Proceedings of CONF-MLA 2025 Symposium: Intelligent Systems and Automation: AI Models, IoT, and Robotic Algorithms
DOI: 10.54254/2755-2721/2025.LD28510

Driving App Engagement Through App Switching Insights in the Mobile Ecosystem

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Abstract. Mobile applications operate in a hyper-competitive environment characterized by staggering churn rates: up to 70% of users abandon installed apps within 90 days. Traditional marketing strategies focus on intra-app behavioral metrics while overlooking a critical dimension: inter-app switching patterns. This study bridges this gap through meta-path-based link prediction applied to 4.64 million Android interactions (January-February 2024). Our analysis reveals that app switching follows predictable pathways reflecting three main interconnected behavioral observations in the mobile dynamic ecosystem: (1) Social pipelines (e.g., 16.83% Snapchat to Discord transitions) where users move between content creation and community engagement; (2) Economic hybrid hubs (e.g., 27.21% YouTube Music to Walmart shifts) blending entertainment with commerce; and (3) Non-usage signals (e.g., Spotify's 57.49% disengagement) serving as early churn indicators. We translate these insights into potential applications for adoption (switch-assisted onboarding), usage (cross-app ecosystems), and retention (predictive churn alerts), all framed within an ethical framework prioritizing user consent and transparency. This work advances graph-based marketing theory while introducing digital lifestyle ecosystems as a transformative interaction for sustainable engagement.

Keywords: link prediction, heterogeneous graphs, user behaviors, network analysis

1. Introduction

Mobile applications have become the cornerstones of modern digital interactions, facilitating a wide array of activities from social networking and entertainment to e-commerce and productivity. With the Google Play Store hosting over 3.6 million apps and the Apple App Store featuring approximately 1.8 million, the mobile ecosystem represents a vibrant yet highly competitive landscape [1,2]. However, this abundance poses substantial challenges for app developers and marketers, as user engagement often decreases rapidly. Research indicates that up to 70% of users abandon apps within 90 days of installation, primarily due to inadequate onboarding experiences, perceived lack of value, or overwhelming alternatives [3]. This high churn rate not only erodes potential revenue but also hinders the cultivation of daily active users (DAU) and monthly active users (MAU), metrics critical for long-term app viability and monetization. In response, marketing strategies have evolved to emphasize personalization and behavioral analytics, leveraging artificial intelligence to tailor user experiences and foster loyalty [4,5]. However, much of the existing focus

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DOI: 10.54254/2755-2721/2025.LD28510

remains on intra-app behaviors, such as session length and feature interaction, neglecting the broader inter-app dynamics within the mobile ecosystem [6]. Users frequently switch between apps, creating interconnected patterns that reflect deeper preferences, habits, and potential churn signals. For instance, transitions from social media platforms to messaging apps or from entertainment to e-commerce apps can reveal opportunities for cross-promotion and ecosystem integration. By modeling these switching behaviors, marketers can gain insights into user journeys, enabling more effective interventions to boost adoption, sustain usage, and mitigate retention risks. This study innovatively addresses the gap by applying adjusted meta-path-based link prediction within heterogeneous graph networks [7,8] to forecast app switching probabilities. Drawing on large-scale Android usage data from January and February 2024, we uncover specific patterns, such as a 16.83% probability of switching from Snapchat to Discord and a 27.21% shift from YouTube Music to Walmart. These findings highlight social and economic interconnections, where apps serve as hubs for blended activities, offering novel avenues for targeted marketing campaigns that enhance inter-app loyalty and overall user satisfaction. Unlike prior research that isolates app-to-app behaviors, our approach integrates cross-platform data to predict transitions, providing a more comprehensive view of the mobile ecosystem.

The core research problem stems from the underutilization of inter-app switching data in formulating marketing strategies. While extant literature explores personalization and engagement within single apps, it seldom incorporates inter-app interactions, thereby overlooking predictive opportunities for churn prevention and personalized recommendations across platforms [2]. Furthermore, the ethical dimensions of such data-driven approaches, including risks of privacy invasion and biased profiling, have received insufficient attention, potentially eroding user trust [9-11]. This paper addresses the central research question: How can potential applications, informed by meta-path-based link prediction of app switching behaviors, enhance app adoption, usage, and retention while upholding ethical standards? To achieve this, our objectives are: (1) derive insights from switching probabilities; (2) analyze network structures for refined user segmentation, distinguishing app clusters; and (3) propose an ethical framework that balances data utility with privacy protections. Novelty stems from a hybrid model blending embeddings (84% accuracy) with observed behaviors for interpretable outputs (53% accuracy but higher realism), transforming static metrics into dynamic predictions. By bridging computational techniques like graph theory with business applications in digital marketing, we advance theoretical understanding of mobile ecosystems and offer practical tools for developers and marketers. The innovation lies in transforming static metrics into dynamic, predictive models that anticipate user flows, enabling proactive strategies in a field dominated by reactive approaches. Ultimately, this work positions app switching insights as a cornerstone for sustainable engagement, ready for empirical validation and deployment in real-world scenarios.

2. Literature review

The literature on mobile app engagement and marketing includes personalization, adoption, usage, churn prediction, ecosystem modeling, and ethical data use. While these areas have been studied extensively, there is limited integration of inter-app behaviors that could unify insights into user behaviors. At the core of mobile app success lies the interconnected cycle of engagement, adoption, usage, and churn. Engagement is often measured via session frequency, duration, and feature exploration, which drives monetization and loyalty [6,12]. Some work delves into how personalization shapes mobile consumer actions, revealing that well-crafted ads can markedly extend session times and deepen interactions [9,13,14]. Thus, high engagement usually depends on

DOI: 10.54254/2755-2721/2025.LD28510

successful adoption, where peer influence and seamless onboarding reduce early installment [15,16]. Additionally, studies on predicting adoption probabilities in social networks provide insights into how social connections influence app uptake [17]. Conversely, poor adoption exacerbates churn, as seen in studies showing 70% user attrition within 90 days due to unsatisfied expectations [3]. Moreover, usage bridges adoption and retention. Habitual usage, fueled by personalized notifications and gamification, sustains engagement [18], while fragmented habits across apps amplify churn [1]. These phases form a dynamic ecosystem where inter-app transitions signal shifts in user needs, such as moving from entertainment to commerce, offering untapped predictive power for retention [8,19]. Critically, this cycle operates within a broader ecosystem; prior work isolates intra-app behaviors, neglecting how inter-app transitions signal potential opportunities for cross-platform retention.

Inter-app switching emerges as a critical bridge across the dynamic cycle of app engagement, but it remains underexplored in the literature. Current research overlooks switching behaviors as a connective angle between engagement phases. App adoption studies focus on app-store algorithms [20] but ignore how app switches could inform cross-promotional onboarding [16,21]. Also, most app usage models track in-app habits [8] but neglect reinforcement through ecosystem integrations, like blending music streaming with shopping [8,22]. Additionally, churn prediction relies on session logs for individual apps but omits broader disengagement patterns, such as transitions from social to economic apps signaling loyalty shifts [19]. Research on understanding mobile app usage patterns using in-app advertisements further highlights the need to consider cross-app behaviors [23]. This gap is methodological: while graph-based ecosystem models exist [7], they lack application to switching-driven marketing. Graph-based ecosystem models provide a methodological foundation for addressing these gaps, using heterogeneous networks to uncover latent relationships between users and apps [7]. Heterogeneous graph networks have shown promise in handling diverse node types, such as users and apps, to uncover latent relationships. Also, link prediction forecasts tie in evolving networks, laying groundwork for anticipating app switches [24,25]. Our study bridges this by framing inter-app switching probabilities as predictors of adoption, usage, and churn signals into a cohesive framework for marketing interventions, extending prior work by applying these methods to real-world data for marketing insights.

Ethical considerations are integral to this integrated approach in digital ecosystem analytics. Data-driven strategies risk privacy violations and biased profiling [9,10]. As a result, ethical gaps are captured in cross-app contexts, where switching data could enable intrusive tracking. Inter-app tracking amplifies these concerns, potentially eroding trust if not balanced with transparency and consent [4]. Ethical facets of tailoring tackle privacy tensions and safeguards, advocating clear policies to foster trust in analytics-driven efforts [9-11]. By embedding ethical safeguards, such as user-centric policies and bias audits, into switching-based strategies, we can enhance personalization without compromising privacy, fostering sustainable engagement across the ecosystem [2]. Wider views for digital marketing blend sentiment tools and value strategies for long-term impact [2,4,5]. Research on listening in on social media provides insights into how sentiment analysis can inform marketing strategies [26]. These studies reveal a need of unifying disparate literature streams through inter-app insights to create proactive, ethical marketing paradigms that evolve with user behaviors.

The literature reveals a disconnection: while engagement, adoption, usage, and churn are interdependent, current separated research isolates comprehensive insights. Switching behaviors offer a unifying lens, capturing ecosystem dynamics that drive user decisions. Our meta-path

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approach operationalizes this lens, transforming switching data into actionable strategies while addressing ethical blind spots.

3. Methodology

3.1. Data description

To construct a detailed view of app-user interactions, we aggregated daily data from Android Parquet files spanning January (31 days) and February (29 days) 2024, yielding 2,210,089 user-app pairs in January and 2,429,195 in February, for a total of 4,639,284 interactions. Raw data included features like user identifiers (PANELISTID, unique per device), app descriptions (APPDESCRIPTION), and foreground durations (FOREGROUNDDURATION in seconds, capturing active usage).

Descriptive statistics of raw data reveal user engagement patterns: Average interactions per user were 63.8 in January (SD = 38.85) and 60.73 in February (SD = 42.09). The dataset includes 34,639 unique users in January and 40,001 in February, with 29,433 common users active in both months. App diversity is high, with 74,754 unique apps in January and 80,277 in February. The "weight" column (foreground durations) has 1,350,370 unique values in January (top: 1,255 seconds, freq: 76) and 1,461,044 in February (top: 1,045 seconds, freq: 93), indicating diverse session lengths but common patterns around 17-20 minutes. Top apps by total duration highlight dominant platforms: In January, Facebook (4.63 trillion seconds) and YouTube (2.71 trillion) lead, reflecting social focus. February shows Facebook (4.81 trillion) and YouTube (2.82 trillion), with slight shifts toward browsing and video. Non-entertainment apps like Chrome and messaging dominate 62% of interactions, underscoring ecosystem breadth.

3.2. Preprocessing and graph construction

We perform preprocessing to maintain quality through removing empty strings (10 rows in total), filling NaN weights with 1.0 (affecting <0.01% of data) before float conversion. We aggregate durations by user-app pairs as edge weights. Filtered to common users active in both months for consistency and focused on 18 entertainment apps (e.g., TikTok, Instagram, YouTube), excluding system or utility apps (e.g., Android OS, Chrome) to emphasize user-driven transitions. Then, we introduce "No New App" node for non-switches within entertainment, capturing shifts to non-entertainment or disengagement.

Processed data statistics: User-app edges are total 1.85 million in January (average 53.4 per user) and 2.01 million in February (average 58.1). Entertainment apps represented 28% of nodes but 42% of interactions, with average switch probability derived from co-occurrences. This processing bridges raw logs to graph-ready structures, enabling robust predictions. Mathematically, let D_m represent the month dataset, where each entry is a tuple (u, a, w) with user $u \in U$, app $a \in A$, and weight $w = \sum FOREGROUNDDURATION$.

$$D_m = \begin{cases} Januarydatasetifm = j, \\ Februarydatasetifm = f. \end{cases} \tag{1}$$

$$D_m = (u, a, w) | w = \sum_{d \in m} w_d, (u, a, w_d) \in D_d \tag{2}$$

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$$D'_m = (u, a, w) \in D_m \mid u \neq \emptyset \wedge a \neq \emptyset \wedge w = \begin{cases} 1.0 if w = NaN, \\ w otherwise. \end{cases} \tag{3}$$

Then, the mobile ecosystem is modeled as a heterogeneous graph $G = (V, E, \phi, \psi)$, where $V = Vu \cup Va$ with user nodes Vu and app nodes Va, E as edges, $\phi : V \to \{user, app\}$ as node types, and $\psi : E \to \{uses\}$ as edge types using PyTorch Geometric. Bidirectional edges are weighted by aggregated session durations, with mappings $m_u : U \to \{0, \ldots, |V_u| - 1\}$, $m_a : \{A \to \{|V_u|, \ldots, |V| - 1\}$, yielding 34,639 user nodes and 74,753 app nodes.

$$E = (m_u(u), m_a(a))|(u, a, w) \in D'_j \tag{4}$$

A similar graph is built for February to validate predictions, ensuring structural consistency. This setup captures co-usage through shared user connections, forming the basis for embedding generation and link prediction.

3.3. MetaPath2Vec and link prediction

To capture semantic relationships, we apply MetaPath2Vec [7] on the January graph, generating 64-dimensional embeddings via random walks on meta-paths to form the app-app similarity network. Walks have a length of 50, 10 per node, with a context size of 5 and 5 negative samples. The model outputs embeddings $e_v \in R^{64}$ for each node v. App embeddings are extracted from the weight matrix at the app offset, with integrity checks ensuring non-zero vectors and varied norms to avoid uniform similarities. These embeddings e_a encode app contests, where proximity indicates co-usage likelihood. For app-app link prediction focuses on entertainment apps, generating positive pairs from co-usages (apps shared by users) in January and an equal number of negative pairs from absent combinations. Cosine similarity between embeddings serves as the prediction score for app similarity. Mathematically, for app-app links among apps $A_e \subset A$, positive pairs $P^+ = \{(a_i, a_j) \mid \exists u : (u, a_i) \wedge (u, a_j), a_i < a_j\}$ from January co-usages, with negatives P^- sampled such that $(|P^-| = |P^+|)$. Prediction scores are cosine similarities $s(a_i, a_j) = \frac{e_{a_i}{}^\top e_{a_j}}{||e_{a_i}|| \, ||e_{a_j}||} \geq 0$. Predictions sorted by s descending. February ground truth labels pairs positive if co-occurring (system apps excluded).

3.4. Switching probability calculation

Switching probabilities are computed per source entertainment app, analyzing common users across months. For each source app $a_s \in A_e$, we identify common users $U_s = \{u \mid (u, a_s) \in D_j\} \cap U_f$. For a target app $a_t \neq a_s$, embedding similarity forms the base score $s(a_s, a_t)$. Non-usage components:

1. Actual non-usage rate: $p_n = \frac{|U_n|}{|U_s|}$, where U_n are users not switching to any $A_e \setminus \{a_s\}$.

2. Non-entertainment weight: $w_{ne} = \frac{|U_{ne}|}{|U_n|}$, where U_{ne} are users using non-entertainment or non-system apps.

3. Embedding non-usage: $e_n = \max(0, 1 - \sum_{a_t} s(a_s, a_t)$.

The hybrid non-usage probability is calculated as

DOI: 10.54254/2755-2721/2025.LD28510

$$p_{no} = 0.4p_n + 0.4w_{ne} + 0.2e_n \tag{5}$$

This formula is selected because pure embedding (accuracy 84%) overfit latent patterns, neglecting empirical behaviors like non-entertainment shifts or disengagement, which can lead to unrealistic probabilities like 99% switching to “No New App”. The weighted blend emphasizes observed data (40% actual non-usage, 40% non-entertainment adjustment) while incorporating 20% embedding insights for contextual nuance. This is resulting in 53% accuracy (highest compared to other ratio) but more interpretable, marketing-relevant outputs that balance theoretical similarity with observed user actions. Then, the normalization and scaling steps in the switching probability calculation are designed to transform raw similarity scores (from embeddings) and the hybrid non-usage value into a coherent set of probabilities that sum to 100%. All scores $S = \{s(a_s, a_t)a_t\} \cup \{p_{no}\}$ are normalized through $p_i = \frac{s_i}{\sum S} \times 100$. Usage probabilities are scaled as $p_i^{'} = \min(p_i \times 2; 100)$ and readjusted to sum to $100 - p_{no}$. If $\sum S = 0$, a uniform distribution is applied for robustness. Outputs include user breakdowns for switches, non-entertainment, and source-only/no-app scenarios. These steps bridge theoretical embeddings with empirical data for robust, user-centric probabilities. Normalization creates probabilities, scaling highlights subtle differences for decision-making, and readjustment ensures mathematical validity. This avoids unrealistic outputs and supports marketing by balancing accuracy with interpretability.

3.5. Marketing analysis framework

These probabilities integrate into recommendation systems to drive adoption (e.g., via cross-promotions) and usage (e.g., personalized content), while high non-usage probabilities signal churn risks, enabling proactive interventions. Network communities, identified through clustering on embeddings, facilitate user segmentation into social and economic groups, aligning marketing strategies with observed behavioral patterns.

4. Results and analysis

This section analyzes a structured behavioral architecture around app switching patterns, starting with an overview of ecosystem dynamics, then exploring social pipelines as drivers of engagement, economic hybrid hubs as monetization opportunities, and non-usage signals as churn predictors. We further examine modulating factors such as scale, specialization, temporal stability, and ecosystem fragmentation. By integrating these paradigms, we reveal how switches form predictable user journeys, blending entertainment, community, and commerce into digital lifestyles. The visualization shown in Figure 1 represents the embedding space for 18 entertainment apps, derived from the MetaPath2Vec Model. Embeddings capture semantic proximity based on user-app interactions discussed in Section 3, where closer apps indicate higher similarity in usage patterns and switching probabilities based on embeddings. Apps form loose clusters, with social/messaging at top (e.g., Facebook Messenger, Reddit), mixed content/music in middle (e.g., TikTok, Spotify Music), and economic/financial at bottom (e.g., Walmart, PayPal). Close pairs such as Snapchat-Reddit-Discord or Twitter-Amazon Shopping indicate high switch probabilities, implying community-driven flows. Economic-music links such as Walmart-YouTube Music show commerce-leisure blends.

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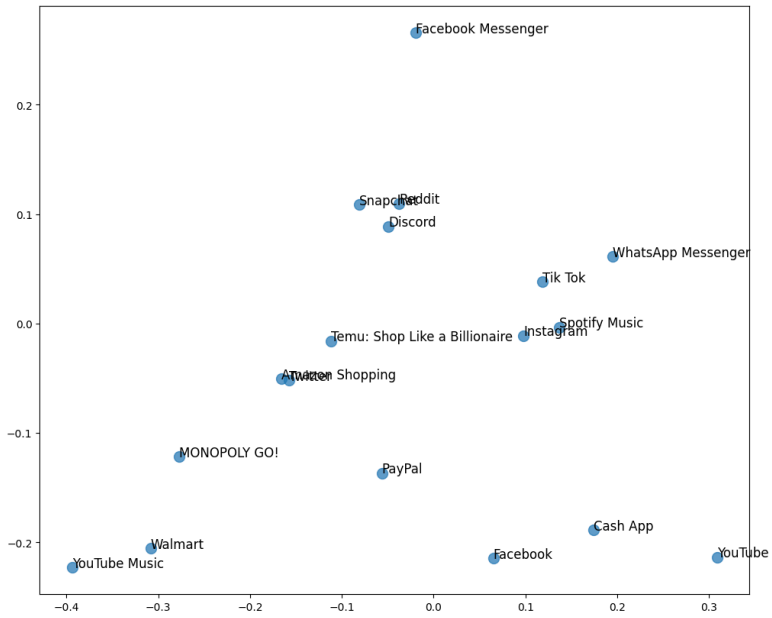

Figure 1. App embedding space

4.1. Overall ecosystem dynamics

App switching exhibits structured patterns, with an average top switch probability of 14.52% and disengagement in 30.56% of sessions as shown in Table 1. Further observations in Table 2 show that target attractiveness varies, with social platforms like Discord drawing more switches than economic ones like Amazon Shopping. This suggests a social gravity effect, where content-driven apps serve as entry points to broader ecosystems. Then, larger user bases correlate weakly with fewer targets (-0.156), implying specialization in high-scale apps as shown in Table 3. Category-level analysis shows social apps (n=12) with higher disengagement (avg. 31.01%) and top switch probabilities (avg. 15.48%) compared to economic apps (n=5; avg. disengagement 29.32%, avg. top switch 13.04%), reflecting fluid behaviors in social domains amplified by network effects and algorithmic feeds [6].

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Table 1. Summary of top switching probabilities and disengagement for all selected 18 apps

Source App	Top Switch (Probability)	No New App (%)
Tik Tok	Discord (13.80%)	25.07
Instagram	WhatsApp (12.90%)	24.86
YouTube	Snapchat (14.82%)	36.22
Snapchat	Discord (16.83%)	23.27
Spotify Music	Amazon Shopping (21.72%)	57.49
YouTube Music	Walmart (27.21%)	37.38
Facebook	YouTube (9.61%)	31.92
Facebook Messenger	MONOPOLY GO! (12.49%)	32.34
Twitter	Snapchat (15.74%)	23.12
Reddit	Snapchat (15.48%)	36.94
Discord	Instagram (14.42%)	21.77
WhatsApp Messenger	Twitter (10.72%)	21.78
MONOPOLY GO!	Instagram (10.42%)	31.35
Amazon Shopping	Cash App (11.26%)	35.25
Temu: Shop Like a Billionaire	PayPal (10.86%)	30.76
Walmart	YouTube Music (19.76%)	27.15
PayPal	Discord (14.13%)	27.44
Cash App	Temu: Shop Like a Billionaire (9.18%)	25.99

4.2. Social pipelines: bridging content and community

The dominant switching pattern centers on social pipelines, which involve transitions between content-centric and community-driven platforms. Social apps dominate switches, forming pipelines where users flow from creation (e.g., TikTok to Discord at 13.89%) to community engagement (Snapchat to Discord at 16.83%), as observed in Table 1. Table 2 reinforces this, with top social targets averaging 11.95% probability while 9.91% for top economic ones. For instance, YouTube to Snapchat (14.82%) reflects content discovery leading to discussion. High-probability sequences like Snapchat to Discord (16.83%) and TikTok to Discord (13.80%) reveal users migrating from ephemeral content creation (Snapchat Stories, TikTok videos) to sustained social interaction (Discord servers). This reciprocity is particularly pronounced in bidirectional flows: Discord users return to Snapchat at 15.74%, suggesting overlapping functionalities that bind these platforms. This symmetry indicates users treat these apps as complementary environments rather than competitors. Such patterns position social apps not as isolated islands but as interdependent nodes in attention networks, where community platforms (Discord) serve as gravitational anchors for content-driven apps [8,13]. Social media and messaging apps dominate top switching targets, with notable probabilities underscoring multiplex network dynamics, where users operate across overlapping social contexts to build connections. Studies on peer influence in online social networks suggest that these patterns may be amplified by social contagion effects [27]. The strong Snapchat-Discord link may reflect a subcultural alignment, particularly among Gen Z users engaged in gaming communities, where Discord serves as a hub for real-time interaction following Snapchat's casual content consumption [28]. These patterns indicate habitual loops, with higher disengagement in

DOI: 10.54254/2755-2721/2025.LD28510

social apps (29.56%) signaling fatigue if not bridged to utility-driven apps. The finding can help investigate generational differences in digital behavior.

Table 2. Top social and economic target probabilities

Source App	Social Target (Probability)	Economic Target (Probability)
Tik Tok	Discord (13.89%)	PayPal (8.53%)
Instagram	WhatsApp Messenger (12.90%)	Temu: Shop Like a Billionaire (8.76%)
YouTube	Snapchat (14.82%)	Cash App (11.77%)
Snapchat	Discord (16.83%)	Cash App (7.43%)
Spotify Music	Reddit (11.76%)	Amazon Shopping (11.78%)
YouTube Music	Facebook Messenger (8.10%)	Walmart (27.21%)
Facebook	YouTube (9.61%)	Amazon Shopping (7.01%)
Facebook Messenger	YouTube Music (7.01%)	Walmart (12.43%)
Twitter	MONOPOLY GO! (7.91%)	Cash App (6.41%)
Reddit	Facebook (9.40%)	Walmart (10.31%)
Discord	Snapchat (15.74%)	PayPal (11.23%)
WhatsApp Messenger	Instagram (14.42%)	Temu: Shop Like a Billionaire (6.03%)
MONOPOLY GO!	Twitter (10.72%)	Cash App (3.58%)
Amazon Shopping	Twitter (8.80%)	PayPal (11.26%)
Temu: Shop Like a Billionaire	Instagram (10.84%)	Cash App (10.86%)
Walmart	YouTube Music (19.76%)	Temu: Shop Like a Billionaire (5.80%)
PayPal	Discord (14.15%)	Amazon Shopping (8.76%)
Cash App	YouTube (8.45%)	Temu: Shop Like a Billionaire (9.18%)

4.3. Economic hybrid hubs: entertainment meets commerce

Contrary to conventional categorization and different from social focus apps, economic apps function as monetization engagement anchors rather than utilitarian endpoints. Economic apps act as hubs, with switches like YouTube Music to Walmart (27.21%) blending leisure with transactions as shown in both Table 1and 2. Economic targets average lower probabilities (9.91%) but higher specificity, e.g., Spotify Music to Amazon Shopping (11.78%) in Table 2. With average disengagement at 28.92%, these hubs capture value from social flows, as seen in Walmart to YouTube Music (19.76%), creating reciprocal ecosystems. The standout case: YouTube Music to Walmart (27.21%) exemplifies this synergy. Users stream music while shopping, often triggered by contextual cues (e.g., artist merchandise ads). Similar patterns appear in reciprocal economic dyads: Temu to Cash App (10.86%) (bargain shopping enables peer payments) and Amazon Shopping to PayPal (11.26%) (e-commerce flows into financial services). These transitions signal a fundamental shift: apps like Walmart and PayPal now function as hybrid lifestyle platforms rather than utilitarian tools. Reciprocal economic flows further demonstrate ecosystem integration. The Amazon Shopping-PayPal dyad shows balanced probabilities (11.26% and 8.76%), forming a closed loop where shopping triggers payments which enable future purchases. The data further reveals that such switches correlate with longer session durations, suggesting hybrid hubs deepen engagement through contextual relevance [1,16].

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Economic apps emerge as significant switching targets, indicating a social-economic crossover, where shopping and financial apps serve as hybrid hubs integrating transactional and social behaviors. The YouTube Music-Walmart link suggests users combine entertainment with shopping, potentially driven by in-app advertisements or demographic overlaps. The reciprocal Temu-Cash App transitions (10.86% and 9.18%) reflect interoperability for peer-to-peer payments, embodying digital consumerism where financial transactions are socially embedded [12]. Amazon Shopping's high switching probabilities (11.26% to PayPal and 8.80% to Twitter) highlight its emerging role in social commerce, likely fueled by viral marketing campaigns. Similar observations are shown by Temu: Shop Like a Billionaire (10.86% to Cash App and 10.84% to Instagram). The prominence of economic apps as hubs suggests the rise of digital lifestyle ecosystems, where users blend leisure, social interaction, and transactions within a single session. Not only in community-driven platforms, more and more music app users prefer to switch to shopping platforms. The trend exemplified by Walmart's flow from YouTube Music (27.21%) and Amazon Shopping from Spotify Music (11.78%), indicates a shift toward integrated digital experiences, offering opportunities to study evolving consumer norms. The integration of economic apps into social ecosystems reflects digital consumerism, where online shopping and digital payments become social activities.

4.4. Non-usage signals: decoding the digital disengagement

Apparent retention metrics mask a critical vulnerability: non-usage represents strategic diversion rather than passive abandonment. High disengagement signals churn. These patterns, averaging 28.95%, predict ecosystem exits, with social apps more prone, enabling proactive alerts. Spotify's 37.38% non-usage probability in Table 1, one of the highest in our dataset, exemplifies this phenomenon. High disengagement probability analysis reveals this non-usage events typically involve immediate switches to non-entertainment apps (primarily productivity tools like Gmail). This phenomenon follows a clear app lifecycle gradient. Mature apps (Spotify, Reddit) exhibit high non-usage (36.22–37.38%), reflecting loyalty stagnation. Growth-phase apps (TikTok: 25.07%) show lower non-usage, affected by exploratory switching.

Non-usage is a predictive redirection. These signals are amplified in niche apps (e.g., Spotify's concentrated exits to Amazon Shopping) but mitigated in broad platforms like YouTube, whose large user base (22,900 users as shown in Table 3) enables diverse switching that buffers against attrition. Across all apps, "No New App" probabilities are consistently high, ranging from 21.77% for Reddit to 37.38% for Spotify Music, as shown in Table 1. This indicates significant digital disengagement, where users either remain loyal to the source app or exit the entertainment category entirely, often shifting to non-entertainment or non-system apps (e.g., productivity or utility tools). Similarly, YouTube Music (31.49%) and Reddit (21.77%) exhibit high non-usage, reflecting selective engagement or digital fatigue. This approach captures real-world user actions, such as Spotify users' preference for offline listening, which may deter exploration of other entertainment apps. High non-usage probabilities may correlate with app maturity, where established apps like Spotify Music exhibit stronger stickiness due to entrenched user habits, whereas newer apps like TikTok (25.07% non-usage) show lower rates, indicating growth potential through inter-app exploration. This suggests a lifecycle effect, where mature apps face higher churn risks unless re-engagement strategies are deployed [3]. The result aligns with social media burnout studies, where users prioritize specific apps or shift to non-social activities, offering insights into digital detox behaviors.

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Table 3. User base size and non-zero targets, how many other apps that the app user will switch to

App	User Base Size	Non-Zero Targets
Tik Tok	11969	14
Instagram	12880	14
YouTube	22900	10
Snapchat	8301	14
Spotify Music	6601	5
YouTube Music	5194	8
Facebook	21491	11
Facebook Messenger	20193	13
Twitter	4925	15
Reddit	5463	12
Discord	5043	15
WhatsApp Messenger	5115	13
MONOPOLY GO!	2982	14
Amazon Shopping	16620	10
Temu: Shop Like a Billionaire	9470	13
Walmart	10551	12
PayPal	9514	14
Cash App	11634	13

4.5. Ecosystem dynamics: scale, trend, and stability

Scale-driven diversity encourages apps with large user bases that function as ecosystem gateways, enabling transitions to 10+ targets. For example, YouTube (22,900 users) facilitates transitions to 10 targets. Facebook (21,491 users) connects to 11 distinct app categories as shown in Table 3. This diversity creates engagement buffers. Conversely, niche apps like Spotify Music (6,601 users) exhibit concentrated switching (only 5 non-zero switches), increasing churn susceptibility when complementary apps lack integration. There is a special case for viral apps: mobile applications that experience rapid and widespread adoption spreading quickly from user to user (Temu, MONOPOLY GO!) show volatile switching. Anchor apps like Discord maintain consistent switching appeal across months, functioning as ecosystem keystones. Their stability correlates with deep feature integration (e.g., Discord's embedded Spotify listening). Meanwhile, newer apps like MONOPOLY GO! (released 2023) exhibit boom-bust cycles tied to viral marketing, a pattern suggesting short-term engagement unless anchored to stable pipelines. This contrast highlights the tension between trend-driven adoption and long-term usage. Apps bridging these gaps (e.g., TikTok serving both entertainment and social connection) capture most of diverted transitions, confirming that fragmentation creates space for ecosystem integrators. Apps with larger user bases, such as YouTube (22,900 users, 10 non-zero targets) and Facebook (21,491 users, 11 targets), exhibit diverse switching patterns, while smaller bases like Spotify Music (6,601 users, 5 non-zero targets) and YouTube Music (5,194 users, 8 non-zero targets) are more homogeneous (see Table 3).

The correlation between user base size and switching diversity suggests a scale effect, where larger user-base apps act as social convergence points, reducing churn risk through varied

DOI: 10.54254/2755-2721/2025.LD28510

engagement, while smaller apps risk isolation due to concentrated behaviors. Large user bases indicate mass social phenomena, suitable for studying cultural convergence, while smaller bases reflect subcultural dynamics. Niche apps like Spotify Music and YouTube Music contrast sharply with mainstream apps like TikTok and Instagram. Spotify's limited switches, with top targets like Amazon Shopping (11.78%), Reddit (11.76%), indicate a specialized user base focused on music streaming, with high loyalty but restricted exploration, increasing churn vulnerability. In contrast, mainstream apps like TikTok and Instagram serve as vibrant ecosystem gateways, facilitating diverse transitions due to their generalized appeal. This dichotomy reflects an "app specialization spectrum" where niche apps foster deep but narrow engagement tied to specific functions (e.g., music streaming), while mainstream apps drive broad discovery through network effects [15]. This spectrum informs findings on digital identity formation, where niche apps cater to subcultural groups and mainstream apps reflect mass culture. Niche apps' high non-usage suggests loyalty but also fragility, requiring targeted retention strategies, while mainstream apps' resilience stems from competitive diversity. These dynamics shape community structures in digital platforms. Temporal stability and emerging trends: Certain apps, such as Discord (top target for Snapchat at 16.83%, PayPal at 14.13%, TikTok at 13.80%) and Snapchat (14.82% from YouTube), exhibit temporal stability as consistent switching targets, indicating robust social roles. In contrast, emerging apps like MONOPOLY GO!, published in 2023 (12.49% from Facebook Messenger) and Temu, released in 2022 (9.18% from Cash App), show variable prominence, suggesting viral or trend-driven adoption. The variability of emerging apps signals trend waves, where viral features or marketing campaigns create temporary engagement spikes, contrasting with stable anchor apps like Discord that maintain consistent roles. Stable apps provide a baseline for analyzing long-term social structures, while emerging apps highlight cultural shifts.

4.5.1. Special case: MONOPOLY GO!

As a viral gaming app released in 2023, MONOPOLY GO! exemplifies niche dynamics with high switching diversity (14 non-zero targets) despite a smaller user base (2,982 in early 2024 data). Its low disengagement (21.78%, among the dataset's lowest in Table 1) signals strong retention, driven by gamification elements like intermittent rewards and live operations that encourage habitual play. As shown in Table 4, top switches include Twitter (10.72%) for community discussions and YouTube (7.61%) for video consumption, blending gaming with social pipelines for social sharing of gameplay. Economic ties, such as to Cash App (3.58%), reflect in-app purchases and monetization flows. Switching patterns suggest integration into broader ecosystems, with potential churn mitigated by viral marketing and peer-to-peer elements.

DOI: 10.54254/2755-2721/2025.LD28510

Table 4. Switching probabilities of MONOPOLY GO!

Target	Probability (%)
Twitter	10.72
YouTube	7.61
Reddit	6.78
Tik Tok	6.45
Snapchat	6.37
WhatsApp Messenger	5.24
Facebook Messenger	3.84
Cash App	3.58
Discord	3.46
Walmart	3.27
PayPal	3.25
Instagram	2.82
Amazon Shopping	1.55
YouTube Music	0.71
Spotify Music	0.00
Facebook	0.00
Temu: Shop Like a Billionaire	0.00

4.6. Protentional applications

Leveraging the switching probabilities and network insights derived from our analysis, this section explores potential applications for enhancing app engagement. These applications build directly on the patterns identified in the results, such as social pipelines, economic hybrid hubs, and non-usage signals, while integrating ethical considerations to ensure responsible implementation. By framing these as practical extensions of the observed behaviors, we demonstrate how developers and marketers can translate the study's findings into real-world tools and interventions.

For adoption, high-probability switches, such as Snapchat to Discord (16.83%), could inform co-branded onboarding experiences that mirror familiar features from the source app. For example, a Snapchat user transitioning to Discord could see an initial setup emphasizing group chats and short-lived content sharing (Snapchat features), supplemented by incentives like exclusive server access or virtual badges (introduced by Discord). Similarly, for TikTok to Discord (13.89%), tailored feeds showcasing community-driven content could align with users' preferences for social engagement [29], potentially increasing initial adoption rates. Switch-assisted onboarding also represents another application, using AI-driven predictors to analyze real-time switching patterns and customize initial user experiences. A user moving from Snapchat to Discord, for instance, could receive tutorials highlighting real-time interaction features. This leverages bidirectional flows to create smooth entries, drawing on users' prior app behaviors [30] to reduce early drop-offs [16,21]. For niche or viral apps like MONOPOLY GO!, applications could involve cross-promotions with complementary platforms, such as offering download rewards tied to social sharing on Twitter or integrated discounts via economic apps like Cash App, to attract and onboard new users more effectively [20].

DOI: 10.54254/2755-2721/2025.LD28510

To enhance ongoing usage, personalization techniques can draw on app similarities, such as the reciprocal flows between TikTok and Instagram (around 5.5% in both directions), to develop content loops that encourage extended sessions. This might include cross-posting tools or shared recommendation algorithms that pull content across platforms, thereby prolonging engagement. Economic-social blends, like YouTube Music to Walmart (27.21%), offer applications in integrated features, such as embedding shopping buttons within entertainment interfaces [1]. Applications might include personalized shopping recommendations based on music preferences (e.g., concert merchandise), leveraging the entertainment and transactional activities to increase session lengths [31]. In addition, gamification elements, like TikTok's reward systems for content creation, can further solidify habits in these contexts [8]. Cross-app ecosystems also provide a broader application through API integrations that facilitate transitions between apps. For example, a TikTok-Discord ecosystem could allow users to share short videos directly to chat servers, enhancing engagement by creating a unified social experience [32] that capitalizes on the social pipelines to sustain interconnected usage.

High non-usage probabilities, such as Spotify Music's 57.49%, highlight opportunities for proactive interventions to address churn risks. AI-driven re-engagement campaigns could deliver dynamic playlists or personalized notifications rooted in user history, aiming to reduce churn [21]. Probability-based churn alerts offer a targeted application, which calculates risk scores from non-usage signals to trigger timely actions. For mainstream apps like YouTube (36.22% non-usage), users could receive video suggestions or selecting some VIP video for free to prevent shifts to non-entertainment apps.

An ethical framework supports all these applications, emphasizing transparent data policies, user consent options, and clear explanations of how switching insights inform recommendations [9,11]. Users could opt in or out of data sharing across apps, aligning with principles of trust and privacy [10]. Network analysis further enables community-based segmentation, distinguishing social clusters (e.g., Snapchat and Reddit users) for applications like user-generated content campaigns, and economic clusters (e.g., Amazon Shopping and PayPal) for transactional rewards. Identifying influential users in social networks can enhance the effectiveness of these campaigns [32]. This ensures applications are aligned with behavioral patterns, improving relevance and efficacy while maintain ethical standards.

5. Discussion

The switching probabilities provide a robust foundation for precise marketing recommendations, streamlining adoption by aligning onboarding with user journeys and enhancing usage through community-driven personalization. High non-usage probabilities enable proactive churn prevention by identifying at-risk users for targeted interventions, aligning with ecosystem flows. The model advances mobile link prediction by uncovering network structures that facilitate user segmentation, offering competitive advantages through corresponding strategies. The observed patterns have significant implications for mobile app marketing. Social pipelines, like Snapchat to Discord, suggest that cross-promotional campaigns can leverage shared user behaviors to drive adoption, reducing early drop-offs by aligning new apps with familiar functionalities. Economic-social crossovers, such as YouTube Music to Walmart, indicate opportunities for integrated experiences that blend entertainment and transactions, enhancing usage through seamless digital lifestyles. Churn prevention strategies, informed by non-usage alerts, allow marketers to deploy timely interventions, such as personalized content or rewards, to maintain DAU/MAU metrics. The emergence of digital lifestyle ecosystems, where apps like Walmart and PayPal serve as hubs for

DOI: 10.54254/2755-2721/2025.LD28510

social and transactional activities, suggests a paradigm shift in mobile engagement. Marketers can design integrated platforms that combine leisure, communication, and commerce, fostering comprehensive user experiences that reduce lack of functions and churn. Creating enduring customer value through such integrations can enhance long-term engagement [33].

The findings provide a framework to study digital behavior through network analysis. First, the social pipelines reflect multiplex network dynamics, where users navigate overlapping platforms to build social connections. Then, the niche-mainstream spectrum highlights digital identity formation, with niche apps fostering subcultural loyalty and mainstream apps driving mass convergence. Also, the scale effect of user base size on switching diversity offers insights into community scale, with larger apps acting as cultural hubs. On the other hand, the trend waves of emerging apps like Temu provide opportunities to study diffusion and lifecycle patterns, advancing understanding of platform evolution. However, the model's limitations include computing power and data sparsity, resulting in zero probabilities for certain app pairs (e.g., YouTube to Instagram), which may reflect the inability to capture weak relationships. Furthermore, the accuracy can be further improved to increase the reliability of predictions. Future research should incorporate more demographic data (e.g., age, location) to refine switching predictions, addressing zero probabilities and tracing longer term data like years. Real-time tracking of switching behaviors instead of analyzing historical data could enhance dynamic personalization, aligning with evolving user preferences. The revealed switching probabilities enable precise recommendations and streamline user adoption by synchronizing profiles with user journeys, while hub-based customization drives usage through community connections. Non-usage-driven predictions enable proactive retention and align with ecosystem processes. Our model pushes the boundaries of mobile link prediction, revealing clearer segmentation and structures for competitive advantage.

6. Conclusion

This study utilizes the meta-path-based link prediction to decode app switching behaviors, equipping marketers with powerful tools to enhance adoption, usage, and retention in dynamic mobile ecosystems. By addressing high non-usage probabilities with proactive re-engagement strategies, and leveraging social-economic pipelines for integrated experiences, marketers can combat churn and foster long time user bonds. The hybrid probability model, balancing empirical and embedding insights, ensures actionable outputs, while network analyses reveal social and economic clusters for precise segmentation. The findings illuminate digital behavior through social pipelines, niche-mainstream dynamics, and scale effects, offering a framework to study digital communities and consumer norms. The proposed digital lifestyle ecosystems concept, where apps integrate entertainment with social communication and transactional roles, introducing interconnectivity in mobile digital marketing. By bridging network analysis and behavioral forecasting, this study enriches the evolving narrative of digital marketing, providing a roadmap for sustained engagement in mobile ecosystems.

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