

Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization

Sudipkumar Ghanvat ¹, Shreya Joshi ², Rohan Jamdagni ³, Aditi Shintre ⁴,

1. *Data and Artificial Intelligence, VRIO Digital Dallas, Richardson, USA*

2. *Data Science, American Airlines, Fort Worth, USA*

3. *Web Engineering and Technology, Principal Solution Architect, Zeptta, Austin, USA*

4. *Operations and Marketing, Neowesolutize Technology Pvt Ltd, Pune, IND*

Received: April 17, 2026 | Review began: June 03, 2026 | Review ended: June 26, 2026 | Published: July 27, 2026

© Copyright 2026

This is an open access article distributed under the terms of the Creative Commons Attribution License CC-BY 4.0., which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract

With the rise in mobile application usage, competition for user attention has become more intense, and the demand for intelligent and personalized engagement strategies has grown. Despite the significant progress made in emotion recognition, context-aware computing, and adaptive recommendation systems, the research is still scattered in many different fields. This review aims to fill this gap by exploring the new paradigm of Adaptive Attention-Based Marketing (AABM) that combines real-time emotion detection, context-aware sensing, and adaptive decision-making to improve mobile app engagement. The literature review was carried out in a structured manner using the Scopus database, and the period of literature search was from 2018 to 2025. There were 408 records identified and screened, 40 studies were included in the final qualitative synthesis. The review covers advances in multimodal emotion recognition, context recognition, and Artificial Intelligence (AI) for personalization, such as machine learning, deep learning, contextual bandits, and reinforcement learning. The results show that three key enablers for AABM are multimodal sensing, contextual intelligence, and adaptive learning algorithms. Its applications span e-commerce, gamified systems, mobile notifications, and the healthcare sector, showcasing its ability to enhance engagement, retention, and user experience. However, challenges remain regarding privacy, transparency, multimodal data availability, and long-term evaluation. This review brings together existing knowledge and identifies research gaps, as well as directions for the development of privacy-aware and ethically responsible adaptive engagement systems.

Categories: Social media and customer relationship management, Digital Marketing, Marketing Communication

Keywords: adaptive attention-based marketing, real-time personalization, emotion recognition, context-aware systems, reinforcement learning

Introduction And Background

Mobile apps have become an essential platform to conduct commerce, entertainment, learn, and interact in the contemporary digital ecosystem. Mobile-first digital ecosystems have grown at a brisk pace, creating a fierce competition for users' attention in apps and online services. As per the Digital 2025 Global Overview Report, the world population with mobile phones reached about 5.78 billion (nearly 70.5% of the world's population) in 2025, and the world population with internet use crossed the 5.56 billion mark ([DataReportal, 2025](#)). India has become one of the fastest-growing digital ecosystems. The Digital 2025 India report estimated approximately 806 million internet users in India in early 2025, reflecting continued growth in mobile connectivity, app-based services, and digital consumer engagement ([DataReportal, 2025](#)). As the number of mobile apps, digital commerce, and customized online services grows rapidly,

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

competition for the user's attention is growing, as is exposure to notifications, ads, and engagement prompts from multiple platforms. Thus, engaging the user in a timely, context-appropriate and non-intrusive way is a technological challenge, as well as a strategic requirement for any modern mobile platform.

This ubiquity has provided a more competitive environment than ever before, where keeping the attention of the user has become a challenge as well as an opportunity. According to scholars, this is what they refer to as the attention economy, where the attention of users is considered a scarce and valuable resource (Vettehen and Schaap, 2023). The providers of mobile apps are in a never-ending competition to capture, maintain, and keeping the attention of users in a world where people are constantly bombarded with notifications, adverts, and engagement alerts. Traditional methods like push notifications that remain static or segmentation based on demographic and past behavior often prove inadequate. They tend to interrupt users at the wrong moment or provide irrelevant information, which not only decreases engagement but can also cause frustration, message saturation, and churn (Pielot et al., 2014). Marketing research and practice are experiencing a paradigm shift in order to overcome these limitations. The advent of adaptive marketing models integrating real-time indicators of user interactions and environments has created new opportunities in the optimization of engagement. The key to this change is the development of affective computing and context-aware systems that allow mobile applications to identify the emotional state of a user and his/her situational context. The current methods of emotion recognition include sentiment analysis of textual messages and keystroke dynamics, as well as multimodal methods that integrate the analysis of facial expression, speech prosody, and patterns of use (Khare et al., 2024). On the same note, context recognition uses device sensor data, e.g. location, activity recognition, and device state (battery level, network connectivity), to determine whether a user is commuting, working, or relaxing at home. Collectively, these insights provide unmatched possibilities to create messages that are timely, contextually relevant, and emotionally aligned.

The rise of Adaptive Attention-Based Marketing (AABM) is a result of the integration of emotion and context in marketing. Unlike traditional personalization that is based on user behavior in the past and predetermined segmentation rules, AABM is proactive and adaptive, constantly adding contextual information and user interactions in real time to marketing decisions. Mobile apps can use machine learning models and dynamic decision-making processes to decide on the content to be delivered, the timing for its delivery, and the manner in which it is presented to maximize user engagement. For example, contextual bandit algorithms and reinforcement learning models have been used to optimize the delivery of content and interventions over time, adapting to the context of users and the feedback they provide, thus improving the effectiveness of the campaigns and long-term user engagement (Cai et al., 2023). Emotion-aware systems have shown enhanced consumer reactions to offers or promotions based on their correspondence with real-time affective conditions in e-commerce and digital advertising, and psychological sensitivity is a key value in marketing (Gupta and Bansal, 2023) (Khurana, 2026). Nevertheless, AABM implementation is not without difficulties. Privacy and ethics are among the most critical issues. To be able to infer the user emotions and contexts, it is necessary to access sensitive behavioral and sensor data, which may also provoke questions of consent, transparency, and possible misuse. Another identified serious ethical risk is the possibility of manipulative personalization, where systems use emotions to fuel engagement or sales (Huang and Rust, 2021). To overcome such obstacles, the more recent literature focuses on privacy-preserving models, including on-device inference, federated learning, and differential privacy, to make sure that sensitive data is not sent to centralized computers (Khare et al., 2024). Moreover, Explainable Artificial Intelligence (XAI) systems are also being suggested to achieve transparency in adaptive decision-making so that end-users could comprehend why a specific message was provided at a specific time.

Despite significant advances in emotion recognition, context-aware computing, adaptive recommendation systems, and reinforcement learning-based personalization, the existing body of knowledge remains dispersed across multiple research domains. Most current research focuses on one aspect of adaptive engagement, like emotion detection, contextual sensing, notification optimization, or personalized recommendations, in particular application contexts. As a result, there is limited work on the synthesis of these technological capabilities as a whole in a unified framework of adaptive mobile engagement. Specifically, the combination of emotion-aware sensing, context intelligence, adaptive

How to cite this article:

Ghanvat S, Joshi S, Jmagnani R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

decision-making, engagement optimization, and ethical governance has not been thoroughly discussed in the context of mobile marketing. This fragmentation necessitates a structured review of the existing developments, research gaps, and a coherent conceptual basis for AABM.

This review paper is placed in this fast-changing interdisciplinary context and analyzes the evolution of emotion and context-aware adaptive marketing systems in mobile application environments in the last decade. Special focus is given to literature published from 2018 to 2025, with some regard to seminal works in the past years, which laid the groundwork for the theories of affective computing, user engagement, and context-aware computing. The review covers peer-reviewed journal papers, conference papers, preprints, and some industry and working papers on emotion recognition, multimodal sentiment analysis, adaptive recommendation systems, mobile notifications, and engagement optimization. The review has a global focus but focuses on developments of general interest in a variety of digital consumer ecosystems. The conceptual framework of affective computing and context-aware interaction has been introduced in early studies, but recent developments in smartphone sensing, wearable technologies, multimodal artificial intelligence, and reinforcement learning have enabled real-time adaptive marketing in a technically feasible and commercially scalable manner. In this manner, this review aims to achieve three main objectives: (1) summarizing existing emotion and context recognition technologies for mobile marketing; (2) reviewing the evolution of adaptive decision engines and recommendation strategies for user engagement optimization; and (3) critically analyzing the ethical, privacy, and trust-related issues of deploying such systems at scale. The review synthesizes these viewpoints to highlight the potential for an interdisciplinary field in the near future, AABM, and to underscore the importance of responsible design, transparent governance, and future empirical testing.

A systematic review approach was used to identify, screen and analyze literature relevant to the selected research domains to ensure a structured and transparent literature synthesis. The second section presents the design of the review, the literature search strategy, the screening process, and the analysis of the existing research on AABM.

Review

Methodology of review

Review Design and Approach

The study is based on a structured narrative review with a bibliometric analysis approach to analyze recent advancements in AABM by leveraging real-time emotion recognition, context-aware computing, and mobile engagement optimization. This review aimed to uncover the most salient technological trends, application fields, research trends, and new challenges where mobile marketing, affective computing, human-computer interaction, and AI meet.

The methodological approach used is a combination of systematic literature retrieval and descriptive quantitative analysis of publication metadata and qualitative thematic synthesis of the retrieved literature. This hybrid review format allowed for a comprehensive overview of the research field as well as a detailed analysis of the conceptual evolution relevant to AABM. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram illustrating the literature search, screening, eligibility assessment, and final study inclusion process adopted for this review is shown in Figure 1.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

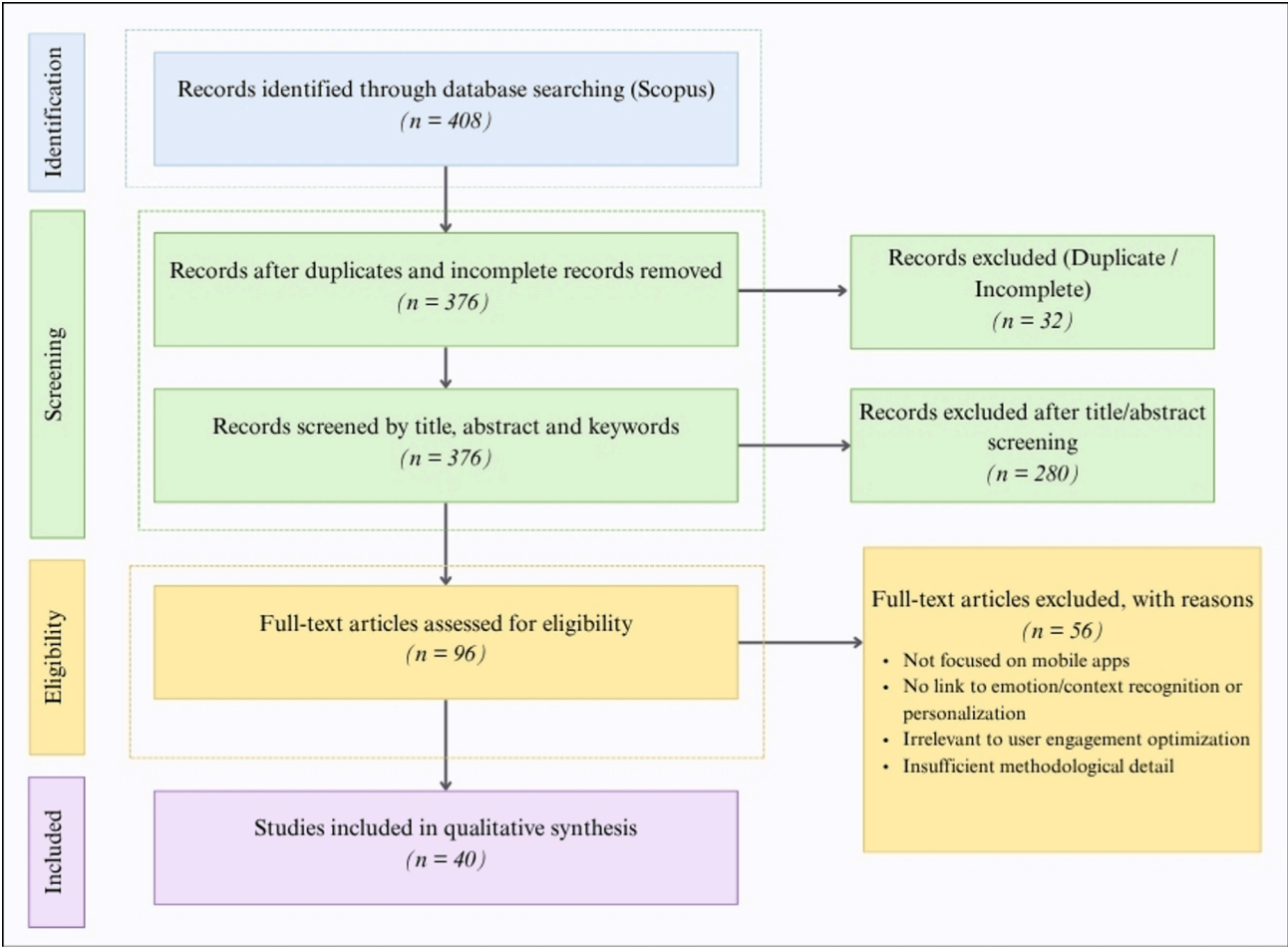


FIGURE 1: PRISMA flow diagram illustrating the literature search, screening, eligibility assessment, and final study inclusion process adopted for this review

Source: Authors' creation, adapted from the PRISMA 2020 flow diagram framework proposed by Page et al. (Page et al., 2021). PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

The review mostly covers literature published from 2018 to 2025, with a few earlier foundational studies included when relevant to provide the theoretical background of affective computing, user engagement, and context-aware systems.

Data Source and Search Strategy

The literature search was performed using the Scopus database, which was chosen because it covers a wide variety of disciplines, including computer science and engineering, business, and digital technology research areas and includes peer-reviewed journals, conference proceedings, and review articles.

The search was done with a combination of emotion recognition, affective computing, mobile interaction, user engagement, and personalization-related keywords. The main search method used was the TITLE-ABS-KEY search field to get documents containing these concepts in the title, abstract, or author keywords.

The principal search query used for literature retrieval was as follows:

TITLE-ABS-KEY(("emotion recognition" OR "affective computing" OR "emotion-aware")
AND ("mobile application*" OR smartphone OR "mobile interaction"))
AND PUBYEAR > 2017

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. Cureus J Bus Econ 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

AND PUBYEAR < 2026

A focused secondary query was also conducted using keywords related to context awareness, user engagement, and personalization to enhance the relevance of studies for mobile marketing applications. The search was restricted to the Scopus database and limited to publications between 2018 and 2025, written in English. Eligible document types included journal articles, conference papers, review articles, and book chapters. Additionally, the search focused on research areas such as emotion recognition, context-aware computing, mobile interaction, personalization, recommendation systems, and user engagement. Applying these criteria resulted in the retrieval of 408 records from Scopus, which constituted the bibliographic dataset used for subsequent screening, selection, and analysis.

Screening and Selection Criteria

The retrieved records were exported from Scopus in CSV format and screened through a multi-stage review process. The first screening process included the elimination of duplicate and incomplete bibliographic records. Titles, abstracts, and author keywords were then checked manually to assess their relevance to the scope of this study.

Inclusion Criteria

Studies were included in the review if they addressed emotion recognition, affective sensing, or multimodal emotional analysis and involved mobile applications, smartphone-based systems, or mobile interaction environments. Eligible studies also explored context-aware computing, personalization, recommendation systems, or adaptive user interfaces, with a particular emphasis on enhancing user experiences through intelligent adaptation. Furthermore, studies that examined user engagement, mobile notifications, attention optimization, or digital interaction behaviors were considered relevant. To ensure comprehensive coverage of the research domain, both empirical and non-empirical contributions were included, provided they offered conceptual, methodological, experimental, or review-based insights that advanced the understanding of adaptive engagement optimization in mobile and context-aware environments.

Exclusion Criteria

Studies were excluded if they were restricted to non-mobile or unrelated application environments, or if they lacked a direct focus on emotion recognition, context awareness, adaptive user engagement, or closely related research themes. Duplicate records identified during the screening process were removed to avoid redundancy. In addition, studies that did not provide sufficient bibliographic details, methodological descriptions, or empirical information necessary for evaluation and analysis were excluded from the review. Following the screening and relevance assessment stages, the remaining studies were retained and formed the final dataset for thematic synthesis, bibliometric analysis, and interpretation of research trends related to adaptive engagement optimization in mobile and context-aware systems.

Data analysis procedure

Bibliometric visualization and descriptive analysis techniques were applied to the extracted data with the help of Python. The publication metadata, such as publication year, document type, author keywords, and affiliations, were processed to produce analytical summaries of the literature landscape. Using Python 3.14.0 in Jupyter Notebook 7.4.7 (JupyterLab 4.4.10). The principal libraries used were pandas 2.3.3 for data preprocessing and analysis, Matplotlib 3.10.7 for visualization, and Python's built-in 'collections.Counter' for frequency analysis.

The analysis of the reviews was carried out on five complementary dimensions:

Publication Trend Analysis

The evolution of research activity over the last seven years (2018-2025) was analyzed based on the annual publication trends.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. Cureus J Bus Econ 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

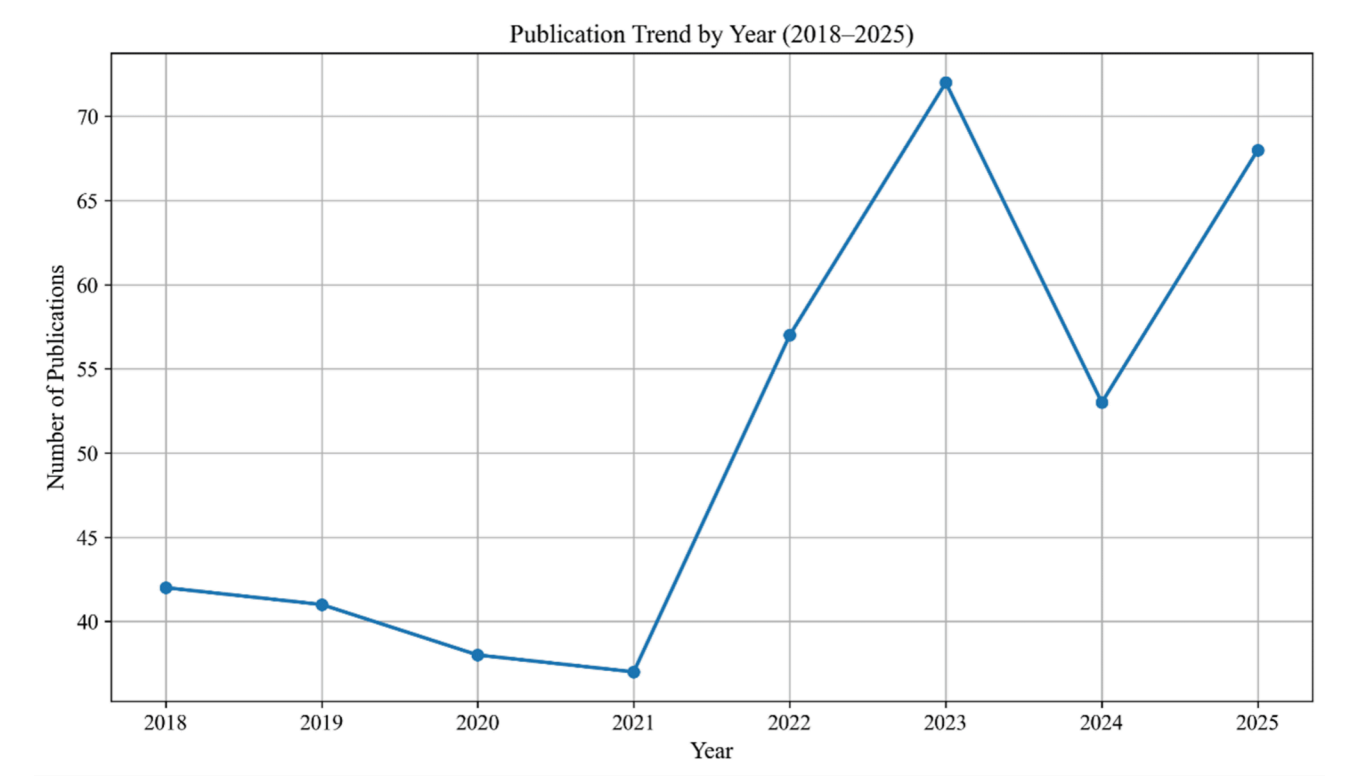


FIGURE 2: Annual publication trend of studies
Source: Author’s own analysis based on Scopus database records

The temporal trend of the research output related to AABM is shown in Figure 2 between 2018 and 2025. The rise in publications since 2021 signifies the growing academic and industrial interest in real-time emotion sensing by users, context-aware decision systems, and AI-driven personalization in mobile application ecosystems. The trend shows that the research on affective computing has moved from basic research to practical implementation of adaptive engagement optimization frameworks on mobile platforms.

Document Type Distribution Analysis

In order to examine the nature of the scholarly contributions in the retrieved, document type analysis was performed.

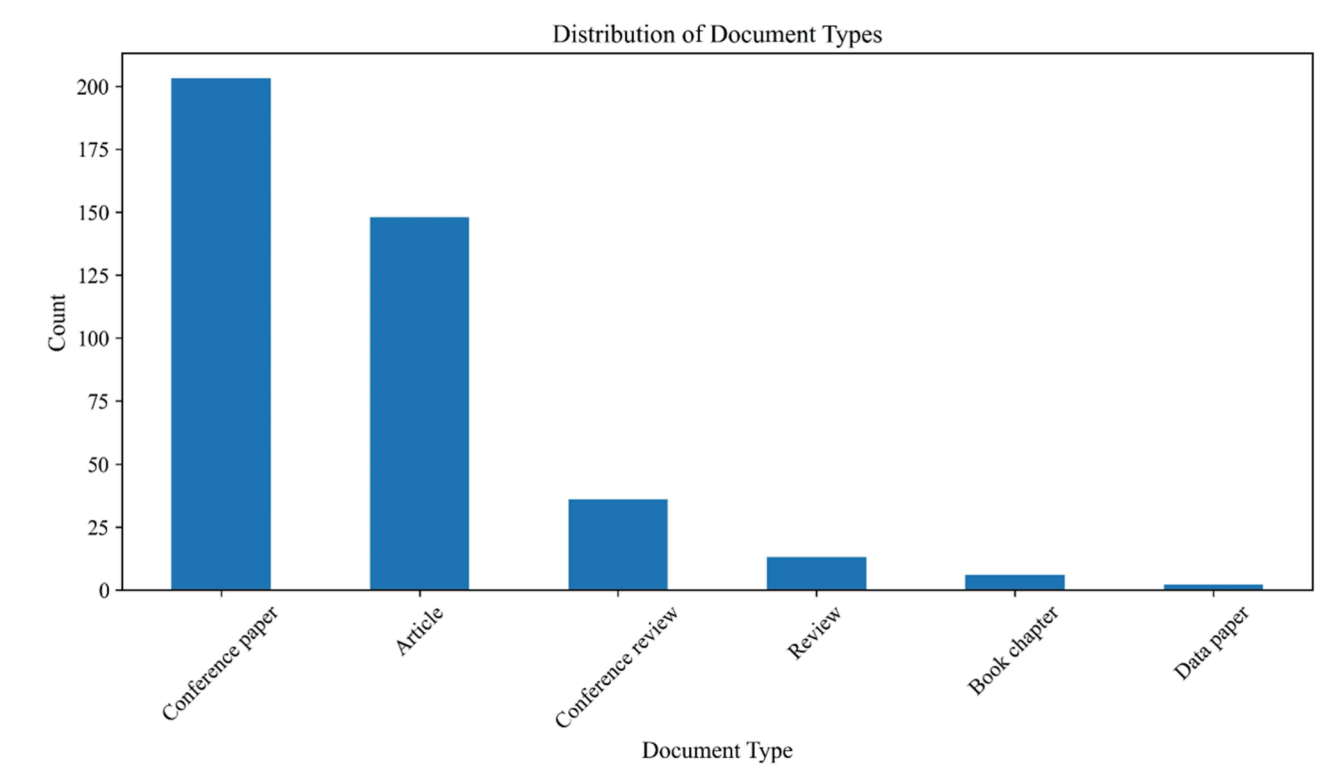


FIGURE 3: Distribution of document types across the retrieved Scopus dataset used for the review

Source: Author’s own analysis based on Scopus database records

The majority of publications were conference papers, followed by journal articles, as shown in Figure 3. Smaller numbers of conference reviews, review papers, and book chapters were also found. The predominance of conference literature suggests that the field is still evolving at a fast pace, with many new developments in technology first reported in conference literature and then consolidated in journals.

Keyword Co-occurrence and Topic Analysis

The author keywords were extracted and frequency analysis was carried out to find the dominant concepts of research and concentration of topics in the literature.

How to cite this article:

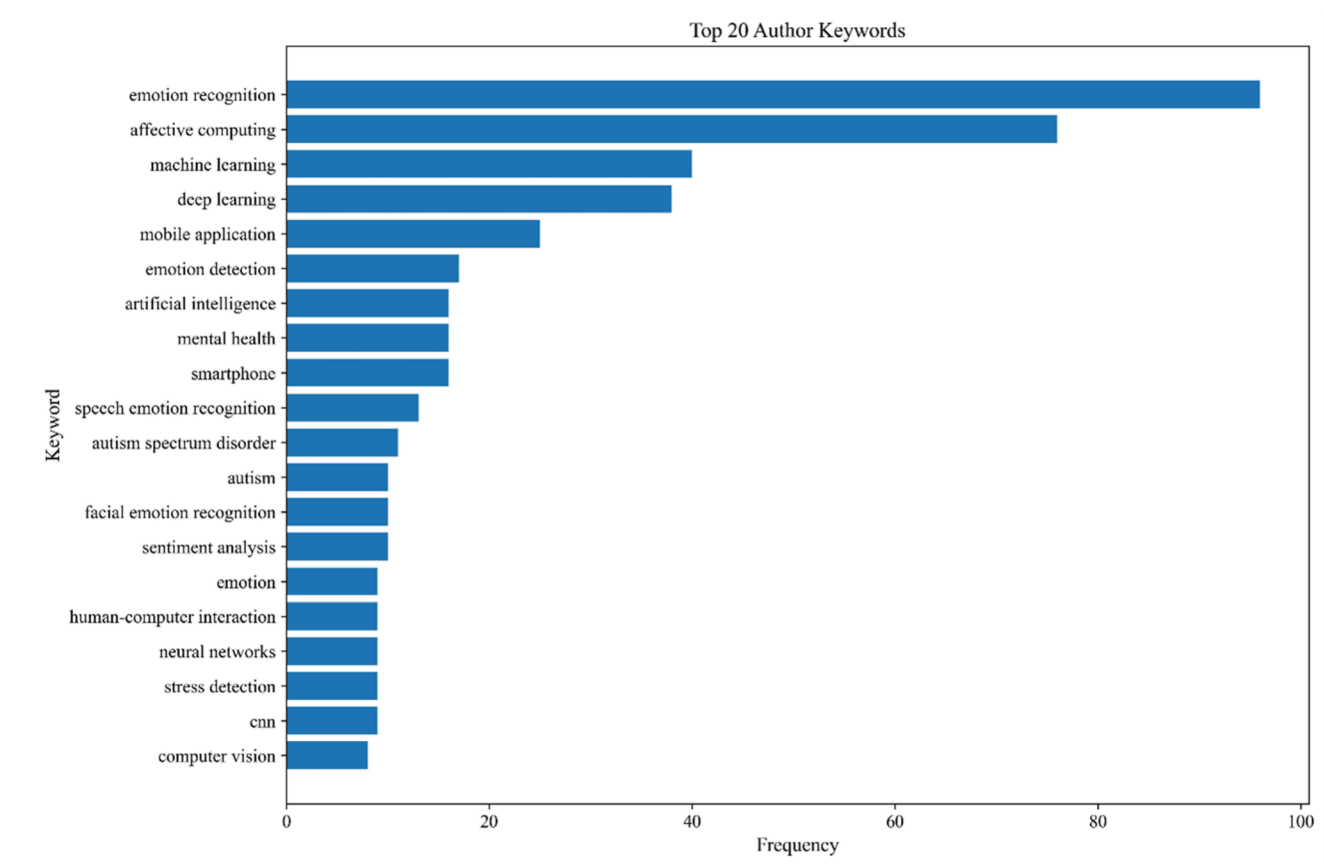


FIGURE 4: Frequency distribution of the top author keywords identified within the selected literature

Source: Author’s own analysis based on Scopus database records

The most frequent author keywords for the bibliographic data are shown in Figure 4. The literature is dominated by keywords like emotion recognition, affective computing, machine learning, deep learning, and mobile application, which confirms the strong influence of emotion sensing, computational behavioral analysis, and mobile interaction modeling on the current research on AABM. The keyword distribution agrees with the interdisciplinary convergence between the fields of AI, human-computer interaction, and personalized mobile engagement research.

Country-wise Research Output Analysis

Author affiliation data was used to conduct country-level analysis to reveal global research distribution.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. Cureus J Bus Econ 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

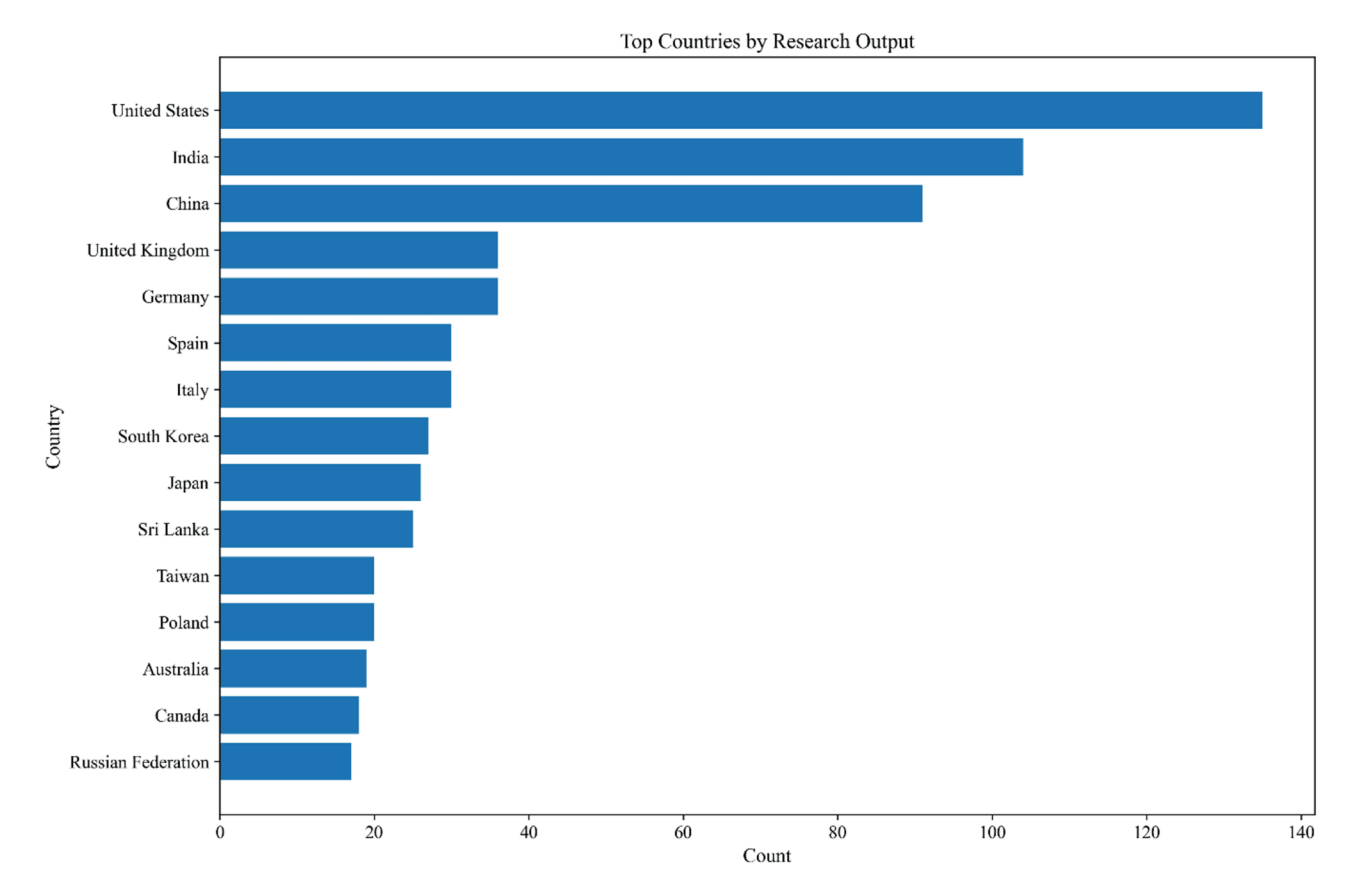


FIGURE 5: Country-wise distribution of literature

Source: Author’s own analysis based on Scopus database records

The geographical distribution of publications that have contributed to the review is illustrated in Figure 5. Strong research activity exists in the field of emotion-aware mobile systems and adaptive personalization technologies, with the highest research output in the United States, India, and China. The wide cross-sector participation suggests that real-time emotion and context recognition for mobile engagement optimization is becoming a field of international research that has the potential to be relevant to both developed economies and those that are rapidly digitizing.

This geographical distribution underscores the worldwide spread of emotion-aware mobile system research, and also points to growing involvement from new digital ecosystems, such as Asia.

Thematic Classification of Literature

For qualitative synthesis, the reviewed studies were grouped into the major thematic categories of the studies, in accordance with the research objective, research methodology, and application focus.

How to cite this article:

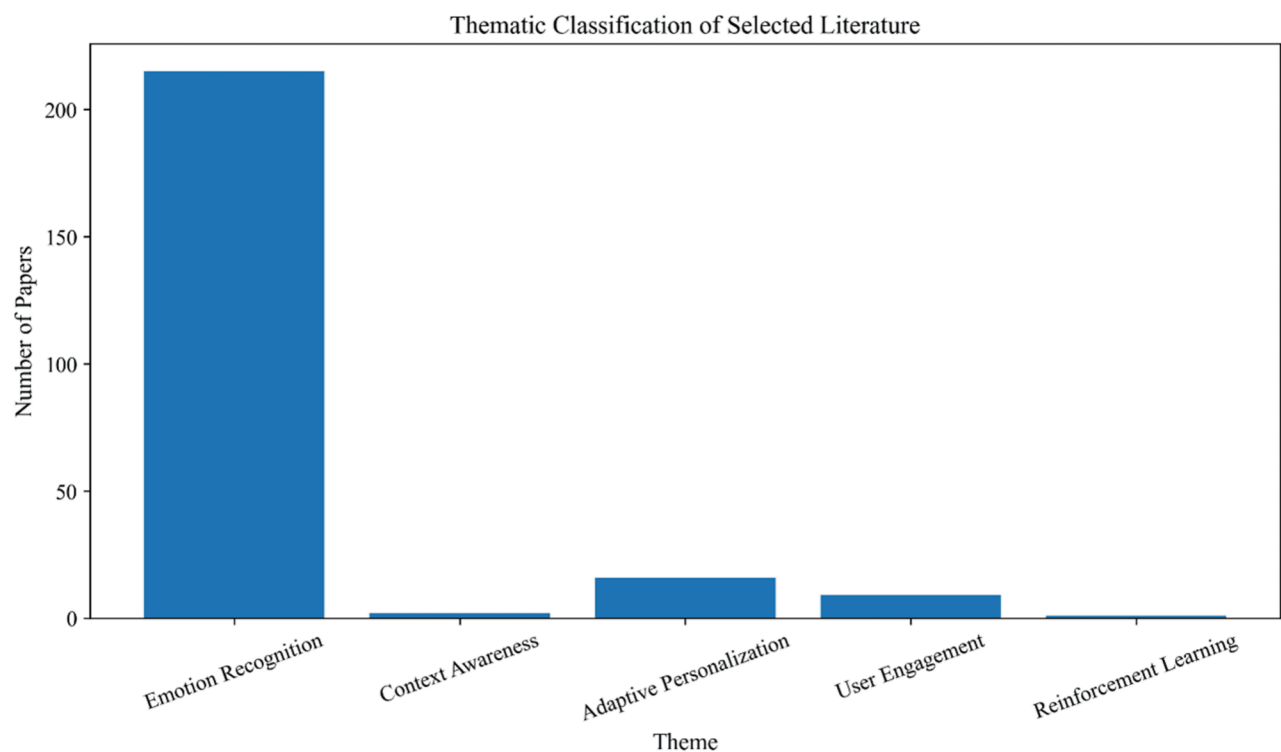


FIGURE 6: Thematic classification of literature

Source: Author’s own analysis based on Scopus database records

The reviewed literature is organized into key thematic areas that support the AABM framework, such as emotion recognition, context awareness, adaptive personalization, user engagement, and reinforcement learning, as shown in Figure 6. The prominence of emotion recognition and adaptive personalization indicates their pivotal importance in facilitating real-time attention-aware marketing systems. As a whole, these thematic clusters illustrate the technical foundation of AABM, in which the detection of emotional state, the contextual inferences, and intelligent decision-making are all interlinked to optimize the engagement and personalized interaction of mobile applications.

The subsequent sections of this review, which cover technological advances, practical applications, and future research directions of the proposed framework for AABM, are based on this thematic classification. The next part of this methodological and analytical framework is an analysis of recent developments of emotion and context recognition technologies that facilitate the real-time interpretation of user state and constitute the main sensing layer in AABM systems.

Advances in emotion and context recognition

Proper identification of feelings and situations of users has become the foundation of AABM. Traditional marketing used fixed demographics and past usage, which did not take into consideration the dynamic aspect of human affect and situational changes. The recent studies have paid more attention to finer-grained, real-time identification of psychological states and environmental indicators and have demonstrated that the marketing intervention, tailored to these signals, can make user receptivity and engagement much higher.

Regarding emotion recognition, Wang et al. introduced a micro-expression recognition algorithm that uses optical flow and PCANet+ to detect subtle facial movements that are commonly linked to suppressed or transient emotions. Their study has shown that the integration of handcrafted optical flow features and a lightweight neural network can be highly

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

performing with lower computational cost. The authors concluded that these methods are especially applicable to mobile and embedded systems, where latency and processing power are crucial parameters (Wang et al., 2022). Likewise, Zhang et al. contributed to the field by creating a privacy-aware facial expression recognition system that runs on an AI-powered microcontroller. Their method reduces the transmission of data and improves user privacy by processing images on the device itself. The research found that edge-based solutions are capable of providing the same recognition accuracy in real time as cloud solutions and are therefore useful in consumer applications where trust and compliance are critical (Zhang et al., 2024).

There has also been a great advancement in context recognition. Vaizman et al. suggested a single concept of multimodal sensors and multi-label classification in real-life situations. Their system categorized several overlapping contexts like commuting, walking, or working using accelerometers, gyroscopes, location, and audio data. Their results emphasized the significance of sensor fusion in the representation of the complexity of day-to-day routines (Vaizman et al., 2018). Continuing this research, Can et al. released a survey on the topic of stress detection in everyday life with smartphones and wearables. They provided a map of physiological, behavioral, and environmental cues that can serve as proxies of stress, highlighting that multimodal data, when coupled with contextual variables, yields more accurate predictions than single-channel methods (Can et al., 2019).

Affective signals that have been examined are the user interaction patterns. Kanjo et al. proposed the system, NotiMind, which uses the responses to the smartphone notifications as an affective sensing channel. In their research, they found that the manner in which the users reject, postpone, or react to the notifications has significant clues about stress and mood (Kanjo et al., 2017). In a similar way, Lim et al. examined the dynamics of keystroke with respect to loneliness and social isolation and found that typing speed, error rates, and rhythm have a relationship with psychological states as compared to daily patterns of use. Collectively, these pieces imply that indirect interaction information can be as informative as direct sensing (Lim et al., 2024). In addition to this, Visuri et al. examined how smartphone users interact with notifications to understand the importance and timing of the content. Their results revealed that notifications are not all disruptive, and contextual cues may forecast user receptivity. This is in line with other studies in multimodal sentiment analysis (Visuri et al., 2019). A survey by Lai et al. gave an overview of methods of multimodal sentiment analysis, which they state is more robust when text, audio, and visual data are combined with context (Lai et al., 2023). Zhao et al. also synthesized fusion strategies in a broad review of deep multimodal data fusion, and transformer-based models were identified as particularly useful in processing heterogeneous streams in real-time (Zhao et al., 2024).

Finally, attention prediction is an emerging dimension. Steil et al. discussed the way in which device-integrated and wearable sensors can predict user attention in mobile interactions. Their findings revealed that eye gaze, motion, and device state could collectively determine whether a user is attentive or distracted and provide direct implications for timing adaptive marketing interventions (Steil et al., 2018). Overall, these papers indicate that the current developments in micro-expression recognition, on-device privacy-preserving emotion analysis, multimodal sensor fusion, and attention forecasting offer the technological basis for AABM. With emotional sensitivity and contextual intelligence, future marketing systems will be able to provide interventions that are highly personalized, yet also situationally appropriate and ethically sound.

The next section builds on these technological advances and introduces the conceptual framework of AABM, detailing how emotion recognition, contextual sensing, adaptive decision-making, and engagement optimization are combined within a single operational model of mobile app engagement.

AABM: conceptual framework

AABM is a paradigm change from the traditional one-size-fits all personalization to real-time adaptive marketing based on the user's emotional state, context, and moment-to-moment receptivity. AABM is not just about segmentation or user preferences, but about continuously analyzing and interpreting behavioral and contextual signals to provide timely, relevant, and emotionally appropriate interventions. Three key components of AABM are as follows: (i) emotion- and context-aware sensing, which gathers behavioral, emotional, and environmental signals; (ii) adaptive decision engines, which interpret these signals to decide on the most suitable engagement response; and (iii) engagement optimization,

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

which provides and continually improves personalized user interactions. As shown in Figure 7, the process of recognizing emotion and context signals is performed by emotion recognition modules and context recognition modules and the result is fed into a consolidated user state profile. This profile provides information to the adaptive decision engine that decides when to engage the user, what content to show, and what to do to the user during that engagement. Responses from the user are then collected in a feedback loop, allowing for ongoing learning and optimization of future interactions, while respecting privacy, transparency, and security boundaries.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

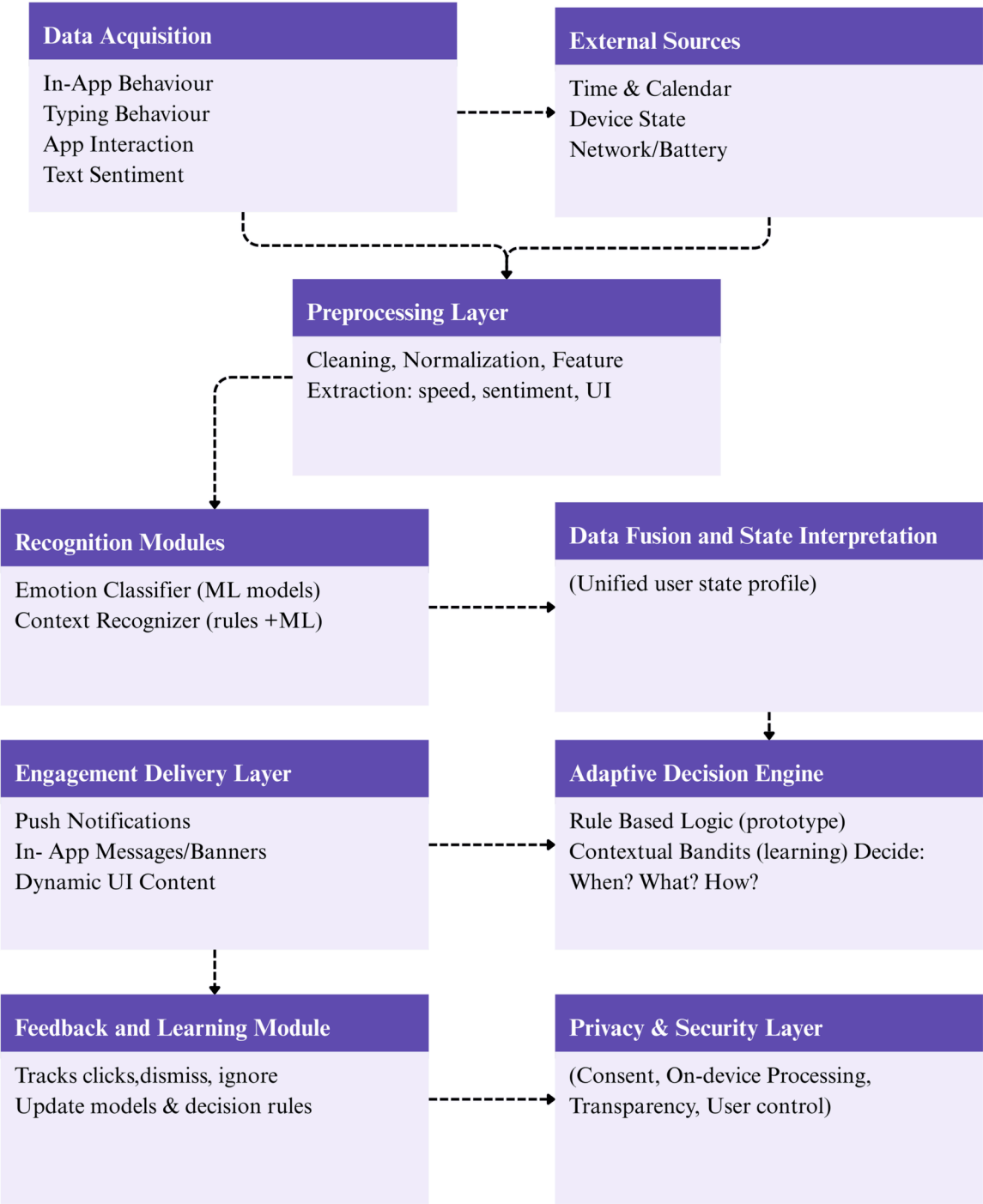


FIGURE 7: Conceptual Architecture of Adaptive Attention-Based Marketing (AABM)

Source: Author’s own creation

Emotion- and Context-Aware Sensing

The initial stage of AABM is to correctly capture and decipher the affective and situational states of users. The current literature demonstrates that emotion-sensitive interfaces can change the experience of the application in real time. As an example, Lakehal et al. came up with CORES, a context-sensitive, emotion-focused recommendation system that combines large language models (LLMs) with retrieval-augmented generation to improve shopping experiences. Their system was 97 percent accurate in personalizing their recommendations, which proves that contextual embeddings combined with affective cues can be effectively used to adapt in real-time (Lakehal et al., 2025). On the same note, Liang et al. investigated multimodal user state recognition with color psychology to dynamically change the interface of mobile applications. Their results revealed that emotionally stimulated designs enhanced positive user engagements and minimized disengagements (Liang et al., 2025).

Technique	Representative Studies	Application Domain	Key Outcomes for AABM
Decision Trees & Traditional ML	(Mishra et al., 2021) (King et al., 2024)	Emotion-aware text recommendation; Receptivity detection in Mobile Health (mHealth); Ecological Momentary Assessment (EMA) compliance prediction	Enabled real-time classification of receptivity and affect, supporting adaptive timing decisions
CNNs & Transfer Learning	(Singh and Dembla, 2023)	Emotion → Music recommendation	Improved personalization accuracy by mapping facial expressions to preferences
Transformers & LLMs	(Lakehal et al., 2025) (Zhang et al., 2023)	Virtual shopping recommender; Multi-objective sequence recommendations	Achieved 97% personalization accuracy (CORES); Enhanced multi-metric performance with DRL-Transformer integration
Contextual Bandits	(Min et al., 2023) (He et al., 2020) (Qassimi and Rakrak, 2025)	Speech endpointing; Mobile commerce; Smart tourism	Optimized timing, CTR, and retention by balancing exploration–exploitation
Reinforcement Learning (RL)	(Wang et al., 2021) (Yuan et al., 2022); (Aguilera et al., 2024) (Lauffenburger et al., 2024) (Zhang et al., 2022)	mHealth notifications; Offline Reinforcement Learning (RL) for mobile; Physical activity Randomized Controlled Trial (RCT); Medication adherence; Long-term recommender satisfaction	RL improved engagement (+19% steps in DIAMANTE), adherence, and long-term user satisfaction

TABLE 1: Key Artificial Intelligence (AI) and Machine Learning (ML) techniques in Adaptive Attention-Based Marketing (AABM)

Source: Compiled by the authors based on reviewed literature

This vision is reinforced by application-specific prototypes. Kumaran et al. have created EChat, an adaptive messaging interface that changes the UI elements based on the user's emotions detected. When the interface changed according to the user, the users stated greater satisfaction and coherence in interactions with messages (Kumaran et al., 2023). Similar results were observed in the entertainment field, as Singh and Dembla revealed that emotion-sensitive music suggestions through transfer learning were significantly more accurate in matching playlists to the mood of the user (Singh and Dembla, 2023). Likewise, Kheiri and Ding (Kheiri and Ding, 2026) presented a comprehensive survey of emotion-aware recommender systems and emphasized that integrating users' emotion into the recommender models can significantly enhance the quality of personalization, user engagement, and recommendation relevance, while also introducing challenges in emotion detection, privacy, robustness, and ethical deployment. These studies collectively show that emotion and context are important factors that mediate user attention, engagement, and satisfaction.

Adaptive Decision Engines

After inferences of user states, the AABM systems are based on decision engines able to modify actions in real time. The classical recommender systems typically maximize short-term goals, including click-through rate (CTR), whereas the more recent developments focus on reinforcement learning (RL) and contextual bandits to maximize short-term and long-term goals. As an example, Min et al. used deep contextual multi-armed bandits to do adaptive endpointing in speech systems, minimizing errors and with low latency. Applying this principle to marketing, contextual bandits are able to identify the best time and tone to use when sending messages (Min et al., 2023). Wang et al. modeled notification policies with RL and showed that behavioral simulator-trained policies were more engaging and did not exceed user limitations (e.g., frequency limits) (Wang et al., 2021). Applying this to real deployments, Yuan et al. introduced an offline RL method to optimize the notification strategies to allow pre-deployment training to be conducted safely and then enable live rollouts (Yuan et al., 2022).

The importance of adaptive decision-making is also demonstrated in field deployments. Mishra et al. and King et al. showed that context and affective indicators of mobile sensors and wearables could predict receptivity to interventions (Mishra et al., 2021) (King et al., 2024). Their models performed well in terms of prediction, with interventions only being possible when the user is the most receptive. In clinical practice, Aguilera et al. found that RL-personalized messages in the DIAMANTE Randomized Controlled Trial (RCT) increased the number of physical activity steps by 19% compared to random or control messages strategies in 24 weeks (Aguilera et al., 2024). On the same note, Lauffenburger et al. in the REINFORCE trial discovered that RL-personalized communications were much more effective at improving medication adherence than the non-RL-personalized approaches (Lauffenburger et al., 2024).

On a large scale, He et al. demonstrated that contextual bandits were able to utilize the browsing context to enhance CTR in large-scale mobile browsing recommendations, and Qassimi and Rakrak extended this approach to multi-objective bandits that trade off CTR and retention in smart tourism recommendations (He et al., 2020) (Qassimi and Rakrak, 2025). To optimize in the long-term, Zhang et al. (Zhang et al., 2022) suggested multi-task RL in recommender systems, which increased the satisfaction of users in the long-term, and Zhang et al. (Zhang et al., 2023) proposed a dynamic multi-objective RL framework, which optimized the performance of the recommender systems on multiple metrics at the same time. These results underline the fact that decision engines should become multi-objective, context-sensitive, and morally sound instead of being focused on myopic CTR optimization (Zhang et al., 2022) (Zhang et al., 2023).

Engagement Optimization

The last pillar of AABM is concerned with the implementation of adaptive sensing and decision-making into the outcomes of tangible engagement. It has been proved that adaptive personalization enhances immediate and long-term user engagement. User receptivity and affective alignment systems are not only beneficial in increasing CTR but also in increasing retention, satisfaction, and compliance in various domains. Adaptive interventions may lead to clinically significant changes, as in DIAMANTE (Aguilera et al., 2024), whereas CORES (Lakehal et al., 2025) demonstrates commercial value in the retail setting. Notably, offline RL and simulators (Wang et al., 2021) (Yuan et al., 2022) have placed an emphasis on how the engagement might be maximized without jeopardizing the trust of the user, by testing the strategies in controlled settings, and only deploying them to live environments once that is achieved.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

Overall, the AABM framework integrates emotion- and context-sensitive sensing, decision engines, and engagement optimization into a feedback loop: sensing user state, predicting receptivity, adaptive decision-making, providing contextually and emotionally congruent engagement, and learning based on feedback. The examined literature demonstrates that this framework is technically possible, empirically proven, and useful in the fields ranging from health to e-commerce. The second frontier is to consider the ethical factors, especially privacy, transparency, and manipulative practices to make sure that AABM provides sustainable value to the users and organizations.

Case studies of adaptive attention-based marketing

Although conceptual models and algorithmic developments prove the technical viability of AABM, applied case studies are important pieces of evidence on how these systems actually work. Table 2 includes the case studies that involve the application of adaptive strategies in the real-life context, including gamified applications, online shops, and mobile notification systems. These studies demonstrate that motivational design, survival models, and sequence-conscious learning strategies can be translated into quantifiable increase in engagement and user experience.

Gamified Mobile Engagement through Push Notifications

Kunkel et al. explored the impact of motivational affordances in push notifications on consumer behavior in a gamified mobile application. They compared progression-based, social, and achievement-focused messages sent to the app users. Based on behavioral data, they discovered that progression notifications were a big boost to engagement and retention, whereas messages that were sent at the wrong time or inappropriately were potentially disengaging. The paper emphasizes that customizing notifications based on the motivational state is better in capturing attention, which is in line with the AABM principle of contextually and emotionally relevant interaction (Kunkel et al., 2023).

Modeling Notification Timing with Survival Analysis

Yuan et al. created a state transition model that is founded on survival analysis to forecast mobile notification responsiveness. Based on massive behavioral logs, they were able to show that responsiveness was a dynamic process that was dependent on past interactions with the user. Their model performed better than the logistic regression baselines and was able to optimize the notification timing and frequency. The case shows how the concept of adapting message delivery to receptivity in the AABM approach can be operationalized using statistical modeling (Yuan et al., 2019).

Sequence-Aware Deep Learning for Pop-up Recommendations

Huang and Kao proposed C-3PO as a deep neural network (DNN)-based framework based on the utilization of click-sequence data to suggest suitable pop-ups. The model also predicted the pop-ups that would draw the interest of the user and reduce redundancy and annoyance. Experimental proof indicated that the method minimized irrelevant prompts and enhanced the click-through rates compared with heuristic approaches. This example shows the importance of sequence-sensitive personalization in adaptive marketing systems by learning behavioral sequences (Huang and Kao, 2019).

Complementary Product Recommendations in E-Commerce

Zhao et al. (Zhao et al., 2017) examined the possibility of integrating mixture models to suggest complementary products through e-commerce push notifications. Their user purchase and browsing histories were included in their system to make relevant product bundles. Empirical analysis showed that contextually selected complementary products had better open and conversion rates than non-adaptive approaches. This case indicates that the ability to adapt the content in the notification improves the marketing results and experience of the user (Zhao et al., 2017).

Knowledge Extraction from Notifications for Personalization

Li et al. (Li et al., 2018) introduced a system that extracts personal knowledge on smartphone push notifications automatically. The system recognized template generalizations of common patterns like travel times or delivery updates by analyzing more than 120 million notifications using template-based methods, maintaining the privacy of the process.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

Their results prove that notifications may be a useful source of contextual data to guide adaptive personalization policies in marketing (Li et al., 2018).

The application of AABM across multiple domains is summarized in Figure 8. The framework illustrates the real-time adaptation of engagement strategies in mobile notifications, gamified apps, e-commerce, and healthcare interventions, all based on user behavior, context, and intent.

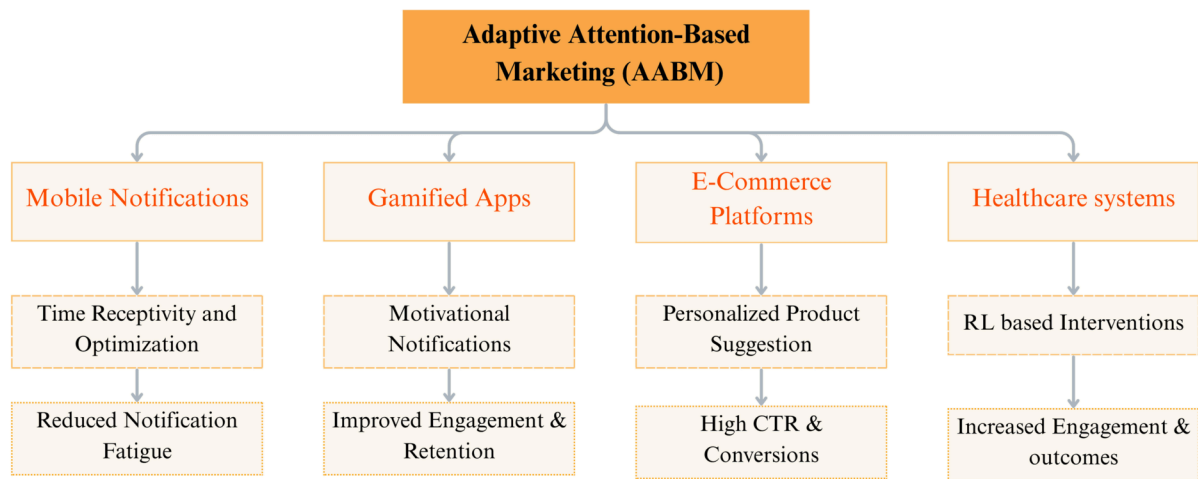


FIGURE 8: Applications of Adaptive Attention-Based Marketing across multiple domains

Source: Author’s own creation

In all these areas, AABM enables notifications and interactions that are time-sensitive, motivating, personalized, and based on reinforcement learning to enhance engagement and to minimize user fatigue and perceived intrusiveness. Collectively, these case studies highlight that context-aware timing, content personalization, and adaptive decision-making can significantly enhance user engagement, retention, and interaction quality. The results also further validate the three pillars of the AABM framework: user-state sensing, adaptive decision-making, and engagement optimization.

However, important technical, ethical, and governance issues arise when considering the large-scale use of AABM. The next section addresses the major obstacles of privacy, transparency, user trust, algorithmic bias, and responsible deployment of adaptive attention-based systems in the real world of mobile environments.

Challenges and ethical considerations

AABM has technical and ethical challenges in its implementation. Technically, it is still challenging to create robust models of real-time emotion and context recognition because of the noisy data, small training data, and the generalizability of models to different users and contexts. In addition, adaptive decision engines need to optimize both short-term metrics (e.g. click-through rate) and long-term metrics (e.g. retention and trust), necessitating multi-objective optimization methods.

AABM has ethical issues related to privacy, transparency, and autonomy. Table 3 outlines ethical challenges in AABM and possible safeguards, including privacy-preserving methods and fairness checks. Facial recognition of emotions, typing, or tracking of locations may be an intrusive form of surveillance and can lead to the abuse of sensitive information. Unless the users know it, their affective states and receptivity are inferred in real time, posing the risk of covert manipulation. Moreover, the unequal treatment of different demographic groups could also be caused by biases in sentiment or

How to cite this article:

recognition models, which increases the issue of fairness. Responsible deployment can solve these problems by focusing on privacy-preserving computation, express consent, bias audits, and regulation (GDPR) compliance (Voigt and von dem Bussche, 2017) (Jobin et al., 2019). Ethical adoption requires balancing between innovation and fairness and user trust.

Concern	Risk	Mitigation Strategies
Privacy of sensitive data	Intrusive surveillance from emotion/context recognition (e.g., facial data, location, typing behavior)	On-device processing, anonymization, federated learning
Transparency & consent	Users unaware of real-time affective inference → covert manipulation	Clear disclosures, opt-in consent, user dashboards showing data usage
Manipulation & autonomy	Exploiting vulnerable states (stress, loneliness) to drive engagement	Ethical design frameworks; limit persuasive interventions; focus on user well-being
Bias & fairness	Unequal performance across demographics (age, ethnicity, culture)	Fairness-aware algorithms, bias audits, diverse training datasets
Regulatory compliance	Non-compliance with GDPR/AI Act in emotion recognition	Data minimization, explicit consent, algorithmic audits, regulatory alignment

TABLE 2: Ethical challenges in AABM

Source: Compiled by the authors based on reviewed literature. AABM, Adaptive Attention-Based Marketing

Limitations of the review

There are several limitations to this review that must be taken into account when interpreting the findings. The literature search was conducted within the Scopus database, which might have missed relevant literature available in other databases like Web of Science, PubMed, IEEE Xplore, and ACM Digital Library. Second, the review was limited to publications from 2018 to 2025; a few seminal studies were included to provide background concepts. As a result, some earlier contributions may not have been captured comprehensively. Thirdly, only English-language publications were included, which could add language bias and exclude relevant work that is published in other languages. Lastly, a standardized screening and thematic analysis procedure was used, but classification and interpretation of studies may be subject to some degree of subjectivity. The review, despite its limitations, gives a broad overview of recent advances in AABM and outlines the research trends, challenges, and future directions.

Future research directions

Future work on AABM should be directed toward enhancing technical performance and responsible deployment. One of the key challenges is the development of non-invasive multimodal emotion and context recognition models that can integrate behavioral, emotional, and contextual signals in real-time without being computationally expensive for mobile applications. These systems should also be more adaptable in terms of culture, user groups, and digital environments. The use of transformer-based architectures and multi-objective reinforcement learning presents promising avenues for enhancing adaptive decision-making, ensuring a balance between immediate engagement targets and long-term outcomes like trust, retention, and user satisfaction. Meanwhile, privacy-preserving techniques such as federated learning, on-device inference, edge AI, and explainable AI (XAI) mechanisms will play a crucial role in minimizing data

How to cite this article:

exposure, enhancing transparency, and empowering users with more control. Future research should also focus on the use of standardized multimodal benchmark datasets, cross-platform evaluation frameworks, and longitudinal real-world studies to better understand the long-term impact of AABM on engagement behaviour, digital well-being, consumer trust, and consumer agency. In general, the future of AABM hinges on the development of intelligent engagement systems that are adaptive, privacy-conscious, transparent, and ethically responsible for various mobile ecosystems.

Conclusions

AABM is a major step forward in personalized mobile engagement as it combines real-time emotion recognition, context-aware sensing, and adaptive decision-making into a single intelligent engagement framework. AABM allows for more dynamic and emotionally resonant interactions that continuously respond to user behavior, context, and attentional receptivity, as opposed to traditional personalization methods that are based on static preferences or demographic segmentation. This review summarizes the progress in affective computing, mobile sensing, reinforcement learning, recommender systems, and adaptive marketing to establish AABM as a new interdisciplinary paradigm for mobile engagement optimization.

The literature reviewed shows significant advances in multimodal emotion recognition, adaptive personalization, and reinforcement learning-based engagement systems, which have been applied to gamified environments, e-commerce, healthcare interventions, and mobile notification environments. However, several important research gaps remain unresolved. Current research is constrained by the absence of large-scale multimodal datasets that combine emotional, behavioral, and contextual signals in a variety of real-world settings. Furthermore, most existing evaluation methods focus on short-term engagement measures and/or laboratory experiments, with limited evidence of real-world deployments over extended periods. Issues of privacy safeguarding, explainability, algorithmic bias, and manipulative personalization still impact user trust and large-scale adoption.

Thus, future research should focus on privacy-aware adaptive architectures, explainable decision systems, longitudinal user studies, and standardized evaluation frameworks beyond click-through rates to trust, retention, and digital well-being outcomes. The future viability of AABM will rely not only on technological innovations but also on the proper, transparent, and ethical implementation of intelligent engagement systems in the changing digital environment.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Acquisition, analysis, or interpretation of data: Aditi Shintre, Sudipkumar Ghanvat, Shreya Joshi, Rohan Jamdagni

Drafting of the manuscript: Aditi Shintre, Shreya Joshi, Rohan Jamdagni

Critical review of the manuscript for important intellectual content: Aditi Shintre, Sudipkumar Ghanvat

Concept and design: Sudipkumar Ghanvat, Rohan Jamdagni

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

Payment/services info: All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

References

1. Aguilera A, Arévalo Avalos M, Xu J, et al.: [Effectiveness of a digital health intervention leveraging reinforcement learning: results from the Diabetes and Mental Health Adaptive Notification Tracking and Evaluation \(DIAMANTE\) randomized clinical trial](#). Journal of Medical Internet Research. 2024, 26:e60834. [10.2196/60834](#)
2. Can YS, Arnrich B, Ersoy C: [Stress detection in daily life scenarios using smart phones and wearable sensors: A survey](#). Journal of Biomedical Informatics. 2019, 92:103139. [10.1016/j.jbi.2019.103139](#)
3. Cai T, Jiang J, Zhang W, et al.: [Marketing budget allocation with offline constrained deep reinforcement learning](#). Proceedings of the sixteenth ACM international conference on web search and data mining. 2023, 186--194. [10.1145/3539597.3570486](#)
4. DataReportal: [Digital 2025: India](#). 2025,
5. Gupta T, Bansal S: [AI-driven emotional recognition in digital ads: A novel approach to consumer engagement](#). Journal of Marketing & Supply Chain Management. 2023, 2:1-7. [10.47363/jmscm/2023\(2\)131](#)
6. He X, An B, Li Y, Chen H, Guo Q, Li X, Wang Z: [Contextual user browsing bandits for large-scale online mobile recommendation](#). Proceedings of the 14th ACM Conference on Recommender Systems. Association for Computing Machinery (ACM), New York, NY, USA; 2020. 63-72. [10.1145/3383313.3412234](#)
7. Huang THD, Kao HY: [C-3PO: Click-sequence-aware deeP neural network \(DNN\)-based Pop-uPs recOmmendation](#). Soft Computing. 2019, 23:11793-11799. [10.1007/s00500-018-03730-5](#)
8. Huang MH, Rust RT: [A strategic framework for artificial intelligence in marketing](#). Journal of the Academy of Marketing Science. 2021, 49:30-50. [10.1007/s11747-020-00749-9](#)
9. Jobin A, Ienca M, Vayena E: [The global landscape of AI ethics guidelines](#). Nature Machine Intelligence. 2019, 1:389-399. [10.1038/s42256-019-0088-2](#)
10. Kanjo E, Kuss DJ, Ang CS: [NotiMind: utilizing responses to smart phone notifications as affective sensors](#). IEEE Access. 2017, 5:22023-22035. [10.1109/access.2017.2755661](#)
11. Khare SK, Blanes-Vidal V, Nadimi ES, Acharya UR: [Emotion recognition and artificial intelligence: A systematic review \(2014-2023\) and research recommendations](#). Information Fusion. 2024, 102:102019. [10.1016/j.inffus.2023.102019](#)
12. Kheiri K, Ding C: [Kheiri K, Ding C](#). ACM Transactions on Recommender Systems. 2026, [10.1145/3813108](#)
13. Khurana S: [AI and Neuromarketing in Retail and E-Commerce: Enhancing the Shopping Experience and Conversion](#). Reshaping Business at the Intersection of Neuromarketing and AI. IGI Global Scientific Publishing, 2026. 1-34. [10.4018/979-8-3373-5997-7.ch001](#)
14. King ZD, Yu H, Vaessen T, Myin-Germeys I, Sano A: [Investigating receptivity and affect using machine learning: ecological momentary assessment and wearable sensing study](#). JMIR mHealth and uHealth. 2024, 12:e46347. [10.2196/46347](#)
15. Kumaran R, Doshi VN, Chen SX, Nargund AA, Höllerer T, Sra M: [EChat: An Emotion-Aware Adaptive UI for a Messaging App](#). Adjunct Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23 Adjunct). Association for Computing Machinery (ACM), 2023. 1-3. [10.1145/3586182.3616698](#)
16. Kunkel T, Hayduk T, Lock D: [Push it real good: the effects of push notifications promoting motivational affordances on consumer behavior in a gamified mobile app](#). European Journal of Marketing. 2023, 57:2592-2618. [10.1108/ejm-06-2021-0388](#)
17. Lai S, Hu X, Xu H, Ren Z, Liu Z: [Multimodal sentiment analysis: A survey](#). Displays. 2023, 80:102563. [10.1016/j.displa.2023.102563](#)
18. Lakehal A, Alti A, Annane B: [CORES: Context-aware emotion-driven recommendation system-based LLM to improve virtual shopping experiences](#). Future Internet. 2025, 17:94. [10.3390/fi17020094](#)
19. Lauffenburger JC, Yom-Tov E, Keller PA, et al.: [The impact of using reinforcement learning to personalize communication on medication adherence: findings from the REINFORCE trial](#). npj Digital Medicine. 2024, 7:39. [10.1038/s41746-024-01028-5](#)
20. Li Y, Yang Z, Guo Y, Chen X, Agarwal Y, Hong JI: [Automated extraction of personal knowledge from smartphone push notifications](#). 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA. 2018, 733-742. [10.1109/BigData.2018.8621866](#)

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. Cureus J Bus Econ 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

21. Liang R, FNU F, Liang Y, Ye Z: [Emotion-aware interface adaptation in mobile applications based on color psychology and multimodal user state recognition](#). *Frontiers in Artificial Intelligence Research*. 2025, 2:51-57. [10.71465/fair241](#)
22. Lim S, Kim C, Cho BH, Choi SH, Lee H, Jang DP: [Investigation of daily patterns for smartphone keystroke dynamics based on loneliness and social isolation](#). *Biomedical Engineering Letters*. 2024, 14:235-243. [10.1007/s13534-023-00337-0](#)
23. Min DJ, Stolcke A, Raju A, Vaz C, He D, Ravichandran V: [Adaptive endpointing with deep contextual multi-armed bandits](#). *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Rhodes Island, Greece. 2023, 1-5. [10.1109/ICASSP49357.2023.10097142](#)
24. Mishra V, Künzler F, Kramer JN, Fleisch E, Kowatsch T, Kotz D: [Detecting receptivity for mHealth interventions in the natural environment](#). *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2021, 5:1-24. [10.1145/3463492](#)
25. Page MJ, McKenzie JE, Bossuyt PM, et al.: [The PRISMA 2020 statement: an updated guideline for reporting systematic reviews](#). *BMJ*. 2021, 372:n71. [10.1136/bmj.n71](#)
26. Pielot M, Church K, De Oliveira R: [An in-situ study of mobile phone notifications](#). *MobileHCI '14: Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services*. 2014, 233-242. [10.1145/2628363.2628364](#)
27. Qassimi S, Rakrak S: [Multi-objective contextual bandits in recommendation systems for smart tourism](#). *Scientific Reports*. 2025, 15:13669. [10.1038/s41598-025-89920-2](#)
28. Singh KK, Dembla P: [A study on emotion analysis and music recommendation using transfer learning](#). *Journal of Computer Science*. 2023, 19:707-726. [10.3844/jcssp.2023.707.726](#)
29. Steil J, Müller P, Sugano Y, Bulling A: [Forecasting user attention during everyday mobile interactions using device-integrated and wearable sensors](#). *MobileHCI '18: Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services*. 2018, 1-13. [10.1145/3229434.3229439](#)
30. Vaizman Y, Weibel N, Lanckriet G: [Context recognition in-the-wild: Unified model for multi-modal sensors and multi-label classification](#). *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2018, 1:1-22. [10.1145/3161192](#)
31. Vettehen PH, Schaap G: [An attention economic perspective on the future of the information age](#). *Futures*. 2023, 153:103243. [10.1016/j.futures.2023.103243](#)
32. Visuri A, van Berkel N, Okoshi T, Goncalves J, Kostakos V: [Understanding smartphone notifications' user interactions and content importance](#). *International Journal of Human-Computer Studies*. 2019, 128:72-85. [10.1016/j.ijhcs.2019.03.001](#)
33. Voigt P, Von dem Bussche A: [The EU General Data Protection Regulation \(GDPR\): A Practical Guide](#). Springer International Publishing, Cham; 2017. [10.1007/978-3-319-57959-7](#)
34. Wang S, Guan S, Lin H, Huang J, Long F, Yao J: [Micro-expression recognition based on optical flow and PCANet+](#). *Sensors*. 2022, 22:4296. [10.3390/s22114296](#)
35. Wang S, Zhang C, Kröse B, van Hoof H: [Optimizing adaptive notifications in mobile health interventions systems: reinforcement learning from a data-driven behavioral simulator](#). *Journal of Medical Systems*. 2021, 45:102. [10.1007/s10916-021-01773-0](#)
36. Yuan Y, Muralidharan A, Nandy P, Cheng M, Prabhakar P: [Offline reinforcement learning for mobile notifications](#). *CIKM '22: Proceedings of the 31st ACM International Conference on Information & Knowledge Management*. 2022, 3614-3623. [10.1145/3511808.3557083](#)
37. Yuan Y, Zhang J, Chatterjee S, Yu S, Rosales R: [A state transition model for mobile notifications via survival analysis](#). *WSDM '19: Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*. 2019, 123-131. [10.1145/3289600.3290981](#)
38. Zhang J, Xie X, Peng G, et al.: [A real-time and privacy-preserving facial expression recognition system using an AI-powered microcontroller](#). *Electronics*. 2024, 13:2791. [10.3390/electronics13142791](#)
39. Zhang Q, Liu J, Dai Y, Qi Y, Yuan Y, Zheng K, Tan X: [Multi-task fusion via reinforcement learning for long-term user satisfaction in recommender systems](#). *KDD '22: Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 2022, 4510-4520. [10.1145/3534678.3539040](#)

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. *Cureus J Bus Econ* 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>

40. Zhang X, Shang Y, Ren Y, Liang K: [Dynamic multi-objective sequence-wise recommendation framework via deep reinforcement learning](#). Complex & Intelligent Systems. 2023, 9:1891-1911. [10.1007/s40747-022-00871-x](#)
41. Zhao F, Zhang C, Geng B: [Deep multimodal data fusion](#). ACM Computing Surveys. 2024, 56:1-36. [10.1145/3649447](#)
42. Zhao H, Si L, Li X, Zhang Q: [Recommending complementary products in e-commerce push notifications with a mixture model approach](#). SIGIR '17: Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval. 2017, 909-912. [10.1145/3077136.3080676](#)

How to cite this article:

Ghanvat S, Joshi S, Jamdagni R, et al. (July 27, 2026) Adaptive Attention-Based Marketing: A Review of Emotion- and Context-Aware Approaches for Mobile App Engagement Optimization. Cureus J Bus Econ 3 : es44404-026-00184-z. DOI <https://doi.org/10.7759/s44404-026-00184-z>