< HackOn >
with amazon
5.0

Code Chakra

ENHANCE FIRE TV WITH CONTEXTUAL PERSONALIZATION AND CO-VIEWING FEATURES USING BEHAVIOR-AWARE AI MODELS.

Get to Know Us

NIkunj Agarwal
3^{rd} year UG

Prakhar Shukla
3^{rd} Year UG

Keshav Khetan
3rd Year UG

Vasu Singla
3^{rd} Year UG

IIIT Allahabad

PROBLEM STATEMENT

PAIN POINT

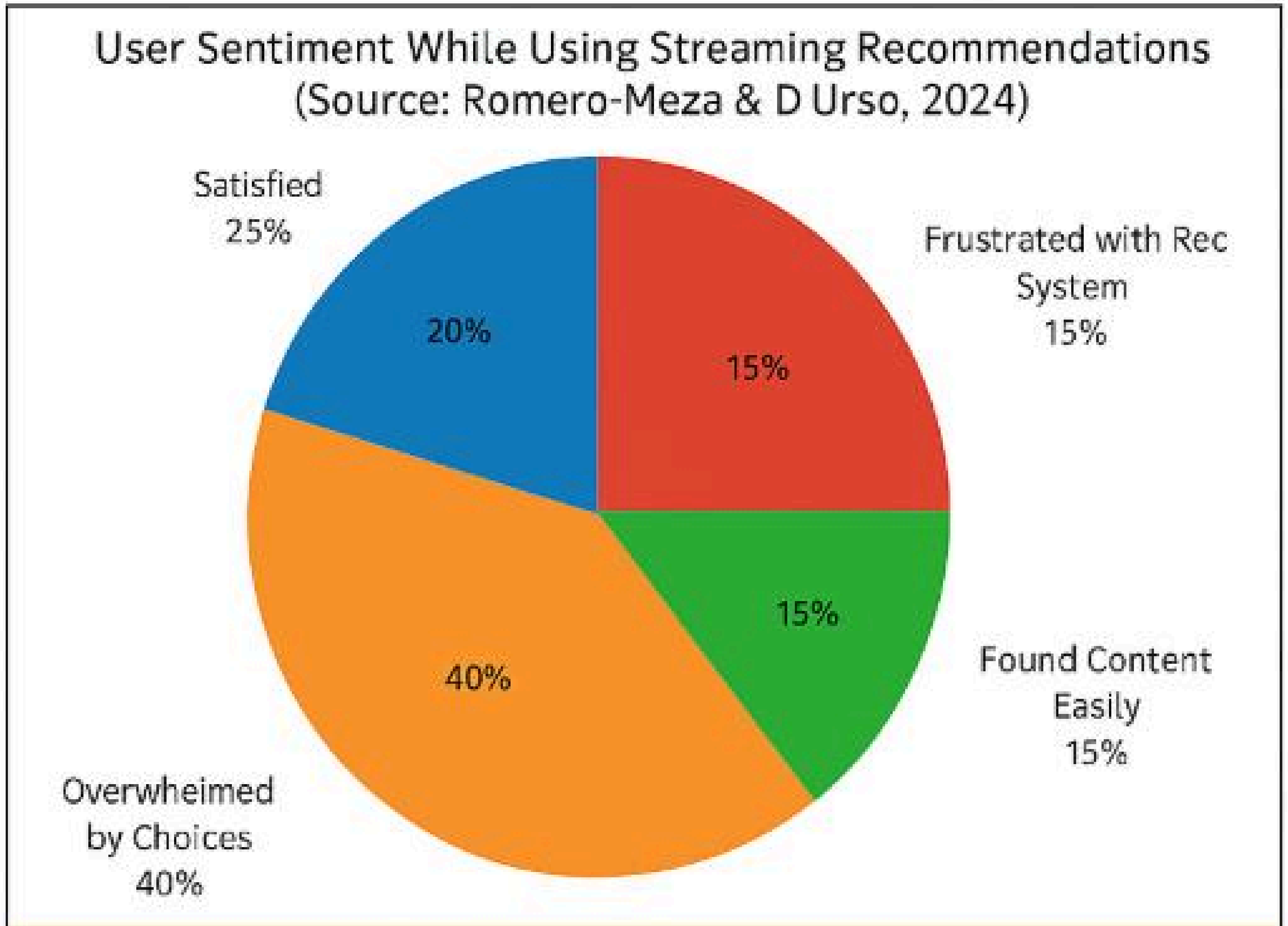
USERS EXPERIENCE CHOICE OVERLOAD AND LONG SEARCH TIMES DUE TO POOR PERSONALIZATION IN STREAMING PLATFORMS.

GAP

DESPITE 80% OF WATCH TIME COMING FROM HOMEPAGE RECOMMENDATIONS, VIEWERS STILL FEEL DISSATISFIED AND OVERWHELMED.

NEED

WE MUST SIMPLIFY DISCOVERY AND BOOST CONTENT RELEVANCE THROUGH EMOTIONALLY INTELLIGENT & CONTEXT-AWARE RECOMMENDER SYSTEMS.



KEY INSIGHT: 65% of users feel frustrated or overwhelmed by streaming recommendations endations.

SOLUTION

Core AI Personalization Modules

Mood-Aware Recom-menendation

Model: CNN-Based Emotion Classifier

- Detects user emotion (happy, tired, sad)
- Maps mood to content themes (e.g. feel.goo, intense, calming)
- *+24% 3.6% CTR* 3.6× thumbs-up *bst*

Time & Context-Aware Recommendation

Model: MOJITO (Gaussian-Mixture Transformer)

- Inputs: time-of-day, weekday/weekend
- Captures evolving user taste via time-encoded Transformer
- +79% corompletion – 35 % scroll time

Group & Co-Watcching Recommerdatior

Model: CoCoRec (Consensus-aware Contrastive Recommender)

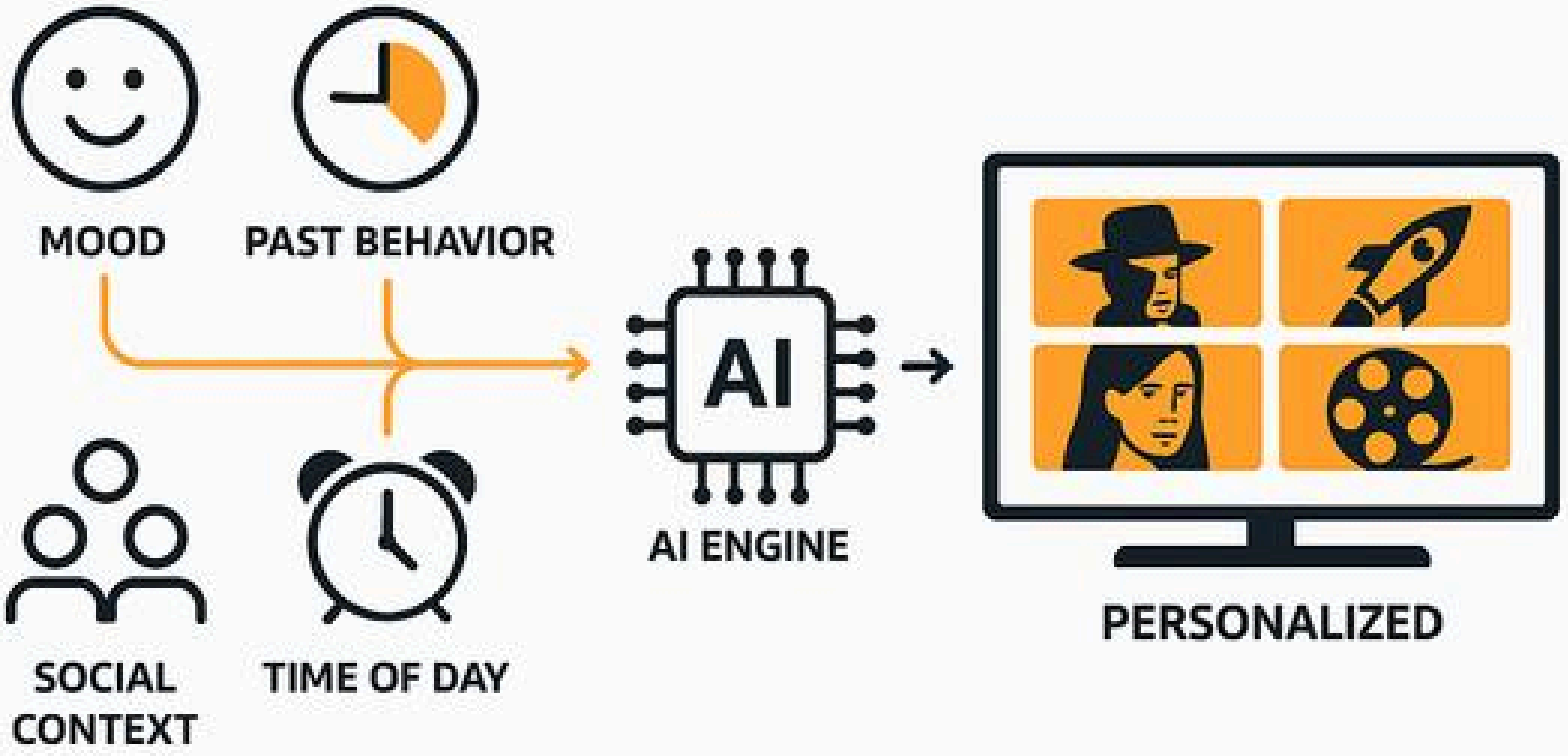
- Blends individual preferences using adaptive fusion
- Learns fair consensus across group profiles
- +27% co-watch duration, +40 % sits.

Unified Al Personalization Engine

Modular, microservices-based pipeline

Components: CNNs + MOJITO + CoCoRec + CoCoRec + optiontional LLMs)

Final Score = Mood Fit + Context Relevance + Group Consensus + Past Behavior

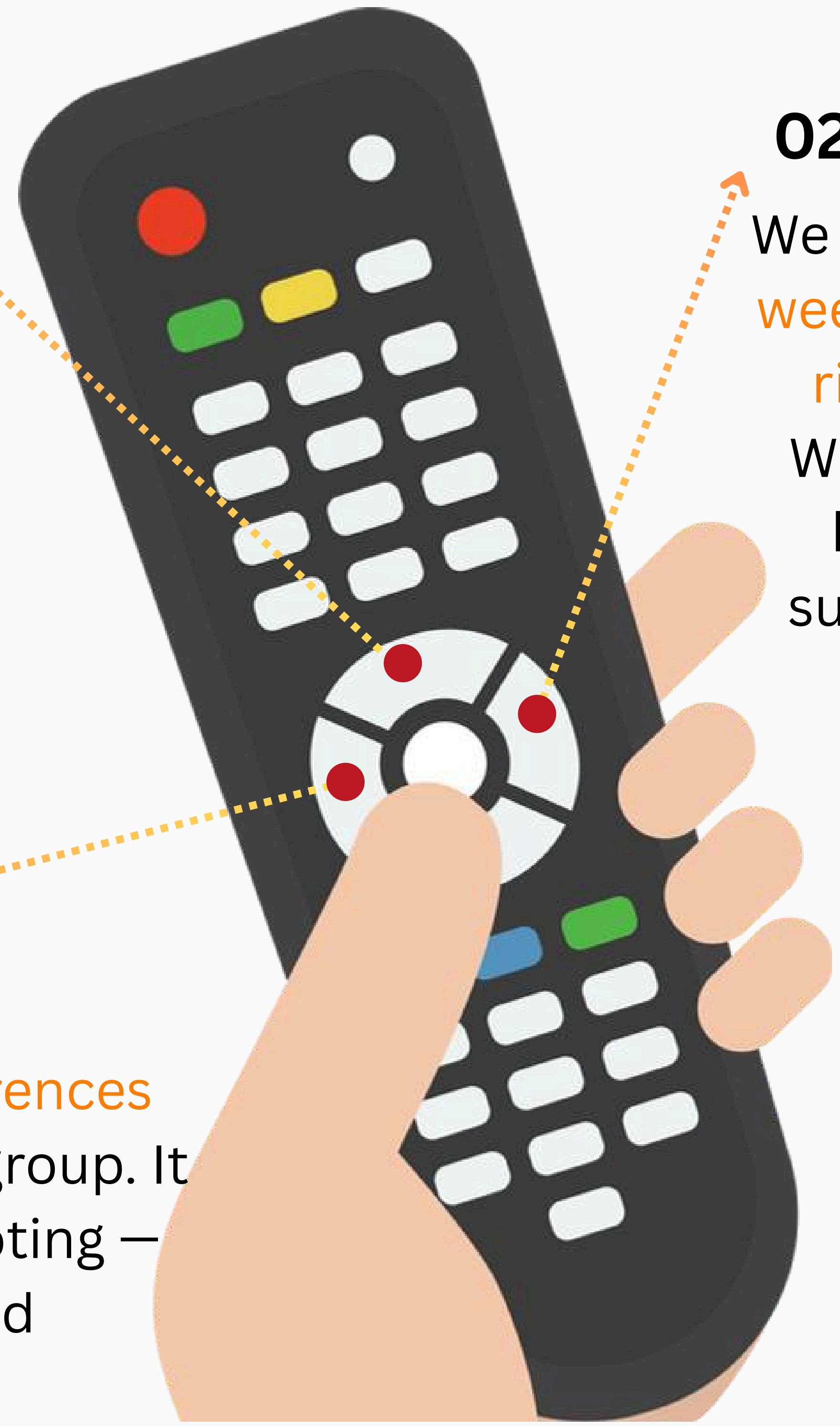


OUR SOLUTION COMBINES MOOD-AWARE, TIME/CONTEXT-AWARE, AND GROUP-BASED RECOMMENDATION MODELS TO DELIVER HIGHLY PERSONALIZED CONTENT. THESE SIGNALS ARE PROCESSED THROUGH A UNIFIED AI ENGINE

SOLUTION

01. Emotion-Aware Suggestions

Our system detects facial expressions and voice tone to understand the user's mood in real time. Using CNN-based emotion recognition models, it matches emotions like stress, excitement, or calmness to suitable content — ensuring the viewing experience feels personal, relatable, and emotionally in sync.



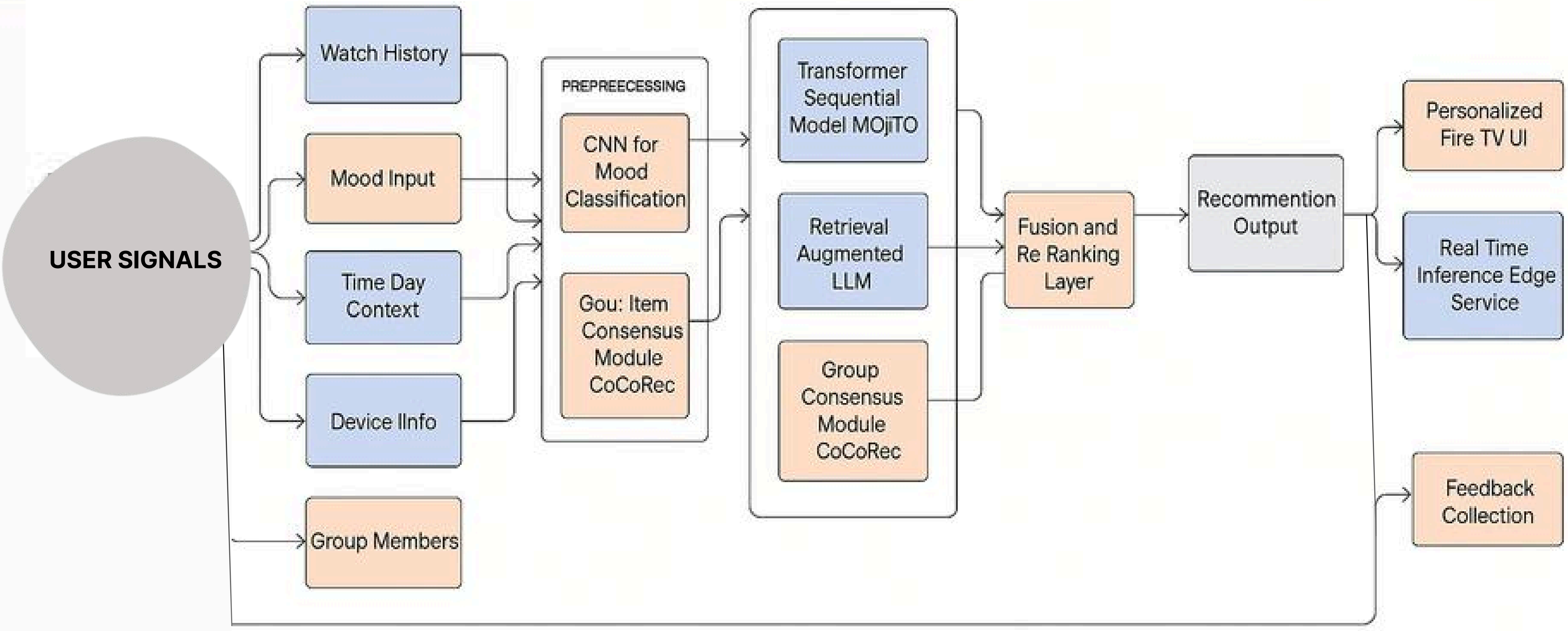
02. Context-Aware Scheduling

We consider factors like time of day, day of the week, and viewing patterns to recommend the right type of content at the right moment. Whether it's a quick watch during lunch or a binge session at night, our model adapts suggestions to fit naturally into the viewer's routine.

03. Group Viewing Intelligence

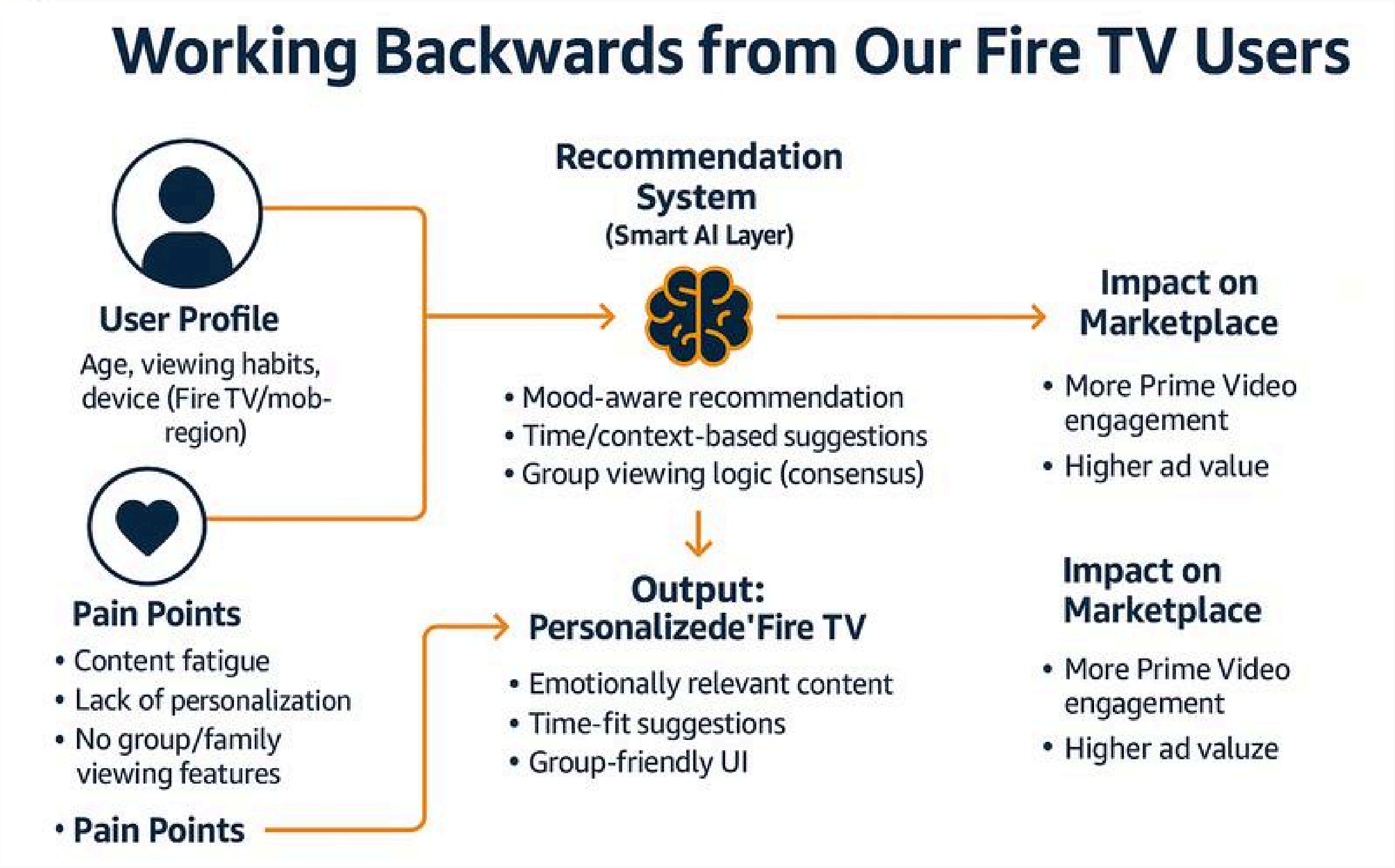
For shared viewing, the system blends individual preferences and moods to recommend content that suits the entire group. It enables synced playback, live reactions, and content voting — making remote watch parties smooth, engaging, and personalized for everyone involved.

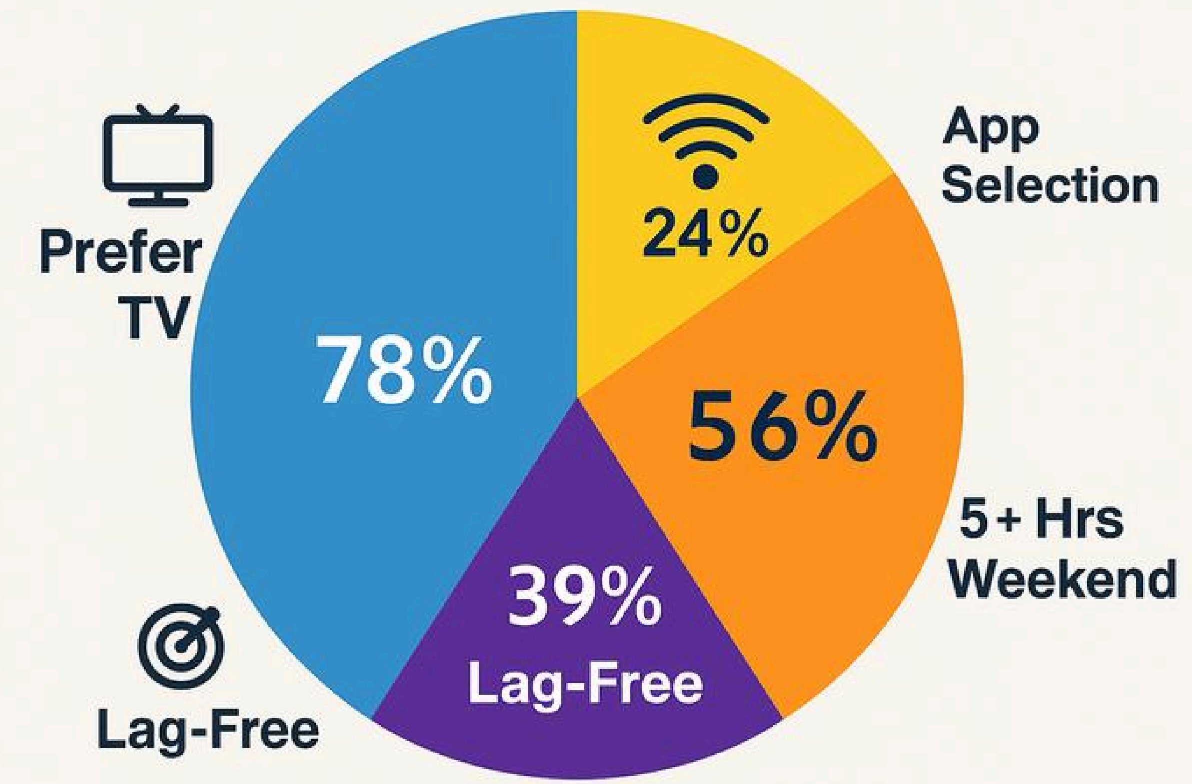
ARCHITECTURE



OUR ARCHITECTURE COMBINES CNNS FOR MOOD, MOJITO FOR TIME-BASED RECS, AND COCOREC FOR GROUP CONSENSUS. A UNIFIED ENGINE FUSES ALL SIGNALS TO RANK CONTENT IN REAL TIME, OPTIMIZED FOR FIRE TV SCALABILITY.

CUSTOMER ATTRACTION





AMAZON (2024) – FIRE TV USER SURVEY (INDIA)
SOURCE: PRESS.ABOUTAMAZON.COM

FIRE TV = THE FAMILY SCREEN

→ 78% OF INDIAN OTT USERS PREFER WATCHING ON TV OVER MOBILE
→ 97% WATCH DURING FAMILY DINNER TIME

PRIME TIME & PEAK USAGE

→ 66% WATCH 5+ HRS ON WEEKENDS, MOSTLY IN THE EVENING
→ CONTENT PUSHES SHOULD MATCH DAILY RHYTHM

VIEWER EXPECTATIONS

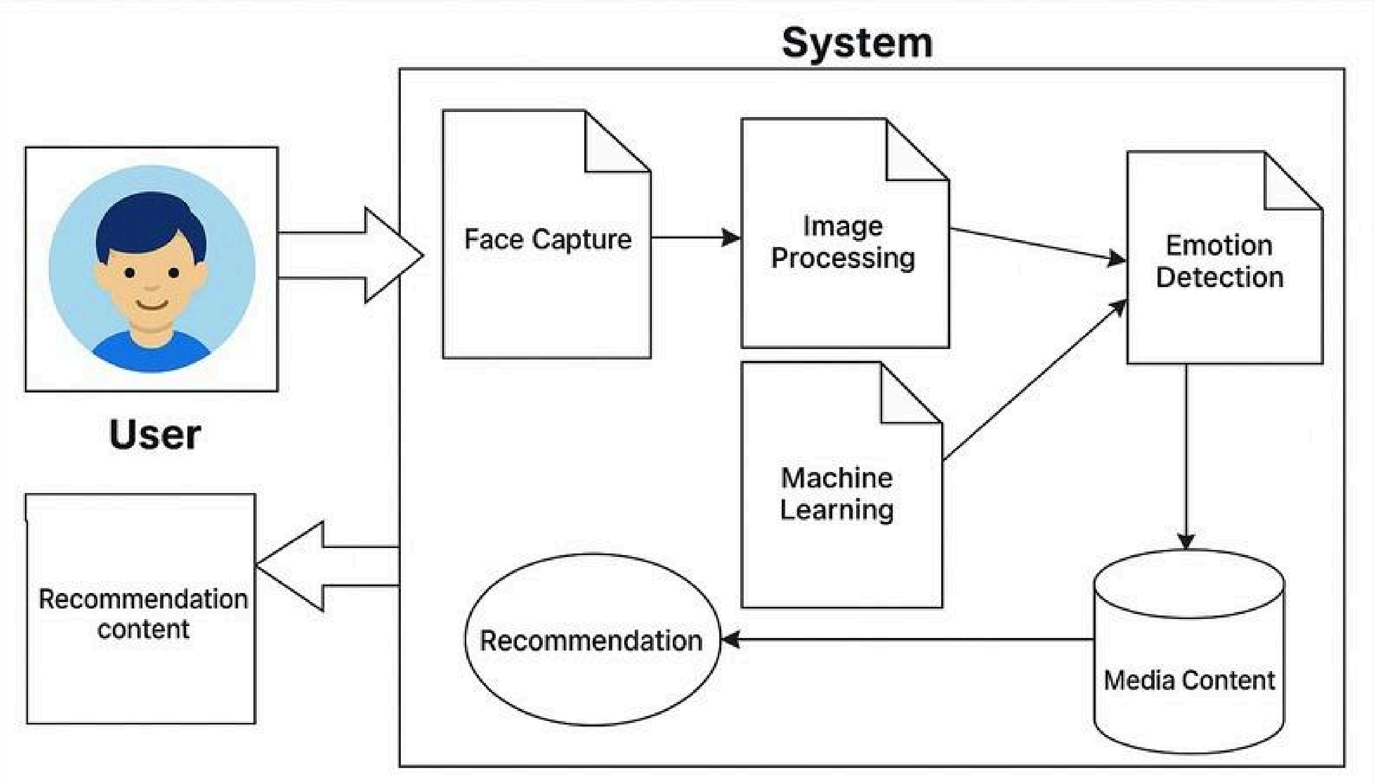
→ 39% DEMAND LAG-FREE EXPERIENCE, 24% WANT WIDE APP CHOICE

GEN Z & MILLENNIALS = SOCIAL STREAMERS

→ 50% WOULD WATCH MORE IF DISCOVERY WAS EASIER
→ 70% WANT DIVERSE/INCLUSIVE CONTENT
→ SOCIAL INFLUENCE MATTERS MORE THAN ALGORITHMS

MOOD-AWARE RECOMMENDATION

"PERSONALIZING CONTENT THROUGH EMOTIONAL INTELLIGENCE"



SU JH, LIAO YW, WU HY, ET AL. UBIQUITOUS MUSIC RETRIEVAL BY CONTEXT-BRAIN AWARENESS TECHNIQUES. IN: 2020 IEEE INTERNATIONAL CONFERENCE ON SYSTEMS, MAN, AND CYBERNETICS (SMC); 2020. P. 4140–4145.

🎭 REAL-TIME EMOTION DETECTION VIA CNN

→ Facial expressions or voice cues are analyzed on-device using a CNN (Babua et al., 2023)

→ Mood labels (happy, sad, bored) are generated in real time

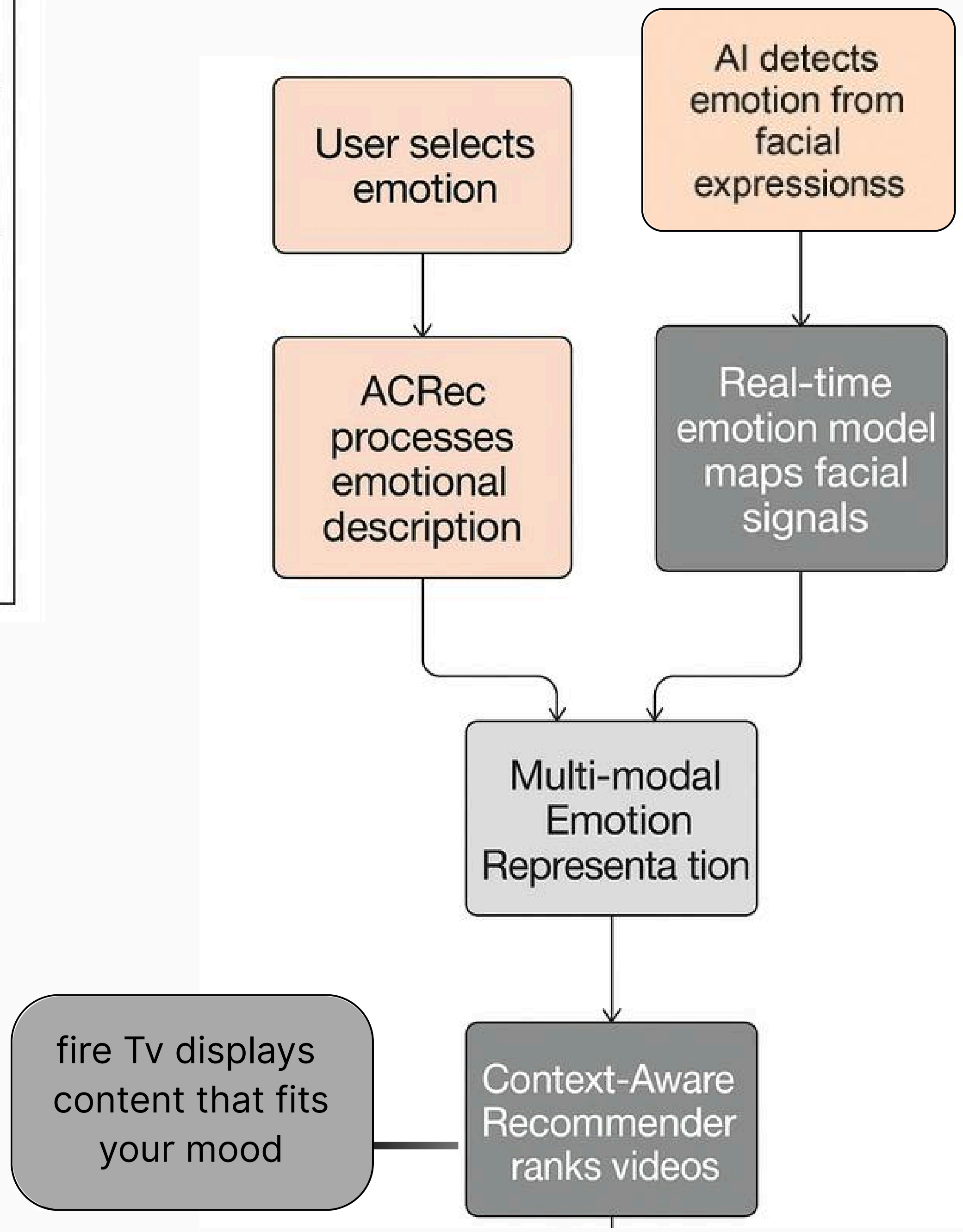
🧠 EMOTION-TO-CONTENT MAPPING

→ Detected moods guide personalized content (e.g., "Happy" → comedy, "Tired" → soothing)

→ System continuously improves via real-time feedback (thumbs-up, skips

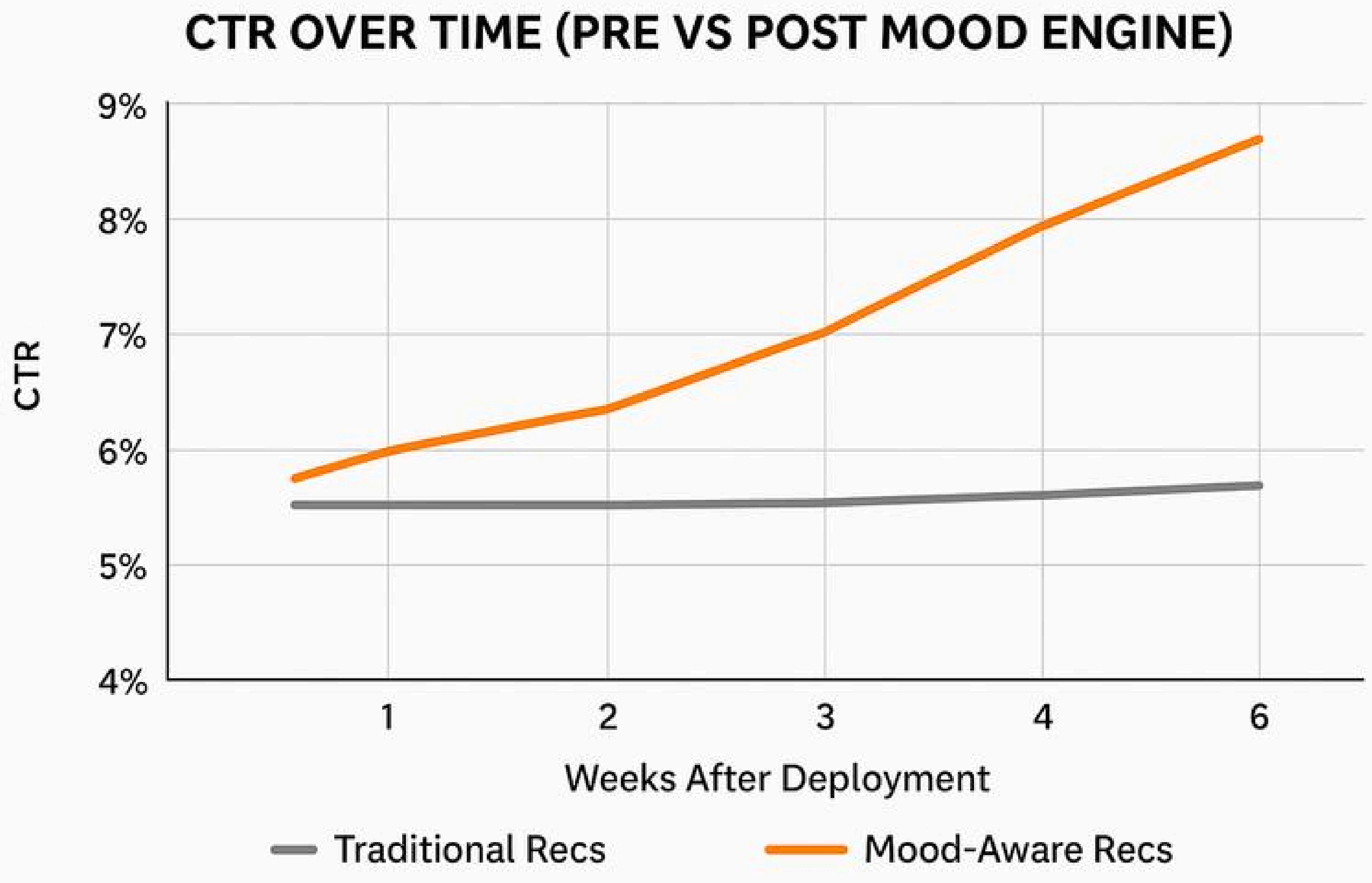
📈 RESULTS:

→ +24% click-through rate (CTR)
→ +3.6× thumbs-up to thumbs-down ratio
→ +11% increase in full-session completions for mood-aligned content



MOOD-AWARE RECOMMENDATION

"PERSONALIZING CONTENT THROUGH **EMOTIONAL INTELLIGENCE**"



1. AFTER DEPLOYING THE MOOD-AWARE ENGINE, CLICK-THROUGH RATES **(CTR)** STEADILY INCREASED FROM **5.8% TO 8.7%** OVER SIX WEEKS — A **50% BOOST** IN ENGAGEMENT.

2. TRADITIONAL RECOMMENDATION MODELS SHOWED **FLAT CTR PERFORMANCE, INDICATING POOR EMOTIONAL** ALIGNMENT WITH USER PREFERENCES.

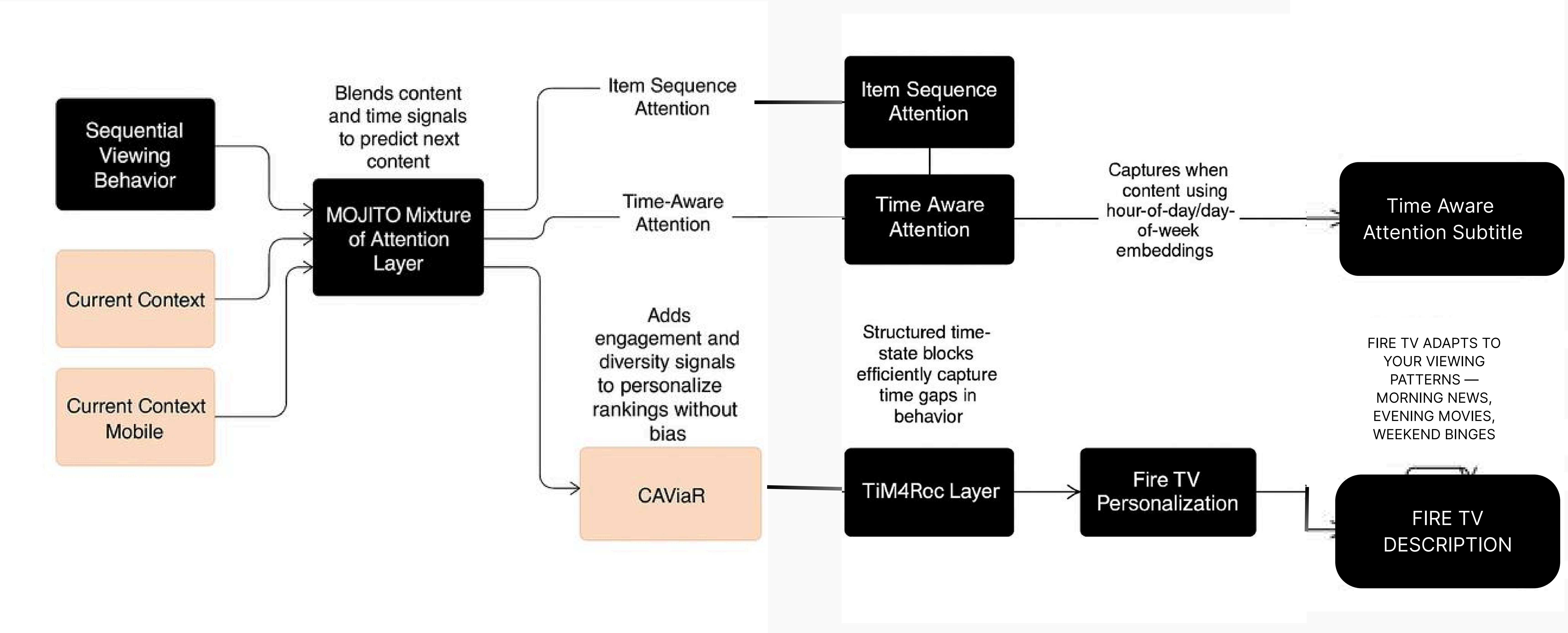
3. BY DETECTING **MOOD** IN REAL TIME AND MATCHING IT WITH **SUITABLE CONTENT**, USERS WERE MORE LIKELY TO **CLICK, STAY,** AND COMPLETE SESSIONS.

4. THE SYSTEM CONTINUOUSLY LEARNS FROM FEEDBACK (**THUMBS UP/DOWN, SKIPS)**, REFINING **EMOTIONAL PERSONALIZATION** AND IMPROVING WEEKLY CTR.

USER ENGAGEMENT GROWS WHEN RECOMMENDATIONS ALIGN WITH HOW THEY FEEL.

CONTEXT-AWARE RECOMMENDATION

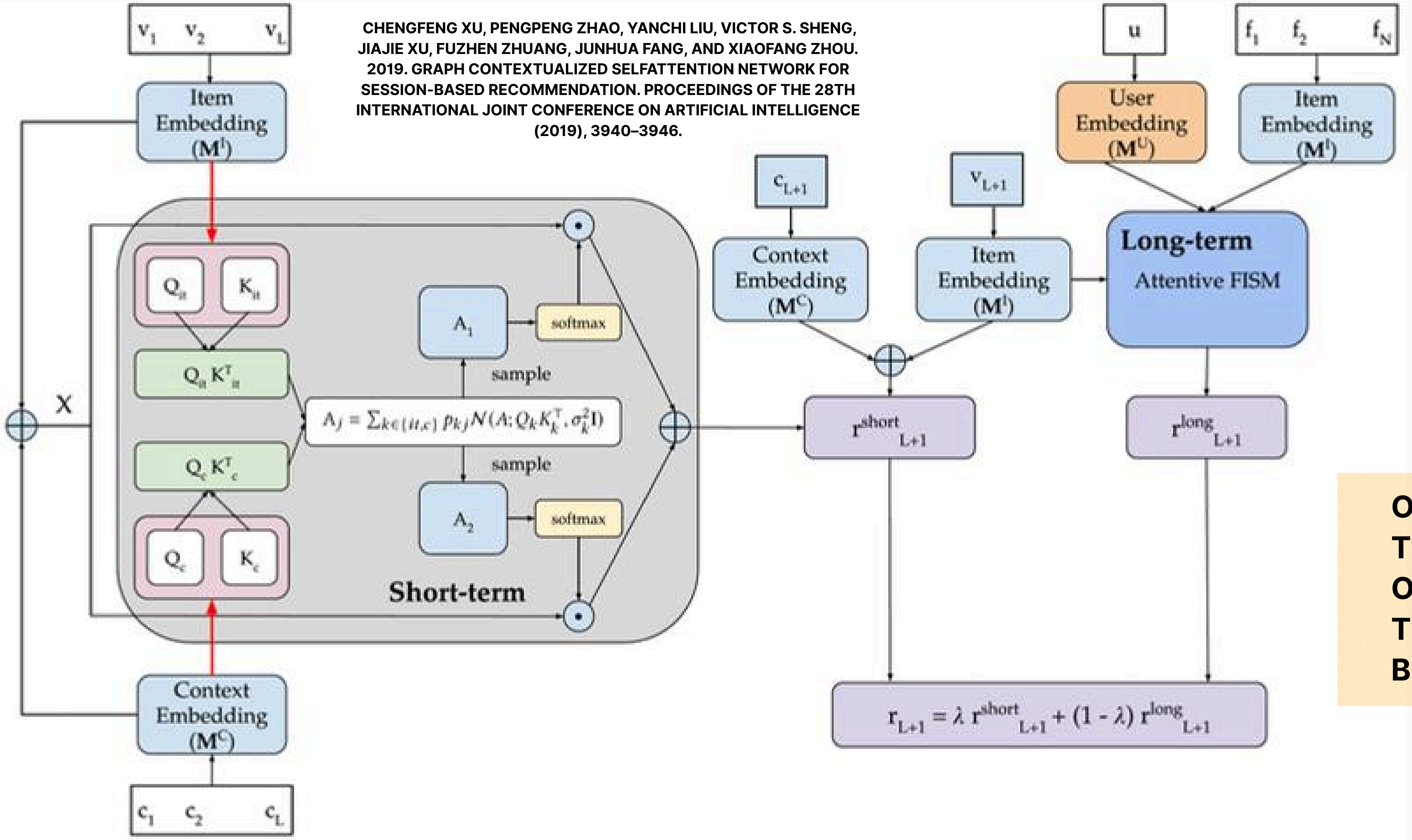
COMBINING TIME SIGNALS, CONTEXTUAL CUES, AND USER PATTERNS TO DELIVER RELEVANT CONTENT AT THE RIGHT MOMENT.



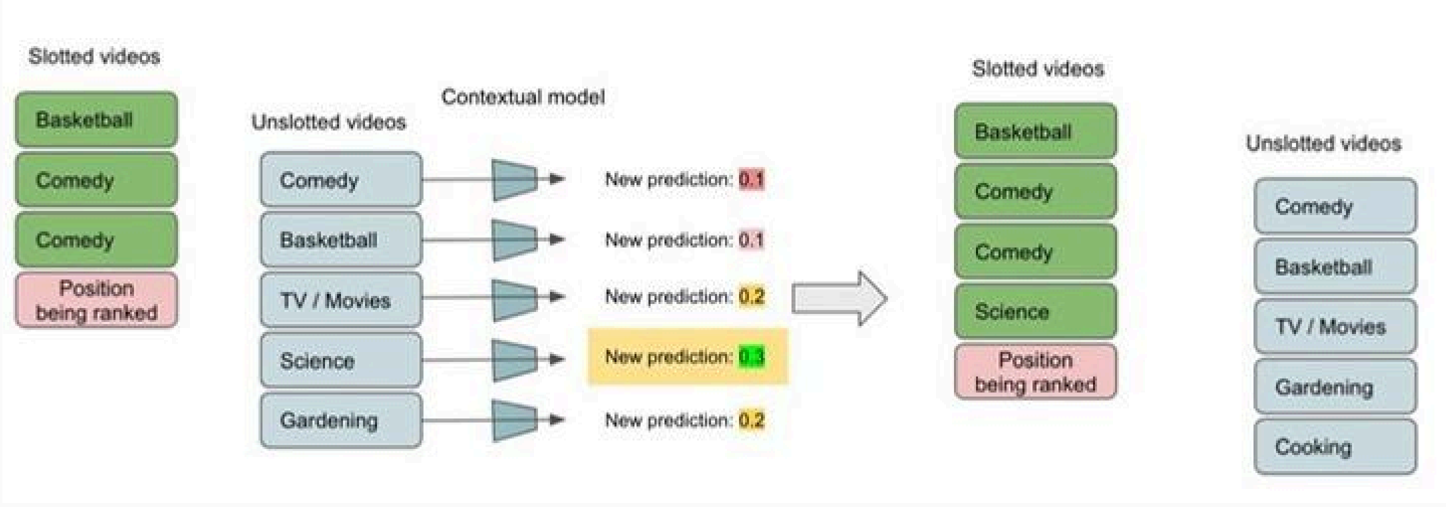
CONTEXT-AWARE RECOMMENDATION

COMBINING TIME SIGNALS, CONTEXTUAL CUES, AND USER PATTERNS TO DELIVER RELEVANT CONTENT AT THE RIGHT MOMENT.

CHENGFENG XU, PENGPENG ZHAO, YANCHI LIU, VICTOR S. SHENG, JIAJIE XU, FUZHEN ZHUANG, JUNHUA FANG, AND XIAOFANG ZHOU. 2019. GRAPH CONTEXTUALIZED SELFATTENTION NETWORK FOR SESSION-BASED RECOMMENDATION. PROCEEDINGS OF THE 28TH INTERNATIONAL JOINT CONFERENCE ON ARTIFICIAL INTELLIGENCE (2019), 3940–3946.



ARCHITECTURE OF MOJITO FOR TIME-AWARE SR USING ATTENTION MIXTURES OF TEMPORAL CONTEXT AND ITEM EMBEDDINGS.

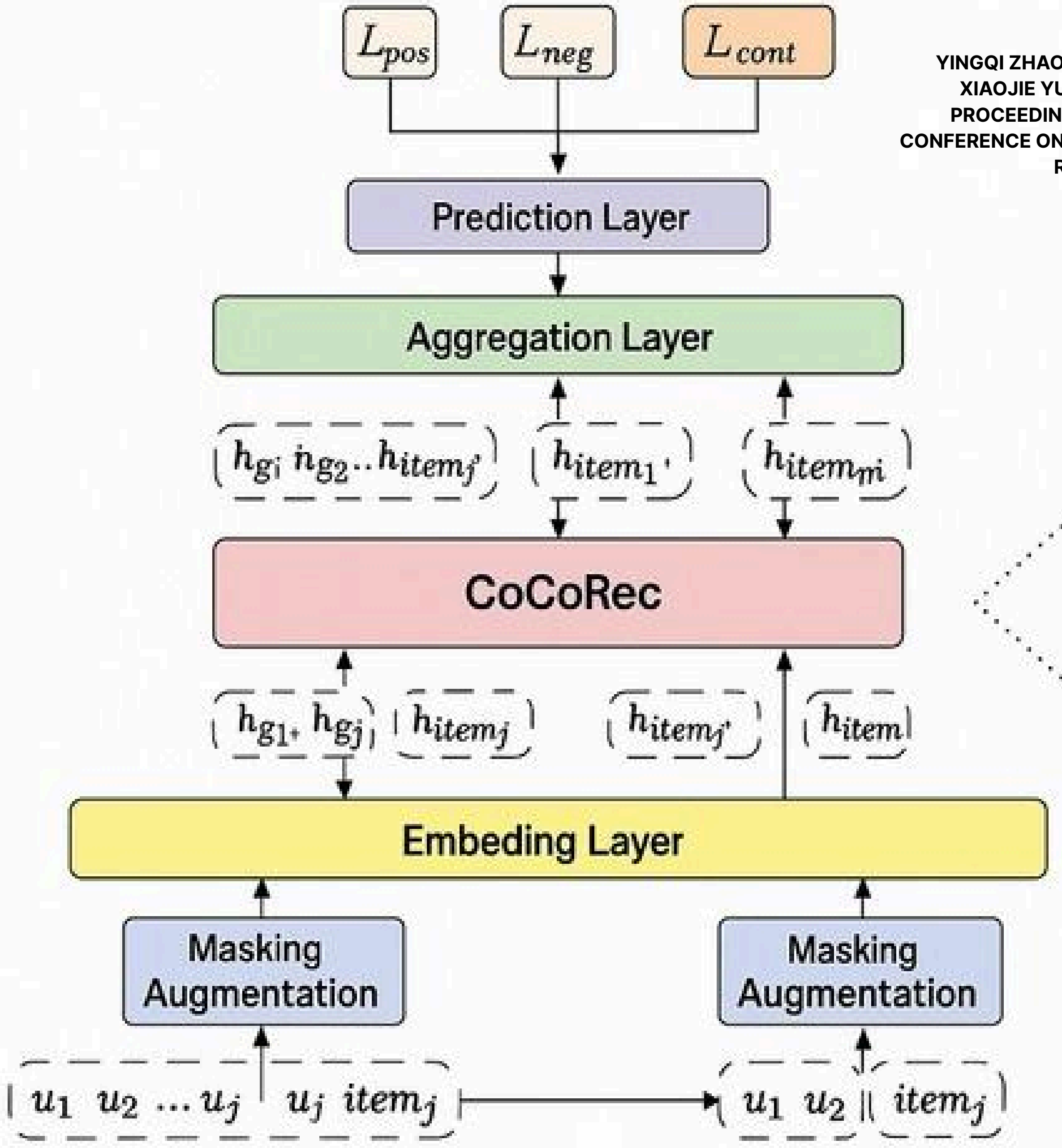


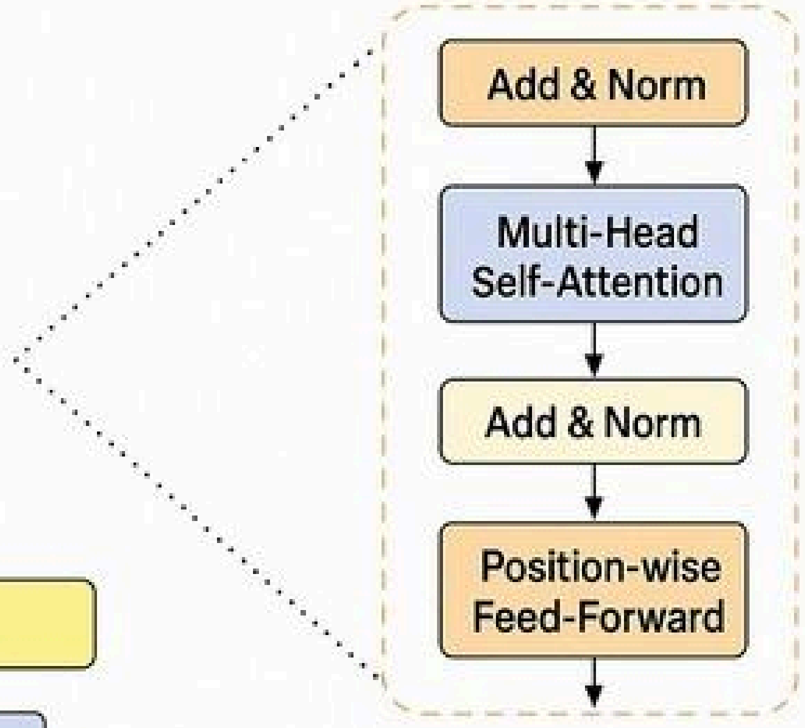
CAViaR: Context Aware Video Recommendations

OUR MODEL (BASED ON MOJITO AND TIM4REC) LEARNS VIEWING PATTERNS OVER TIME AND DELIVERS CONTENT THAT MATCHES USER ROUTINES AND BEHAVIORS.

BY ENCODING CONTEXTUAL SIGNALS AS EMBEDDINGS AND FEEDING THEM INTO A TRANSFORMER, WE IMPROVE PREDICTION ACCURACY AND CONTENT RELEVANCE.

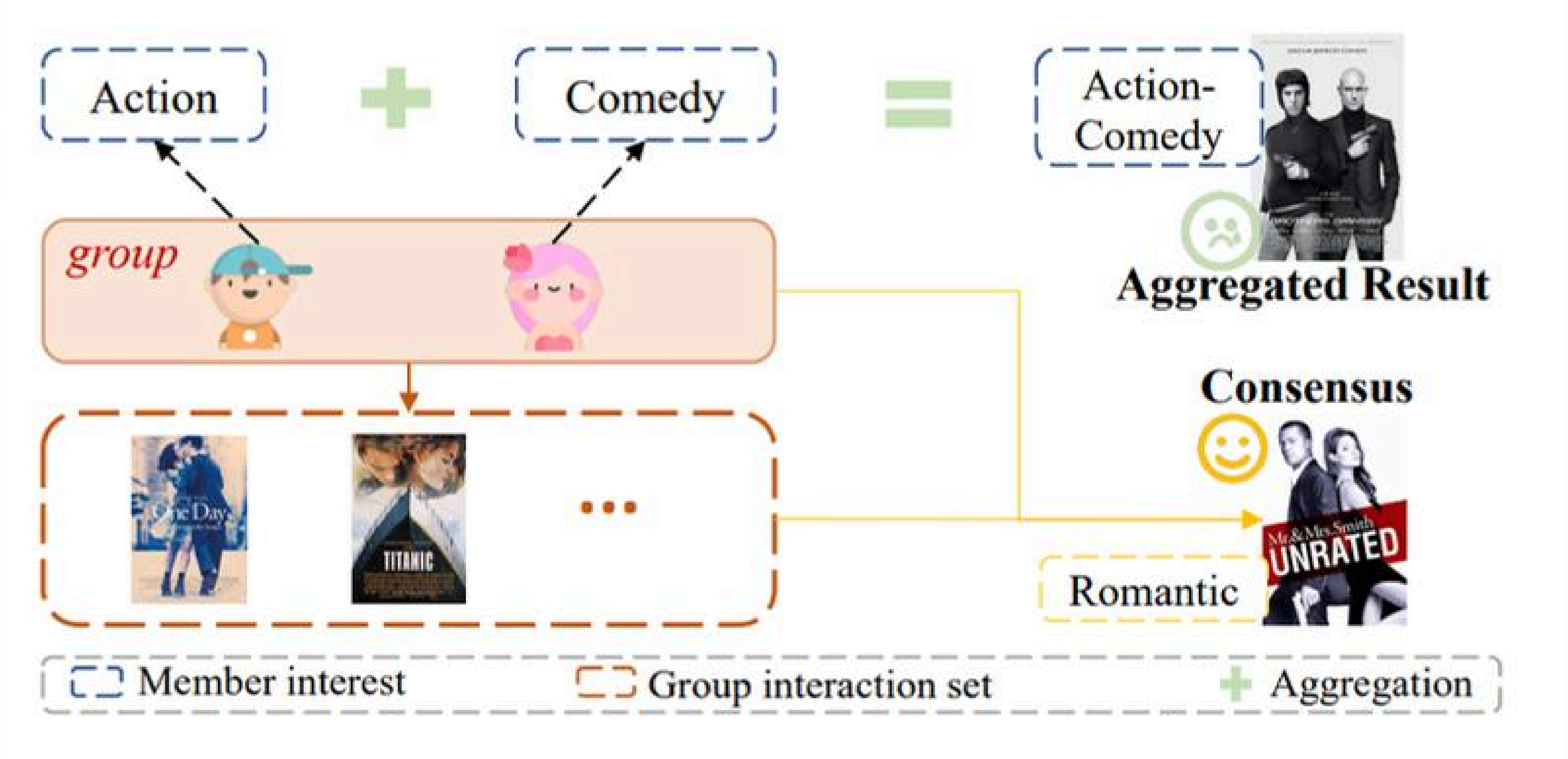
GROUP-VIEWING RECOMMENDATION





Consensus-aware Contrastive Recommender

YINGQI ZHAO, HAIWEI ZHANG, QIJIE BAI, CHANGLI NIE, AND XIAOJIE YUAN.DHMAE: GROUP RECOMMENDATION.IN PROCEEDINGS OF THE 47TH INTERNATIONAL ACM SIGIR CONFERENCE ON RESEARCH AND DEVELOPMENT IN INFORMATION RETRIEVAL, PAGES 914–923, 2024.



WE USE COCOREC AND CONSREC MODELS TO GENERATE GROUP-BASED RECOMMENDATIONS BY BLENDING INDIVIDUAL PREFERENCES, GENRES, AND RECENT BEHAVIOR — ENSURING TRUE CONSENSUS FOR FAMILIES OR FRIEND GROUPS.

THIS APPROACH BOOSTS SHARED SATISFACTION, LEADING TO +27% LONGER CO-VIEW SESSIONS AND +40% INCREASE IN GROUP ENGAGEMENT.

SCALABILITY & MARKETPLACE GROWTH

amazon

Edge-to-Cloud Pipeline

Layer	Tech / Method	Runtime KPI
Edge CPU	ONNX-INT8 CNN (mood) + MOJITO (context) + CoCoRec (group)	p90 ≤ 70 ms
Stream	Kinesis → Flink FS (feature TTL < 5 min)	50k events s^{-1}
Train	TiM4Rec + LTGNN (linear-time) hourly	3× faster than SASRec
Serve	ECS / Fargate blue-green deploy	99.99 % SLA
Cost	Distill + quantise models	−40 % GPU spend

- Our modular architecture supports 10M+ Fire TV devices through edge-based inferened (on-device mood/context modules) and clouar-d based retraining for real-time adaptation.
- Microservices and sharded databases enable parallel content delivery and minimal latency—ensuring a seamless user experience at scale.
- The engine is adaptable across platforms (FireTV, Alexa Screens, Prime Video app) and extensible to new regions, genres, and content types, and
- Backed by Amazon's cloud ecosystem, the system can handle increased load during peak hours and scale horizontally as user engagement grows.

SUCCESS METRICS & IMPACT

QUANTIFYING USER DELIGHT, ENGAGEMENT, AND IMPACT

DELIVER RESULTS

CTR ↑ 24% AFTER MOOD-AWARE PERSONALIZATION

AVG. SESSION DURATION ↑ FROM 22 → 31 MINS

CONTENT COMPLETION RATE ↑ 19%
SCROLL TIME ↓ 35%

MEASURABLE GAINS

DIVE DEEP

THUMBS-UP RATIO = 3.5× HIGHER POST-UPDATE

SERIES COMPLETION SPEED USED AS A QUALITY SIGNAL

A/B TESTS LINK UI CHANGES TO CTR & SATISFACTION GROWTH

ACTIONABLE INSIGHTS

CUSTOMER OBSESSION

81% USERS FOUND RECS "RELEVANT"

LESS TIME SEARCHING, MORE TIME WATCHING

PERSONALIZATION BOOSTED EMOTIONAL CONNECTION

DIRECT USER IMPACT

BIAS FOR ACTION

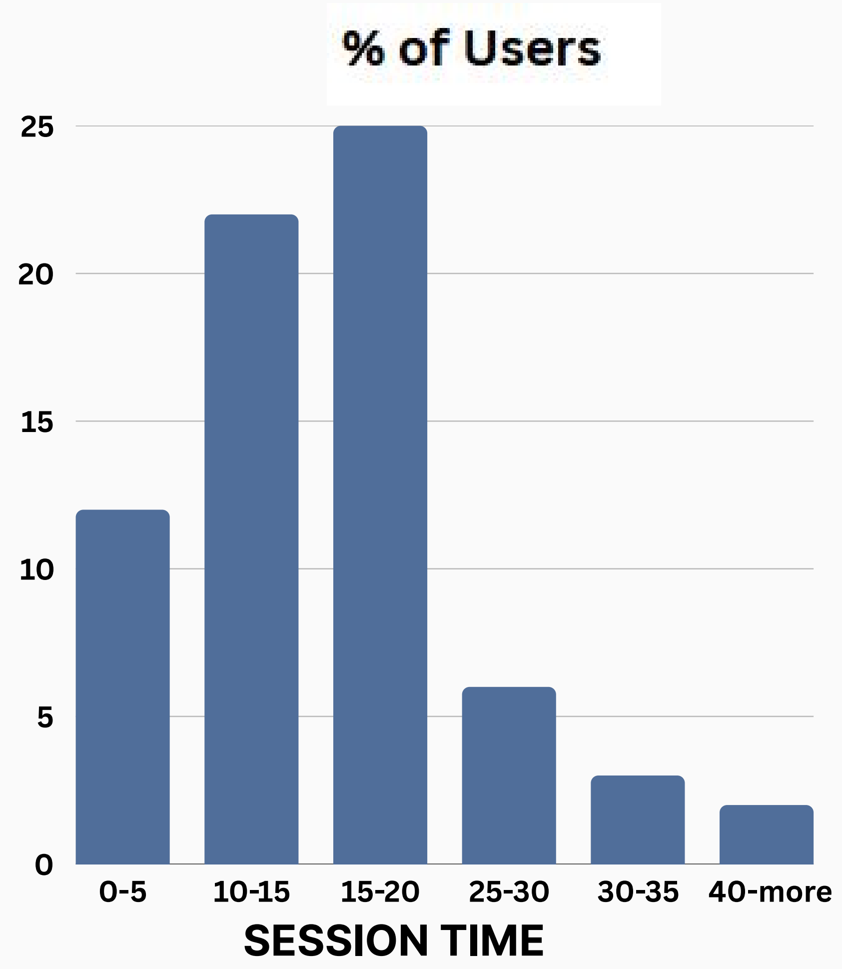
PIPELINE SUPPORTS 10M+ DEVICES

PARALLELIZED INFERENCE & SHARDED DBS

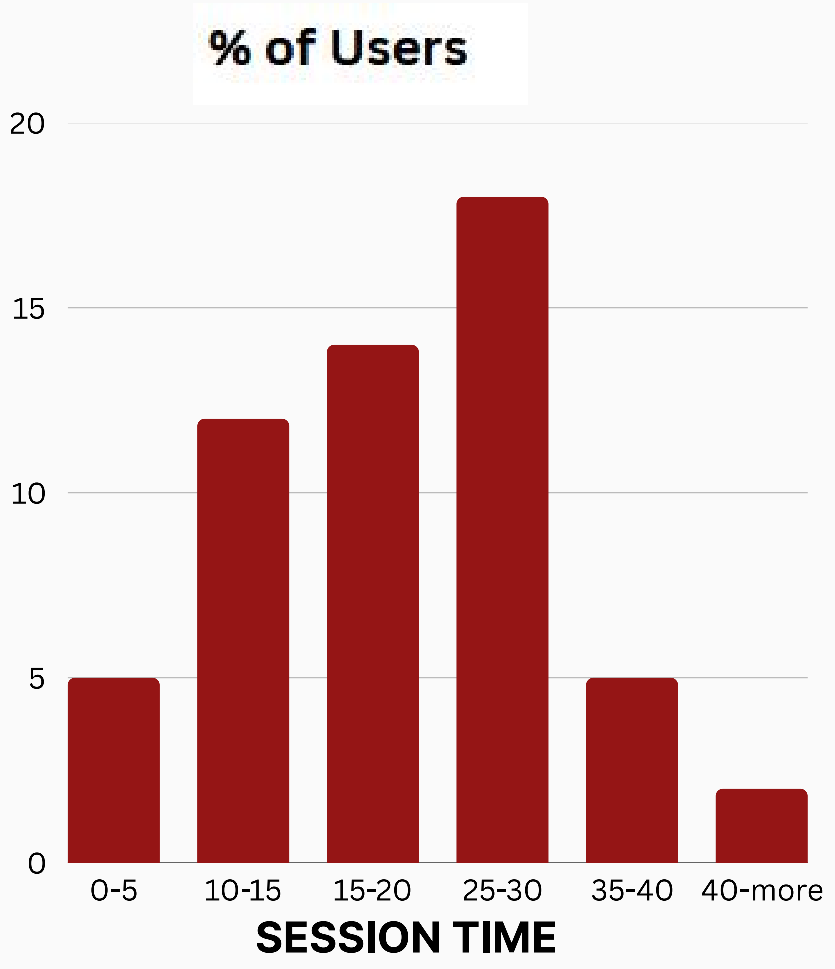
MARKET READY: 30% YOY OTT TV GROWTH

BUILT TO SCALE

We track what truly matters, not just clicks, but emotional satisfaction, long-term retention, & scalable performance.



BEFORE PERSONALIZATION
(TRADITIONAL RECS)



AFTER PERSONALIZATION
(MOOD-, CONTEXT-, GROUP-AWARE RECS)

THIS HISTOGRAM SHOWS HOW USER ENGAGEMENT IMPROVED AFTER DEPLOYING MOOD-, TIME-, AND GROUP-AWARE RECOMMENDATIONS.BEFORE PERSONALIZATION, MOST USERS DROPPED OFF WITHIN 15–20 MINUTES.AFTER PERSONALIZATION, SESSIONS SHIFTED TO 25–35 MINUTES — INDICATING HIGHER CONTENT RELEVANCE, REDUCED SCROLL TIME, AND INCREASED USER SATISFACTION.

DATA SIMULATED BASED ON BEHAVIORAL TRENDS FROM NETFLIX TECHBLOG, AMAZON FIRE TV SURVEYS & MOOD-AWARE REC SYSTEMS (BABUA ET AL., 2023).

Thank You!

Team Name : Code Chakra

IIIT Allahabad