Data-Driven Success Prediction of Android Mobile Applications on the Google Play Store: A Systematic Literature Review using PRISMA

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ABSTRACT

Every day number of mobile apps are added or removed from the Google Play Store platform depending upon app's popularity in market place. Several attributes of an app, attributes that are either internal to or external to it, can perform a substantial role in deciding whether the app will be successful or not. In this paper, the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) are used for presenting a systematic literature review for success prediction for Android Mobile Apps before they are launched on the Play Store market. With the help of this SLR, developers and researchers can check existing models that can be used for predicting the success of an app. Apart from presenting existing approaches; the author has tried to assist in building a new success prediction model by identifying a few features/factors that can make a mobile soft-ware/application a success or failure. This paper formulates five Research Questions (RQs) and precedes the entire PRISMA process to find the answers to them. The answers to the RQs will help to devise a new success prediction model for mobile apps in the future.

Keywords: ***Mobile Applications, Prediction, Android, Systematic Literature Review, Machine Learning, PRISMA.***

I. Introduction

As the market for mobile phones has drastically increased in the last two decades, the development and deployment of apps on their respective App Stores have also increased. From many other mobile OS, Android apps play a major role in the mobile software industry. Google Play Store on Android mobile devices provides access to millions of apps to work on. Daily, this platform is flooded with an enormous number of fresh apps. Developers of these apps are in anticipation that their hard work will not go in vain and try to build an app that will be successful in this competitive market. It would be really beneficial for the developers to know in advance if their app will be successful or not before uploading it on Google Play Store. It would prove to be highly advantageous for developers to have a method that can aid in predicting the success possibility of an application. The success of an app can be ascertained by features like ratings, number of installs, and reviews rather than the revenue it generates. Generally, many apps in the Play Store are not charged; the revenue generated by the subscriptions, in-app purchases, and in-app advertisements is practically unknown. Although many apps are added on play store daily, only a few apps achieve their monetary benefits and endure in their respective competitive marketplaces. It would be really helpful if the possibility of app success could be ascertained in advance. In light of this, the present study presents a Systematic Literature Review (SLR) of existing techniques using Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) [1] for predicting the success of mobile apps. PRISMA is a widely adopted method designed to improve the reporting of systematic reviews. It provides guidelines to ensure transparent and complete reporting, thereby facilitating assessment of study quality. An additional key contribution of the study is ascertaining the features of mobile apps that cause the app to be a success or a failure.

This paper is organized as follows. Section II presents the research methodology adopted for the systematic literature review based on the PRISMA framework. Section III reports the main results obtained from the selected studies and answers the formulated research questions. Section IV highlights the main contributions of this work. Section V discusses the findings, identifies the existing research gaps, and outlines future research directions. Section VI presents the threats to validity, and Section VII concludes the paper.

II. Methodology

This study adheres to the guidelines provided by PRISMA [1] for conducting a Systematic Literature Review (SLR). The overview of the systematic literature review is presented in fig.1.The different phases in PRISMA-SLR are further presented in the following sections.

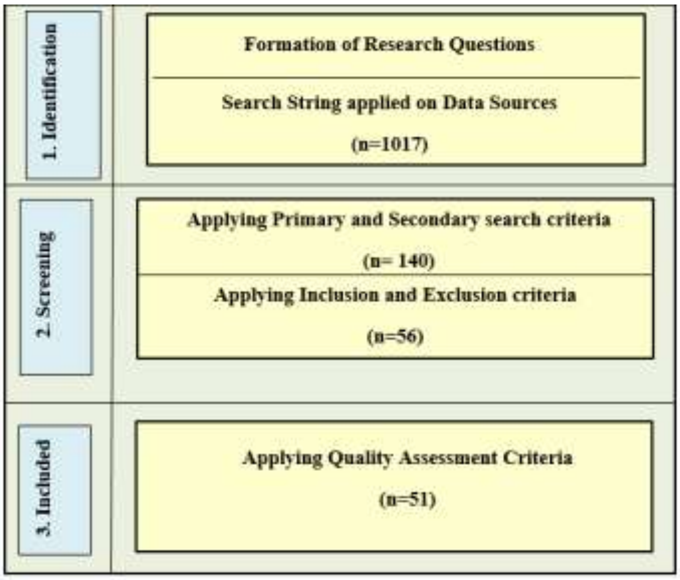

Figure 1. PRISMA Framework

A. Stage 1: Identification

Effective identification of various studies from existing databases and other resources is crucial for the successful implementation of PRISMA-SLR. Formation of research questions is the first step in identifying what needs to be searched. The guidelines proposed by [2] based on PICOC (Population, Intervention, Comparison, Outcomes, and Context), are followed to structure research questions. PICOC in this PRISMA-SLR is outlined as depicted in Table I. In the identification stage, relevant studies related to mobile application success prediction were searched across several electronic databases. These included SpringerLink, ACM Digital Library, Elsevier ScienceDirect, IEEE Xplore, Scopus, ResearchGate, InderScience, and other sources such as Google Scholar and ProQuest. To ensure that the search was comprehensive, keywords were derived from the research questions using the PICOC framework. Different synonyms of the keywords were also included, and logical operators such as AND and OR were used to combine them. In addition, wildcard characters were used to capture different variations of the search terms. The search string was applied to the titles, abstracts, and keywords of publications in the selected databases. Using this search strategy, a total of 1017 studies were initially retrieved from all databases.

TABLE I. PICOC WITH EXPLANATION

PICOC	Explanation
Population	Android Mobile Apps
Intervention	Success prediction techniques/methods/models.
Comparison	Mobile app success prediction techniques with each other
Outcomes	Mobile app success prediction methods and features of mobile apps that are believed to be significant for determining the success prediction
Context	Review current studies' success prediction techniques

1. Formation of Research Questions (RQs). The principal objective of this review study is to answer the following RQs:

RQ1. What factors contribute to the success or failure of an app?

RQ2. What techniques are used to predict app success in existing studies?

RQ3. Which machine learning models are applied for app success prediction?

RQ4. What evaluation metrics are used to assess these models?

RQ5. Which public datasets are utilized in existing studies?

2. Identifying keywords and Describing Search String

The second step of the identification stage is setting up a search strategy to ascertain the search string from primary data sources. The guidelines provided by [3] were followed to define the search string by analyzing the main keywords in RQs, synonyms of the keywords, and any other spellings of the words. The following are the identified keywords and their synonyms are shown in Table II:

TABLE II. LIST OF KEYWORDS AND SYNONYMS

Keywords	Synonymous Terms
Prediction	Estimating, estimate, prediction, predicting, predict, assessment, forecasting, forecast, calculation, calculate, calculating
Mobile Application	Mobile software, Mobile Apps, Mobile project
Success Probability	Chance, Prospect, Possibility, Probability, Liability, Likelihood, Reasonableness, Presumption, Outlook, Anticipation, Expectation, Trend
Method	Process, techniques, model, approaches
Features	characteristics, attribute, factors
Machine Learning	supervised Learning, unsupervised learning, classification, regression, classifier

Based on the identified keywords, the search string was obtained by joining synonymous terms using the ‘OR’, other keywords using logical ‘AND’ and wildcard character (′*′). Here wildcard character represents 0, 1, or any number of alphanumeric characters. The following is the query string that has been searched in different databases:

("Mobile Application" OR "Mobile App" OR "Mobile Software" OR "Android Application") AND ("Success" OR "App Success" OR "Popularity" OR "Adoption" OR "User Acceptance") AND ("Predict*" OR "Forecast*" OR "Estimat*" OR "Assessment") AND ("Machine Learning" OR "Supervised Learning" OR "Unsupervised Learning" OR "Classification" OR "Regression" OR "Predictive Model")

3. Databases for Literature searching

The online databases for searching the keywords are SpringerLink, ACM, Elsevier, Research Gate, InderScience, IEEE Xplore, Scopus and others (Google scholar, ProQuest).

4. Search Process

The subsequent step involves applying a search string to selected digital data sources in for locating relevant studies. A total of 1017 results were obtained using the chosen search string.

B. Stage 2: Screening

The findings obtained from the previous stage are further refined through two phases of search criteria i.e., primary and secondary search phases. In the Primary Search Phase, the results from data sources are monitored to include the search string in title and abstracts. The search string is again refined each time to check the outcome and analyzed for better results. Additionally, results are restricted to peer-reviewed conference papers and journal papers. The duplicate titles and abstracts are removed. In the secondary search phase, a technique called snowball tracking [4] is used for studying all the references of primary studies to exploit further studies and increase the chances of inclusion of important papers in the systematic literature review. Table III lists the refined results from data sources after the primary and secondary search phase.

In the screening stage, the collected studies were carefully filtered to remove irrelevant or duplicate papers. First, all records from different databases were combined into a single dataset, and duplicate entries were removed. After removing duplicates, the titles and abstracts of the remaining studies were reviewed to identify papers that were relevant to the topic of mobile app success prediction. Next, predefined inclusion and exclusion criteria were applied to further refine the selected studies.

TABLE III. OVERVIEW OF SCREENING SEARCH RESULTS

Data Sources	Relevant Search Results
SpringerLink	06
IEEE Xplore	23
ACM Digital Library	11
Elsevier Science Direct	33
ResearchGate	10
Scopus	38
InderScience	05
Others (Google Scholar, ProQuest)	14
Total	**140**

The findings obtained from the different investigations conducted using the predefined search term in electronic databases were examined based on the criteria for inclusion and exclusion.

Inclusion Criteria

1. Papers that describe mobile app success factors are included.
2. Papers that focus on techniques for mobile app success prediction are included.
3. All papers that have used machine learning techniques and belong to mobile app success prediction only.
4. Papers written in the English language only.
5. Papers published in peer-reviewed journals are included.

Exclusion Criteria

1. Paper that does not use a success prediction technique but belongs to the mobile app domain is excluded.
2. Papers that have used Machine learning techniques but do not aim at the successful prediction of mobile apps are excluded.
3. Papers that are not written in English are excluded.
4. Duplicate papers from different data sources are removed.

The inclusion and exclusion criteria resulted in 56 suitable studies out of 140.

C. Stage 3: Included

Finally, at the last stage, the 56 suitable studies that were passed in the inclusion criteria are further checked for Quality Assessment. In this stage, the full texts of the selected studies were examined in detail to determine their suitability for inclusion in the review. A quality assessment process was carried out using seven evaluation questions developed based on previous systematic review guidelines. To minimize possible bias during the selection process, the quality assessment was carried out independently by two reviewers. Each reviewer evaluated the selected studies using a predefined set of seven quality assessment questions. Each study was scored using a three-point scale: Yes (2 points) when the criterion was clearly addressed, Partially (1 point) when it was only partly addressed, and No (0 points) when the criterion was not addressed. After the independent evaluations were completed, the scores from both reviewers were compared. In cases where there were differences in the scores, the reviewers discussed the study and reached a mutual agreement. This process helped improve the consistency of the evaluation and reduced the chances of selection bias. The questions have been prepared using the guidelines defined in [3]. Questions are: -

Q1. Is the research scope and context plainly specified?

Q2. Was the paper clearly declaring the aims it wants to achieve?

Q3. Are Machine Learning methods for mobile apps success prediction fine defined?

Q4. Are the accuracy measures for prediction completely interpreted?

Q5. Has the research process been adequately documented?

Q6. Have all research questions been adequately answered?

Q7. Have the key findings been clearly linked to credibility, accuracy, and dependability?

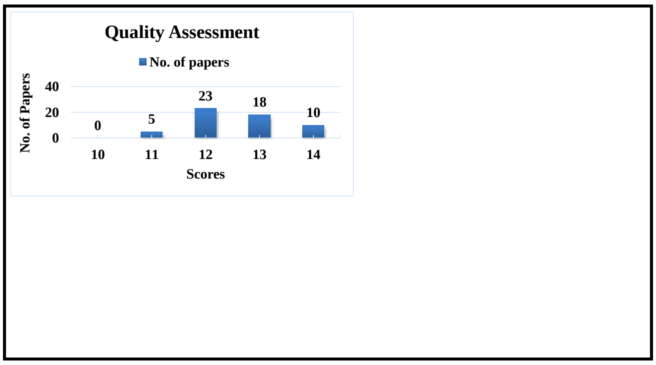

Figure 2. Quality assessment scores for Selected Studies

The papers with median score of 12 are expected to pass the quality assessment. Fig. 2 presents the results of quality assessment. So, finally, five studies were excluded from the initial set of 56 selected papers due to low methodological quality. Consequently, a total of 51 studies were included for the final analysis.
Finally, the total quality score for each study was calculated. Papers that did not meet the required quality threshold were excluded from the review. As a result of this assessment process, five studies were removed due to low methodological quality, and 51 studies were retained for the final analysis.

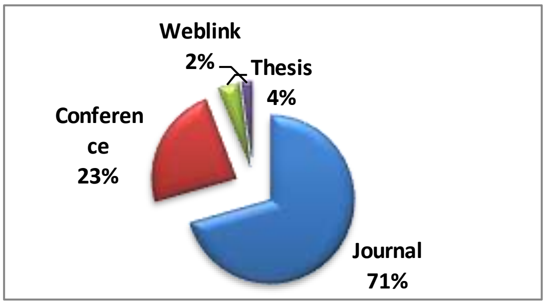

Figure 3. Publication Sources for Selected Studies

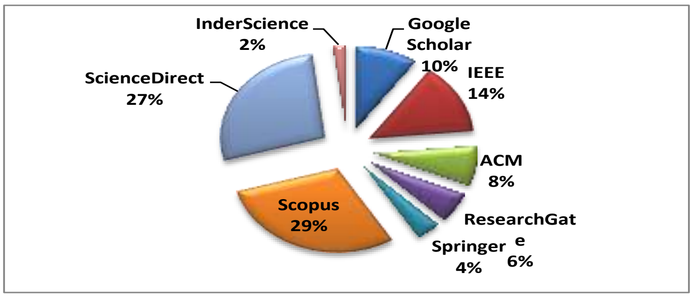

Figure. 4. Selected papers from various Data Sources

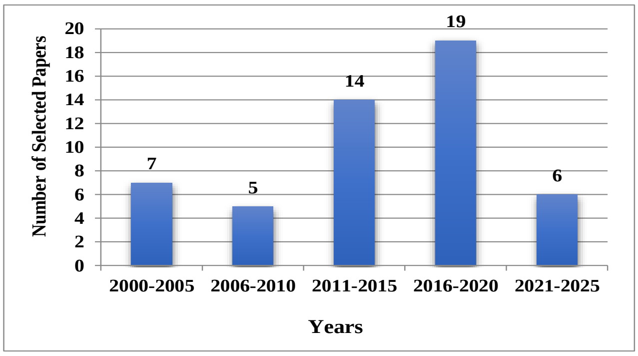

Figure. 5. Distribution of chosen Studies

III. RESULTS

The answers to the issues posed by PRISMA-SLR are defined in this section. First, an outline of selected studies is presented. Then results for all five RQs are reported.

A. *Overview of Studies*

Fig. 3 illustrates the distribution of publication sources for the final selected 51 studies. Fig. 4 shows the distribution of selected papers from various data Sources. The distribution timeline from 2000 to 2025 for selected papers is presented in fig. 5.

B. *Results Reporting on RQ1*

Fig. 1 illustrates the answers in response to the RQ1, What makes an app a bad/low-quality app? Various studies by [5], [6], [7], [8] presents reasons that could cause an app to fail:

1. Developer Aspect: Insufficient proficiency of app developers in app development, limited resources, lack of understanding of user needs and expectations, unfamiliarity with the target audience, and inadequate communication among app developers.

2. User Aspect: Users play a crucial role in determining the fate of an application. The success or failure of an app can be greatly influenced by its actions. Issues such as application/system freezes, crashes, slow responsiveness, high battery consumption, excessive ads and promotions all have a significant impact on the overall performance of the app.

3. Technical details Aspect: Mobile app developers and vendors often struggle to effectively communicate the technical specifications of their apps to the end users. This lack of clear information can lead to significant harm to the success of the app. It is important to note that high-end games require high-end mobile devices for optimal performance. However, without proper technical details, users may mistakenly download and attempt to play these games on incompatible mobile devices.
4. Marketing Aspect: Insufficient marketing efforts and ineffective marketing strategies can lead to a decline in return on investments, resulting in disappointment and frustration. In order to reach a larger audience, developers need to collaborate with ad agency providers to promote their apps. However, another challenge they face is the lack of trust in these ad network providers. Advertising an app through agencies can be costly, making trust a crucial factor when making such investments.
5. App Development Life Cycle Aspect: The primary reason is that the app developers fail to adhere to the various phases of the development life cycle. Many app developers commence the development process without gathering requirements or having a proper design in place. Insufficient training and experience with app development software development kits (SDKs). Inadequate testing practices are implemented. App developers often prioritize the functional aspects of the app and overlook crucial security and performance testing, which are essential components of any app.

A description of Mobile App Success Factors is provided through a review of previous research reports. Fig. 6 presents the number of studies supporting the identified success factors in this research. Some of the success factors were identified for investigation under this study:

- Subjective Norms: The intent to use mobile apps can be influenced by the opinions of one's friends, and the adherence to social norms can also impact this decision. [9], [10], [11], [12], [13], [14].
- Perceived Compatibility: Compatibility measures the level of conformity between newly released products. [9], [11], [15], [16], [17].
- Perceived Playfulness: The notion of perceived playfulness pertains to the interaction between users and information systems, stemming from their focus, inquisitiveness, and delight. [7], [9], [18], [19], [20].
- Satisfaction: Satisfaction is obtained through practical application, which ultimately influences the users' intention to continue. [9], [16], [17], [21], [22].
- Perceived Usefulness: This refers to the extent to which an individual perceives that the utilization of a specific product or system will improve their job performance [7], [9], [19], [21], [23], [24], [25], [26].
- Perceived Ease of use: This is the extent to which an individual perceives that utilizing a specific product or system will be uncomplicated. [7], [9], [18], [24], [27], [28].
- Content Quality: Quality of data supplied by Apps [8], [29], [30], [31].
- Reliability: Refers to App crashes or other causes for an app not working as anticipated [8], [17], [26], [32].
- Security: It deals with the probable harm of personal data, protection, possible disclosure to deceit, and malicious action on the web [8], [25], [32], [33], [34].
- Design Quality: It refers to the user interface, i.e., what users, when they are engaging with your app, see, touch, and experience on their phone [7], [8], [17].
- Usefulness: Professed usefulness of the app, its functionality, and services [8], [25], [26], [35], [36], [37].
- Performance: It indicates how the app is functioning and how responsive the app is to the end-user [8], [25], [36], [37], [38].
- Social Media integration: Allows users to easily share content with their friends on social networks [7], [17], [39].
- Regularly updated: It means there is a certain system of mobile app updates which arise from out of necessity, such as bug fixing, new feature release, and so on [17].

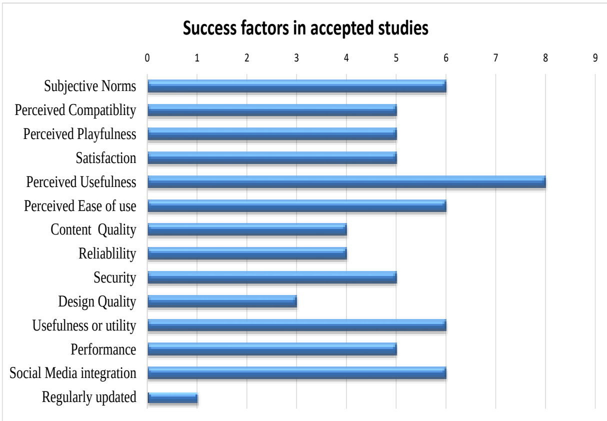

Figure 6. Success factors in accepted Studies

A comparison of the selected studies shows that some success indicators appear more frequently than others. Among the reviewed papers, user ratings were one of the most commonly used indicators of app success, appearing in roughly 70% of the studies. Similarly, the number of installs or downloads was used in about 65% of the studies. In addition, user reviews and review sentiment were considered in approximately 45% of the studies, as they provide insights into user satisfaction and experience. Other application-related attributes, such as app size, category, and content rating, were included in nearly 40% of the studies. These findings suggest that most researchers rely heavily on user interaction data when analyzing or predicting the success of mobile applications.

C. Results Reporting on RQ2, RQ3 and RQ4

The focus of answering RQ2 and RQ3 is on various techniques (general and machine learning) used to predict the success of apps used in existing studies. A summary of the results from each reviewed study is given below.

In the paper by [40], the author used the mobile app data from the Google Play Store. From the data available, the author extracted the features of apps and then used a modeling approach to conclude that predictions can be made using features like the number of installs and user ratings. The author concluded that PCA with Linear regression presented the best pattern for prediction.

In the paper by [25], the authors focused on API quality along with other features of the app for the success of the mobile app. They determine this quality on the basis of bugs removed in APIs and the modifications that were made in API methods.

Another approach by authors in [41] considered versions released for the apps to recommend the app based on its success. They addressed that the rating for an app, which is a major factor for the success of an app, highly changes when a new version of the same application is released.

Mueez et al. [42] considered a dataset obtained from the Google Play Store to predict the success of an app. They based their prediction first on features like ratings, the length of the app name, and the number of installs for an app. Then they took the reviews under consideration to make a prediction.

Suleman et al. [43] also used the dataset from Google Play Store and then worked on seven features having 10839 apps in the dataset. They used machine learning techniques to predict the success of apps. The emphasis of their study concluded what type of model drove finest to predict app ratings.

In the paper by [44], the authors distinguished the apps on the basis of their popularity of the apps. They collected data sets from two marketplaces, GitHub and the Google Play Store. Then they introduced social and technical factors to understand how they affect the popularity of an app and, hence, the success.

The paper by [45], the focus of authors for predicting the success of mobile apps on Google Play was based on user rating and the number of installs of apps. The authors analyzed a repository of the Google Play Store and applied various machine learning algorithms. The authors later concluded that the SVM model generated the most accurate predictions.

In the study [46], the authors operated on a dataset of Android apps and implemented data evaluation by means of machine learning methods. They then aimed to understand features/factors in apps that most impact their success.

In the research by [47], the authors presented a repository consisting of 100 successful and 100 unsuccessful apps from the Google Play Store. This repository consisted of 34 features, which are used as an input to a neural network to predict the success of an app on the Play Store.

The paper presented by [48], the authors collected data from the Google Play store having 10,841 mobile apps with features such as app size, free or paid. Then the authors presented a model by using mobile app features and user review into the model to predict the possible rate.

The authors in [49] suggested a framework that predicts the success of a mobile app not only based on no. of installs, ratings, and reviews but also the sentiments of customers. They have applied various machine learning algorithms on a dataset collected from Google Play Store Data. Lastly, they incorporated the Voting Ensemble technique to improve the accuracy of algorithms.

In the study by [50], the authors intended to predict the success of an app based on the ratings of app on Google Play Store. The authors used machine learning Algorithms for predicting success. The dataset for analysis and prediction is collected from Kaggle platform.

In a study by [51], the authors only presented explanatory analysis for an dataset from Google Play store having 2,67,000 apps. Their analysis can help app developers on how to make better judgments on app reachability to their intended customers.

The authors in a study [52], presented the success prediction as a classification problem. They started by classifying the mobile apps grounded on numerous degrees of success. Based on this theory, the authors used various classification models with the goal to comprehend app's success. The models are then assessed centered on their performance rates.

The paper by [53], a dataset from the Apple App store was utilized, having exclusive apps comprised of gaming and productivity categories. The author examined ratings of an app and reviews affect the no. of downloads of the mobile app. The authors recounted that the ratings and reviews directly affect no. of downloads.

In the paper by [54], a predictive network analytics, deep learning, and artificial intelligence are used, that focused on the developer-oriented aspect of an app. They worked on two aspects of the problem. One was focused on recommending developers to distinguish the suitable customers. The second work focused on providing perceptions in terms of design principles and factors for the app developers to exhaust the possibilities for app success.

The study by [55], the authors used a dataset from Google Play Store to forecast the success of the app. Again, the authors extracted features of apps available in the dataset and employed machine learning techniques to analyze data from varied metrics and ascertain relationships.

Table IV depicts a summarized comparison of various existing success prediction approaches (answer to RQ2 and RQ3). It can be inferred that machine learning techniques are mostly followed as an approach for prediction in the majority of the research papers. The factors that affect each method are also listed for prediction. Each method is evaluated on some parameter. Table V lists the prominent evaluation metrics followed in existing studies and thus answers RQ4.

TABLE IV. COMPARISON OF EXISTING SUCCESS PREDICTION APPROACHES

Study	Factors	ML	Algorithm Used	Statistical Tests	Success Indicator
[25]	App size, category, reviews, rating	No	Multiple Linear Regression	R,R^2	
[41]	Ratings, review, versions	No	Version Aware rating prediction	RMSE, MAE	User Ratings
[42]	App name, category, content rating, installs, rating, last updated, type, rating text, review text, size	Yes	Random Forest, XBoost Classifier, K-NN,SVM	MSE	RMSE, MAE / Accuracy, F1
[43]	Review, size, install, type, content rating, version, user rating	Yes	Linear Regression, Decision Tree, Logistic Regression, Naïve Bayesian, K-Mean Clustering, KNN,ANN	MSE, RMSE,MAE, R,R^2	User Ratings and Update Frequency
[44]	User app downloads, avg rating, activities forks on GitHub	No	Multiple Linear Regression	R,R^2	Installs / Downloads
[45]	Installation no, user rating, category, size, price	Yes	KNN, SVM, Random Forest	MSE	User Ratings
[56]	Review, rating, category, size, install, type, content, genre, last updated	Yes	Back propagation (ANN), Deep learning (HIVE)	MSE, MAPE	User Ratings
[46]	Content rating, installs	Yes	SVM, random forest, Linear regression	MSE,R,R^2	Installs / Downloads
[47]	Name, No. of packages, No. of classes, No. of Methods, LOC, size, rating	Yes	MLP, SVM, Random Forest, Decision trees, ANN,LVQ, NPR,PCA	MSE	User Ratings
[48]	Category, reviews, size, installs, type, price, content rating, android version	Yes	Random forest, MLP, gradient boosting, Logistic regression	MSE	User Ratings
[49]	Installs, rating, review, type, size, price, genre, user group, last updated, android version	Yes	KVM, SVM, Decision trees, Random Forest	MSE	User Ratings
[50]	App category, rating, review, installs, size, type, price, content rating, genre	Yes	KNN, SVM, Linear regression, Random Forest, K- means clustering	MSE, R,R^2	User Ratings
[51]	App category, rating, review, installs, size, price, paid/free	No	N.A., only analysis	N.A.	N.A.
[52]	rating, installs, size, price, type	Yes	KNN, SVM, logistic regression, Random Forest, Decision trees, SGD	Precision, recall, F-score, Accuracy	Installs count / Downloads
[53]	App rating, size, App ver (major), App ver (minor), revenue, app name, app value, Downloads, reviews, update Regency	Yes	Regression, Random Forest	MSE, R,R^2	Installs count / Downloads
[55]	Rating, reviews, size, installs, type, price, content rating, genre, last update	Yes	Random Forest, Decision trees, SVM, SGB, GRU	Precision, recall, F-score, Accuracy	Review Sentiment

TABLE V. EVALUATION METRICS USED BY DIFFERENT STUDIES

Evaluation metrics	Various Studies
R,R^2	[25],[43],[44],[46], [50],[53]
RMSE,MAE	[41],[43]
MSE	[42],[43],[45],[46],[47],[48],[49],[50],[53]
Cost function	[56]
Precision, recall, F-score, Accuracy	[52],[55]

The analysis of prediction approaches shows a clear shift towards machine learning methods in recent research. Approximately two-thirds of the reviewed studies (around 68%) applied machine learning algorithms for success prediction. In comparison, about 22% of the studies relied on traditional statistical models such as regression analysis. The remaining 10% of the studies mainly focused on exploratory data analysis or conceptual approaches rather than predictive modeling. This trend highlights the increasing importance of machine learning techniques in analyzing large-scale app store datasets. Among the studies that used machine learning techniques, several models were applied repeatedly across the literature. The most frequently used models include Random Forest, Support Vector Machines, and k-Nearest Neighbors, followed by Artificial Neural Networks and Decision Tree-based models. These models are often preferred because they can capture complex relationships between different app features and success indicators. In particular, ensemble methods such as Random Forest are commonly used due to their ability to improve prediction performance and reduce over fitting.

The reviewed studies also differ in the evaluation metrics used to measure prediction performance. Many studies that use regression-based models report metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). On the other hand, studies that treat success prediction as a classification problem frequently report Accuracy, Precision, Recall, and F1-score. This variation reflects the fact that researchers define and measure mobile app success in different ways depending on the research objective.

By combining both qualitative observations and quantitative summaries, several important insights emerge from the literature. First, user engagement indicators, particularly ratings, install, and reviews, are consistently used as key predictors of mobile app success. Second, machine learning techniques are increasingly preferred over traditional statistical methods for analyzing app store data.

As noted in the reviewed studies, the concept of mobile application success is not measured in the same way across the literature. Different researchers use different indicators, such as ratings, number of installs, download, or user reviews. While each of these metrics provides useful information about app performance, treating them as identical measures of success can make it difficult to compare results across studies. To address this issue, the success indicators identified in the selected studies were grouped into broader categories. This classification helps provide a clearer and more consistent understanding of how success is measured for applications available on the Google Play Store.

The categorized success indicators used in the reviewed studies are summarized in Table VI.

TABLE VI. CATEGORIZATION OF MOBILE APP SUCCESS INDICATORS

Category	Success Indicators	Description	Example Studies
Popularity-based indicators	Number of installs, downloads, market reach	Indicates how widely an application is adopted and how visible it is in the marketplace	[40], [44], [52] [53]
User satisfaction indicators	User ratings, reviews, review sentiment	Reflects the level of satisfaction and overall experience reported by users	[42],[45], [49] [55]
Engagement-based indicators	Update frequency, continued usage, user interaction	Represents how actively users interact with and continue to use the application over time	[41], [43], [48]

This classification shows that the success of a mobile application cannot be explained by a single metric. Instead, it is influenced by several dimensions, including popularity, user satisfaction, and user engagement. Organizing success indicators into these categories helps improve the comparability of findings across different studies.

D. *Results Reporting on RQ5*

The last research question, RQ5, dealt with public datasets has been used in the existing studies is summarized in Table VII.

TABLE VII. PUBLIC DATASETS FOR MOBILE APPS

Study	Dataset size	Prediction Category	Link to Dataset
[26]	7097	Regression Modeling	https://www.cs.wm.edu/semeru/data/fse-android-api/
[57]	1,624	Machine learning classification/similarity learning model	https://sites.google.com/site/appsimilarity
[42]	10841	Regression, Classification (Decision Tree), Random Forest	https://www.kaggle.com/code/rajeshjnv/ml-to-visualization-prediction-of-app-ratings
[58]	1179	Multiple linear regression	http://androsec.rit.edu/home
[47]	200	Regression, clustering, time series, Anomaly Detection, Association Rules	https://github.com/mehrdadr68/Android-Successful-Or-Failed-Apps-Repository
[59]	43041	Classification	https://github.com/mayurgpt07/Opinosis
[43]	10839	Classification (sentimental analysis)	https://www.datacamp.com/workspace/datasets/dataset-python-google-play-store-apps
[60]	50	Regression, Text Mining	https://www.kaggle.com/datasets/souravghosh01/google-play-store-app-details
[44]	814	Multiple linear regression	https://sites.google.com/view/app-saner-2019

IV. CONTRIBUTION OF WORK

This study makes several contributions to the field of mobile application success prediction, particularly for applications available on the Google Play Store. The key contributions of this research are outlined below:

1. Systematic Review of Existing Studies:

The study provides a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to examine previous research on predicting the success of Android mobile applications.

2. Identification of Important Success Factors:

Through the review process, several important factors influencing the success or failure of mobile apps were identified, including technical features, user experience, and market-related aspects.

3. Overview of Prediction Techniques:

The paper reviews different approaches used in earlier studies for app success prediction, including both traditional statistical methods and machine learning techniques.

4. Analysis of Machine Learning Models and Evaluation Metrics:

The study highlights commonly used machine learning algorithms and evaluation metrics that researchers apply when predicting mobile app success.

5. Summary of Publicly Available Datasets:

Another contribution of this work is the collection and presentation of datasets that have been used in previous research for mobile app success prediction.

6. Identification of Research Gaps:

Finally, the study points out several limitations in current research and suggests possible directions for future studies to develop more effective models for predicting mobile app success. Overall, this review helps researchers and developers better understand existing work in this area and provide a foundation for future research on mobile app success prediction.

V. DISCUSSION, RESEARCH GAP AND FUTURE WORK

The findings from the PRISMA-SLR for different RQs are presented in previous sections. The findings of this systematic literature review provide a clearer understanding of the current research trends in mobile application success prediction. By analyzing the selected studies using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, several common patterns and observations can be identified regarding success factors, prediction techniques, and datasets used in existing research. One of the key observations across the reviewed studies is the strong influence of user-related indicators on the success of mobile applications. Features such as user ratings, number of installs, and user reviews are frequently used as indicators of app success, particularly for applications available on the Google Play Store. These indicators reflect user engagement and satisfaction, which makes them important factors when predicting whether an application will perform well in the marketplace. Another important trend identified in the literature is the increasing use of machine learning techniques for predicting mobile app success. Earlier studies mainly relied on statistical methods such as regression analysis to examine the relationship between app features and success indicators. However, more recent studies have started using machine learning models such as decision trees, support vector machines, random forests, and neural networks. These models are capable of capturing more complex relationships within large datasets and therefore can provide better predictive performance. The comparison of different prediction techniques also suggests that ensemble and advanced machine learning models often perform better than traditional statistical methods. Models like random forest and neural networks are particularly useful when large datasets with multiple features are available. However, the effectiveness of these models largely depends on the quality of the dataset and the selection of relevant features. Despite these advancements, several limitations can still be observed in the current body of research. One major challenge is the lack of a consistent definition of app success. Different studies measure success using different indicators, such as ratings, download counts, number of installs, or review sentiment. Because of this variation, it becomes difficult to directly compare the performance of prediction models across different studies. Another limitation identified in the literature is that many predictive models do not fully incorporate important success factors. Although factors such as usability, reliability, design quality, and user satisfaction are widely recognized as important for app success, they are not always included in prediction models. Instead, many studies rely mainly on easily measurable indicators like ratings and installs. In addition, the availability of standardized and publicly accessible datasets is still limited. While several studies use datasets collected from the Google Play Store, differences in dataset size, feature selection, and data preprocessing methods make it challenging to reproduce and compare results across studies. Overall, the findings of this review highlight the growing importance of data-driven approaches for predicting mobile app success. At the same time, they emphasize the need for more consistent evaluation methods, better datasets, and more comprehensive prediction models that combine technical, user-related, and market-related factors. These improvements could help researchers and developers build more accurate and reliable models for predicting the success of mobile applications in the future.

For the prediction of the success of a mobile app, the identified features/factors may have an impact ranging from being inconsequential to noteworthy. The author finds it to be a research gap and considers it a potential research direction for future investigation. In the future, a survey can be utilized that investigates the influence of individual factors on the prediction of success from users and developers. Based on the survey analysis and data from existing repositories of mobile apps, a new prediction model will be proposed. Also, the lack of standardized success definitions and evaluation protocols hampers cross-study comparability. Future research should aim to establish benchmark datasets, unified success operationalization, and consistent evaluation metrics, enabling more meaningful comparison and reproducibility across studies.

VI. THREATS TO VALIDITY

This section presents threats to the validity of SLR. Three major validity threats, i.e., construct validity, internal validity, and external validity threat is discussed. This PRISMA-SLR paper may suffer from construct validity as it may not assert coverage of all significant studies. Even though the author has tried to espouse a decent search strategy and used applicable search strings to alleviate this threat. Most of the reported studies are from the last two and a half decades, from the year 2000 till 2025, and fear that some studies might have been missed. Internal Validity threat deals with the data extraction during SLR. After collecting the results from various sources, the author created a database in Excel sheet format consisting of details regarding year, author names, title, journal or conference paper, main highlights of the study, etc. But still, there may be room for internal validity for the correctness of the extraction by the author. Regarding the external validity threat, the findings from five RQs are used as a basis to draw a conclusion for SLR. There can be an incapability to derive less generalized conclusions. The features/factors reported in RQ1 may not be an exhaustive list. Prior studies define the success of an app based on different perspectives shown in Table VI; this heterogeneity limits the direct comparability of predictive models and results across studies. The author has attempted to recapitulate the results of SLR from distinct facets of existing prediction methods, but it may overlook the in-depth analysis of the conclusions.

VII. CONCLUSIONS

This paper presents the current state-of-the-art for success prediction of mobile app software before its launch on the Play Store through PRISMA-SLR. In SLR, 51 papers are shortlisted from the initial search result of 586 through different digital data sources to address five Research Questions (RQs). The key results in the form of answers to RQs are presented. RQ1 of the SLR provided critical success factors of mobile apps that play a very important role for its success on the Play Store. A comparison of various existing approaches to success prediction is presented as an answer to RQ2, RQ3, and RQ4. Most of the existing approaches are based on Machine Learning techniques, which form the models on some available datasets or repositories of mobile apps. The information on available datasets of mobile apps is also presented as an answer to RQ5. Later, it was concluded that critical success factors are not adopted in existing approaches to predict success. And there is no formal model that solely reflects these factors. Some discussions and research gaps are stated, and concrete future research possibilities in the success prediction of mobile apps are presented. Lastly, three threats to validity are reported that might infer the research study.

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