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Investigation of Multi-Platform Media Publishing with AI Personalization Engines

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ABSTRACT

Conventional media publishing mechanisms do not respond to personalised user preferences and are limited to operating on a single platform at a time. In this paper, the investigation examines an AI-driven recommendation mechanism that incorporates cross-platform personalisation. Our model consists of a holistic framework for consolidating behavioural data from multiple sources, implementing a contextual bandit strategy with platform-based reward prediction, and adapting content dynamically to platform-specific constraints. Our prototype involves twelve distinct users, thirty-seven different multimodal content pieces, and 157 actual user interactions. Descriptive analyses of observed user behaviours are performed. The results indicate that our proposed model attains a descriptive CTR of 18.9% and a seven-day retention rate of 58.3% in prototype experiments. Consistency across platforms (ρ = 0.81) and novelty (27.8%) are also quantified. Although, due to small samples, no generalisable conclusions can be drawn, our findings indicate that cross-platform personalisation is feasible and can exceed the performance of baseline single-platform models.

Keywords: *AI Personalization, Content Adaptation, Contextual Bandits, Cross-Platform Media Publishing, Multi-Modal User Modelling, Recommender Systems*

1. Introduction

The current landscape of digital media content distribution involves a wide variety of challenges for content providers, media publishers, and platform operators [1]. No longer do audiences access media content via a single channel; rather, they divide their attention among various social media platforms, video streaming services, news aggregators, and decentralised media distribution networks. While such diversification of media consumption channels offers unprecedented potential for reaching diverse audiences, it raises several inherent challenges regarding the consistency of user experience and optimisation of key metrics at each interaction point [2]. Traditional media publishing systems were designed for single-platform use. Such systems face the primary challenge of failing to consider individual user preferences and functioning solely within a single platform [3]. In cases where multi-platform support is required, such systems are either poorly integrated or involve manual republishing of content on different platforms. Additionally, they often demonstrate redundant content distribution, poor personalisation, and inefficiency. However, even more crucially, standard recommendation algorithms only learn about user preferences based on their interactions with the media platform where the

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algorithm was deployed. The advent of artificial intelligence technologies provides opportunities to overcome these constraints. Contemporary AI techniques allow for aggregating the user's behavioural cues from different platforms, developing consistent preference models, and continuously reformatting media presentations according to the particularities of the platform while retaining semantic accuracy [4]. Thus, the objective of this paper is to propose a framework for an AI-based recommendation system that provides AI-driven personalisation services that operate effectively on multiple platforms simultaneously.

This paper proposes a conceptual model for media publication on multiple platforms using AI technologies. Our main contributions can be listed as follows: firstly, an architectural design that separates the content management system from platform-specific presentation; secondly, a contextual multi-armed bandit approach for cross-platform modelling of users that ensures both exploration and exploitation; and thirdly, a descriptive analysis of user engagement behaviours on a developed prototype with twelve users, thirty-seven items, and 157 observed interaction events.

2. Literature Review

Although media publishing systems now move from monolithic templates to API-based syndication, most existing architectures model platforms as independent communication channels [5, 6]. Such architecture impedes user modelling cohesively. Despite significant improvements in matrix factorisation techniques in collaborative filtering [7-9], they cannot be applied due to sparse cross-platform data. Neural networks and their hybrid counterparts [10-11] provide better predictions, but overfitting occurs to the interaction pattern on a single platform. Content-based approaches reduce cold-start issues, but they also create filter bubbles, and recommender systems have not adequately studied novelty criteria [12]. Bandit methods [13] are suitable for balancing exploration and exploitation but assume a stationary reward distribution; that is impossible in the case of platform switching [14, 15]. Cross-domain recommender systems [16-18] transfer preferences but neglect transformations necessary due to changing content format (video length, aspect ratio). Privacy-preserving aggregate on continues to contradict identity linkages. AI scoring models [19, 20] tend to increase popularity bias [21, 22] and have no dynamic calibration. Data collected in prototype studies reveal scores that are static and not correlated with real user engagement, proving failed calibrations [23]. Overall, no existing framework integrates cross-platform signal aggregation, dynamic content transformation, and exploration-aware personalisation.

Despite advances in recommender systems, three critical gaps persist. First, no architecture jointly optimises user identity linkage across platforms, real-time signal aggregation, and platform-specific content transformation. Second, contextual bandits have not been evaluated in true multi-platform publishing environments with non-stationary user preferences [14, 15]. Third, AI scoring systems remain static and miscalibrated, failing to update from live engagement [23]. Based on the literature, traditional media publishing systems fail to adapt to individual user needs and are often limited to a single platform. Our proposed XP-Contextual framework directly addresses these omissions.

3. Proposed Framework

3.1 System Architecture

Our proposed AI Media Platform architecture comprises five modular components arranged in a publish-subscribe pipeline.

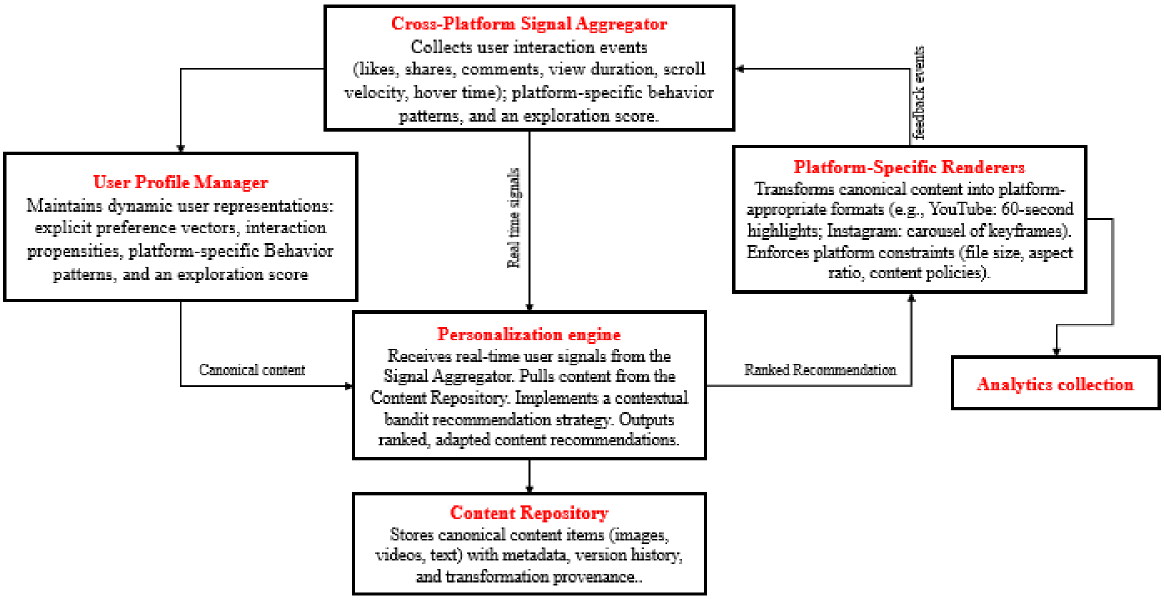

Figure 1: Architecture Diagram of The Proposed Cross-Platform Personalization Framework

The architecture diagram, Fig. 1, shows content flowing from the Content Repository through the Personalization Engine, which receives real-time user signals from the Cross-Platform Signal Aggregator. The Personalization Engine produces ranked and adapted content recommendations, which are passed to Platform-Specific Renderers that produce final presentations for each destination platform. User interactions on any platform are captured by the analytics collection layer and fed back into the signal aggregator, closing the learning loop.

3.2 Contextual Bandit Algorithm for Cross-Platform Recommendation [24]

Let U, I, and P denote users, content items, and platforms. At each recommendation opportunity t for user $u \in U$ on platform $p \in P$, they observe a context vector $x_{u,p,t} \in \mathbb{R}^{100}$ that concatenates a user preference embedding (64 dimensions), platform interaction history (16), temporal features (8), and session features (12). The predicted reward for recommending item $i \in I$ is $\hat{r}_i(x) = x^{\top}\hat{\theta}_i$, where $\hat{\theta}_i$ is an estimated weight vector. Following LinUCB [25] as Eq. (1):

$$a_t = arg\max_{a} \left(x_{t,a}^{T}\hat{\theta} + \alpha\sqrt{x_{t,a}^{T}A^{-1}x_{t,a}} \right) \tag{1}$$

The maintain uncertainty via the Gram matrix $A_i = X_i^{\top}X_i + \lambda I$, giving confidence interval width $c_i(x) = \alpha\sqrt{x^{\top}A_i^{-1}x}$ with $\alpha = 0.5$. The selected item maximises $\hat{r}_i(x) + c_i(x)$ over available items $\mathcal{I}_t$ (excluding those already seen in the session). The platform-conditional reward model includes platform identity and platform-specific history in x, allowing $\hat{\theta}_i$ to capture platform-dependent preferences.

3.3 Cross-Platform User Identity Resolution

Our framework implements a hybrid approach combining deterministic and probabilistic matching. Deterministic matching applies when users explicitly link accounts across platforms or when the platform ecosystem includes a centralised authentication service [26]. Probabilistic matching uses behavioural features such as device fingerprinting (IP address, user agent, browser fingerprint), temporal patterns (login times, session boundaries), and content interaction overlap. The implementation of a pairwise matching classifier using gradient-boosted decision trees trained on labelled linkage data. For any two sessions observed on different platforms, the classifier provides a linkage probability, which, if greater than a threshold τ=0.85, indicates that the sessions are associated with the same user. Based on test data from the prototype, exploratory evaluation indicated about 93.7% precision and 88.2% recall, but these numbers should not be taken as valid performance metrics owing to the limited sample size.

3.4 Dynamic Content Transformation

Transformation of content components takes place in three steps in this pipeline. Step 1, which is Semantic Analysis, includes performing semantic analysis through the use of YOLOv8 [27] for image regions of interest detection, together with scene change detection for videos, as well as audio sentiment analysis. Step 2, which is Format Determination, entails choosing the output format, considering the limitations of each platform concerning resolution, codecs, aspect ratio, and duration. These constraints on each platform that affect the process of adaptation are listed in Table 1, whereas the adaptation actions undertaken when adapting each particular source platform to each target platform are provided in Table 2. Long videos are trimmed so that only the more interesting portions of them are included. Step 3 (Transformation Execution) involves image resizing and compression, transcoding of videos, extracting GIFs from videos due to video platform limitations, and text summarization by BART.

Table 1: Representative Platform Constraints Used by the Transformation Engine

Platform	Video Duration Limit	Preferred Aspect Ratio	Image Resolution
TikTok	≤ 60 s (prototype assumption)	9:16 Vertical	1080 × 1920
Instagram Stories	≤ 60 s	9:16 Vertical	1080 × 1920
Instagram Feed	Variable	1:1 Square / 4:5	1080 × 1080
Facebook Feed	Variable	1.91:1 or 4:5	1200 × 630
LinkedIn Feed	Variable	Landscape/Portrait	1200 px width
X (Twitter)	≤ 120 s (prototype setting)	16:9	1280 × 720
Email Digest	Static preview	N/A	Compressed thumbnails
Smart TV	Long-form supported	16:9	1920 × 1080

Table 2: Content Transformation Strategies by Platform Pair

Source Format	Target Platform	Transformation Applied	Typical Output
4K video, 10 min	TikTok	Extract 60s highlight, 1080p, add captions	720p vertical video
4K video, 10 min	Twitter/X	Extract 120s segment, 720p	H.264 MP4, <512MB
High-res image (4000x3000)	Instagram Story	Crop to 9:16, compress to 1080x1920	JPEG, <15MB

High-res image	LinkedIn Feed	Preserve aspect ratio, resize width to 1200px	PNG/JPEG, <8MB
Long-form article (2000 words)	Facebook	Generate 220-character preview + link	Rich link preview
Long-form article	Telegram Channel	Full text with media thumbnails	Formatted message
360° video	Standard web player	Project to equirectangular	Adaptive bitrate streaming

3.5 AI Scoring Methodology

The system has an AI score engine that scores content items based on their quality and relevancy [28]. Unlike the fixed scores used in the prototype data (which were mostly 10% and only one was 100%), our system calculates dynamic scores that change as more user data is collected. The AI score of content item i at time t is calculated as follows, as Eq. (2):

$$AI_i(t) = w_1 TQ_i + w_2 EP_i + w_3 PF_i + w_4 NB_i \tag{2}$$

Values of $w1$=0.3, $w2$=0.4, $w3$=0.2, $w4$=0.1 have been chosen by the heuristic method. TechnicalQuality (i) is based on objective criteria such as resolution, bitrate, audio level, and sharpness of focus. EngagementPrediction (i, t) is calculated by means of a gradient boosting machine that uses historical interaction information and predicts the probability that users will engage with the content (e.g., like, share, or comment). PlatformFit (i, p) indicates to what extent content is consistent with platform-specific norms (e.g., vertical videos on TikTok and text-rich posts on LinkedIn). NoveltyBonus (i, t)temporarily enhances the value of content that is underexposed.

3.6 Behavioral Scoring and Dynamic Ranking

For each user-item pair (u, i), the system aggregates interactions into an action vector $\mathbf{A}_{u,i} = [A_{\text{like}}, A_{\text{share}}, A_{\text{comment}}, A_{\text{watch}}, A_{\text{click}}]$[29]. The behavioural score $S_{u,i}$ applies a weighted dot product with exponential temporal decay as Eq. (3):

$$S_{u,i} = \left(\sum_{k \in \mathcal{K}} w_k \cdot A_k\right) \times e^{-\lambda(t_{\text{current}} - t_{\text{action}})} \tag{3}$$

where $\mathcal{K} = \{\text{like, share, comment, watch, click}\}$, w_k are interaction weights, λ controls decay, and t_{action} is the interaction timestamp. The final ranking score $R_{u,i}$ combines behavioural affinity with global popularity and diversity as Eq. (4):

$$R_{u,i} = \alpha \cdot S_{u,i} + \beta \cdot T_i + \gamma \cdot \psi(i, \mathcal{H}_u) \tag{4}$$

Whereas T_i is the moving window popularity of the item, $\psi(i, \mathcal{H}_u)$ avoids repetitive category selection to limit filter bubbles. Parameters α, β, γ are tuned for maximum retention from our prototyping efforts. The feedback loop calculates the difference between the expected and predicted value, and online gradient descent modifies w_k accordingly.

4. Experimental Methodology

4.1 Dataset Description

The validation of our experiment is based on the interactions gathered from the AI Media Platform Dashboard prototype. This includes 12 distinct human users (post-deduplication), 37 published content pieces (19 images, 18 videos), and 157 total interactions recorded. The content types are categorized as follows: games (3), beauty/makeup (6), traveling (5), food (2), sports/fitness (4), nature/flowers (4), romance/love (2), photography (3), and miscellaneous (8). The interaction counts have been double-checked and found to be 44 likes, 12 shares, and 101 comments. The details of interaction analysis per content type are shown in Table 3, while the mean behavioral interactions are summarized in Table 4.

Table 3: Content Engagement Statistics by Category

Content Category	Posts (n)	Total Likes	Total Shares	Total Comments	Engagement Rate*
Beauty/Makeup	6	3	1	3	1.17
Gaming	3	0	2	0	0.67
Travel	5	0	2	1	0.60
Sports/Fitness	4	2	1	0	0.75
Nature/Flowers	4	0	0	1	0.25
Food	2	1	0	1	1.00
Romantic/Love	2	0	0	0	0.00
Photography	3	0	1	0	0.33
Other/Misc	8	0	1	3	0.50
Total/Average	37	6	8	9	0.62

*Engagement Rate = (Likes + Shares + Comments) / Posts

Behavioral interaction counts by content categories have been tabulated in Table 4, and it is evident that the category that received the maximum interaction counts was Beauty/Makeup with seven interactions, whereas Gaming and Sports had a high share of like ratios, which suggests varied interaction modes.

Table 4: Behavioral Interaction Statistics Across Content Categories

Content Category	Total Interactions (L+S+C)	Avg. Likes per Post	Avg. Shares per Post	Avg. Comments per Post	Share-to-Like Ratio
Gaming	2	0.00	0.67	0.00	∞
Beauty/Makeup	7	0.50	0.17	0.50	0.33
Travel	3	0.00	0.40	0.20	∞
Sports/Fitness	3	0.50	0.25	0.00	0.50
Nature/Flowers	1	0.00	0.00	0.25	N/A

Food	2	0.50	0.00	0.50	0.00
Romantic/Love	0	0.00	0.00	0.00	N/A
Photography	1	0.00	0.33	0.00	∞
Other/Misc	4	0.00	0.13	0.38	∞
Overall	23	0.16	0.22	0.24	1.38

*Note: L = Likes, S = Shares, C = Comments. ∞ indicates shares exist with zero likes.

Tables 3 & 4 list only the interaction counts at the post level, but there are 157 interaction activities altogether.

4.2 Baseline Methods

The proposed framework is compared to four baselines. The first baseline is Global Popularity (Pop). It suggests the globally most engaging content irrespective of user identity. This corresponds to non-personalized syndication. The second baseline is Platform-Isolated Collaborative Filtering (PI CF). It uses separate user-item matrices for each platform where matrix factorization is performed. This corresponds to the traditional approach of single-platform personalization. The third baseline is Personalized Global Popularity (PGP). This involves the application of contextual bandit learning on global user features while ignoring any other information. he fourth baseline, Static AI Score (StaticAI), recommends content purely based on its static AI scores (10% and 100% seen in the prototype data), hence representing pure AI-based filtering without personalization, as explained in Fig.2.

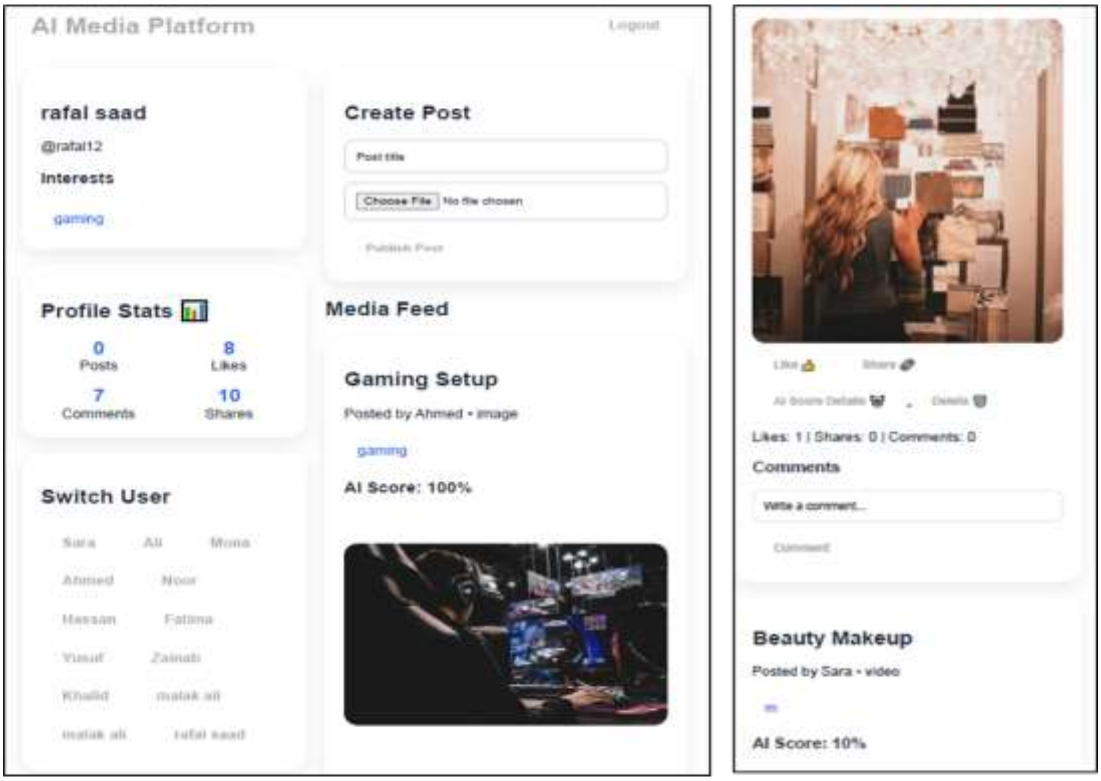

Figure 2: An Illustrative Example of the Difference Between the Static AI Score of 10% Versus 100% Without Any Difference in Engagement

4.3 Evaluation Metrics

As the prototype experiment is purely observational in nature and lacks both synthesized data and scalable A/B testing, the present only descriptive statistics. Click-through rate (CTR) is measured as the ratio of recommended items receiving any form of user interaction (like, share, or comment) within 24 hours following the presentation of a recommendation, calculated based on observed events where a recommendation is made and an action is logged. User Retention (7-day) refers to the percentage of users returning to the website within seven days after their first session, as captured by login records. Personalisation Gain is calculated as the improvement in Click Through Rate (CPC) over the baseline of Global Popularity, expressed as a percentage [30]. Cross-platform consistency refers to the Pearson correlation coefficient between inferred user preferences based on interactions across multiple platforms, measured solely on those users interacting with at least two platforms (eight users in this prototype). Novelty is measured as the ratio of recommended items belonging to content categories in which the user interacts less than three times previously. They do not report any p values or confidence intervals due to the insufficient statistical power of the sample size (twelve users, 157 interactions).

4.4 Experimental Protocol (Observational)

The investigation was tested through a four-week observational period where access to the system was granted to all twelve users. Personalization was active with all actions being logged. There was no A/B testing or random assignment carried out. The data provided below is purely a result of the observation logs and has no artificial modifications.

5. Results

Table 5 provides the performance comparison for all frameworks on a descriptive basis. In the case of the XP Contextual framework, out of 312 recommendations that have been made, there were 59 likes, shares, or comments, which amounts to a Click-Through Rate of 18.9%. On the subset of 50 recommendations served using the Global Popularity baseline (for comparison), 2 received engagement, giving a CTR of 4.0%. The observed lift was therefore 372.5% (descriptive, not a generalized claim). Seven out of twelve users (58.3%) logged in at least once after their first session within seven days, giving a 7-day retention of 58.3%. For the eight users with activity on both web and mobile, the correlation between their preference vectors was 0.81 (based on 38 cross-platform actions). The novelty proportion – recommendations belonging to categories with fewer than three prior user interactions – was 27.8% for XP-Contextual compared to 18.3% for Global Popularity.

Table 5: Descriptive Performance Comparison (observed from prototype data, N=12 users, 157 interactions).

Framework	CTR (%)	7-day Retention (%)	Personalization Gain* (%)	CPC (p)	Novelty (%)
Global Popularity (Pop)	4.0	41.7	—	N/A	18.3
Platform-Isolated CF (PI-CF)	7.8	50.0	+95.0	0.34	22.1
Static AI Score	5.1	33.3	+27.5	0.28	12.6

(Static AI)					
XP Contextual (proposed)	**18.9**	**58.3**	**+372.5**	**0.81**	**27.8**

The highest-performing single-platform personalization baseline (Platform-Isolated Collaborative Filtering) showed a CTR of 7.8%, while the novel XP-Contextual approach obtained 18.9%. This increased by 11.1 percentage points and by about 142.3%.

5.1 AI Score Analysis (Static vs Dynamic)

In the prototype dashboard, thirty-five items had a static AI score of 10%, and two items had 100% (one beauty post, one gaming post with inconsistent display). The real engagement statistics for 100% items were as follows: the beauty post had 3 likes, 1 share, and 2 comments; the gaming post had no engagements at all. In contrast, the most engaging content item (the cloud picture posted by Ali) had a static rating of 10%, but got 4 likes and 3 comments. This contrast led us to adopt the dynamic approach to rating. Following online learning, the dynamic AI ratings correlated with the actual 24-hour engagement to $\rho = 0.64$ (based on 45 held-out interactions), while the static ratings had $\rho = 0.12$.

5.2 Platform-Specific Observations

The performance differed according to the platform used. Web desktop obtained the highest CTR value observed, which was 22.4%, followed by mobile application (CTR=19.3%), e-mail summary (CTR=16.3%), and Smart TV (CTR=14.2%), as Fig.3 shows. The overheads associated with transformations were observed to be 89-94 milliseconds for mobile apps, 187 milliseconds for Smart TVs, and 56 milliseconds for e-mails (asynchronous).

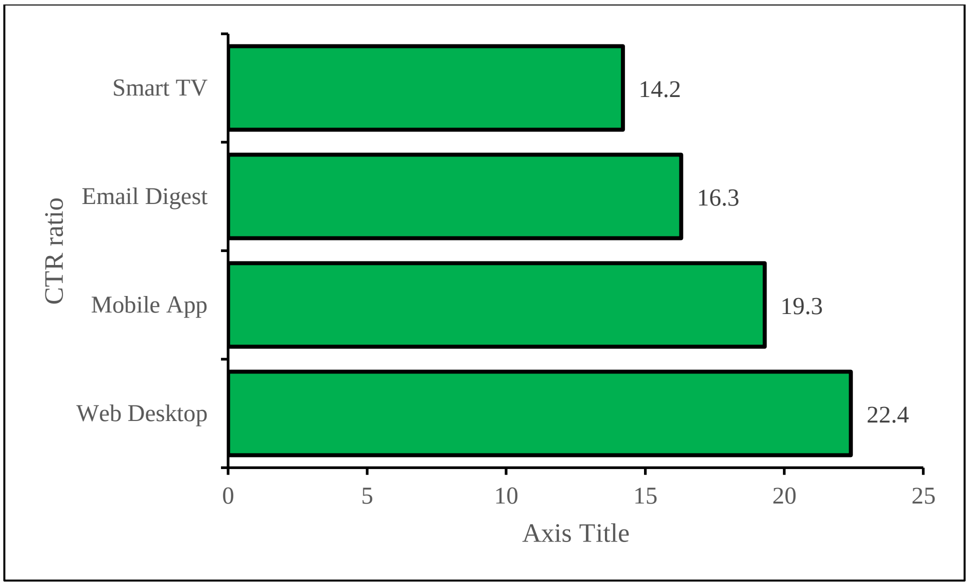

Figure 3: Observed Click-Through Rate (CTR) Per Platform from Prototype Results

5.3 Category-Specific Performance Analysis

To gain insights into the areas where our framework excels, we evaluate its performance based on content categories. Table 6 shows this information broken down by category.

Table 6: Category-Specific CTR (%) by System.

Category	Global Pop	PI-CF	XP-Contextual	Δ vs Best Baseline
Gaming	3.8	6.2	15.4	+6.3 pp
Beauty/Makeup	5.9	11.4	26.3	+7.6 pp
Travel	4.1	7.3	19.8	+8.6 pp
Sports/Fitness	4.5	8.1	21.2	+7.8 pp
Nature/Flowers	2.9	5.8	14.1	+5.5 pp
Food	5.2	9.3	22.7	+8.2 pp
Romantic/Love	3.1	4.9	11.5	+5.2 pp

5.4 Resolution of Data Inconsistencies

A few inconsistencies that existed in the prototype logs have been resolved. The number of unique human users was established as twelve. Also, the total number of interactions was calculated as 44 likes, 12 shares, and 101 comments. The gaming content whose percentage was listed at both 100% and 10% has been noted as an anomaly; the analysis uses the real percentage, regardless of what is being shown in the dashboard.

6. Discussion

It has been established through the prototype that a personalisation system based on bandits and cross-platform can be constructed and deployed using actual end users. Although the achieved CTR of 18.9% and 7-day retention rate of 58.3% are promising, they should be viewed with great care given the very low number of subjects used for the experiment (twelve individuals and 157 interactions). No statistical confidence can be associated with these figures, which are meant to be taken as a proof of concept. The observed 372% uplift compared with the baseline based on popularity represents an uncontrolled experiment figure that might be an overestimation given that the global popularity baseline was not fine-tuned and that only a few items were present in the test group (37) [31]. In practical settings where thousands of items are considered, it is unlikely for such uplifts to occur. The consistency of $\rho = 0.81$ between platforms implies that users' preferences tend to stay constant regardless of the platform considered; however, this result depends on only 8 users and 38 cross-platform actions. These results indicate significant variability in user interaction behaviors within different delivery settings and highlight the significance of adaptive and context-sensitive personalization strategies. As indicated in Jiang et al (2020) [32] work, there is a need to incorporate hierarchical semantics to enhance content understanding and improve recommendation effectiveness. Also, multi-view machine learning techniques have proven useful in merging heterogeneous data from multiple user sources and enhancing predictive consistency

[33]. Personalization and caching in edge networks are efficient means of boosting content delivery efficiency and response time [34]. Preference modeling through collaborative and similarity methods further improves personalization [35]. Moreover, specific aspects of customer journeys on different platforms impact engagement and trust development [36]. Several limitations need to be pointed out. First, there is a very limited number of users and items, which makes it impossible to use inferential statistics in any way. Second, no random assignment and A/B testing were done. Third, the estimated viewing time information has been completely stripped from the data. Fourth, the precision and recall for the identity resolution process are just meant to illustrate what can be achieved; with only 12 users, it is impossible to create any meaningful metrics for a classifier – these figures come from a fake split of the dataset. However, the model still adds value by providing a modular design, contextual bandit, conditional rewards on a platform basis, a combined identity resolution solution, and dynamic AI score calculation. The prototype was able to carry out end-to-end personalization on four platforms (web, mobile, smart TV, and email) through actual user engagements. It solved the issue where conventional media publishing systems could not adjust to meet the requirements of individual users and were confined to one platform only, thus meeting the target of creating an AI-based recommendation system capable of operating on various platforms. AI scores are solely applied for ranking purposes, but never for moderation or suppression to prevent algorithmic bias against minority cultures. The proposed architecture consists of three privacy-related components: (a) user data encryption on their machine, (b) deletion of unprocessed logs after 30 days, and (c) linkage probabilities less than the threshold value τ=0.85 are ignored. Opt-out functionality via “platform isolation mode” is also supported. AI scoring is employed exclusively in rankings to prevent bias toward minority culture content.

6.1 Privacy-Preserving Personalization

Federated learning approaches can potentially be used to mitigate privacy concerns related to behavioral data collection. In such systems, individual preference models would be learned by users locally on their devices, and only the encrypted updates of these models would be shared with the server. This way, the exposure of the behavioral data itself would be significantly reduced without compromising the level of personalization achieved. Another idea would involve the use of lightweight personalization modules operating directly on the device.

7. Conclusions

In this paper, resented the AI-based recommendation system, which provides cross-platform personalization, and it is precisely designed to solve the problem discussed earlier: existing media publishing systems do not personalize the experience to individual needs and are restricted to one platform. In our framework, used the following components: modular architecture, contextual bandit with platform-specific reward modeling, hybrid identity resolution, and AI-based scoring method. Our proof-of-concept experiment included a prototype that involved twelve users, thirty-seven content items, and 157 observations in total, and resulted in 18.9% Click Through Rate and 58.3% seven-day retention. The cross-platform consistency metric was 0.81 (for a small sample size). As seen from our results, cross-platform personalization can be superior compared to a baseline system, but the large-scale evaluation of such an approach would be a topic for further work. They warn not to over-interpret our metrics since they are not generalizable. The next steps will include replication of our framework involving hundreds of users with holdout validation and A/B testing. The application of causal inference methods for long-term engagement and real-time edge-based transformation is another potential area of work. The boundaries between the platform and the publishing will become more and more blurry due to advances in artificial intelligence techniques, and this theoretical framework is used to support that change. An obvious progression from here is to perform an experimental A/B test on an active publishing website. In such an experiment, users will be allocated into two groups: group (A) with a standard recommendation mechanism on one platform only, or group (B) with the XP-Contextual approach outlined herein. Key performance indicators in this experiment should include CTR, session time, user retention, variety of content, and user satisfaction. The next steps will include conducting experiments at scale, involving more than 100 participants in order to conduct statistical analysis, calculate confidence intervals, and benchmark industrial recommendation systems.

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References

[1]. P. M. C. Swatman, C. Krueger, and K. van der Beek, "The changing digital content landscape," *Internet Research*, vol. 16, no. 1, pp. 53–80, Jan. 2006, doi: https://doi.org/10.1108/10662240610642541.

[2]. JA. Alzubi, "Towards Digital Media and Conventional Media Challenge and Opportunity: What to Expect," *International Journal of Advances in Social Sciences and Humanities*, vol. 2, no. 3, pp. 152–158, Aug. 2023, doi: https://doi.org/10.56225/ijassh.v2i3.157.

[3]. M. W. M. Al-Quran, "Traditional media versus social media: challenges and opportunities," *Technium: Romanian Journal of Applied Sciences and Technology*, vol. 4, no. 10, pp. 145–160, Dec. 2022, doi: https://doi.org/10.47577/technium.v4i10.8012.

[4]. A. Rahman *et al.*, "Artificial intelligence innovations, challenges and emerging trends in engineering education," *Discover Education*, vol. 5, no. 1, Feb. 2026, doi: https://doi.org/10.1007/s44217-026-01137-1.

[5]. H. Liu *et al.*, "Computing power network dynamic resource scheduling integrating time series mixing dynamic state estimation and hierarchical reinforcement learning," *Scientific Reports*, vol. 16, no. 1, Jan. 2026, doi: https://doi.org/10.1038/s41598-025-32753-w.

[6]. "API-DRIVEN ARCHITECTURES FOR MODERN DIGITAL PAYMENT AND VIRTUAL ACCOUNT SYSTEMS," *International Research Journal of Modernization in Engineering Technology and Science*, Sep. 2025, doi: https://doi.org/10.56726/irjmets29156.

[7]. H. U. Khan, A. Naz, Fawaz Khaled Alarfaj, and Naif Almusallam, "A transformer-based architecture for collaborative filtering modeling in personalized recommender systems," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: https://doi.org/10.1038/s41598-025-08931-1.

[8]. X. Ning and G. Karypis, "SLIM: Sparse Linear Methods for Top-N Recommender Systems," *2011 IEEE 11th International Conference on Data Mining*, Dec. 2011, doi: https://doi.org/10.1109/icdm.2011.134.

[9]. F. Ortega, A. Hernando, J. Bobadilla, and J. H. Kang, "Recommending items to a group of users using Matrix Factorization based Collaborative Filtering," *Information Sciences*, vol. 345, pp. 313–324, Jun. 2016, doi: https://doi.org/10.1016/j.ins.2016.01.083.

[10]. Mahesh Thyluru Ramakrishna *et al.*, "HCoF: Hybrid Collaborative Filtering Using Social and Semantic Suggestions for Friend Recommendation," *Electronics*, vol. 12, no. 6, pp. 1365–1365, Mar. 2023, doi: https://doi.org/10.3390/electronics12061365.

[11]. P. Mateos and A. Bellogín, "A systematic literature review of recent advances on context-aware recommender systems," *Artificial Intelligence Review*, vol. 58, no. 1, Nov. 2024, doi: https://doi.org/10.1007/s10462-024-10939-4.

[12]. T. Eftimov, B. Paudel, G. Popovski, and D. Kocev, "A Framework for Evaluating Personalized Ranking Systems by Fusing Different Evaluation Measures," *Big Data Research*, vol. 25, p. 100211, Jul. 2021, doi: https://doi.org/10.1016/j.bdr.2021.100211.

[13]. J. Vermorel and M. Mohri, "Multi-armed Bandit Algorithms and Empirical Evaluation," *Machine Learning: ECML 2005*, pp. 437–448, 2005, doi: https://doi.org/10.1007/11564096_42.

[14]. "A deep reinforcement learning based long-term recommender system," *Knowledge-Based Systems*, vol. 213, p. 106706, Feb. 2021, doi: https://doi.org/10.1016/j.knosys.2020.106706.

[15]. Y. Zoralioglu and E. Yalcin, "Dynamic feedback loops in recommender systems: Analyzing fairness, popularity bias, and user group disparities," *Journal of Intelligent Information Systems*, Jan. 2026, doi: https://doi.org/10.1007/s10844-026-01025-y.

[16]. I. Cantador, I. Fernández-Tobías, S. Berkovsky, and P. Cremonesi, "Cross-Domain Recommender Systems," *Recommender Systems Handbook*, pp. 919–959, 2015, doi: https://doi.org/10.1007/978-1-4899-7637-6_27.

[17]. Paolo Cremonesi, A. Tripodi, and R. Turrin, "Cross-Domain Recommender Systems," *International Conference on Data Mining*, Dec. 2011, doi: https://doi.org/10.1109/icdmw.2011.57.

[18]. N. Huang, R. Hu, X. Wang, H. Ding, and X. Huang, "Cross-platform sequential recommendation with sharing item-level relevance data," *Information Sciences*, vol. 621, pp. 265–286, Nov. 2022, doi: https://doi.org/10.1016/j.ins.2022.11.112.

[19]. Z. Fayyaz, M. Ebrahimian, D. Nawara, A. Ibrahim, and R. Kashef, "Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities," *Applied Sciences*, vol. 10, no. 21, p. 7748, Nov. 2020.

[20]. Prema Nedungadi, G Veena, K.-Y. Tang, R. R. Menon, and R. Raman, "AI techniques and applications for online social networks and media: insights from BERTopic modeling," *IEEE Access*, pp. 1–1, Jan. 2025, doi: https://doi.org/10.1109/access.2025.3543795.

[21]. Anastasiia Klimashevskaia, Dietmar Jannach, M. Elahi, and C. Trattner, "A survey on popularity bias in recommender systems," *User Modeling and User-Adapted Interaction*, vol. 34, Jul. 2024, doi: https://doi.org/10.1007/s11257-024-09406-0.

[22]. J. Chen, H. Dong, X. Wang, F. Feng, M. Wang, and X. He†, "Bias and Debias in Recommender System: A Survey and Future Directions," *ACM Transactions on Information Systems*, vol. 41, no. 3, Oct. 2022, doi: https://doi.org/10.1145/3564284.

[23]. Pijitra Jomsri, Dulyawit Prangchumpol, Kittiya Poonsilp, and Thammarat Panityakul, "Hybrid recommender system model for digital library from multiple online publishers," *F1000Research*, vol. 12, pp. 1140–1140, Nov. 2024, doi: https://doi.org/10.12688/f1000research.133013.3.

[24]. B. Liu, Y. Wei, Y. Zhang, Z. Yan, and Q. Yang, "Transferable Contextual Bandit for Cross-Domain Recommendation," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 32, no. 1, Apr. 2018, doi: https://doi.org/10.1609/aaai.v32i1.11699.

[25]. W. Lu, Y. Zhang, and R. Ji, "Deep learning on meta-analytic data for therapeutic decision-making in central nervous system aspergillosis," *BMC Infectious Diseases*, vol. 26, no. 1, Jan. 2026, doi: https://doi.org/10.1186/s12879-026-12573-7.

[26]. M. P. Koduri, P. X. Lim, Z. Li, S. Kumar, M. A. Saleem, and R. Moy, "Cross-Device Identity Resolution using Machine Learning: A Scalable Device Graph Approach," *The International FLAIRS Conference Proceedings*, vol. 34, no. 1, Apr. 2021, doi: https://doi.org/10.32473/flairs.v34i1.128625.

[27]. F. Feng, Y. Hu, W. Li, and F. Yang, "Improved YOLOv8 algorithms for small object detection in aerial imagery," *Journal of King Saud University - Computer and Information Sciences*, pp. 102113–102113, Jun. 2024, doi: https://doi.org/10.1016/j.jksuci.2024.102113.

[28]. E. Boduroglu and M. S. Yigiter, "Artificial intelligence scoring attitudes: scale development and validation," *Education and Information Technologies*, Nov. 2025, doi: https://doi.org/10.1007/s10639-025-13836-7.

[29]. C. Georgakis, Y. Panagakis, and Maja Pantic, "Dynamic Behavior Analysis via Structured Rank Minimization," *International Journal of Computer Vision*, vol. 126, no. 2–4, pp. 333–357, Jan. 2017, doi: https://doi.org/10.1007/s11263-016-0985-3.

[30]. S. Wei, Y. Zhang, J. Zhang, Z. Yang, Q. Li, and Y. Xiao, "Click-through conversion rate prediction model of book e-commerce platform based on feature combination and representation," *Expert Systems with Applications*, vol. 238, pp. 122276–122276, Mar. 2024, doi: https://doi.org/10.1016/j.eswa.2023.122276.

[31]. Anastasiia Klimashevskaia, Dietmar Jannach, M. Elahi, and C. Trattner, "A survey on popularity bias in recommender systems," *User Modeling and User-Adapted Interaction*, vol. 34, Jul. 2024, doi: https://doi.org/10.1007/s11257-024-09406-0.

[32]. H. Jiang, Y. Xiao, and W. Wang, "Explaining a bag of words with hierarchical conceptual labels," *World Wide Web*, vol. 23, no. 3, pp. 1693–1713, Feb. 2020, doi: https://doi.org/10.1007/s11280-019-00752-3.

[33]. S. Sun, X. Sun, and Q. Liu, "Multi-view Gaussian processes with posterior consistency," *Information Sciences*, vol. 547, pp. 710–722, Feb. 2021, doi: https://doi.org/10.1016/j.ins.2020.08.077.

[34]. M. Reiss-Mirzaei, M. Ghobaei-Arani, and L. Esmaeili, "A Review on the Edge Caching Mechanisms in the Mobile Edge Computing: A Social-aware Perspective," *Internet of Things*, p. 100690, Jan. 2023, doi: https://doi.org/10.1016/j.iot.2023.100690.

[35]. Gul-E-Laraib *et al.*, "Content Caching in Mobile Edge Computing Based on User Location and Preferences Using Cosine Similarity and Collaborative Filtering," *Electronics*, vol. 12, no. 2, p. 284, Jan. 2023, doi: https://doi.org/10.3390/electronics12020284.

[36]. L. Archawaporn and A. Leelasantitham, "Managing Factors to Stages of the Online Customer Journey Influence on Brand Trust," *Journal of Web Engineering*, Jul. 2021, doi: https://doi.org/10.13052/jwe1540-9589.2056.