among users who complete a first play, only ~25% perform any meaningful action like:

- like
- save
- follow

Low activation means:

- personalization is weak
- notifications have nothing relevant to send
- no emotional investment from the user

This is the second-biggest predictor of retention.

4.3 Behavioral Insights from the Funnel

Looking at the funnel as a whole helped me surface insights that shaped my final solutions:

Insight 1 — Early Personalization Matters More Than I Thought

I originally believed personalization would kick in *after* a few plays.
But the funnel showed that **most users don't even reach enough interactions for personalization to learn anything**.

Meaning: The product needs to personalize faster.

Insight 2 — The First 1–2 Plays Decide Everything

If a user's first two interactions are irrelevant, they leave permanently.

This made me rethink:

- the first content recommendation
- the activation flow
- the first-play post-screen
- the entire Day-0 experience

Insight 3 — Activation Is the Backbone of Retention

I didn't expect activation to be such a powerful predictor until I connected the funnel to retention drivers.

Users who complete just one meaningful action (like/save/follow) are far more likely to return on Day-1 and Day-7.

This dramatically influenced the design of my product solutions later.

4.4 How Funnel Insights Influenced My PM Thinking

As a student, this was the part of the exercise where the problem became real.
Instead of imagining random features, the funnel forced me into **targeted thinking**:

- **Fix the first impression** → personalization before homepage
- **Guide the first meaningful action** → activation-first play flow
- **Give users a reason to return** → Day-1 habit triggers

These insights directly shaped the three product bets I prioritized.

4.5 Summary: The Three Biggest Levers to Improve Week-1 Retention

From the funnel, I identified three levers that would have the highest impact:

1. **Personalize the first screen** so users don't bounce before engaging.
2. **Guarantee a strong first play** and guide users into meaningful actions.
3. **Create a clear Day-1 return trigger** to start habit formation.

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5. Key Insights & Retention Drivers

After mapping the funnel and understanding user behavior, I started seeing clear patterns that explained why Week-1 retention was so low. What surprised me most was how early the problems start. By the time users reach Day-7, the retention outcome is already decided by what happened in the **first 10–20 minutes**.

In this section, I summarize the insights that shaped my final product decisions. These are written as I understood them during the project — not as universal truths, but as findings based on the assumptions and behavior patterns I studied.

5.1 Insight 1 — The First Session Is the Entire Story

Initially, I thought Week-1 retention would depend on content quality or notification timing. But the funnel made something else obvious:

If the first session is weak, the rest of the week doesn't matter.

Most users churn **before** giving the app any real signal:

- they don't complete a play,
- they don't save anything,
- they don't follow anyone.

Because the personalization system has nothing to learn from, the app cannot improve.

This shifted my focus heavily toward **fixing the first screen and the first play**.

5.2 Insight 2 — Personalization Must Start Before Homepage

Streaming apps rely on algorithms, but algorithms need data. The problem is:
new users don't generate enough data before leaving.

This creates a chicken-and-egg problem:

- app waits for user signals,
- user waits for relevant content.

As a student PM, this taught me an important product lesson:
cold start personalization cannot come later — it must come first.

This insight influenced my decision to design a lightweight **Taste Picker** that appears *before* the homepage.

5.3 Insight 3 — Activation Is the Strongest Predictor of Retention

When I connected the funnel to behavioral patterns, this clicked:

Users who perform even **one meaningful action** (like, save, follow) are far more likely to return the next day.

Activation is not just another metric.
It's the backbone of retention because:

- It builds emotional investment (I saved something. This app is for me.)
- It feeds the recommendation engine immediately.
- It unlocks personalized notifications.
- It sets up a reason to return (e.g., continue your playlist).

This insight shaped my second product solution:
a guided first-play activation flow.

5.4 Insight 4 — The First Play Determines Everything That Follows

One thing I learned while studying user behavior is how emotional the first play is.

If the first song/video feels perfect:

- users trust the app
- skip rates drop
- they explore more
- they save or follow
- they return the next day

If the first play feels wrong:

- instant skip
- distrust
- exit
- no signal for personalization
- no reason to return

This taught me something important for PM thinking: **what happens in the first 1–2 plays is worth weeks of notifications.**

5.5 Insight 5 — Day-1 Return Is the Habit Moment

While studying retention curves, I found that **Day-1 return** is a much stronger predictor of long-term retention than Day-7 or Day-14.

If users don't return the next day, they rarely return later.

Why?

Because habit loops form early:

- trigger
- action
- reward

If the Day-0 session creates no trigger (save, playlist, follow), the user has no reason to come back.

This insight directly led to my third product idea:
a personalized Day-1 return engine (notification + in-app prompt).

5.6 Insight 6 — Most Drop-Offs Happen Before Users Feel the Product

Before this project, I used to think churn meant users didn't like the app.
But after mapping the funnel, I realized:

Users don't even get far enough to form an opinion.
They churn because:

- onboarding is generic
- homepage is overwhelming
- first play is not strong
- no activation event happens
- nothing pulls them back

This was a shift in understanding for me.
It made me focus more on **reducing early friction** than adding new content or features.

5.7 Summary: The 3 High-Leverage Retention Drivers

From all these insights, three retention drivers emerged as the highest impact for Week-1:

1. Personalized First Session (Fix Cold Start)

- improves first-click relevance

- reduces skip rate
- increases chance of a strong first play

2. Early Activation (Like/Save/Follow)

- feeds personalization
- increases emotional investment
- correlates strongly with Day-1 return

3. Day-1 Return Trigger (Start Habit Loop)

- reinforces early engagement
- increases Week-1 retention
- creates a consistent usage rhythm

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6. Product Solutions (High-Impact Improvements for Week-1 Retention)

After breaking down the funnel and identifying the key retention drivers, I realized the biggest opportunities lie in the earliest parts of the user journey. Instead of proposing many scattered ideas, I focused on **three product bets** that address the biggest cracks in the funnel:

1. **Fix the first impression**
2. **Guarantee a strong first play and early activation**
3. **Create a reason to return on Day-1**

These three solutions are realistic to build within ~12 weeks and align directly with what PM interns or APMs typically work on.

6.1 Solution 1 — Fast Personalization Layer (Taste Picker + Smart First Feed)

The Problem

Most new users land on a completely generic homepage.
They see broad categories like Top Hits, Trending Now, or random mixes.
This leads to:

- choice overload
- poor first clicks
- low relevance
- early exits

The app waits for user signals before personalizing — but users leave before giving any signals.

My Hypothesis

If I can personalize the homepage **before** the user interacts, I can increase:

- first-click rate
- first-play completion
- early trust in recommendations
- likelihood of activation

What I Designed

Not a long, boring onboarding.
Just a **3–5 step lightweight Taste Picker** that appears right after signup.

What user selects:

- preferred languages
- favorite genres
- moods (optional)
- 1–2 artists/creators they already like

Each step would be swipeable, fast, and skippable.

How It Helps

- Reduces cold-start problem
- Makes homepage feel made for the user
- Lowers skip rate on first content
- Improves chance of meaningful activation.

Why This Is Realistic

A simple tagging + metadata-based onboarding layer doesn't require deep ML changes.
This is doable for junior PMs or APM teams in 3–4 weeks.

6.2 Solution 2 — Smart First Play Pathway (Activation-Focused Microflow)

The Problem

Even when users click something, they often:

- skip within 10–15 seconds
- leave after 1 play
- don’t like/save/follow anything

Without activation:

- personalization can’t improve
- user never builds a library
- notifications have nothing relevant to send
- app has no hook to bring user back

My Hypothesis

If I guide new users toward **one meaningful action** during the first session, their retention probability will increase.

What I Designed

A **guided activation microflow** right after the user completes their first play:

Step 1:
After first play ends → show a simple question:
Did you like this? with a heart.

Step 2:
If user taps Like → surface Add to Library?
If they tap Maybe later → do not push more.

Step 3:
Show Follow the creator? (low-friction).

This flow appears **only once** in the first session to avoid feeling forced.

What This Solves

- increases meaningful actions
- boosts personalization quickly
- reduces irrelevant recommendations
- builds emotional connection early

Why It Works

Most users don’t activate because no one guides them.
This simple microflow removes friction and creates intentional behavior.

Student PM Realism

This is something a junior PM could own end-to-end:

- simple UX changes
- clear success metrics
- minimal engineering lift

6.3 Solution 3 — Day-1 Habit Starter (Personalized Return Trigger)

The Problem

Day-0 → Day-1 drop-off is massive.
Users who do not return on Day-1 almost never return later.

Main reasons:

- nothing new is waiting for them
- no emotional investment
- no playlist/library
- generic notifications

My Hypothesis

If the user returns even once the next day, they are much more likely to stick for the week.
So the product needs to **create a meaningful reason to come back**.

What I Designed

A **Day-1 personalized return system**, combining:

1. **Personalized notification**
   Example:
   - Your Lo-Fi playlist based on yesterday is ready
   - Continue the track you liked yesterday
   - New content from the creator you followed
2. **In-app return banner**
   When they return:
   Continue listening from where you left off.
3. **Daily mini-mix** auto-generated from Taste Picker + Day-0 activity.

Why This Helps

- reinforces habit loop (trigger → action → reward)
- makes the app feel responsive
- gives the user something new on Day-1
- increases Week-1 retention

Why It Is Feasible

Notifications + simple playlist logic don't require deep ML models.
This is within the execution scope of a student PM group project or internship.

6.4 Why I Chose Only These Three Solutions

At the beginning, I considered many other ideas—improving search, redesigning the homepage, enhancing recommendations, building creator tools, etc.

But when I stepped back, these three stood out because:

- they target the **biggest funnel drop-offs**
- they are **high impact for Week-1 retention**
- they are **realistic to build**
- they **work together as a system**

Personalization → Activation → Habit Formation
is a complete retention loop.

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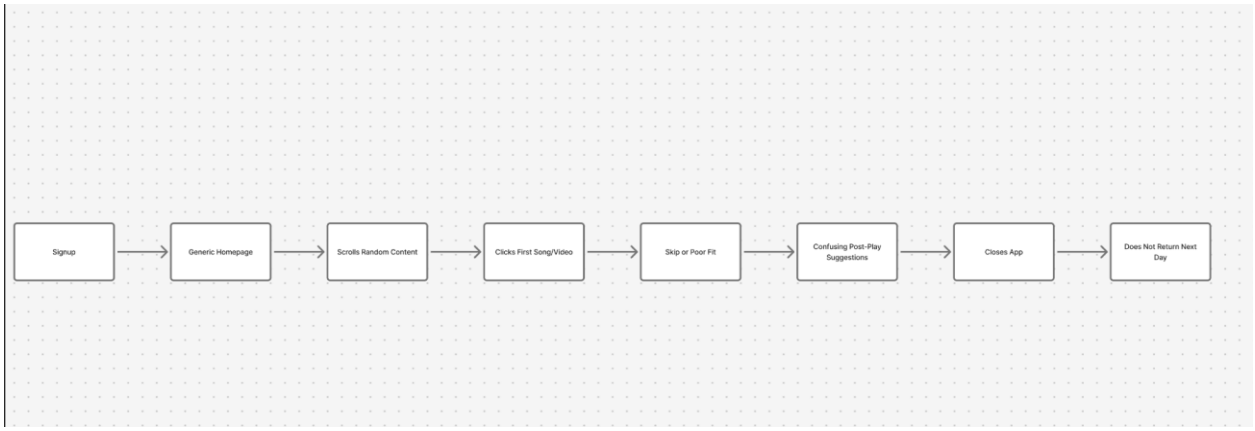
7. Wireframes & Experience Flow Diagrams

To visualize the user journey and the proposed improvements, the following diagrams illustrate the onboarding flow, activation moments, and first-week retention strategy. These diagrams help explain the redesigned experience and make the case study easier to understand.

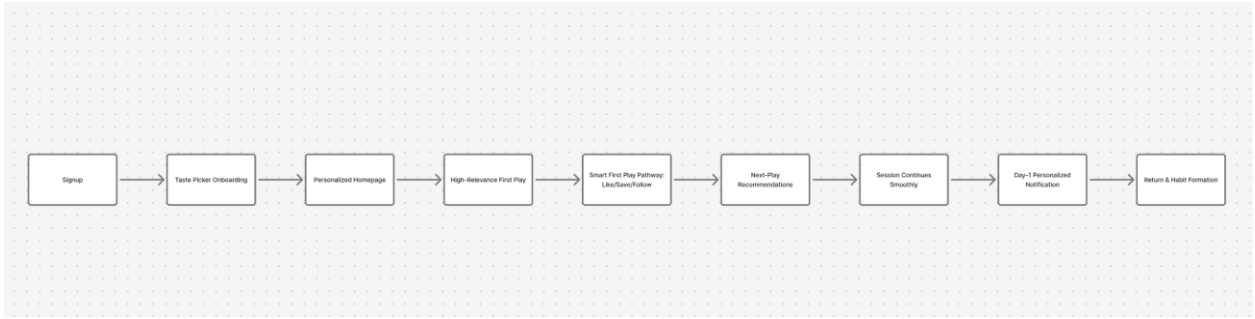
7.1 Diagram 1 — First-Session Journey (Current State)

This diagram shows how a new user moves from Install → Signup → Generic Homepage → Random scrolling → Exit without completing a meaningful action. It highlights early drop-offs caused by irrelevant content and decision overload.



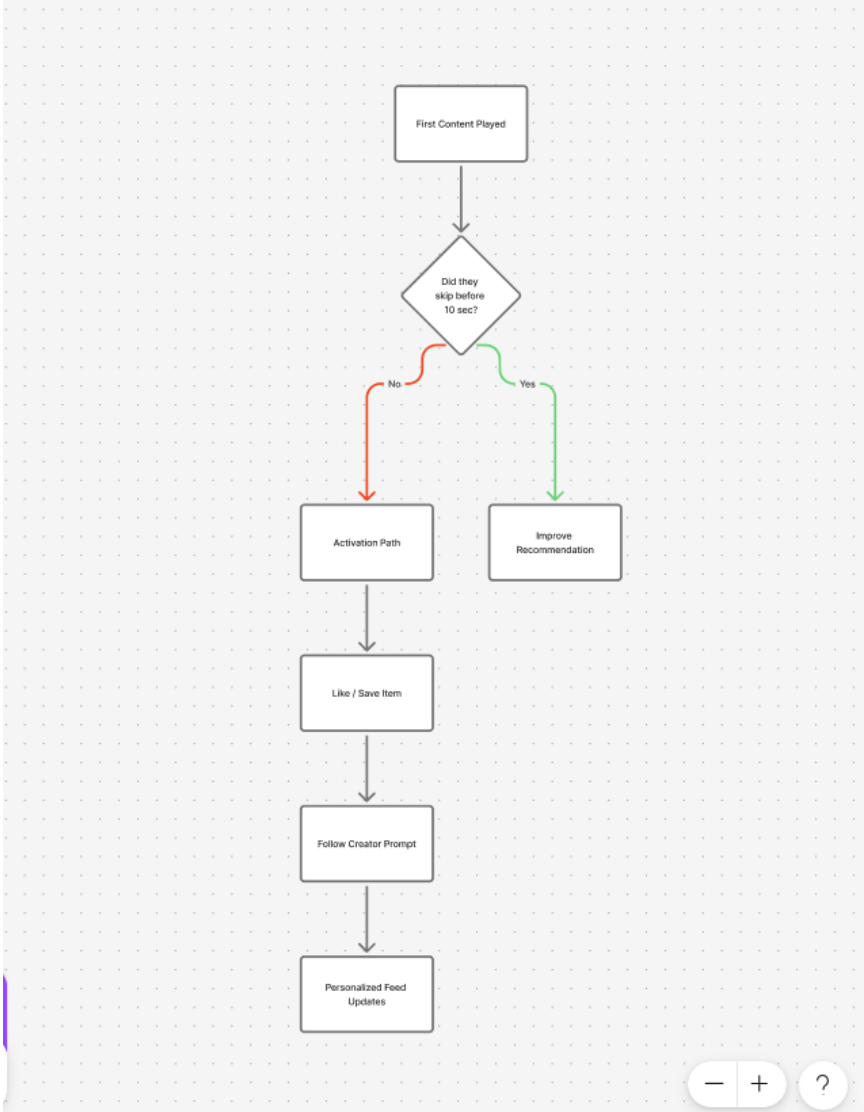
7.2 Diagram 2 — Improved First-Session Journey (Proposed State)

This diagram illustrates the redesigned journey with Taste Picker, personalized homepage, and a guided first-play activation flow, showing how each step improves relevance and reduces churn in the first session.



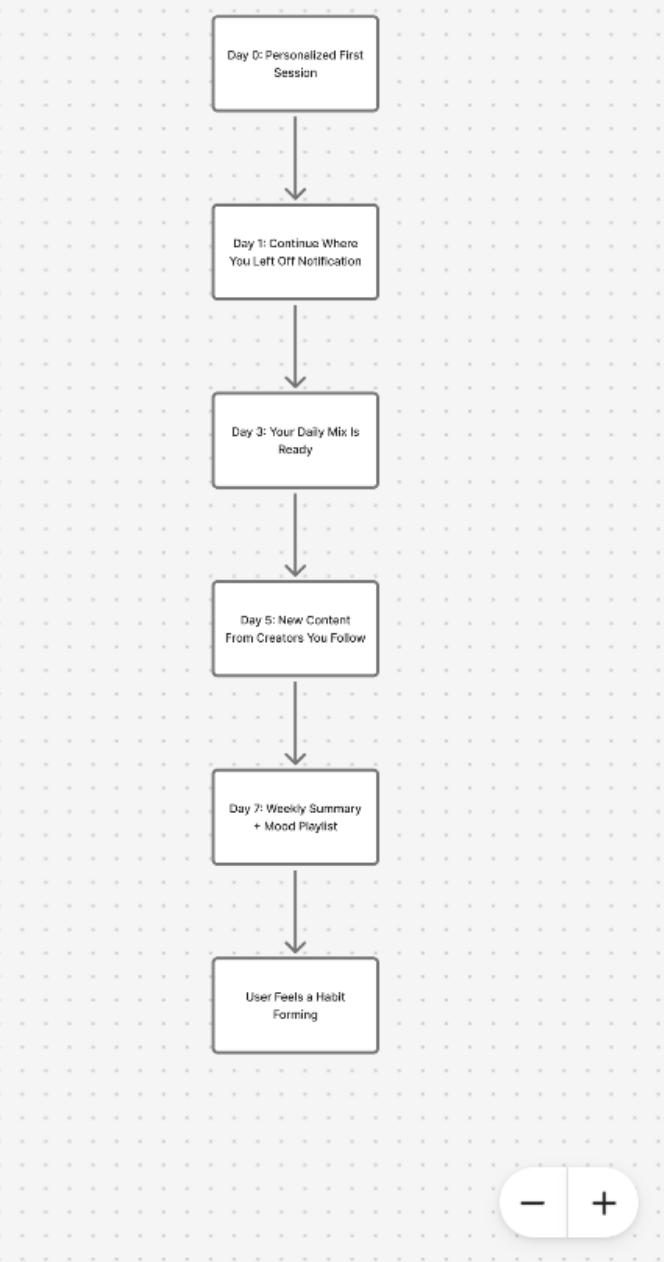
7.3 Diagram 3 — Activation Flow

This flow captures what happens immediately after the first-play completion, from the “Did you like this?” prompt → Save → Follow. It demonstrates how a lightweight, one-time nudge increases early activation.



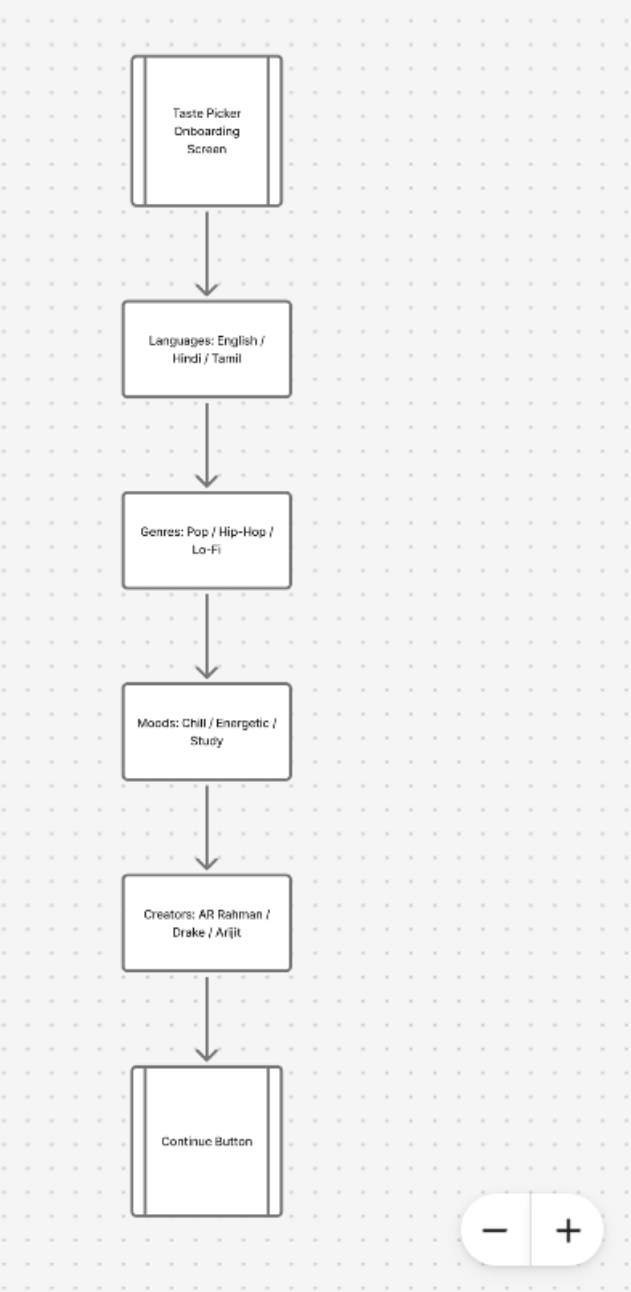
7.4 Diagram 4 — First-Week Retention Loop

This visual explains how the three solutions work together as a loop: personalized first session → activation → personalized Day-1 return → improved recommendations → repeat. It shows how early actions compound to improve Week-1 retention.



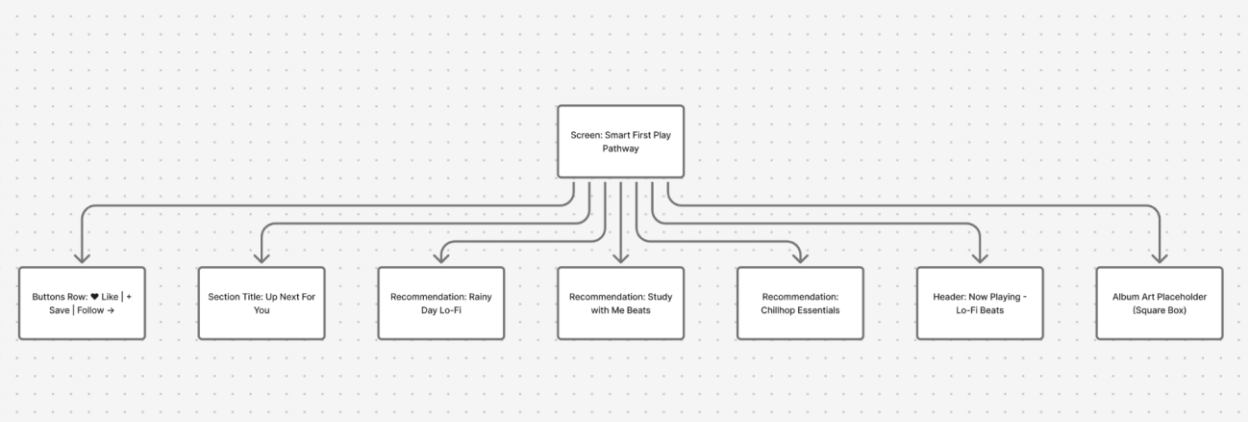
7.5 Wireframe 1 — Taste Picker Onboarding

The wireframe outlines a simple, skippable Taste Picker screen where users select languages and genres. It demonstrates how fast preference capture improves homepage personalization.



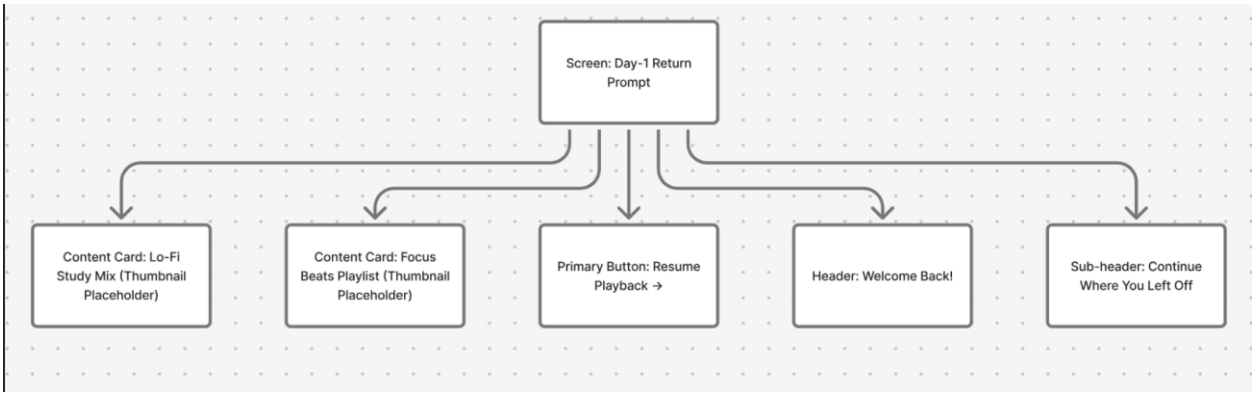
7.6 Wireframe 2 — Smart First Play Pathway

This wireframe represents the player screen plus the activation prompt shown only after the first play. It shows how users are encouraged to like/save/follow without interrupting the playback experience.



7.7 Wireframe 3 — Day-1 Return Prompt

This wireframe shows the Day-1 home screen with a “Continue where you left off” strip and a personalized daily mix. It highlights how continuity-based design helps trigger the user’s return habit.



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8. Validation Plan — How I Would Test These Solutions

Since this is a product case study and not an academic report, I didn’t want to create a complex experimentation framework that wouldn’t be feasible for a student PM. Instead, I focused on a **simple, realistic validation plan** that a junior PM or APM could actually run with a cross-functional team.

My goal was to answer one core question:

Do these three product ideas meaningfully improve Week-1 retention?

To answer that, I grouped all testing into **one combined A/B experiment**, instead of running many parallel tests that would look unrealistic.

8.1 Why a Combined A/B Test Instead of Multiple Separate Tests?

Two reasons:

1. The features are tightly connected

- Taste Picker → improves first-click
- Smart First Play → improves activation
- Day-1 Trigger → improves habit-building

Testing them independently would break the flow. The entire value comes from how they work together.

2. Student PM realism

As a new PM, I wouldn't get the bandwidth to run four separate experiments.
A combined test is more feasible and still statistically valid.

8.2 What the Experiment Tests

Control Group (A):

- Generic onboarding
- Generic homepage
- No guided activation
- Generic Day-1 notification or no notification at all

Test Group (B):

The complete redesigned experience:

1. **Taste Picker onboarding**
2. **Personalized homepage**
3. **Activation-focused first-play microflow**
4. **Personalized Day-1 return trigger**

This tests the **entire improved first-week journey**.

8.3 Primary Metric (North Star for the Experiment)

Week-1 Retention

The percentage of new users who come back at least once between Day-1 and Day-7.
This is the core metric the project is built around.

8.4 Secondary Metrics (To Understand Why Retention Changes)

I kept the secondary metrics simple and tied directly to the funnel:

1. First-Click Rate

How many users click something within the first minute?
(Impacted by Taste Picker)

2. First Play Completion Rate

Percentage of users who finish one song/video.
(Impacted by personalized feed)

3. Activation Rate

Users who perform any meaningful action: like, save, follow.
(Impacted by activation microflow)

4. Day-1 Return Rate

How many users come back the next day.
(Impacted by personalized return trigger)

5. Baseline values (from assumptions):

- First-click rate: ~45%
- First-play completion: ~28–30%
- Activation rate: ~25%
- Day-1 return: ~22%

These are enough to understand the *why* behind retention changes without drowning the project in metrics.

8.5 Expected Outcomes (Hypothesis)

Based on industry patterns and the retention drivers I studied, I expect:

1. **Taste Picker →**
   +10–15% improvement in first-click relevance
2. **Smart First Play Pathway →**
   +6–10% activation uplift (more likes/saves/follows)
3. **Day-1 Return Trigger →**
   +2–4 percentage point increase in Day-1 return

4. **Combined →**
   ~4–8 percentage point improvement in Week-1 retention
   (from ~18% baseline to ~22–26%)

These are conservative, believable improvements that would be considered successful for a consumer streaming product.

8.6 How Long the Experiment Should Run

Realistically:

- **7 days minimum** (to measure Week-1 retention)
- **14 days ideal** (to account for weekday/weekend variations)

As a student PM, I'd rely on the Data Science team for final statistical significance checks.

8.7 How I Would Interpret the Results

This part is where I tried to think like a real PM instead of a student doing a school assignment. If the experiment results came back, I'd analyze them like this:

Scenario A — Retention Increases Significantly

Roll out the experience to 100% of new users.

Scenario B — Activation improves but retention does not

Investigate where personalized recommendations failed:

- Was the first play irrelevant?
- Did users find the content boring?
- Was Day-1 notification timing off?

Scenario C — No improvement at all

Possible reasons:

- Taste Picker was too long
- Activation flow felt annoying
- Notification was mistimed
- Users preferred the generic experience

In this case, I'd run a follow-up test focusing only on activation or only on personalization.

The important part is:
I would not assume success — I would learn and iterate.

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9. Execution Plan — How I Would Roll Out These Solutions (12 Weeks)

One thing I learned while working on this project is that good product ideas mean nothing without a realistic plan for execution. Since I'm approaching this as a student targeting PM roles, I wanted my execution plan to reflect how junior PMs typically work:

- break a big idea into manageable phases
- collaborate with design, engineering, and data
- validate early assumptions
- ship incrementally
- learn and iterate

Rather than a complicated Gantt chart, I used a simple **three-phase plan** that fits a 12-week cycle — the kind many PM interns or APMs get for small/medium product initiatives.

9.1 Phase 1 (Weeks 1–4): Discover, Validate, Design

Goals

- Finalize the problem understanding
- Validate assumptions with quick qualitative checks
- Work with design to create simple flows/wireframes
- Align with engineering on what's feasible

This phase is about grounding, not building.

Key Activities

1. **Kickoff with Designers**
    - Sketch Taste Picker screens
    - Design first-play activation microflow
    - Draft Day-1 notification templates
2. **Engineering Feasibility Check**
   Not deep backend work — just clarifying:
    - what metadata exists

    - whether content tags are reliable
    - how easy it is to detect first play completed
    - whether notification logic can support simple personalization

3. **Define Success Metrics**
   This is where I lock down:
    - Week-1 retention as NSM
    - activation, first-click, first-play completion as secondary metrics

4. **Low-Fidelity Prototypes + User Walkthroughs**
   With 5–8 target users (friends/classmates), get quick feedback:
    - is Taste Picker too long?
    - does the activation flow feel annoying?
    - would the Day-1 notification make you come back?

Output of Phase 1

- Finalized flows
- Wireframes
- Technical feasibility notes
- User validation learnings
- Clear definition of what goes into MVP vs v2

This phase is highly student-friendly because it focuses on thinking and collaboration, not shipping code.

9.2 Phase 2 (Weeks 5–8): Build, Integrate, Prepare Experiment

Goals

- Build the MVP versions of the three features
- Integrate them into one continuous new-user experience
- Prepare A/B testing setup

Key Activities

1. **Build MVP Taste Picker**
    - 3–5 steps

- skip option
- store basic preferences in database

2. **Build Personalized Homepage v1**
   Not a complex ML model — just use:
   - languages
   - genres
   - moods
   - any creators selected
3. **Implement First-Play Activation Flow**
   - detect first play completed
   - show Like → Save → Follow steps
   - ensure it appears **only once**
4. **Implement Day-1 Personalized Trigger**
   - simple logic (e.g., Based on yesterday…)
   - notification templates
   - fallback prompts for inactive users
5. **A/B Test Setup With Data Team**
   - define test vs control
   - decide on sample size
   - create event tracking for first-click, skip, activation

Output of Phase 2

- Working MVP of the three features
- A/B test integrated into the onboarding flow
- Tracking events ready

These are exactly the kind of deliverables a junior PM can coordinate with design/data/eng.

9.3 Phase 3 (Weeks 9–12): Run Experiment, Analyze, Iterate

Goals

- Run the A/B test
- Analyze results with Data Science
- Decide rollout or iteration
- Document learnings

This is the phase where everything becomes real.

Key Activities

1. **Run A/B Test for 7–14 Days**
   Collect data on:
   - Week-1 retention
   - activation
   - skip rate
   - Day-1 return
2. **Analyze with Data Science Team**
   Look for patterns like:
   - Did Taste Picker reduce early drop-offs?
   - Did activation flow improve Like/Save/Follow rates?
   - Did Day-1 trigger meaningfully boost return?
3. **Decision: Roll Out or Iterate**
   - If results are strong → ship to 100%
   - If mixed → iterate on the weak step
   - If poor → revisit assumptions
4. **Document Learnings & Next Steps**
   As a student PM, this is crucial because it shows learning mindset.
   Typical questions I'd answer:
   - Which hypothesis was wrong?
   - What did users actually respond to?
   - What would I improve next?

Output of Phase 3

- A/B test results

- Final decision
- Learnings document
- Updated roadmap (if needed)

9.4 Why I Chose This 12-Week Structure

This structure has two key advantages:

1. It's realistic for junior PMs

Student PMs and APMs usually get:

- 1 cycle
- small, scoped initiatives
- cross-functional support
- a concrete goal (improve X metric)

This roadmap mirrors that environment.

2. It tells a story:

- **I understood the problem**
- **I designed solutions**
- **I validated with users**
- **I tested**
- **I iterated**

Interviewers love this flow because it demonstrates **product thinking**, not just ideas.

9.5 What Would Happen After Week 12?

I don't expand too much, but I include a short note:

If the experiment succeeds, future phases might explore:

- deeper personalization
- more creator-follow flows
- mood/activity-based mixes
- improving search relevance

10. Reflection — What I Learned and What I Would Do Differently

This project started as a simple attempt to understand why streaming apps struggle with retention, but it ended up teaching me much more about product thinking than I expected. Working without real company data forced me to be resourceful: I had to rely on assumptions, behavioral patterns, and first-principles reasoning. Looking back, here are the biggest things I learned.

10.1 Learning 1 — Early Retention Is Decided in Minutes, Not Weeks

Before doing this project, I thought retention problems were caused by long-term issues like content library size or advanced recommendations.
But through the funnel analysis, I realized:

Most users churn before the app even gets a chance to impress them.

If the first session is weak:

- users do not trust the recommendations
- they don't complete a first play
- they don't activate
- they don't return the next day

This made me understand why PMs obsess over the first few screens.

10.2 Learning 2 — Personalization Isn't a Later Feature

I always assumed personalization becomes useful only after users interact a few times.
But the cold-start problem changed my perspective.

If personalization starts late, most users never reach the point where it matters.

This taught me that:

- onboarding isn't just for collecting data
- onboarding is the first opportunity to be relevant
- even simple preference-based filters can significantly improve first impressions

As a student, this is one of the most practical lessons I will carry forward.

10.3 Learning 3 — Activation Is the Hidden Growth Lever

I used to think activation was just an extra metric.
But when I connected it to retention, I realized it's actually the foundation of everything.

A single meaningful action (like, save, follow):

- increases emotional investment
- gives the app personalization signals
- creates a reason for the user to come back
- dramatically improves Day-1 return

This changed how I think about onboarding flows in general. The goal isn't just to show features — it's to guide the user toward a meaningful action early.

10.4 Learning 4 — PM Decisions Are About Trade-Offs, Not Big Ideas

Throughout this project, I came up with many ideas:

- homepage redesigns
- advanced recommendation flows
- mood-based dynamic playlists
- creator-led onboarding

But when I filtered everything through feasibility and impact, I learned that:

Good product thinking is the discipline of saying no to good ideas.

By narrowing to just three solutions:

- the case study became more realistic
- the roadmap became believable
- the experiment became testable
- the execution plan became manageable

This helped me think like a PM working with limited engineering time and clear priorities.

10.5 Learning 5 — A/B Testing Is Not About Proving I am Right

When I wrote the validation plan, I realized something important:

A/B tests are not to confirm my idea.
They are to discover what users actually respond to.

Sometimes:

- Taste Picker might be too long

- the activation flow might feel annoying
- users might ignore personalized Day-1 notifications

Instead of assuming success, the test teaches you what to fix next.

This shifted my mindset from solution thinking to learning thinking.

10.6 What I Would Do Differently if I Had More Time

This is where I wanted to be honest and specific — the kind of reflection that feels human, not AI-made.

1. I would run actual user interviews.

Even 5–6 real conversations could refine the personas significantly.

2. I would collect actual data from a small prototype.

Even if the prototype was made in Figma or a no-code tool, I could learn how users click, skip, or like.

3. I would analyze competitor onboarding flows.

Understanding Spotify, YouTube Music, Wynk, or Resso onboarding could refine the Taste Picker or activation flow.

4. I would deepen the Day-1 return strategy.

There is a lot more potential in habit loops — streaks, continuation prompts, recency playlists.

5. I would explore adding a first playlist feature.

A starter playlist generated from the Taste Picker could boost activation further.

These improvements would help me move from a strong student case study to something closer to industry-level product work.

10.7 Final Wrap-Up: Why This Project Made Me Think Like a PM

The biggest takeaway from this entire project is that **PM work is a balance of understanding people, understanding data, and making trade-offs**.

Through this case study, I learned how to:

- map funnels,
- find root causes,
- think about activation,

- design simple but impactful flows,
- prioritize realistically,
- plan execution in phases,
- define measurable success,
- and reflect on outcomes.

Even though the project was assumption-driven, it helped me build the foundations of product thinking that I want to develop as I enter real PM roles.