Mobile Applications that Incorporate AI for Information Search and Recommendation: A Systematic Literature Review

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***Abstract*—The inclusion of artificial intelligence (AI) has become essential for mobile application development, allowing improved personalization and optimization of the user experience. Over the past decade, smart mobile devices have been observed to enhance user experience across a variety of needs. The main objective of this study is to evaluate AI-powered mobile applications that utilize intelligent search mechanisms and more accurate recommendations and analyze their impact on addressing these user needs. The databases used were Scopus, ScienceDirect, Web of Science, and EBSCO. A filtering process using Prisma and a document quality assessment process was performed to select the most relevant articles. The study posed four questions related to the topic. The results showed that mobile apps for search and recommendation are mainly based on hybrid approaches (collaborative and content-based filtering) and deep learning (autoencoders, LSTMs/transformers, and BERT-type semantic retrieval embeddings), complemented by classic techniques (matrix factorization, SVM, K-NN, and trees/boosting) and contextual personalization (location, time, activity). It was concluded that these AI additions benefited users and met their search and recommendation needs. Furthermore, these mechanisms are advancing by leaps and bounds, as we now talk about more precise search and recommendation with voice, images, and even video.**

***Keywords*—AI algorithms; recommendation algorithms; mobile applications; search algorithms; AI for information**

I. Introduction

Artificial intelligence (AI) has become an important component of mobile app development [1], allowing for the implementation of recommendation algorithms that personalize and optimize the user experience. These algorithms can analyze a large amount of data to provide accurate and appropriate suggestions that enhance user interaction with the application.

For example, work-related applications such as LinkedIn, Indeed and Glassdoor stand out for connecting candidates and employers through personalized recommendations.

In the educational sector, applications like Coursera, Duolingo and Khan Academy integrate intelligent systems to customize the teaching content for each student, and in navigation, Google Maps and Waze use AI techniques to optimize routes and provide real-time contextual information. [1].

The integration of artificial intelligence into mobile applications is particularly important for information searches in the public and private sectors. Artificial intelligence provides a personalized learning experience and adapts to the needs and pace of each user.

This study provides an overview of how modern technology, especially artificial intelligence, has the ability to guide and recommend, allowing sugggestions to be personalized based on user needs, facilitating not only searches but also the exchange of information and advice between users. This fosters growth and innovation in the technological field.

Applications that include artificial intelligence significantly differentiate themselves in operational efficiency and user experience by providing a more intuitive and personalized interaction [1], [2]. This is in contrast to traditional applications, which often offer a more general and less adaptive experience.

Among the benefits of using mobile applications with artificial intelligence is the personalization of content, which improves the ability to offer accurate recommendations based on user behavior [2], [3]. These benefits not only improve user satisfaction but also increase app retention.

The most important factors contributing to the adoption and success of AI applications are ease of use, adherence to recommendations, and the ability to adapt to changing user needs [2]. These factors are important to ensure that applications are not only adopted but also thrive in a competitive market.

The need to study this topic stems from the exponential rise of mobile technology and its impact on users. As more people rely on their mobile devices, it's important to understand how artificial intelligence can improve this experience and what challenges must be overcome for effective implementation of this technology.

The main objective of this study is to conduct a systematic review to identify and analyze the use of artificial intelligence in mobile applications, which involve information search and recommendation within the application. It also analyzes the different AI algorithms and techniques that are commonly used, and determines the sectors in which it has been most frequently applied.

This study will recommend solutions to improve the integration of artificial intelligence into search and recommendation. Using a PICOC approach, the impact of these applications on the efficiency and effectiveness of everyday use will be analyzed.

II. Gaps in the Literature

Despite advances in the integration of artificial intelligence (AI) into educational mobile applications, significant gaps in the existing literature have been identified. Of the 58 studies analyzed, only seven focus specifically on the education sector. These works address use cases such as learning personalization, interactive content delivery, and automated assessment. However, none focus on job opportunity recommendations for university students or graduates, highlighting a lack of research on the application of AI for career guidance in this demographic.

Most AI-powered educational applications focus on features such as content classification, interactive simulations, and recommendation systems based on collaborative filtering, recurrent neural networks (GRUs), and text mining. These technologies, while effective in personalizing learning, do not address the specific needs of students seeking guidance in their transition to the labor market in which they work [2], [3], [4], [5].

Also, the lack of studies that integrate AI in mobile applications for job recommendation and professional development in the university environment limits the understanding of how these technologies can support students in planning their careers [5], [6], [7]. In addition, there is a lack of research that evaluates the effectiveness of these applications in real contexts, considering factors such as adaptability to different academic disciplines and the diversity of student profiles [7], [8], [9].

Therefore, this gap in the literature highlights the need for future research exploring the design and implementation of AI-powered mobile applications aimed at recommending job opportunities for university students and graduates. Such studies should consider the integration of technologies such as natural language processing, machine learning, and adaptive recommendation systems that can offer personalized guidance based on users' academic profiles and career aspirations [9].

III. Research Methodology

This study is based on a systematic review of the extraction of scientific articles from various scientific databases using the PRISMA methodology.

The PARSIFAL tool, a specialized platform for conducting systematic literature reviews, was used. This tool facilitates the organization and management of research through structured searches in academic databases, ensuring transparency and reproducibility of the process.

The research focuses on scientific publications related to artificial intelligence in mobile applications, given that the information is relevant and can be used. This study provides context for mobile applications on various platforms, offering a comprehensive view of the differences between applications that employ artificial intelligence and those that do not.

A. Research Questions

To assess the scope of mobile applications incorporating artificial intelligence (AI), particularly those dealing with user experience, application usability effectiveness and technological adoption, it is essential to have previous research demonstrating the results achieved. To achieve the objectives of this systematic literature review, the process has been structured into three main phases: review planning, review execution and review documentation, as shown in Fig. 1. This approach ensures a comprehensive and systematic analysis of mobile applications that integrate AI, comparing them with those that do not use this technology [5].

In addition, a detailed protocol was developed for the review, which established search filters and defined the study area in the context of mobile applications. The research questions guiding this review are shown in Table I.

TABLE I. DEFINING THE RESEARCH QUESTIONS

Nro	Research questions	Reason
RQ1	What artificial intelligence methods, techniques, and algorithms are used in mobile applications for information recommendation and search?	Helps identify which AI methods and algorithms are used to improve recommendations and search in mobile apps.
RQ2	Which artificial intelligence algorithms or techniques were most frequently used in mobile information search and recommendation applications?	It allows you to know which algorithms are the most common and effective in mobile recommendation and search applications.
RQ3	In which areas or sectors were smart applications for information recommendation and search most widely used?	Helps you discover the sectors where AI-powered apps for recommendation and search have the greatest impact.
RQ4	What are the limitations and challenges in using artificial intelligence in mobile applications for information search and recommendation?	Help identify challenges and obstacles in using AI in mobile apps to improve search and recommendation.

B. Search Strategy

A systematic search was carried out in four databases: Scopus, ScienceDirect, EBSCO Host, and Web of Science (WoS) to compile research on the use of mobile applications that integrate artificial intelligence techniques. The time range considered was 2020 to 2026, allowing us to focus on recent and relevant studies.

Search strings were constructed using Boolean operators (AND, OR, NOT), combining terms related to artificial intelligence, mobile applications, search and recommendation functionalities, as well as user experience and technical aspects. In addition, exclusion filters were applied in some databases to exclude publications related to the medical field. The exact strings used are presented in Table II.

C. PRISMA Method

When conducting a systematic review on artificial intelligence in mobile applications, PRISMA helps structure the review process to be clear and reproducible. This is especially important in a field as dynamic as AI, where the literature can be extensive and varied [10].

TABLE II. SEARCH CHAIN FOR EACH DATABASE

Database	Search string
Web of Sciencie	("artificial intelligence" OR "ai" OR "machine learning" OR "deep learning" OR "neural networks") AND ("mobile application" OR "mobile app" OR "smartphone application" OR "app") AND ("search" OR "recommendation" OR "suggestion" OR "discovery" OR "ranking function" OR "search algorithm") AND ("user experience" OR "ui" OR "ux" OR "personalization" OR "interaction") AND ("algorithm" OR "model" OR "system" OR "framework")
Science Direct	("artificial intelligence" AND "mobile applications")AND ("machine learning" OR "deep learning") NOT ("health" OR "covid 19" OR "Medical")
Scopus	("artificial intelligence" OR "ai" OR "machine learning" OR "deep learning" OR "neural networks") AND ("mobile application" OR "mobile app" OR "smartphone application" OR "app") AND ("search" OR "recommendation" OR "suggestion" OR "discovery" OR "ranking function" OR "search algorithm") AND ("user experience" OR "ux" OR "personalization" OR "interaction") AND ("algorithm" OR "model" OR "system" OR "framework")
Ebsco	("Artificial Intelligence" OR "IA" OR "Machine learning" OR "deep learning") AND ("mobile applications" OR "Mobile apps") AND ("algorithm") NOT ("Health" OR "Covid 19" OR "Medical")

In this review, we begin by identifying a large number of papers related to AI in mobile applications. Using the PRISMA flowchart, we document each stage of the selection process, from the initial identification of 6,138 articles to the final selection of 58 relevant articles. This flowchart facilitates understanding and ensures transparency of the selection process, as shown in Fig. 1.

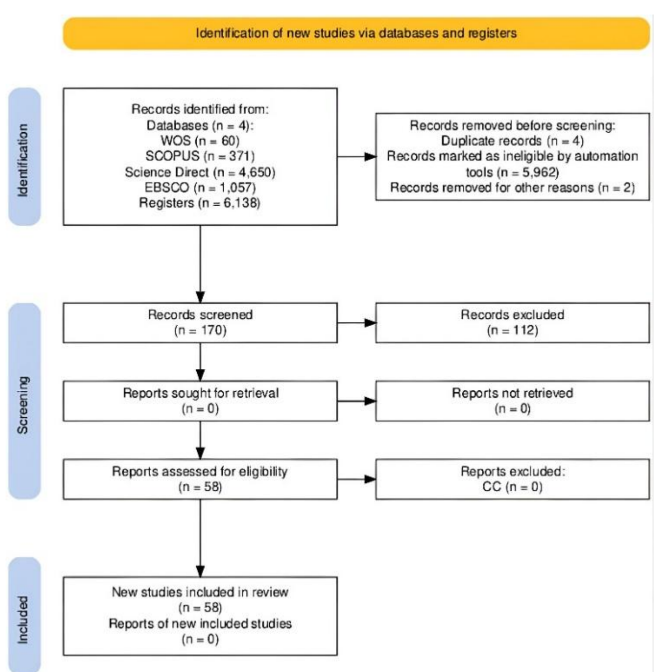

Fig. 1. Article selection process.

In accordance with PRISMA, we pre-specified and fully reported the eligibility criteria used to screen the studies. We included peer-reviewed articles on mobile apps that implement AI techniques and that examine user outcomes, such as acceptance, behavior, or satisfaction with everyday use. We excluded records that did not focus on mobile apps, that did not directly employ AI, or that were non-empirical works, as well as duplicates.

Study selection followed a two-stage process documented in a PRISMA flowchart with the counts of records identified, reviewed, excluded, and included, along with the reasons for exclusion. For the studies, we extracted key variables and conducted a narrative synthesis. In the context of AI for mobile apps, this synthesis highlights how search and recommendation algorithms relate to user satisfaction and acceptance and identifies areas where evidence remains limited.

D. Stages

Moving on to the stages, this process of selecting and filtering papers for this study is carried out through a systematic approach and in successive stages, applying specific search, filtering, inclusion, and quality criteria in the selected databases (WoS, Science Direct, Scopus, and EBSCO). The initial search generated a high volume of papers, which were reduced and evaluated through six main stages, detailed below:

1) Stage 1 – No filters: This is the initial phase of searching for all possible information related to the research topic without using any exclusion or selection criteria. The main objective here is to thoroughly review and gather the most appropriate data, documents, or articles, although some may not be useful in the end. The search strings used in this stage are shown in Table II.

2) Stage 2 – Basic filters: Internal filters were applied to each database to restrict results to the last five years (2020 to 2026), select open access scholarly and review articles, and limit the languages to English and Spanish for WoS, Science Direct, and Scopus, and English only for EBSCO HOST. After this step, 1,485 records remained that met these requirements.

3) Stage 3 – Initial inclusion and exclusion criteria by database: This consisted of applying our specific inclusion and exclusion criteria mentioned in the methodology, which varied slightly depending on the database. Articles with sources that were not part of the study were discarded, such as: “Rehabilitation”, “Geochemistry”, “Operations Research”, “Management Science”, “Physics or Mechanics”, “clinical”, “health”, “Covid”, “Human”, “Healthcare”, “Autism”, “covid-19”, “Diabetes”, “Diagnosis” and “impaired”, which led to obtaining 176 articles.

4) Stage 4 – Duplicate removal: Duplicate articles across different databases were identified and removed. This is critical to ensuring the quality and accuracy of the analysis, yielding 170 independent references.

5) Stage 5 – Specific inclusion and exclusion criteria: Additional inclusion criteria were applied, such as analyzing the impact of AI on mobile applications and recommendation algorithms, and exclusion criteria were applied, eliminating studies outside the fields of engineering, AI, and mobile applications. The inclusion and exclusion criteria used are shown in Table III and Table IV.

TABLE III. INCLUSION CRITERIA

Nro	Inclusion Criteriaa	Reason
CI1	Articles that analyze the impact of AI on users' daily lives and the technology's acceptance in mobile applications.	This criterion is important for understanding the impact of this technology on the daily lives of users who adopt it. It also allows us to assess the technology's viability in the market and its growth potential.
CI2	Articles that address Mobile Applications.	This is important because it ensures that the selected articles provide information directly applicable to the development and use of AI in the mobile environment.
CI3	Articles that address artificial intelligence (AI) applied to mobile application development.	These studies are key to understanding the methodologies, tools, and architectures used to integrate AI into these types of applications.
CI4	Articles that discuss machine learning and digital technologies that contribute to improving user efficiency and convenience.	Including studies that analyze these technologies allows us to understand how machine learning models optimize the functionality of mobile applications, benefiting personalization, speed and precision in interaction.
CI5	Articles that include recommendation algorithms in mobile applications.	This ensures that research focusing on the development and effectiveness of recommendation systems is investigated.

TABLE IV. EXCLUSION CRITERIA

Nro	Exclusion Criteria	Reason
CE1	Duplicate articles	Removing duplicate articles is standard in review research; this prevents repetition and makes sure each study offers fresh, relevant information.
CE2	Studies not related to engineering, software development, mobile applications, computer science, artificial intelligence, or digital technologies.	Focusing on these areas ensures the reviewed studies are both technically sound and practically useful, excluding research that doesn't offer applicable knowledge for developing or implementing AI in mobile apps.
CE3	Research into digital technologies for non-mobile platforms, such as desktop applications or back-end systems without mobile functionality.	By focusing only on studies of mobile platforms, we can be sure the articles we choose offer insights specific to the unique challenges and benefits of mobile environments.
CE4	Research that addresses AI technologies, machine learning, or algorithms, but is not applied in the context of mobile applications	This selection process eliminates studies unrelated to mobile apps, concentrating the review on research relevant to the unique challenges and environment of mobile devices.
CI5	Posts focused on AI applications that are not related to mobile apps or recommendation algorithms.	Ensures that selected articles focus on specific application areas that seek to improve the user experience on mobile devices.

6) Stage 6 – Quality assessment: Articles that passed the preceding stages were evaluated using an eight-question quality checklist. A minimum score of 4 was required to proceed. The criteria assessed methodological rigor and the extent to which user acceptance of AI in mobile applications was analyzed. Table VI lists the 58 studies that met the threshold and advanced to the final stage.

The general summary of the total number of articles we obtained at each stage can be seen in Table V.

Finally, we evaluated the relevance of each article to our quality questions, awarding 1 point for a complete answer, 0.5 for a partial answer, and 0 for no direct evidence. Of the 58 articles evaluated, all achieved an average of 5.45 points, confirming their suitability for in-depth analysis. Each article's results are shown in Table VI.

Articles that passed Stage 6 were evaluated in a final phase to determine their contribution to the research questions. This evaluation ensured that the studies aligned with the established thematic lines: efficiency improvement, popularity, technological trends, use cases, impact of recommendation algorithms, and challenges in user experience. Specific research questions addressed the following topics:

- Improving efficiency through AI-based mobile applications.
- Current technological trends in AI applications.
- AI use cases in the fields of employment and education.
- Impact of recommendation algorithms on user experience.

E. Keyword Analysis

To identify the thematic axes, a co-occurrence map was created with VOSviewer 1.6.x, applying the association strength algorithm of van Eck and Waltman [11]. We worked exclusively with Scopus, the most cited database and with the greatest initial coverage in this study. Each node of the graph represents an author's keyword; its size indicates the frequency, and the thickness of the links reflects the intensity of co-occurrence.

- Fig. 2: We started with a corpus of 371 articles. The 170 terms we chose fell into five groups, with machine learning, artificial intelligence, and mobile apps being the most common. This shows how important AI is for mobile devices.
- Fig. 3: Cleaned-up corpus (31 articles). Following PRISMA filtering and quality control, the resulting graph showed 16 terms in two clusters:
    - Technical (red): machine learning, deep learning, natural language processing, mobile applications.
    - Evaluation with users (green): human, controlled study, procedures.

The reduction from five to two clusters indicates that the most rigorous evidence focuses on: i) AI techniques for mobile personalization andii) experimental studies with users. Furthermore, the absence of terms such as "job recommendation" or "career guidance" corroborates the previously identified gap: the lack of research that provides professional guidance to students and graduates through AI-powered mobile applications.

TABLE V. DATABASE RESULTS

Database	Results						
	Stages						
	Stage 1	Stage 2	Stage 3	Stage 4		Stage 5	Stage 6
WOS	60	36	23		23	10	58
SCOPUS	371	78	46	5	41	31	
Science Direct	4650	1127	69		69	7	
Ebsco Hostt	1057	244	38	1	37	10	
Total	6138	1485	176	-6	170	58	58

TABLE VI. MOBILE APPS WITH AI: METHODS AND TECHNOLOGIES

Method / Technique	**Recommendation Algorithm**	**What is it for?**
Filter and Recommendation [12], [13], [14] Systems Evaluation and QA [15], [16] Data Extraction and Preprocessing [12], [17] Statistical Analysis [18], [19] Sequential Modeling and Transitions [19], [20] Probabilistic Methods and Game Theory [21] Classical ML Algorithms [20], [22], [23], [24] Hyperparameter Optimization [20], [25] Deep Learning and Neural Networks [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39] Architectures Advanced Neural Processing [29], [31], [40] Image and Sensor Processing [14], [31] Natural Language and Text Processing [35], [41], [42], [43] Dialogue and Text Generation [41], [44] User Profiling and Behavior [15], [45] Ranking and Output Combination [19], [20], [28], [33], [34], [38], [42], [44]	Machine Learning (generic) [14], [23], [28], [30], [31], [33], [34], [38] Tree and Ensemble Algorithms Random Forest [22], [24] Random Survival Forest [23] Logistic Regression [17], [19] Gaussian Process Regression [21] Clustering and K Means Neighbors [15] K-Nearest Neighbors (KNN): [23], [40] Neural Language Processing (NLP) [16] Neural Networks (Deep Learning) CNN [20], [27], [29], [32], [33], [34], [35], [36], [37], [38], [41] RNN [44] LSTM [36], [37], [44] GRU ANN SNN (also: Generic Deep Learning) Supervised Learning Algorithm (Generic) Combined / Advanced Vision, Methods: Mask R CNN, Faster R CNN, K Means Algorithm	Content and feature based recommendation [15], [28], [32], [37], [38], [42], [43], [45] Behavior-based and collaborative recommendation [44] Prediction based on biomedical and clinical data [18], [22], [23], [27], [34], [35] Detection based on security patterns and anomalies [19], [30] Optimization based on performance and resources [20], [21], [24], [25], [33], [36], [40] Adaptive interfaces based on user signals [14], [16], [17], [26], [29], [31], [39], [41]
Method / Technique	**Search Algorithm**	**What is it for?**
Machine Learning [46] Deep Learning [47] Random Forest [48] Neural Networks (CNN) [47] Data Preprocessing, [48] KNN SVM	NLP [46] CNN [47] Logistic Regression [48]	Search based on efficiency and user experience [46] Classification based on visual features and deep learning[47] Analysis based on text mining [48]

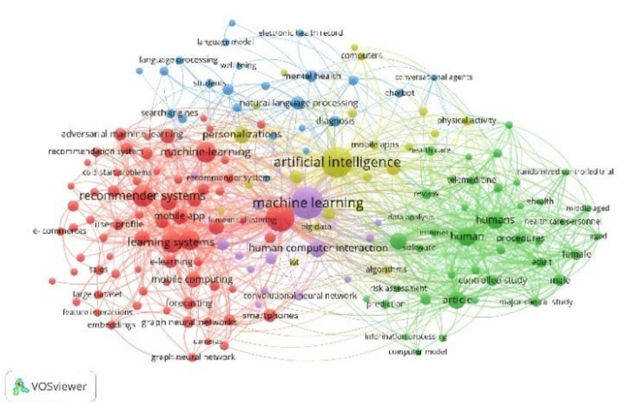

Fig. 2. Image of Scopus keywords before filters.

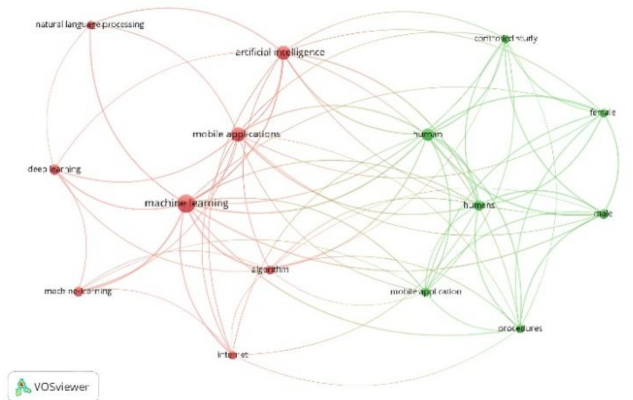

Fig. 3. Scopus keywords image after applying the filters.

IV. RESULTS

Below, the results obtained from the Parsifal platform will be explained, both as selected and accepted articles, and the articles that respond to the research questions posed in Table I will also be detailed, each question with its respective answer.

A. Descriptive Results

1) Article by source: The pie chart (see Fig. 4) summarizes the relative contribution of each database to your search:

- Science Direct 39.7 % provides the majority of the results, almost four out of ten.
- Scopus 25.9 % is the second most prominent source, with just over a quarter.
- EBSCO remains the most important at 21.3 %, covering approximately one-fifth of records.
- Web of Science 13.2 % contributes the smallest portion, about one in eight results.

These four databases cover the entire range of findings, with Science Direct leading by far and Web of Science having the smallest share.

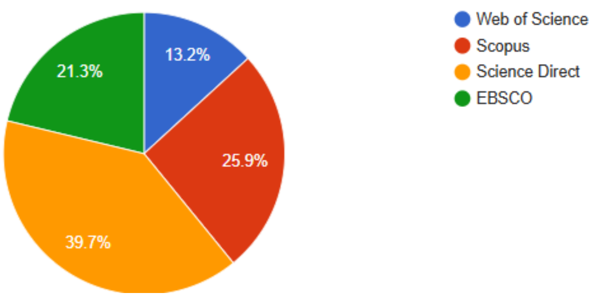

Fig. 4. Percentage distribution of results by database.

2) Accepted articles: For this research, based on the databases and search strings used in each, a total of 6,138 articles were selected, and after a multistage filtering process, only 58 were ultimately accepted for the study (see Fig. 5). Web of Science shows the highest acceptance rate (16.7%), followed by Scopus (9.4%). EBSCO has a medium-low rate (1.1%), while Science Direct, despite being the source with the most articles retrieved, provides the lowest proportion of accepted articles (0.2%).

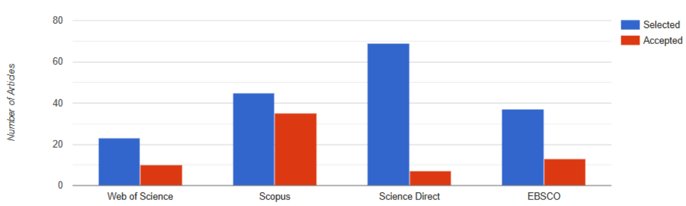

Fig. 5. Number of articles selected and accepted by the database.

B. Answer to Each Research Question

The answers to each of the research questions are presented below. Each answer will be based on the content of the selected articles that provide specific evidence.

1) What artificial intelligence methods, techniques, and algorithms are used in mobile applications for information recommendation and search?

Mobile applications that integrate artificial intelligence for information recommendation and search employ a variety of advanced methods and techniques, including machine learning algorithms (such as decision trees, logistic regression, Random Forest, KNN, and clustering), deep learning techniques (including convolutional neural networks –CNN–, recurrent networks –RNN, LSTM, GRU–, and advanced architectures such as Mask R-CNN and Faster R-CNN), as well as hybrid approaches that combine recommendation, classification, and ranking of results. Other methods, such as data extraction and preprocessing, feature selection, and natural language processing (NLP), are also used to analyze user behavior and to improve the understanding and retrieval of textual information.

2) What AI algorithms or techniques were frequently used in mobile information recommendation applications?

The reviewed studies emphasize the use of neural networks (including various deep learning models) because they simultaneously learn item characteristics and user preferences, generating highly accurate recommendations even with heterogeneous data (text, images, clicks). Traditional machine learning algorithms, such as SVM, KNN, or trees, are also used when a lightweight model that can run quickly on the device is needed. Many studies combine these two types with clustering, which groups users or content to initiate recommendations when there is little historical information. Content filtering has proven useful for suggesting items similar to those already viewed, while natural language processing (NLP) techniques help interpret queries or reviews and enrich the user profile. Finally, methods such as Random Forest occasionally appear for classification tasks within the system, but are not the core of the recommendation process, as summarized in Table VII.

TABLE VII. MOST FREQUENTLY USED ALGORITHMS

Articles	Tendencies
[14], [15], [16], [30]	Filtering and Recommendation (by content)
[24], [25], [28], [45]	Deep learning
[14], [23], [28], [30], [31], [33], [34], [38]	Machine learning
[16], [46]	Natural language processing
[20], [27], [29], [32], [33], [34], [35], [36], [37], [38], [41]	Neural Networks
[48]	Random Forest
[19], [20], [28], [33], [34], [38], [42], [44]	Clusters

3) In which areas or sectors were intelligent applications for information recommendation and search most used?

The sectors where intelligent applications for information recommendation and search were most widely applied were healthcare, technology, entertainment, and education. The healthcare sector stood out for its personalized diagnostic and monitoring systems; technology and entertainment demonstrated advanced use of algorithms, such as collaborative filtering, NLP, and neural networks to personalize content, with high potential for adaptation to the work context. Although no applications aimed at job recommendation were found in education, similar techniques were used, demonstrating the transversality of these technologies in different contexts, as shown in Table VIII.

TABLE VIII. SMART APPLICATIONS IN KEY SECTORS FOR INFORMATION RECOMMENDATION AND SEARCH

Sector / Area	Use Cases	Application Type	Technology / AI / Algorithms
Health [18], [22], [23], [25], [26], [27], [29], [39], [44], [46], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61]	1. Personalized and Predictive Clinical Care 2. Support and Automation for Professionals 3. Advanced Analytics and Recommendations	Optimizing medical processes and clinical support with smart technologies. Advanced diagnostics, treatment customization, and intelligent monitoring.	1. Machine Learning and Deep Learning 2. Clinical and Biomedical Processing 3. Multimodal Analysis and Media 4. Adaptive Systems and Personalized Recommendations 6. Technological Infrastructure and IoT
Digital entertainment [38], [62]	1. Movie recommendations on platforms like Netflix, Amazon Prime, and Disney. 2. Personalized short video recommendations on short-form video platforms.	Intelligent recommendation systems for digital content (movies and short videos).	1. Collaborative and Content-Based Filtering Techniques - Knowledge-Based Systems and Hybrid Approaches 2. Deep Learning and Stream Processing 3. User Interest Modeling
Education [15], [30], [40], [47], [63], [64], [65]	- Personalization and learning recommendations - Interactive content delivery - Automated content management, classification, and evaluation	Smart educational apps for: - Personalized recommendations - Automated assessment - Interactive simulations - Content classification - Learning personalization	1. Recommender systems with collaborative filtering 2. GRUs (Recurrent Networks) for adaptive recommendation 3. Text mining and SNNs 4. AI with pattern recognition 5. Physical and 3D simulations 6. NLP and machine learning 7. Knowledge tracking with convolutional CKT
Agriculture [66], [67], [68]	Animal health diagnostics, crop disease detection, and IoT monitoring.	Mobile and smart apps for animal diagnostics, agricultural monitoring, and personalized recommendations.	1. Data-driven diagnosis 2. TAM (Technology Acceptance Model) 3. Convolutional Neural Networks (CNN) 4. Inception v3 5. Deep Metric Learning
Technology [16], [28], [69], [70], [71], [72]	Content personalization, user satisfaction prediction, semantic retrieval, interface and news personalization.	Intelligent apps and platforms for behavioral analysis, contextual personalization, and adaptive interaction.	1. VADER 2. Machine learning 3. Natural language processing (NLP) 4. Matrix factorization (MF) 5. GNNs + HAMP 6. 1. FIS (Feature Interaction Search) 7. 3. Recommendation algorithms
Finance [17]	Smart investment advice through mobile apps.	Multidimensional data analysis to recommend appropriate options.	1. NLP 2. Question and Answer (Q&A) Systems
Cybersecurity [43], [45]	1. Malware detection in Android through API call sequence analysis. 2. Botnet detection in Android through static app analysis.	1. Optimized algorithms to reduce redundant exploration paths. 2. Intelligent mobile threat detection framework.	1. Machine Learning Classifiers 2. Pruning Search 3. Graph Transformation 4. Permissions Review, APIs 5. Supervised ML
Technological Infrastructure [19]	Predicting non-functional attributes (QoS) in cloud services.	Intelligent time-sensitive models for quality prediction.	1. Sequential Modeling (GRU) 2. Probabilistic Discrimination (GAN)
Trade [14], [73]	Voice shopping, personalized recommendations on smart kiosks.	Voice assistants and self-service kiosks with product customization.	1. Voice Assistants (VAs) 2. LLMs 3. Deep learning 4.RFID
Transportation / Automation [36], [41]	1. Emotion recognition and assistance in automated driving. 2. Analysis of user feedback on electric vehicle charging stations.	1. Mobile apps with adaptive neural networks based on device context. 2. Text classification and sentiment analysis.	1. Deep Learning (DNN) 2. AdaScale for real-time dynamic scaling. 3. Deep Learning 4. Transformers (BERT, XLNet) 5. CNNs, LSTMs
Computer Vision / AI [74], [75]	Object recognition in images/videos and analysis of ceramics in cultural heritage.	Apps with neural networks that detect, classify, and group visual objects on the device.	1. ML on mobile devices 2. Faster R-CNN, Mask R-CNN 3. K-means
Mobile Sensing / IoT / Privacy [42]	Crowdsensing of spatial data (location, audio, etc.) for tasks such as environmental monitoring.	Mobile apps with incentives to collect data while protecting privacy.	1. Stackelberg Mechanism 2. Privacy-aware data sharing
Telecommunications / Energy [21]	User opinion analysis using text and sentiment mining.	Mobile applications that extract knowledge from textual feedback.	1. Text mining 2. NLP for topics and emotions
Energy / Smart Home [33], [48]	Energy optimization in homes and buildings through occupancy detection.	Systems with IoT sensors and predictive models to control HVAC.	1. Digital Twins 2. ML for Occupancy 3. CNNs + Wavelet Transform

Tourism / Personal Mobility [37]	Recommendation of places to visit based on user behavior.	Recommendation systems based on location and check-in sequence.	1. InfAM 2. Embeddings 3. Residual network

4) What are the limitations and challenges of using artificial intelligence in mobile applications for information search and recommendation?

Limitations and challenges in the use of artificial intelligence in mobile applications for information search and recommendation were identified in the quality and availability of data, effective personalization in diverse contexts, and ethical concerns related to user privacy. In sectors such as healthcare and education, implementation is limited by the sensitivity of the information and the need to comply with strict data protection regulations. Although technologies such as neural network filtering have proven effective, their performance can always be affected by incomplete or biased data. Poor interoperability between platforms and a lack of common standards make it difficult to integrate these systems into large-scale mobile applications. These aspects are summarized in Table IX.

TABLE IX. LIMITATIONS AND CHALLENGES OF USING INTELLIGENCE IN MOBILE APPLICATIONS FOR INFORMATION SEARCH AND RECOMMENDATION

Search Algorithm	**Limitations**	**Challenges**
- KESS (Keyword Growing + Systematic Search) - Content-based Image Retrieval + Deep Metric Learning (Contrastive Loss)	Search results took 43 seconds longer on average. [46] Inaccurate dance pose evaluation. Limited accuracy in real-life scenarios (71%), biased recognition of foods from one's own country. [73] QoS data shortage; cold start with new users/services.[40] Variable quality and possible noise in crowdsourced data; reliance on student data.[60] Missing important information and challenging viewpoints due to algorithms.[15] Limited accuracy in some visual categories. [22], [53] Validation results in animal models (rats) do not fully reflect human effects. [66]	Ensure user trust and data quality. [27] Improve the accuracy of object recognition and visual recommendations. [39] Various hardware conditions and limited resources on mobile devices. [25] Accurate QoS prediction, improving user experience. [40] Reduce computational cost without losing accuracy. [65] Capture complex user behavior patterns. [37] Improve infrastructure and data quality, ensuring effective personalization. [75] Improve the accuracy of predicting dynamic user interests. [39]
Recommendation Algorithm	**Limitations**	**Challenges**
- Collaborative Filtering - Hybrid Filtering - GRU–GAN - Stacked Autoencoders - Graph Autoencoders - Neural Networks (Deep Learning, Transfer Learning) - Linear and Lasso Regression Models with Genomic Data - Collaborative Filtering (CF) and Matrix Factorization (MF) - Collaborative Filtering, Stacked Autoencoders, Graph Autoencoders - Recommendation Algorithms Based on News Personalization - Adaptive and Personalized ML Techniques - Recommendation Algorithms Based on Medical Evidence + Generative AI (ChatGPT-4) - Diagnostic and Recommendation Algorithms - Conscious Influence in Successive POI Recommendations - CAT-MF Rec Based on DIEN and Cross-Attention Mechanism	- Inaccurate or misguided recommendations (investors, travel itineraries, clinical treatment). [6], [40], [46], [50] - Difficulty distinguishing explicit vs. implicit feedback. [38] - Latency and data quality limit dynamic user profile updates. [18], [27] - Anthropomorphic interfaces or AI do not always increase trust. [63] - Dependencia ciega del usuario sin entender cómo funciona el algoritmo. [15], [37] - Falta de consenso en autoevaluación del estado de ánimo y otros autoinformes. [54] - Modelos grandes (LLM, DL) difíciles de ejecutar en móviles. [65] - Necesidad de adaptación constante a condiciones del hardware (batería, CPU, red). [25] - Complejidad computacional y procesamiento multimodal (rostro, voz, biometría) elevan el consumo de recursos. [26] - Preocupaciones por privacidad y almacenamiento de datos sensibles. [29], [39], [54], [56], [57] - Algoritmos generativos aún con limitaciones de precisión y seguridad. [57] - Alto tiempo de implementación y escasa integración con sistemas existentes (historial electrónico, plataformas de terceros). [56]	- Integrate contextual cues (location, time, usage, history) [86] - Combine demographic, genomic, or microbiome data to personalize clinical interventions [37], [52] - Incorporate continuous - Fusionar filtrado colaborativo, basado en contenido y demográfico sin comprometer escalabilidad. [53] - Integrar modelos de lenguaje grande (LLM) para más precisión y velocidad. [38], [39], [46], [73] - Adaptar modelos a dispositivos con recursos limitados y validar su desempeño. [25], [72] - Integrar reconocimiento de voz, rostro, emociones y texto (PLN) en recomendaciones. [51] - Fusión eficiente de múltiples modalidades para mejorar la personalización. [27], [39], [45], [46], [57] - Ajustar recomendaciones a expectativas, progreso y "olvido" del usuario en tiempo real. [27], [39], [42], [46], [57] - Identificar factores clave que influyen en preferencias cambiantes. [18] - Diseñar UI accesibles que permitan calibrar el nivel de confianza del usuario. [63] - Mejorar la transparencia para evitar cámaras de eco y fomentar la comprensión del sistema.[15], [23] - Garantizar robustez en entornos diversos y culturas distintas. [75] - Aumentar la empatía de la IA para diferentes perfiles y contextos de compra o uso. [41] Salud: personalizar rutas de aprendizaje/coach, recomendaciones de medicación seguras y evaluación de resultados clínicos. Educación: generar rutas de aprendizaje personalizadas y adaptativas. Entretenimiento & otros: integrar contenidos y experiencias altamente personalizadas.[7], [46]

V. DISCUSSION

In this systematic review, we examine how artificial intelligence is integrated into mobile applications for information search and recommendation, addressing four research questions. We reduced the initial corpus from 6,138 records to 58 included studies after applying prespecified eligibility criteria—publication window (last five years), English/Spanish language, software-engineering relevance, and an explicit focus on search or recommendation algorithms. Among the included studies, 39.7% were retrieved from ScienceDirect, 25.9% from Scopus, 21.3% from EBSCOhost, and 13.2% from Web of Science, reflecting differences in coverage and accessibility across databases.

Regarding methods and algorithms (RQ1), the articles studied confirm the dominance of CNN neural networks for visual content and RNN/GRU/LSTM for interaction sequences combined with classic machine learning techniques (decision trees, SVM, k-NN, Random Forest). This coexistence responds to a compromise between precision (achieved by deep models) and lightness (necessary for on-device processing). In addition, there is a growing use of hybrid approaches that combine collaborative filtering and classification, as well as PLN can also be used to obtain knowledge and information from text corpora. Taken together, these techniques show the potential of machine learning algorithms to reduce the workload of human analysts on specific tasks [76].

Regarding the technological trends found in the study (RQ2), the analysis shows that neural networks appear in more than half of the studies, followed by classic collaborative filtering, content-based filtering, and clustering. This pattern indicates that developers prioritize models capable of learning deep representations when resources are available, while using lightweight collaborative, content-based, and clustering techniques for auxiliary tasks such as pre-filtering, cold start, or segmentation. The still-spot presence of Random Forest and other ensembles provides a niche for interpretable and efficient algorithms, especially in domains where system explanation is critical. Computer tools that make users think about products, services or content according to their interests, characteristics and behavior using algorithms [77].

Sectors that were applied (RQ3). Four sectors concentrate the majority of the implementations:

Healthcare. Personalized diagnostic and monitoring systems predominate, requiring clinical precision and regulatory compliance.

Technology and entertainment. Collaborative filtering, NLP, and neural networks are used to personalize content in real time.

Education. Resource recommendation systems, automated assessment, and interactive simulations are being used, although research on job or internship recommendations for students is lacking.

General services (travel, finance, commerce). They use AI to suggest routes, products, or investments, but face greater challenges in terms of trust and regulation.

The underrepresentation of the education sector in job search tasks constitutes a clear opportunity for research and transfer.

Limitations found (RQ4). The identified limitations converge on three axes: Data and accuracy. Scarcity or noise in training sets, cultural biases, and latency when updating profiles affect the quality of recommendations. Resource constraints. Large models increase CPU, battery, and bandwidth consumption; mid-range or low-end devices affect performance. Trust, privacy, and integration. Users often rely on recommendations they don't understand, while concerns persist about the use of biometric data and interoperability with external systems. These limitations pose immediate challenges: optimizing models for edge computing without sacrificing accuracy; efficiently fusing contextual and multimodal signals; designing explainable interfaces that enhance algorithmic literacy; and aligning solutions with ethical and regulatory frameworks, especially in healthcare and finance.

Strengths and limitations: The use of the PRISMA methodology and the coverage of four recognized databases increase the comprehensiveness and transparency of the review.

This systematic review shows that AI drives personalization and efficiencies in mobile search and recommendation applications. Despite this, its widespread adoption faces challenges related to data, technical resources, and user trust. Mapping the different algorithms, sectors, limitations, and opportunities identified a clear gap in the educational field. Very few studies explore the use of mobile AI to facilitate access to academic or training information. Therefore, in future work, it allows us to draw a broader research focused on the development of search and recommendation algorithms that not only prioritize efficiency and precision, but also guarantee transparency in their processes and the protection of sensitive user data. This involves exploring explainability techniques in AI that allow understanding how recommendations are generated and avoiding biases in the information offered. It is also necessary to investigate how these applications can be effectively integrated into learning environments, encouraging the personalization of educational content and adaptability to different learning styles.

Finally, the future of this line of research should focus on the creation of more useful, responsible and ethical mobile applications that respond to the needs of the educational sector, promote pedagogical innovation and contribute to strengthening the quality of the teaching-learning process.

VI. Conclusion

This systematic review study explored how AI is applied in various mobile applications for information recommendation and search, and addressed methods, techniques, and algorithms used in this field, as detailed in the research questions above.

Mobile applications integrated with: AI methods, techniques and algorithms used:

It was observed that these mobile applications employ machine learning algorithms (collaborative filtering, regression, and decision trees) and deep learning algorithms (especially neural networks and their derivatives). It was also observed that these hybrid approaches, which combine recommendation and classification techniques, are used. These algorithms are designed to adapt to the processing limitations of mobile devices, thus improving the accuracy and personalization of search and recommendation results.

Most frequent algorithms in the study:

According to research, the algorithms most commonly used in mobile applications are collaborative filtering, deep neural networks, and hybrid techniques. These approaches are the most widely applied due to their effectiveness in improving the accuracy of results and personalizing the user experience. This trend highlights the importance of these algorithms in improving user interaction with mobile search and recommendation applications.

Different sectors that cover search or recommendation algorithms:

A wide variety of algorithms was observed being applied across different sectors. The healthcare and entertainment sectors were found to be leading the use of search and recommendation algorithms. These sectors have adopted advanced technologies to improve the user experience. It was found that the implementation of recommendation algorithms is significantly lower in the education sector, suggesting an opportunity for improvement and expansion in this field.

Different limitations and challenges in applications for search and recommendation:

After observing mobile applications, it is clear that each one has its own recipe for searching and recommending content. Some rely on well-established techniques, such as collaborative filtering or classic KNN. Others, however, rely on the latest: deep neural networks, context-aware models, and even generative algorithms. The limitations detected include low accuracy, scarcity of interaction data, high dependence on context or user participation, and computational limitations on mobile devices. Recurring themes among the challenges are identified, such as effective personalization, ethical and secure integration, user trust, data quality, and adaptability to diverse and changing contexts. Looking ahead, the development of these applications should focus on making algorithms more accurate, models more transparent, and human interaction more fluid, all without compromising privacy or system performance.

REFERENCES

[1] C.-P. Julio Gustavo, P.-V. Amanda Beatriz, L.-C. Edison José, and G.-F. Segundo Alfredo, “The influence of artificial intelligence on the development of university education,” Revista Científica Arbitrada de Investigación en Comunicación, Marketing y Empresa REICOMUNICAR, vol. 6, 2023, doi: https://doi.org/10.46296/rc.v6i12edespoct.0171.

[2] M. Mercedes et al., “Use of artificial intelligence in mobile devices,” vol. 6, 2022, doi: 10.47230/unesum-ciencias.v6.n3.2022.460.

[3] A. Kaushik, “A Smart Learning Environment Enabled by AI- Powered Recommendations,” 2025. Accessed: Aug. 24, 2025. [Online]. Available: https://ijrpr.com/uploads/V6ISSUE4/IJRPR43365.pdf

[4] Y. Li et al., “An empirical study of AI techniques in mobile applications,” Journal of Systems and Software, vol. 219, p. 112233, Jan. 2025, doi: 10.1016/j.jss.2024.112233.

[5] M. Aucancela, A. G. Briones, and P. Chamoso, “Educational Recommender Systems: A Systematic Literature Review,” in The Barcelona Conference on Education 2023: Official Conference Proceedings, The International Academic Forum(IAFOR), Nov. 2023, pp. 933–951. doi: 10.22492/issn.2435-9467.2023.74.

[6] A. M. Vieriu and G. Petrea, “The Impact of Artificial Intelligence (AI) on Students’ Academic Development,” Educ Sci (Basel), vol. 15, no. 3, Mar. 2025, doi: https://doi.org/10.3390/educsci15030343.

[7] P. Bahalkar, D. Y. Patil, V. P. Society, P. Peddi, and S. Jain, “AI-Driven Career Guidance System: A Predictive Model for Student Subject Recommendations Based on Academic Performance and Aspirations,” 2024. Accessed: Aug. 24, 2025. [Online]. Available: https://healthinformaticsjournal.com/index.php/IJMI/article/view/781/738

[8] M. Y. Mustafa et al., “A systematic review of literature reviews on artificial intelligence in education (AIED): a roadmap to a future research agenda,” Dec. 01, 2024, Springer. doi: 10.1186/s40561-024-00350-5.

[9] F. Trujillo, M. Pozo, and G. Suntaxi, “Artificial Intelligence in Education: A Systematic Literature Review of Machine Learning Approaches in Student Career Prediction,” J Technol Sci Educ, vol. 15, no. 1, pp. 162–185, 2025, doi: https://doi.org/10.3926/jotse.3124.

[10] J. A. Hoyos Muñoz and L. J. Henao Tamayo, “Key Factors in Technology Adoption Processes,” 360: Revista de Ciencias de la Gestión, no. 7, Nov. 2022, doi: 10.18800/360gestion.202207.009.

[11] A. Kirby, “Exploratory Bibliometrics: Using VOSviewer as a Preliminary Research Tool,” Publications, vol. 11, no. 1, p. 10, Feb. 2023, doi: 10.3390/publications11010010.

[12] M. Lan and X. Zhou, “A qualitative systematic review on AI empowered self-regulated learning in higher education,” NPJ Sci Learn, vol. 10, no. 1, Dec. 2025, doi: 10.1038/s41539-025-00319-0.

[13] B. Klimova and M. Pikhart, “Exploring the effects of artificial intelligence on student and academic well-being in higher education: a mini-review,” 2025, Frontiers Media SA. doi: 10.3389/fpsyg.2025.1498132.

[14] E. Gabarron, D. Larbi, O. Rivera-Romero, and K. Denecke, “Human Factors in AI-Driven Digital Solutions for Increasing Physical Activity: Scoping Review,” 2024, JMIR Publications Inc. doi: 10.2196/55964.

[15] Y. R. Du, “Personalization, Echo Chambers, News Literacy, and Algorithmic Literacy: A Qualitative Study of AI-Powered News App Users,” J Broadcast Electron Media, vol. 67, no. 3, pp. 246–273, May 2023, doi: 10.1080/08838151.2023.2182787.

[16] L. Liu, “The Impact of Mobile Applications on Personalized Learning Paths in Dance Education,” International Journal of Interactive Mobile Technologies (iJIM), vol. 19, no. 05, pp. 128–143, Mar. 2025, doi: 10.3991/ijim.v19i05.54525.

[17] S. Mohan, A. Venkatakrishnan, and A. L. Hartzler, “Designing an AI Health Coach and Studying Its Utility in Promoting Regular Aerobic Exercise,” ACM Trans Interact Intell Syst, vol. 10, no. 2, Jun. 2020, doi: 10.1145/3366501.

[18] Y. C. Chen, W. W. Liao, M. C. Su, and Y. H. Lin, “Personalized and self-management: Systematic search and evaluation quality factors and user preference of drug reference apps in taiwan,” J Pers Med, vol. 11, no. 8, Aug. 2021, doi: 10.3390/jpm11080790.

[19] T. Wang, Y. Xu, X. Zhao, Z. Jiang, and R. Li, “Android malware detection via efficient application programming interface call sequences extraction and machine learning classifiers,” IET Software, vol. 17, no. 4, pp. 348–361, Aug. 2023, doi: 10.1049/sfw2.12083.

[20] M. Kaya and Y. Çetin-Kaya, “Seamless computation offloading for mobile applications using an online learning algorithm,” Computing, vol. 103, no. 5, pp. 771–799, May 2021, doi: 10.1007/s00607-020-00873-y.

[21] J. Y. Koh, G. W. Peters, I. Nevat, and D. Leong, “Privacy Considerations in Participatory Data Collection via Spatial Stackelberg Incentive Mechanisms,” Methodol Comput Appl Probab, vol. 23, no. 3, pp. 1097–1128, Sep. 2021, doi: 10.1007/s11009-020-09798-7.

[22] S. Kumar et al., “Machine learning driven web-based app platform for the discovery of monoamine oxidase B inhibitors,” Sci Rep, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-55628-y.

[23] D. M. Kotliar and R. Grosglik, “On the Contesting Conceptualisation of the Human Body: Between ‘Homo-Microbis’ and ‘Homo-Algorithmicus,’” Body Soc, vol. 29, no. 3, pp. 81–108, Sep. 2023, doi: 10.1177/1357034X231151855.

[24] V. Feenstra-Kikken et al., “Effectiveness of the HEAR-Aware App for Adults Not Ready for Hearing Aids, but Open to Self-Management Support: Results of a Randomized Controlled Trial,” Ear Hear, Nov. 2024, doi: 10.1097/aud.0000000000001533.

[25] Y. Wang et al., “AdaScale: Dynamic Context-aware DNN Scaling via Automated Adaptation Loop on Mobile Devices,” Dec. 2024, doi: https://doi.org/10.48550/arXiv.2412.00724.

[26] D. Saisanthiya and P. Supraja, “Heterogeneous Convolutional Neural Networks for Emotion Recognition Combined with Multimodal Factorised Bilinear Pooling and Mobile Application Recommendation,” International Journal of Interactive Mobile Technologies (iJIM), vol. 17, no. 16, pp. 129–142, Aug. 2023, doi: 10.3991/ijim.v17i16.42735.

[27] T. E. Sangers et al., “Position statement of the EADV Artificial Intelligence (AI) Task Force on AI-¬assisted smartphone apps and web-¬based services for skin disease,” Journal of the European Academy of Dermatology and Venereology, vol. 38, no. 1, pp. 22–30, Jan. 2024, doi: 10.1111/jdv.19521.

[28] A. Chaturvedi et al., "Content Recommendation Systems in Web-Based Mental Health Care: Real-world Application and Formative Evaluation," JMIR Form Res, vol. 7, 2023, doi: 10.2196/38831.

[29] G. Ang and E.-P. Lim, "Learning and Understanding User Interface Semantics from Heterogeneous Networks with Multimodal and Positional Attributes," ACM Trans Interact Intell Syst, vol. 13, no. 3, pp. 1–31, Sep. 2023, doi: 10.1145/3578522.

[30] S. Anwar, M. F. Zolkipli, V. Mezhuyev, and Z. Inayat, "A smart framework for mobile botnet detection using static analysis," KSII Transactions on Internet and Information Systems, vol. 14, no. 6, pp. 2591–2611, Jun. 2020, doi: 10.3837/tiis.2020.06.015.

[31] P. A. Valencia-Londoño, H. Cardona-Rodas, and J. A. Jiménez-Builes, "An Educational Inclusion Model for Adults with Diverse Neuromuscular Conditions through the use of an Artificial Intelligence Algorithm," International Journal of Emerging Technologies in Learning (iJET), vol. 19, no. 05, pp. 35–56, Jun. 2024, doi: 10.3991/ijet.v19i05.46619.

[32] M. Li and L. Niu, "Exercise Recommendation with Preferences and Expectations Based on Ability Computation," Computers, Materials and Continua, vol. 77, no. 1, pp. 263–284, 2023, doi: 10.32604/cmc.2023.041193.

[33] A. N. Sayed, F. Bensaali, Y. Himeur, G. Dimitrakopoulos, and I. Varlamis, "Enhancing building sustainability: A Digital Twin approach to energy efficiency and occupancy monitoring," Energy Build, vol. 328, p. 115151, Feb. 2025, doi: 10.1016/j.enbuild.2024.115151.

[34] A.-J. Wetzel et al., "Ethical, Legal, and Social Implications of Symptom Checker Apps in Primary Health Care (CHECK.APP): Protocol for an Interdisciplinary Mixed Methods Study," JMIR Res Protoc, vol. 11, no. 5, p. e34026, May 2022, doi: 10.2196/34026.

[35] Y. Liu et al., "Towards precision oncology discovery: four less known genes and their unknown interactions as highest-performed biomarkers for colorectal cancer," NPJ Precis Oncol, vol. 8, no. 1, p. 13, Jan. 2024, doi: 10.1038/s41698-024-00512-1.

[36] S. Ha, D. J. Marchetto, S. Dharur, and O. I. Asensio, "Topic classification of electric vehicle consumer experiences with transformer-based deep learning," Patterns, vol. 2, no. 2, p. 100195, Feb. 2021, doi: 10.1016/j.patter.2020.100195.

[37] X. Cheng, N. Li, G. Rysbayeva, Q. Yang, and J. Zhang, "Influence-Aware Successive Point-of-Interest Recommendation," World Wide Web, vol. 26, no. 2, pp. 615–629, Mar. 2023, doi: 10.1007/s11280-022-01055-w.

[38] J. Zhang, Z. Zhao, Z. Cai, Y. Feng, L. Zhu, and Y. Sun, "A Cross Attention Transformer-Mixed Feedback Video Recommendation Algorithm Based on DIEN," Computers, Materials and Continua, vol. 82, no. 1, pp. 977–996, 2025, doi: 10.32604/cmc.2024.058438.

[39] J. H. Yi, W. Kang, S.-E. Kim, D. Park, and J.-H. Hong, "Smart Culture Lens: An Application That Analyzes the Visual Elements of Ceramics," IEEE Access, vol. 9, pp. 42868–42883, 2021, doi: 10.1109/ACCESS.2021.3065407.

[40] L. Yu and Y. Duan, "Responsive and intelligent service recommendation method based on deep learning in cloud service," Front Genet, vol. 13, Nov. 2022, doi: 10.3389/fgene.2022.966483.

[41] A. Mari, A. Mandelli, and R. Algesheimer, "Empathic voice assistants: Enhancing consumer responses in voice commerce," J Bus Res, vol. 175, Mar. 2024, doi: 10.1016/j.jbusres.2024.114566.

[42] M. Haering, M. Bano, D. Zowghi, M. Kearney, and W. Maalej, "Automating the Evaluation of Education Apps With App Store Data," IEEE Transactions on Learning Technologies, vol. 14, no. 1, pp. 16–27, Feb. 2021, doi: 10.1109/TLT.2021.3055121.

[43] I. D. Wahyono et al., "Shared Nearest Neighbour in Text Mining for Classification Material in Online Learning Using Mobile Application," International Journal of Interactive Mobile Technologies, vol. 16, no. 4, pp. 159–168, 2022, doi: 10.3991/ijim.v16i04.28991.

[44] A. Nath, S. Mwesigwa, Y. Dai, X. Jiang, and Z. Zhao, "GENEVIC: GENetic data exploration and visualization via intelli- gent interactive console," Bioinformatics, Oct. 2024, doi: 10.1093/bioinformatics/btae500.

[45] N. Omar, Y. M., and F. A., "Machine Learning Model for Personalizing Online Arabic Journalism," International Journal of Advanced Computer Science and Applications, vol. 11, no. 4, 2020, doi: 10.14569/IJACSA.2020.0110484.

[46] H. Ejaz et al., "Comparison of a Novel Machine Learning–Based Clinical Query Platform With Traditional Guideline Searches for Hospital Emergencies: Prospective Pilot Study of User Experience and Time Efficiency," JMIR Hum Factors, vol. 12, 2025, doi: 10.2196/52358.

[47] J. G. Thanikkal, A. K. Dubey, and M. T. Thomas, "An Efficient Mobile Application for Identification of Immunity Boosting Medicinal Plants using Shape Descriptor Algorithm," Wirel Pers Commun, vol. 131, no. 2, pp. 1189–1205, Jul. 2023, doi: 10.1007/s11277-023-10476-3.

[48] B. CRISTINA, B. CRISTINA, M. BOGDAN, and D. IOANA, "Text Mining in Business. A Study of Romanian Client's Perception with Respect to Using Telecommunication and Energy Apps," Econ Comput Econ Cybern Stud Res, vol. 57, no. 1/2023, pp. 221–234, Mar. 2023, doi: 10.24818/18423264/57.1.23.14.

[49] C. Ning et al., "Development and validation of an explainable machine learning model for mortality prediction among patients with infected pancreatic necrosis," EClinicalMedicine, vol. 80, p. 103074, Feb. 2025, doi: 10.1016/j.eclinm.2025.103074.

[50] J. Xiao et al., "Smart Pharmaceutical Monitoring System With Personalized Medication Schedules and Self-Management Programs for Patients With Diabetes: Development and Evaluation Study," J Med Internet Res, vol. 27, p. e56737, Feb. 2025, doi: 10.2196/56737.

[51] P. Zhou, B. Duan, F. Liu, X. Jing, Y. Lei, and X. Li, "Application of Intelligent Robot in the Intelligent Recommendation of Mobile Application Content," Scalable Computing, vol. 26, no. 2, pp. 708–718, 2025, doi: 10.12694/SCPE.V26I2.3978.

[52] R. Alturki, A. I. Alharbi, S. S. Alqahtani, S. Khan, and V. Truong Hoang, "A Proposed Application for Controlling Overweight and Obesity within the Framework of the Internet of Things," Mobile Information Systems, vol. 2021, 2021, doi: 10.1155/2021/7109099.

[53] E. P. Palacpac et al., "Evaluating the Usability, Perceived Performance, and Perceived Effects of KBGAN iHealth© and KBGAN iFeed© Mobile Apps for Buffalo Management in Selected Municipalities in the Philippines," J Buffalo Sci, vol. 13, pp. 31–45, Feb. 2024, doi: 10.6000/1927-520X.2024.13.04.

[54] S. Teles, C. Paúl, P. Lima, R. Chilro, and A. Ferreira, "User feedback and usability testing of an online training and support program for dementia carers," Internet Interv, vol. 25, p. 100412, Sep. 2021, doi: 10.1016/j.invent.2021.100412.

[55] Q. Hao, K. Zhu, C. Wang, P. Wang, X. Mo, and Z. Liu, "CFDIL: A Context-aware Feature Deep Interaction Learning for App Recommendation," Oct. 27, 2021. doi: 10.21203/rs.3.rs-742592/v1.

[56] N. Rasing, S. Janus, M. Smalbrugge, R. Koopmans, and S. Zuidema, "Usability of an app-based clinical decision support system to monitor psychotropic drug prescribing appropriateness in dementia," Int J Med Inform, vol. 177, p. 105132, Sep. 2023, doi: 10.1016/j.ijmedinf.2023.105132.

[57] X. Zheng et al., "Enhancing Security-Problem-Based Deep Learning in Mobile Edge Computing," ACM Trans Internet Technol, vol. 22, no. 2, May 2022, doi: 10.1145/3458931.

[58] S. Rathee et al., "DILIC: An AI-Based Classifier to Search for Drug-Induced Liver Injury Literature," Front Genet, vol. 13, Jun. 2022, doi: 10.3389/fgene.2022.867946.

[59] M. Xiao, Q. Zhou, L. Lu, X. Tao, W. He, and Y. Zhou, "Applying Deep Learning-Based Personalized Item Recommendation for Mobile Service in Retailor Industry," Mobile Information Systems, vol. 2022, pp. 1–11, Jun. 2022, doi: 10.1155/2022/2364154.

[60] N. Mirbahar, K. Kumar, and A. Ali Laghari, "Enhancing Mobile App Recommendations With Crowdsourced Educational Data Using Machine Learning and Deep Learning," IEEE Access, vol. 13, pp. 38778–38792, 2025, doi: 10.1109/ACCESS.2025.3541116.

[61] C. Zhu et al., "AIM: Automatic Interaction Machine for Click-Through Rate Prediction," IEEE Trans Knowl Data Eng, vol. 35, no. 4, pp. 3389–3403, Apr. 2023, doi: 10.1109/TKDE.2021.3134985.

[62] Y. Ariyanto and T. Widiyaningtyas, "A Systematic Review of Movie Recommender Systems," Journal of Engineering and Technology for Industrial Applications, vol. 10, no. 47, pp. 34–41, Jul. 2024, doi: 10.5935/jetia.v10i47.1052.

[63] M. Kopka, M. L. Schmieding, T. Rieger, E. Roesler, F. Balzer, and M. A. Feufel, "Determinants of Laypersons' Trust in Medical Decision AIDS:

Randomized Controlled Trial," JMIR Hum Factors, vol. 9, no. 2, Apr. 2022, doi: 10.2196/35219.

[64] H. D. Sharma, Y. Misra, SumitKumar, B. M. Rao, and Bhupati, "Expanding an Education-based Collision Detection System Created on Virtual Reality and Augmented Reality," International Journal of Interactive Mobile Technologies, vol. 17, no. 17, pp. 108–120, 2023, doi: 10.3991/ijim.v17i17.42831.

[65] D. Jin, H. Yin, and Y. H. Gu, "Shuffle-PG: Lightweight feature extraction model for retrieving images of plant diseases and pests with deep metric learning," Alexandria Engineering Journal, vol. 113, pp. 138–149, Feb. 2025, doi: 10.1016/j.aej.2024.11.052.

[66] Y. Geng et al., "Identification and validation of platelet-related diagnostic markers and potential drug screening in ischemic stroke by integrating comprehensive bioinformatics analysis and machine learning," Front Immunol, vol. 14, Jan. 2024, doi: 10.3389/fimmu.2023.1320475.

[67] M. R. Rafi, F. Hu, S. Li, A. Song, X. Zhang, and Z. O'Neill, "Deep Weighted Fusion Learning (DWFL)-based multi-sensor fusion model for accurate building occupancy detection," Energy and AI, vol. 17, Sep. 2024, doi: 10.1016/j.egyai.2024.100379.

[68] U. A. Bhatti et al., "Deep Learning-Based Trees Disease Recognition and Classification Using Hyperspectral Data," Computers, Materials & Continua, vol. 77, no. 1, pp. 681–697, 2023, doi: 10.32604/cmc.2023.037958.

[69] S. H. Lee, H. Lee, and J. H. Kim, "Enhancing the Prediction of User Satisfaction with Metaverse Service Through Machine Learning," Computers, Materials and Continua, vol. 72, no. 3, pp. 4983–4997, 2022, doi: 10.32604/cmc.2022.027943.

[70] R. Sinha et al., "Leveraging Genomic Associations in Precision Digital Care for Weight Loss: Cohort Study," J Med Internet Res, vol. 23, no. 5, p. e25401, May 2021, doi: 10.2196/25401.

[71] G. Aly Abdelkader, S. Ngnamsie Njimbouom, T. J. Oh, and J. D. Kim, "ResBiGAAT: Residual Bi-GRU with attention for protein-ligand binding affinity prediction," Comput Biol Chem, vol. 107, Dec. 2023, doi: 10.1016/j.compbiolchem.2023.107969.

[72] Md. S. Uddin, W. Slany, and K. J. Hasan, "On-Device Neural Network for Object Train and Recognition using Mobile," International Journal of Interactive Mobile Technologies (iJIM), vol. 18, no. 12, pp. 99–111, Jun. 2024, doi: 10.3991/ijim.v18i12.47895.

[73] G. Ataguba, M. Alhasani, J. Daniel, E. Ogbuju, and R. Orji, "Exploring Deep Learning–Based Models for Sociocultural African Food Recognition System," Hum Behav Emerg Technol, vol. 2024, no. 1, Jan. 2024, doi: 10.1155/2024/4443316.

[74] G. Shaw Jr et al., "Separating Features From Functionality in Vaccination Apps: Computational Analysis," JMIR Form Res, vol. 6, no. 10, p. e36818, Oct. 2022, doi: 10.2196/36818.

[75] O. Oyebode, J. Fowles, D. Steeves, and R. Orji, "Machine Learning Techniques in Adaptive and Personalized Systems for Health and Wellness," Int J Hum Comput Interact, vol. 39, no. 9, pp. 1938–1962, 2023, doi: 10.1080/10447318.2022.2089085.

[76] T. O. Browne, M. Abedin, and M. J. M. Chowdhury, "A systematic review on research utilising artificial intelligence for open source intelligence (OSINT) applications," Int J Inf Secur, vol. 23, no. 4, pp. 2911–2938, Aug. 2024, doi: 10.1007/s10207-024-00868-2.

[77] J. A. García-Sánchez, L. Chavarría-Báez, and E. F. Ruiz-Ledesma, "Recomendation Systems in Education," in Memorias de la Conferencia Iberoamericana de Complejidad, Informatica y Cibernetica, CICIC, International Institute of Informatics and Systemics, IIIS, Mar. 2025, pp. 90–94. doi: 10.54808/CICIC2025.01.90.