



Bumble: Optimising the "First Move" Funnel

Reducing Match-to-Conversation Churn via Data-Driven Features

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Strategic Overview: Addressing High-Friction Activation Points

The Challenge

The 24-hour expiration window, whilst serving as Bumble's unique selling proposition, creates significant pressure for time-constrained users. Our analysis reveals a projected **40% churn rate** between Match and First Message during the critical activation phase.

This friction point represents the highest leverage opportunity for improving Day-1 Retention without requiring new user acquisition.

The Solution

Contextual AI Openers — An assistive feature designed to reduce cognitive load during message initiation whilst maintaining authentic communication.

Projected Impact

- +8% lift in Match-to-Conversation Rate (MCR)
- -30% decrease in Average Time to First Message
- Enhanced user experience for busy professionals



Market Context & The "USP" Paradox

Bumble's core differentiator — "women make the first move" — delivers significant benefits in user empowerment and safety whilst simultaneously creating a unique friction point that requires strategic intervention.

The Differentiator

Women initiate conversations

- Empowers female users with control
- Reduces spam and harassment significantly
- Creates a safer, more intentional dating environment

The Paradox

Time vs. Effort Bottleneck

- 24-hour window creates urgency pressure
- Cognitive load of crafting unique messages
- Mental bandwidth challenges for busy users

The Core Problem: Initiation Fatigue

Users in high-density metropolitan areas such as Delhi and Mumbai frequently receive multiple matches but lack the mental bandwidth to craft thoughtful, unique messages within the 24-hour constraint. The result? Matches expire not due to lack of interest, but due to friction.

Metric	Standard Dating Apps	Bumble's Current Model
Control & Safety	Low	High
Time Pressure	None	High
Initiation Effort	Low	High
Match Intent	Volume-based	Quality-based

User Persona: Understanding Our Core Challenge



Profile

Ananya, The Corporate Analyst

Age: 24 | Location: Gurugram

Profession: Management Consultant

Work Schedule: 60+ hours per week



Behaviour Patterns

High-Intent, Time-Poor User

- Swipes during commute and lunch breaks
- Checks app intermittently throughout day
- Values quality over quantity in connections



The Pain Point

Time Pressure Creates Abandonment

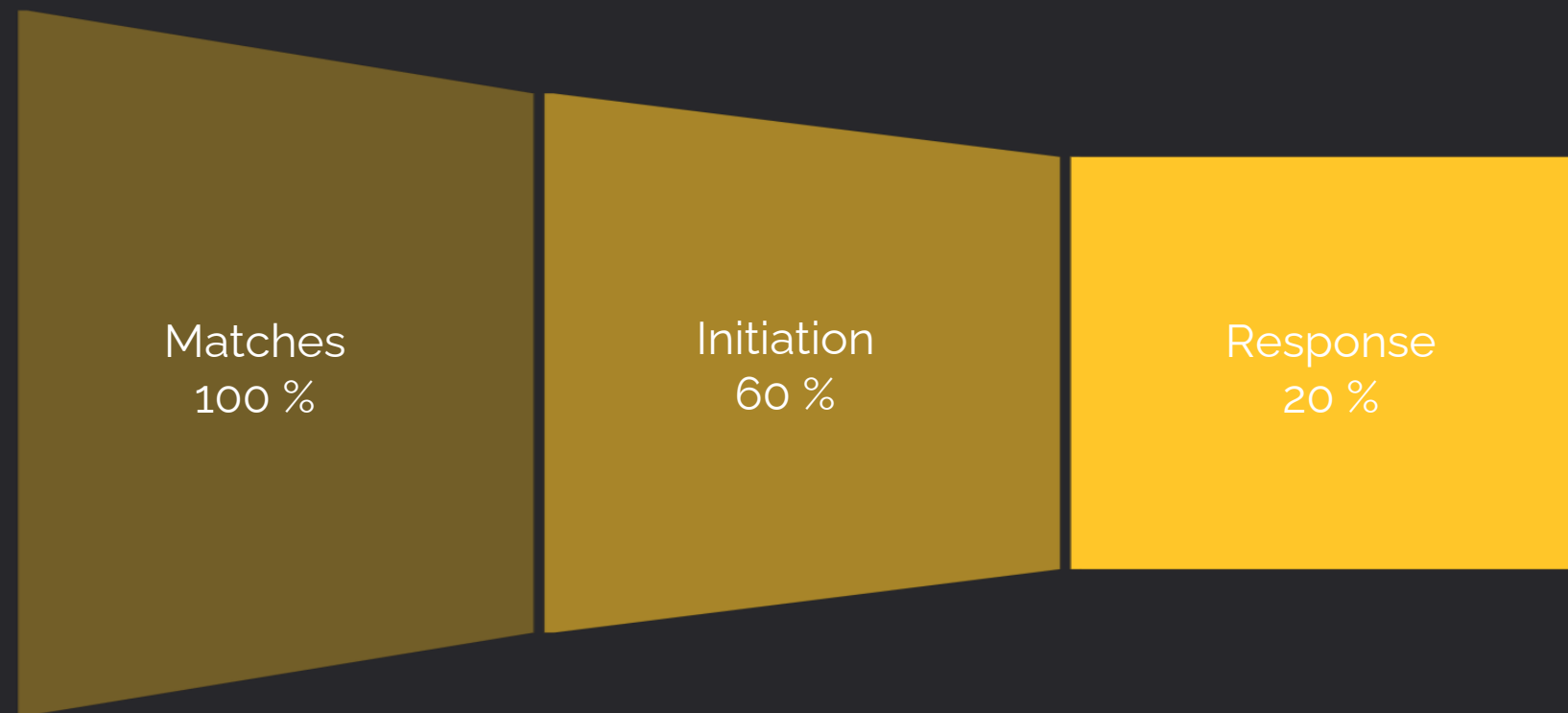
Matches occur during meetings or work hours. By evening, mental fatigue sets in, leading to procrastination and eventual match expiration.

"I get matches during meetings. By the time I open the app at 9 PM, I'm too tired to think of a witty opener. I tell myself I'll do it tomorrow, but then the timer runs out."

— Ananya's User Interview

Key Insight: Ananya represents our target segment — users seeking meaningful connections who need efficiency tools rather than more matches. The solution must reduce friction whilst maintaining authenticity.

Funnel Analysis: Identifying the Critical Drop-Off Point



The transition from Match to Initiation (First Message) represents the **primary leakage point in the entire funnel**, with approximately 40% of matches expiring without any message being sent. This drop-off occurs despite mutual interest being established, indicating that the barrier is not lack of attraction but rather **friction in the initiation process itself**.

40%

Match Expiration

Matches lost without initiation

24h

Time Constraint

Window to send first message

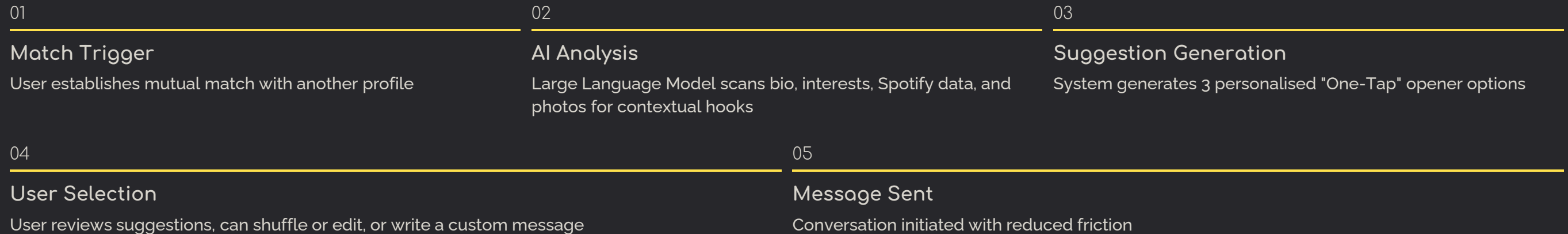
3x

Conversion Gap

Between initiation and response

Proposed Solution: Contextual AI Openers

Introducing an intelligent, context-aware feature that reduces cognitive load whilst maintaining authentic communication. The system analyses match profiles to generate relevant, personalised conversation starters.



Real-World Example

- Match's Profile Information:
- Bio: "Love photography and spicy food"
 - Interests: Travel, Street Food
 - Spotify: Indie Rock playlist

AI-Generated Suggestions

1. "I see you like spicy food! What's the hottest dish you've ever tried?"
2. "Your photography passion caught my eye! What's your favourite subject to shoot?"
3. "Travel and street food — perfect combo! Which city has the best food scene you've visited?"

Value Proposition



Reduces Time-to-Message

Eliminates the "blank page" problem with instant, relevant suggestions



Eliminates Writer's Block

Provides conversational scaffolding whilst allowing personalisation

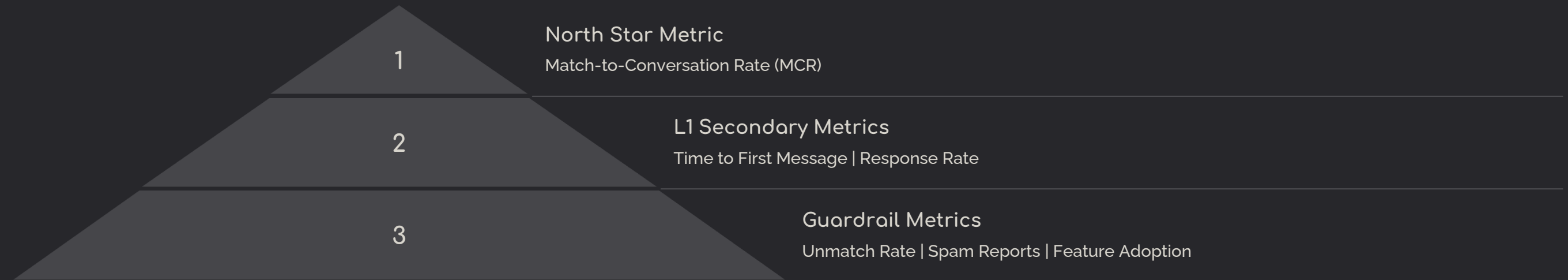


Maintains Authenticity

Suggestions based on actual shared interests, not generic templates

Success Metrics: Measuring Feature Impact

A robust measurement framework ensures we can validate the feature's effectiveness whilst monitoring for unintended consequences. Our metric hierarchy prioritises user outcomes over vanity metrics.



Detailed Metric Definitions

North Star: Match-to-Conversation Rate

Formula: $(\text{Total Matches with } \geq 1 \text{ Message Sent} / \text{Total Matches}) \times 100$

Current Baseline: ~60%

Target: 68% (+8 percentage points)

Rationale: Industry standard lift for feature optimization is 5-10%. A +8% lift represents regaining ~1 in 5 churned users.

Why This Matters: Directly measures the feature's ability to overcome initiation friction

L1 Metrics: Quality & Speed

Average Time to First Message

- Current: ~8.5 hours
- Target: ~6 hours (-30%)

Response Rate

- Goal: Maintain at $\geq 65\%$
- Ensures AI suggestions don't compromise message quality

figures estimated based on industry benchmarks

Guardrail Metric: Unmatch Rate

Critical to monitor whether AI-generated openers lead to increased unmatching or spam reports. Target: No increase beyond 2% variance from baseline. This ensures feature quality and prevents potential brand damage.

Technical Implementation & Tracking Architecture

A robust technical foundation ensures low-latency performance whilst comprehensive event tracking enables data-driven iteration and optimisation.

1

Feature Logic & API Design

- **Trigger:** On_Match_Created (Async Event)
- **Generation:** Background Job (LLM processes profile metadata immediately upon match)
- **Storage:** Redis/Memcached (Pre-calculated suggestions stored with TTL)
- **Endpoint:** GET /api/v1/suggestions (Retrieval only, <50ms latency)

2

Event Tracking Schema

- **icebreaker_shown:** algorithm_version, match_id, suggestions_array
- **icebreaker_selected:** prompt_id, time_to_selection, edited (boolean)
- **icebreaker_dismissed:** match_id, dismiss_reason

Effectiveness Query: Measuring Conversion Impact

This SQL query compares conversion rates between AI-assisted and manual message initiation, enabling precise measurement of feature effectiveness.

```
-- Metric: Match-to-Conversation Rate (MCR) by Experiment Group
SELECT
    assignments.variant_name AS test_group,
    -- Denominator: Total Matches in this group
    COUNT(DISTINCT m.match_id) AS total_matches,
    -- Numerator: Matches that converted to a conversation
    COUNT(DISTINCT msg.conversation_id) AS conversations_started,
    -- The Key Metric
    (COUNT(DISTINCT msg.conversation_id) * 100.0 /
     COUNT(DISTINCT m.match_id)) AS mcr_conversion_rate
FROM experiment_assignments assignments
JOIN matches m
    ON assignments.user_id = m.initiator_id -- Ensure we track the user supposed to make the first move
LEFT JOIN messages msg
    ON m.match_id = msg.match_id
WHERE m.created_at >= '2024-01-01'
GROUP BY 1
ORDER BY 4 DESC;
```

Technical Considerations

- LLM caching strategy for repeated profiles
- Fallback mechanism if API latency exceeds budget
- A/B testing infrastructure for algorithm versions
- Content moderation layer pre-display

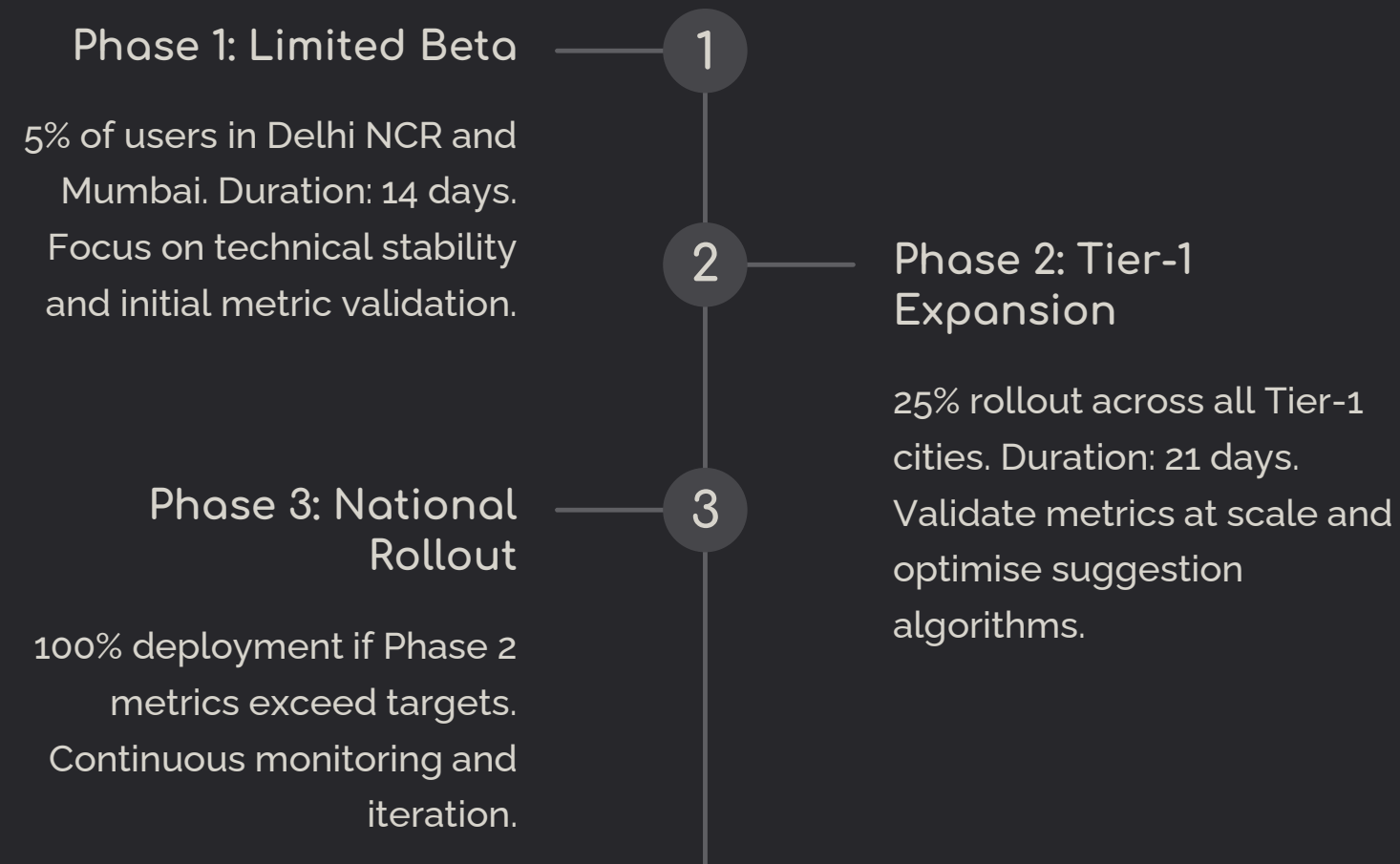
Performance Monitoring

- API response time (p50, p95, p99)
- Suggestion relevance scoring
- Edit rate on AI suggestions
- Error rates and fallback triggers

Go-To-Market Strategy

A phased rollout approach with comprehensive risk management ensures safe, measurable deployment whilst maintaining high product quality standards.

Rollout Strategy: Phased Approach



A/B Test Structure

- 📄 **Control Group:** Standard UI without AI suggestions
- Test Group:** "Smart Openers" button with AI suggestions
- Sample Size:** 15,000 users per group for statistical significance
- Success Criteria:** +8% MCR lift with p-value <0.05

Risk Mitigation & Launch Plan

Risk Assessment & Mitigation Strategies

AI Hallucination

Risk: AI generates factually incorrect or inappropriate suggestions, leading to user dissatisfaction or safety concerns.

Mitigation:

- Implement a robust content moderation layer before displaying suggestions.
- Continuously fine-tune the LLM with safe and relevant conversational data.
- Allow users to flag inappropriate suggestions for immediate review.

Decreased Authenticity

Risk: Users perceive AI suggestions as generic or inauthentic, leading to higher unmatched rates or lower engagement quality.

Mitigation:

- Monitor **Unmatch Rate** and **Spam Reports** as guardrail metrics.
- Ensure suggestions are deeply contextual and allow for user editing to maintain personalization.
- Gather user feedback on suggestion quality and perceived authenticity.

Technical Latency

Risk: Slow API response times for suggestion generation impact user experience and feature adoption.

Mitigation:

- Implement aggressive LLM caching strategies for repeated profiles.
- Develop robust fallback mechanisms if API latency exceeds budget (<400ms).
- Continuously monitor API response times (p50, p95, p99) and optimize infrastructure.

Next Steps & Success Criteria

01

Execute Limited Beta Rollout

Deploy to 5% of users in Delhi NCR and Mumbai for 14 days, focusing on technical stability and initial metric validation.

03

Evaluate A/B Test Success

Analyze results from the test group vs. control group. Success criteria: +8% **MCR lift** with p-value <0.05.

02

Expand to Tier-1 Cities

25% rollout across all Tier-1 cities for 21 days, validating metrics at scale and optimizing suggestion algorithms.

04

National Deployment & Iteration

Proceed with 100% deployment if Phase 2 metrics exceed targets, followed by continuous monitoring and feature iteration.

Thank You

