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Users' Sentiment Analysis toward National Digital Library of India: a Quantitative Approach for Understanding User perception

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Abstract

Sentiment analysis is also known as opinion mining. Sentiment analysis is contextual mining of text which identifies and extracts subjective information in textual data. It is extremely used by business, educational organizations, and social media monitoring to gain the general outlook of the wide public regarding their product and policy. The current study looks for gaining insights into user reviews on the National Digital Library of India (NDLI) mobile app (android and iOS). For this purpose, sentiment analysis will be used. It yields an average of 3.64/5 ratings based on 11,861 reviews. The dataset includes a total of 4560 user reviews in which iOS and the android app have received 33 and 4527 reviews respectively as on 7th Sept 2021. AppBot and AppFollow analytics software is used to extract and collect user review information as raw data. The study shows the reviews of the NDLI mobile app as 2130 positive and 1808 negative sentiments for android & 6 positive and 22 negative sentiments for iOS. The overall sentiment score is found to be 66%. The results of the sentiment analysis show that Android users are more satisfied as compared to iOS users. The most frequent complaints made by the users are functional errors, feature requests and app crashes. Some of the major issues that users have complained about are books that need to be downloaded before reading and some pdfs are blank once opened. The value of this research is getting an insight into the behaviour of users towards using apps on different platforms (Android vs iOS) and provides valuable results for the app developers in monitoring usage and enhancing features for the satisfaction of users. The findings reveal that stakeholders/developers need to pay more attention to make the app more user-friendly.

Keywords: Sentiment Analysis, opinion mining, natural language processing (NLP), national digital library of India (NDLI), deep learning, AppBot, AppFollow, Android Google play store, Apple iOS, mobile phone, smart phone, user rating.

1. Introduction

Mobile apps have a profound impact on all facets of our lives. With ever coming new apps, its market keeps on expanding. The iOS app store entered the market with 500 apps in 2008 which has been risen up to 1.85 million different apps today. Android offers more than 2.56 million apps to its users to choose from. It was estimated the smartphone users will rise to 3.5 billion over the course of 2020 and more connected mobile devices 7.94 billion than the people in the world (retrieved from https://www.businessofapps.com/data/app-statistics/ on 18/09/2021). The average daily usage time of social media users worldwide has been risen from 142 minutes to 145 min in the year 2020 as compared to 2019 (https://www.statista.com/statistics/433871/daily-social-media-usage-worldwide/).

Information technology and the use of mobiles apps have become a part-and-parcel of everyday life of all the people across the world. The advancement and use of educational mobile apps have dramatically risen over the past decade. The content and features of these apps widely vary with respect to their usage, however, the preference of users regarding these educational apps rarely has been examined in prior research.

Users spend 70% of their screen time on mobile devices and apps. The smartphone penetration is expected to double from 468 million to 859 million in 2022 (https://www.assocham.org/newsdetail.php?id=7099). It is projected that India will have 650 million Internet users by 2023 (https://www.statista.com/topics/2157/internet-usage-in-india/). Today, mobile internet traffic accounts for more than 55 percent of total web traffic, while in mobile-first markets such as Asia and Africa, mobile connections account for an even large share of web page views (Statista Research Department, Jul 12, 2021).

Mobile devices, especially smartphones have become omnipresent as they provide critical support in making informed decisions in every sphere of life including education, health, governance, and business. In the context of the Android OS platform available at Google Play, the maximum number of apps available are under the category of Education (272100) (Fig.1) with an average user rating of 4.18 the maximum number of apps available are under the category of Education (272100) (Fig.1) with an average user rating of 4.18.

Table 1: Most popular Google Play Categories

Type of Apps	**Education**	**Music and Audio**	**Business**	**Tools**	**Entertainment**	**Lifestyle**	**Books and Reference**	**Food and Drink**	**Shopping**	**Productivity**
Free app	257,321	187,987	186,217	151,141	151,415	132,810	119,133	123,789	115,805	102,900
Paid app	14,209	3,374	1,910	8,611	4,107	2,851	8,777	636	301	3,981
Total apps	271,530	191,361	188,127	159,752	155,522	135,661	127,910	124,425	116,106	106,881

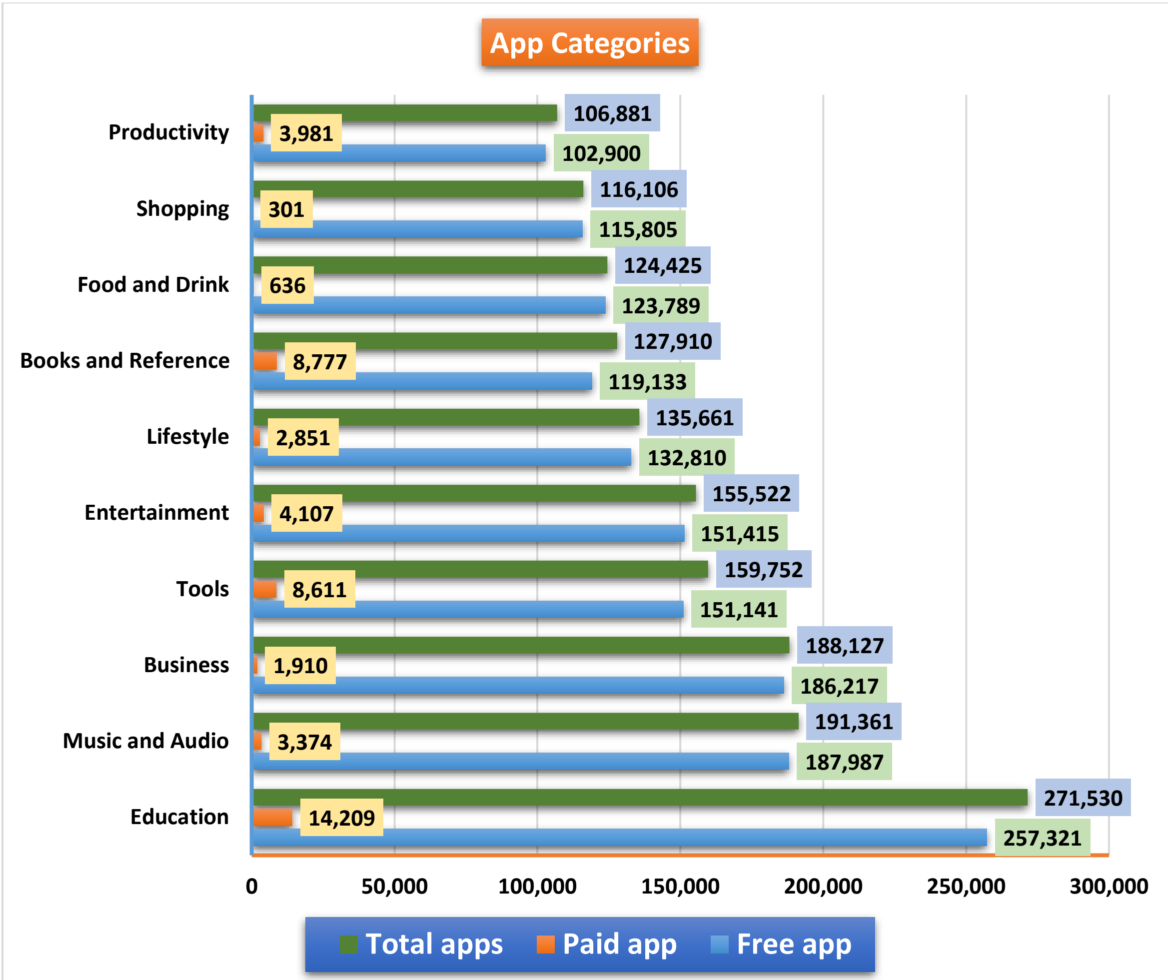

Fig. 1 Most popular Categories of Apps in Google Play Store

Table 1 and Fig. 1 depicts that educational apps (271,530) are in most popular category of Google play store. Education is followed by music and audio apps (191,361) and business apps (188,127) respectively. This is an encouraging finding that educational apps have more users in comparison to other apps. This has to be noticed that books and reference were ranked 7th with 127,910 apps. The NDLI app belongs to the education sector that has 257,321 free apps and 14,209 paid apps.

1.1 SAKSHAT: A One Stop Education Portal

Sakshat (be a lamp unto yourself), an educational helpline was designed by the Ministry of Education (MoE, formerly known as MHRD), inaugurated on 30th October 2006 by former president of India Lt. Dr. A.P.J. Abdul Kalam. Sakshat portal addresses the educational requirements of learners from kindergarten to Ph.D. It facilitates access to vast knowledge resources, educational news, examination alerts, sample papers, and other useful links available on the web. It has an in-built repository of educational resources and an online testing facility. The portal has five functional modules i.e., educational resources, scholarships, testing, super-achievers, interaction. Following is the list of Digital Initiatives enumerated on the SAKSHAT portal in Higher Education:

Table 2: Digital Initiatives of SAKSHAT in Higher Education

Serial No.	Name of Initiative	Description	m-app
1.	SWAYAM: (Study Webs of Active–Learning for Young Aspiring Minds)	National (Massive Open Online Courses) MOOC Portal of India, an initiation of Ministry of Human Resource Development (MHRD).	YES
2.	SWAYAM PRABHA	34 DTH Free to Air (FTA) channels It is a group of 34 DTH channels devoted to telecasting high-quality educational programs on 24X7 basis using the GSAT-15 satellite	YES
3.	NDLI (National Digital Library of India)	One Library All of India that provides educational materials from Primary to Postgraduate levels	YES
4.	E- Shodh Sindhu (E-SS) (Consortium for Higher Education Electronic Resources)	Provides access to e-resources to Universities, Colleges, and Centrally Funded Technical Institutions in INDIA.	NO
5.	Virtual Labs	Provide remote access to simulation-based Labs in various disciplines	NO
6.	e-Yantra	Robotics outreach project, an initiative of IIT Bombay.	YES
7.	eGyankosh	National Digital Repository	NO

8.	Shodh Shuddhi	Provides access to Plagiarism Detection Software (PDS) to all universities/Institutions in India	NO
9.	e-PG Pathshala	A gateway to all Post graduation courses	NO
10.	Nishtha (National Initiative for School Heads' and Teachers' Holistic Advancement)	It is a capacity building program for improving the quality of school education through integrated teacher training.	YES
11.	FOSSEE (Free/Libre and Open-Source Software for Education)	Promotes the use of FLOSS tools in academia and research	NO
12.	Vidwan	The database of profiles of scientists / researchers, developed by INFLIBNET.	NO
13.	Spoken Tutorial	Friendly online discussion forum to promote IR literacy through Open Source Software.	YES
14.	BAADAL	A cloud orchestration and virtualization management software developed by IIT Delhi, initiative by MHRD under NMEICT.	NO

Out of 14 higher education initiatives, only 6 (SWAYAM, SWAYAM PRABHA, NDLI, e-Yantra, Nishtha, Spoken Tutorial) are having their mobile apps Interfaces.

Table 3: Digital Initiatives by SAKSHAT that have Google play App

Sr. no.	Name of Initiative	App Size	Current Version	Developers of the Apps	Viewers of the Apps	Downloads	Release-d date	Updated on
1.	SWAYAM	12MB	3.11.0	IIT Madras	920027	1M+	23 Aug 2016	27 July 2021
2.	SWAYA	7.72	0.04	INFLIBNET	12507512	500K+	7 July	4 Jan

	M PRABHA	MB					2017	2018
3.	NDLI	3.1MB	2.1.0	IIT Kharagpur	31846733	1M+	28 Dec 2018	6 Aug 2021
4.	Spoken Tutorial	353KB	1	Satpute harish	17942101	5000+	11 Dec 2012	11 Dec 2012
5.	e-Yantra	10.06 MB	0.2.5	E-Yantra, ERTS		1000+	15 Aug 2020	20 Nov,2020
6.	Nishtha	9.34 MB	2.0.13	NCERT		500K+	20th Aug 2019	5 Aug,2021

In the above table no. 3, the details of 6 Mobile apps having their mobile apps Interfaces are given out of which e-Yantra is the latest app released on 15th August, 2020 and Spoken Tutorial is the oldest one having 17,942,101 viewers released on 11th December, 2012.

It is interesting to note that NDLI with 3.1 MB app size has the power to deliver the e-content to 75,675,373 resources.

1.2 National Digital Library of India (NDLI)

NDLI pilot project was launched by the Ministry of Education (MoE), formerly (Ministry of Human Resource Development, MHRD) under its National Mission on Education through Information and Communication Technology (NMEICT) to develop a virtual repository framework with a single-window search facility. It is developed, operated, and maintained by the Indian Institute of Technology (IIT) Kharagpur (NDLI 2021). The filtered and federated searching is being used to find the right resource with minimal effort and time in national and international languages. NDLI provides user group-specific services such as Examination Preparatory for School and College students and job aspirants. It is built to provide support for all academic levels including researchers and life-long learners, all disciplines, all popular forms of access devices, and differently-abled learners. NDLI is designed to hold the content of any language and provides interface support for the 10 most widely used Indian languages.

NDLI is a great initiative taken by the MoE to bridge the digital gap by providing access to all academic levels including researchers, life-long learners, and differently-abled learners. It is designed to enable people to learn and grow to their best from all over the world and to facilitate the researchers' inter-linked exploration across the multiple sources. NDLI became a key enabler linking all existing and upcoming digital repositories and educational institutions in India and become partner with libraries across the world. NDLI is available as both web app and mobile apps (android as well as iOS). The NDLI web app can be accessed online at https://ndl.iitkgp.ac.in/.

Table 4: Features of NDLI App

SN	**Details of NDLI App**	
i.	App Size	3.1 MB
ii.	Current Version	2.1.0
iii.	Released On	DEC 28, 2016
iv.	Updated On	AUGUST 6, 2021
v.	Total App Users	20,00,000+ (January 2019)
vi.	Downloads	1m+
vii.	Offered By	MHRD
viii.	Content Academic level	Primary To Post Graduation. school to college to university to life-long learning
ix.	Headquarters	IIT Kharagpur, India
x.	Scope	Multiple Domains Like Technology, Humanities, Science, Agriculture, And Others.
xi.	Resource type	Resources, Ex. books, newspaper, photograph, poster, report, thesis, synopsis, patent, etc.
xii.	Content Form	Various forms such as text, audio, image, video, presentation, animation, application, and simulation.
xiii.	Languages	NDLI can accommodate materials in any language while the User Interface for Browsing and Searching is currently

		available in English plus 12 Indian languages
xiv.	Access restriction	Open, limited, Subscribed, Authorized
xv.	Users	Students, Teachers, Researchers, Librarians, Professionals, Differently-Abled Users and all Life Long Learners.

Table 4 is the brief description of the basic features of the NDLI m-app that include app size, version, released and updated information, total number of users and number of app downloads. It also includes the information regarding its headquarters, developer, domains and resources covered, various forms of content, the language it supports, access restriction, and group of users.

Table 5: Learning Resource Type (Text)

Learning Resource Type	Content Count	Percentage
Article	39,145,165	58.65
Newspaper Article	7,413,837	11.12
Book	6,792,918	10.18
Report	1,221,070	1.83
Notes	1,169,058	1.75
Law Act	874,957	1.31
Law Judgement	870,120	1.30
Thesis	740,635	1.11
Technical Report	716,378	1.07
Historical Record	522128	0.78
Video Lecture	447,652	0.67
Audio Lecture	3,624	0.005
Question Paper	37,663	0.056
Annual Report	32,673	0.049
Newspaper	6,757,833	10.12
Total	**66,745,711**	**100**

Table 5: depicts learning resource type (text) of NDLI app that has 15 categories. Out of 66,745,711 content count, 58.65 percent are articles type that is the largest resource number,

followed by newspaper articles 11.12 percent, books 10.18 percent, Newspaper 10.12 percent, Report 1.83 percent, Notes 1.75 percent, Law act 1.31 percent, Law Judgement 1.30 percent, Thesis 1.11 percent, Technical report 1.07 percent, Historical record 0.78 percent, Video Lecture 0.67 percent, Question Paper 0.56 percent, Annual Report 0.049 percent, and Audio Lecture 0.005 percent respectively.

Table 6: App Content form

Content form	No. of Resources	Percentage
Text	71,765,594	96.72
Image	1,386,443	1.87
Video	607,975	0.82
Audio	245,858	0.33
Presentation	177,815	0.24
Simulation	12,504	0.02
Application	2,381	0.003
Animation	891	0.001
Total	**74,199,461**	**100**

Table 6 shows that NDLI app contents are available in different forms such as text, video, audio, and presentation, etc. One can choose the desired format to retrieve particular materials. Yet, accessing documents depends on how it is restricted by the source organization such as Open, Limited, Subscribed, Authorized, and NDLI. The above table shows the total number of content forms available in the repository, i.e., 74,199,461, where the text 96.72 percent, is the highest number of resource forms available. On the other hand, image, audio, presentation, video, simulation, application, and animation forms are available in less than 2 percent.

Table 7: Access restriction status (Learning Resource in Text)

Access restriction	Report	Theses	Synopsis	Patent	Total	Percentage (%)
Open	402,949	713,577	13,365	151,393	1,281,275	60.13
Limited	630,914	7,559	1,255	120	639,838	30.03

NDLI	13,967	65			14,032	0.01
Subscribed	167,666	2,064	4,262	147	174,139	8.17
Authorized	5,574	15,893		41	21,508	1.01
Total	**1,221,070**	**739,158**	**18,882**	**151,701**	**2,130,811**	**100**

Table 7 highlights the data of Access restriction status (Learning Resource in Text), Overall 2.13 million total in number where the maximum 60.13 percent of resources has full open access, out of which 55.69 percent are theses, followed by reports 31.45 percent, patent 11.82 percent and 1.04 percent synopses. Similarly, 30.03 percent of resources are having limited access, where reports are maximum in number, followed by theses. Likewise, NDLI 0.01 percent access restriction permits a maximum number of reports, followed by theses access. In the same way, the maximum number of reports are subscribed (8.17 percent) access. On the other hand, a maximum number of theses are authorized (1.01 percent) access, followed by reports.

Table 8: Top Sixteen Sources of Distribution

Sources	No of Resources	Percentage
ERIC	1,071,925	2.28
INFLIBNET-Shodhganga	269,702	0.57
US Dept. of ENERGY Office	2,190,831	4.65
Connecting Repositories (CORE)	234,046	0.50
Krishikosh Research System	138,269	0.29
World eBook Library	7,330,568	15.57
Internet Archive-National Agri, Library	143,962	0.31
State Library of Massachusetts	696,081	1.48
CiteSeerX	6,624,390	14.07
arXia.org	1,460,277	3.10
DOAJ	2,620,170	5.57
Internet Archive-JSTOR	259,787	0.55
Library of Congress-Newspaper	6,477,321	13.76
PubMed Central	3,879,626	8.24

Semantic Scholar	10,369,791	22.03
IIEEE Xplore Digital Library	3,310,365	7.03
Total	**47,077,111**	**100**

Table 8 shows, out of 47 million resources, Semantic Scholar (22.03 percent) is the highest resources provider. Similarly, World eBook Library (15.57 percent), CiteSeerX (14.07 percent), Library of Congress-Newspaper (13.76 percent), PubMed Central (8.24 percent), IEEE Xplore Digital Library (7.03 percent), DOAJ (5.57 percent), US Dept. of ENERGY Office (4.65 percent), arXia.org (3.10 percent), ERIC (2.28 percent), State Library of Massachusetts (1.48 percent), INFLIBNET-Shodhganga (0.57 percent), Internet Archive-JSTOR (0.55 percent), Connecting Repositories (CORE) (0.50 percent), Internet Archive-National Agri Library (0.31 percent), Krishikosh Research System (0.29 percent), respectively.

Table 9: Subject Category

Subjects	Content Count	Percentage
Computer Science, Information &General Works	16,461,157	33.62
Philosophy and Psychology	608,857	1.24
Religion	227,158	0.004
Social Science	6,044,663	12.35
Language	191,630	0.39
Natural Science and Mathematics	9,804,062	20.03
Technology	12,750,905	26.05
The Art, Fine & Decorative Arts	1,915,575	3.91
Literature & Rhetoric	951,329	1.94
History & Geography	963,473	1.97
Total	**48,955,336**	**100**

It is shown in Table 9 that considering all subjects in totality, Computer Science, Information &General Works (33.62 percent) is the highest of other subjects. In technology (26. 05 percent) Natural Sciences and Mathematics (20.03 percent), Social Science (12.35 percent), The Arts, Fine and Decorative Arts (3.91 percent), History and geography (1.97 percent) Literature and

Rhetoric (1.94 percent), Philosophy and Psychology (1.24 percent), Language (0.39 percent) and Religion is (0.004 percent).

Table 10: Language- Wise distribution

Languages	No. of Documents	Percentage
English	42,556,527	96.42
Finnish	2,891	0.007
Portuguese	126,930	0.29
Hindi	104,742	0.24
French	444,881	1.01
German	443387	1.005
Swedish	7,128	0.02
Spanish	246,393	0.56
Tamil	24,359	0.06
Sanskrit	19,344	0.04
Bengali	158,504	0.36
Total	**44,135,086**	**100**

Table 10 indicates the Language-wise distribution of the collection and it is shown that the available content in the English language is 96.42 percent, followed by Finnish (0.007 percent) and other languages constituting a total of about 4 percent, out of which 2 percent (approx.) is contributed by French and German.

The goal of the present study is to provide a descriptive outline of the user's sentiments regarding the one such popular mobile app NDLI, to assess the usability of this app and for this the positive and negative rating of the users is collected for sentiment analysis.

1.3 The Concept of Sentiment Analysis

It is never easy to understand the human emotions and reactions that are subject to change over a period of time. To express the feelings and emotions, people use a variety of languages and whatever is said in any regional dialect has a sentiment that is associated with it which might be positive, negative, or neutral. Sentiment analysis is the process to identify the views, emotions, intentions, or sentiments behind a situation, opinion, and piece of text, speech, or any mode of communication used by people. Sentiment analysis uses Natural Language processing to determine the intents of people.

To analyze sentiment means to detect if the feelings and thoughts in the language used for communication are positive, negative, or neutral. For analyzing sentiment, unstructured text data is processed to extract, classify, and understand the feelings, opinions, or meanings expressed across hundreds of platforms. Sentiment Analysis is an advanced technology to analyze and perceive the behavior of a user. It aims to identify how sentiments are expressed in texts and to determine whether these expressions are positive, neutral, or negative toward a subject. Sentiment analysis is also known as Opinion Mining, Sentiment mining, Subjectivity Analysis, Opinion extraction. It is the practice of applying natural language processing (NLP) for text analysis, computational linguistics, and biometrics to systematically identify, extract, qualify and study affective state subjective information such as opinions, attitudes, and feelings expressed in texts.

1.3.1 Definitions of Sentiment Analysis

Sentiment analysis can be defined as a process that automates mining of attitudes, opinions, views and emotions from text, speech, tweets and database sources through Natural Language Processing (NLP) (Kharde, V., & Sonawane, 2016).

Sentiment analysis, also known as opinion mining, is the field of study that analyses people's opinions and attitudes towards entities such as products, services, and topics and their attributes. (Alqaryouti, Omar, 2019).

1.3.2 Sentiment Classification

A basic goal in Sentiment analysis (SA) is to classify the polarity of a given text. Sentiment analysis does this by looking at the document, sentence, or entity feature/aspect and assigning it a polarity — positive, negative or neutral. Beyond polarity sentiment classification, however, has even more advanced possibilities. For example, it can assign emotional states to texts such as "angry", "sad", and "happy". This type of classification is also known as Polarity Classification. It is used to analyse an ample amount of text in which every sample is being labelled as either a positive, negative, or neutral sample depending on the overall response received that is being expressed in that particular text. This type of classification can be carried out at various levels to gain surety over the produced opinion on the set of texts. The higher level of classification in the pyramid will be the difficult level amongst all the levels as it would be having opinions as well as things.

Sentiment analysis provides insights into the opinions and emotions that people express about any brand, product, or service online. It uses natural language processing (NLP) and machine learning to quickly identify the tone of the text, video, or images, which can help brands to identify and react to negative reviews, articles, or other mentions. NLP is the ability of a computer program to understand human language as it is spoken and written, also referred to as natural language. It is a component of artificial intelligence (AI). NLP technique is used to determine whether data is positive, negative, or neutral. In-text analytics, NLP, and machine learning (ML) techniques are combined to assign sentiment scores to the topics, categories, or entities within a phrase.

1.3.3 Types of Sentiment Analysis

Sentiment analysis models focus on polarity (positive/negative/neutral), feelings/emotions (angry/happy/sad), urgency (urgent/not urgent) and intentions (interested/not interested).

Some of the most popular types of sentiment analysis are discussed below:

Table 11: Types of Sentiment analysis

Sl.no.	Type of Sentiment Analysis	Features
i.	Fine-grained Sentiment Analysis	• received feedback from customers • analyzes the sentiments in readily available categories like positive, neutral and negative. • rating option from 1 to 5 scale
ii.	Emotion detection	• detect and understand emotions like happiness, frustration, anger, sadness and so on. • understand why a user feels a specific way, • difficult as people use a collection of words having a different sense of meaning such as sarcasm.
iii.	Aspect-based Sentiment Analysis	• more focused on the aspects/ features of an entity and provides an estimate of the average sentiment expressed

		for each aspect. • support organizations in automatically sorting and analyzing user data for support • more granular approach to analyzing reviews. • Complaints such as glitches or major bugs in some new software applications can also be addressed.
iv.	Intent- based Sentiment Analysis	• classifies textual data automatically • comprehend the intentions behind a large number of the client's questions • automates measures and acquires significant experiences. • empowers organizations to be more user-friendly.

1.3.4 Sentiment Analysis: Models/Approaches/Methods/Algorithms

There are 3 major sentiment analysis algorithms/ models tabulated as below:

Sl.no.	Model	Features
i.	Lexicon/Rule based	• Use NLP algorithm • manually crafting of rules for data classification to determine sentiment. • uses dictionaries of words with positive/negative values to denote their polarity and sentiment strength to calculate a score. • accommodates concepts such as sarcasm, irony and humor for programming that are not easily interpreted by computers.

ii.	Automated/ Machine Learning: a. Traditional Models b. Deep Learning Models	• Use ML algorithms to figure out the essence of the statement. • improves exactitude/quality of the analysis as information can be processed on many criteria without it being too complicated. • faster processing of data with greater precision, better depth of understanding and statistical accuracy to calculate the gist of the original message. 1. Traditional Models require the gathering of a dataset, then processing this data and finally training the algorithm based on the examples. These methods are mainly used for determining the polarity of text. 2. Deep Learning Models provides more precise results than traditional models and includes neural network models.
iii.	Hybrid:	• The combination of machine learning and lexicon-based approaches • most modern, efficient and widely-used approach for sentiment analysis.

2.1 Literature review of Sentiment analysis of using mobile apps:

SIYAM (2018) reviewed 60 smart government apps comprising of 11,912 reviews and focused on aspect-based sentiment analysis (ABSA) and used deep learning techniques and found total numbers of positive reviews were 7506, neutral (691) reviews and negative reviews were 3715. The analysis showed that most of the reviews were positive and highlighted many advantages of deep learning approach. Marlene, Camacho-Rivera (2020) evaluated 10 asthma apps and 373 reviews and used N-Gram models which had highlighted 53.4% (199/373) received high ratings (average ratings of 4 or 5) and 47.2% (176/373) received low ratings (average ratings of 3 or less). Felwah Alqahtani et al. (2020) evaluated 104 mental health apps comprising of 88125 user reviews using machine learning (ML), and then conducted thematic analysis on the reviews and compared the performance of five classifiers using supervised ML algorithms and found the best performing classifier, with F1-score of 89.42%. They conducted a thematic analysis of positive and negative reviews and found 21 negative themes and 29 positive themes. Garousi, Vahid et al. (2020) evaluated 39,425 user reviews from 9 European COVID contact-tracing national apps (50+ apps) and used AppBot analytics tool to extract and mine the user reviews. It was found that users were generally dissatisfied with the nine apps except the Scottish app. Some of the major issues that users had complained about were high battery drainage and doubts on whether apps were really working. Ahmad, Kashif et al. (2021) reviewed 46 different COVID19 applications (including Aarogya-Setu) using AI models for automatic sentiment analysis of 34,534 users' reviews from 46 distinct countries and received 15,587 samples in the positive class while 8178 in negative, 1271 in neutral and 9496 in technical issues classes. Omotosho, Babatunde S. (2021) evaluated 22 commercial banks apps operating in Nigeria comprising 37, 460 reviews adopting the rule-based approach and found the average user rating was 3.5. Furthermore, it was found that about 66 % of the emotions were positive while the remaining 34% were negative. Okuboyejo et al. (2021) evaluated 19709 user reviews of 10 top MOOCs apps (Udemy, Coursera, eDx, Khan academy, Pluralsight, Linkedin learning, Lynda, Skillshare etc.) and used topic modelling technique and found 14005 positive, 4285 negative, and 1419 neutral reviews.

3.1 Research Gap

The growing use of smartphones today has resulted in the rapid development of smart apps. One such educational app is the NDLI, which is a virtual repository of learning resources that integrates all existing digitized and digital content of all educational institutes of India. NDLI has a large user base with active downloads. The inferences drawn from the literature review revealed that no prior study has been conducted to examine and understand the user feedback and problems regarding sentiment analysis of NDLI m-app. Although several studies have been conducted in the area of commerce, marketing, and health but studies about mobile apps launched by the Ministry of Education, Government of India (MoE, GoI) gauging the user sentiments are unavailable.

3.2 Research Problem / Research Motivation:

NDLI aims to bring diverse learners under a single umbrella that allows users like students (of all levels), teachers, researchers, professionals, and other lifelong learners to access this app for their educational needs. Learners' satisfaction toward online searching, retrieval, and content quality are the indicators of this ambitious online service providing e-learning content. The problem is to identify a platform or tool to analyze the already available user reviews to improve in the quality of service (QoS) provided by NDLI app developers. One of the challenges is to understand the real user intent and to classify their views as positive, negative or neutral categories. NDLI app is a globally used app, its users are not restricted to India only. Thus, this study is believed of utmost importance on account of the following reasons:

a. An unstructured large amount of data containing user's opinions about NDLI app
b. The need to have an automated and effective way to understand the sentiment of the users towards the NDLI app.
c. Current studies show that no such research has been done on NDLI
d. Current studies show that research on NDLI apps reviews is limited.

3.3 Research Questions (RQs):

RQ1 How do users perceive the usability of NDLI as a source of scholarly content?

RQ2 What type of sentiments do users have towards the NDLI m-app?

RQ3 Which type of sentiments (positive, negative, or neutral) are more dominating?

RQ4 How Sentiment Analysis deal with strength and weaknesses of NDLI m-app?

RQ5 How app developers/creators can utilize the data to improve the quality of the app to meet its defined objectives?

RQ6 To what extent will users be satisfied with NDLI mobile app version on Android and iOS platform?

3.4. Study Objectives:

The focal point of the study revolves around the sentiment analysis of users of NDLI mobile apps. As such, the study has the following associated objectives:

OB1 To analyse the textual content from user feedback, comments and ratings of the NDLI mobile app users;

OB2 To analyse the sentiments of the users towards the NDLI m-app;

OB3 To examine the dominance of positive or negative sentiments of users regarding the efficacy of the NDLI mobile app;

OB4 To identify the number of documents available in selected learning resource type, i.e. report, patent, synopsis and thesis;

OB5 To identify content and features of the NDLI app associated with positive and negative user ratings;

OB6 To compare the NDLI app reviews as mentioned in Google Android and Apple iOS platforms.

3.5 Rationale of the study:

Sentiment analysis make the app creators/developers thoroughly understand user experience, ease of access, difficulties in information retrieval, app related issues, downloading pdfs, and several other related issues. Sentiment analysis helps in monitoring how NDLI is viewed by the educators, learners and researchers. This enables companies to strategize more effectively and deal with problems before they escalate. The insights are gained through SA of NDLI app helps to analyze huge volume of unstructured and unorganized usage data in an efficient manner that helps to monitor and improve the app. NDLI m-app has 11,853 downloads/active users. However, the Google Play Store rating of NDLI is not very satisfactory (3.6). Sentiment analysis will help in processing huge amount of data in an efficient and cost-effective way to identify critical issues and situations which is difficult to process manually. As the NDLI has a large number of user’s database, it will be useful in improving the app by its developers. There are several apps offered by MoE under NMEICT including SWAYAM. Sentiment analysis of NDLI m-app ensures that all qualitative feedback is translated into actionable insights. This will give a clear vision of what app users think about NDLI.

4.Research Design/Methodology

Mobile app stores (Google and Apple) allow users to rate the app using star ratings and text reviews. The star ratings range on the scale of one to five. Reviews consist of free-text descriptions without having a predefined structure wherein users can freely express their views to describe problems, issues, and desired features. The review is also used to describe impressions, positions, comparisons, and attitudes toward the apps. Online store reviews are free and fast crowd feedback mechanisms that can be used by developers as a backlog for the development process. The study aims to investigate to what extent app development teams can leverage crowdsourcing mechanisms for planning future changes. Specifically, opinion mining is conducted on NDLI mobile application and analysed the impact of user reviews for app success.

4.1Software used to extract and mine the app reviews

The analytics are performed by using AppBot (appbot.co) and AppFollow (appfollow.io) analytics software's which captured, monitored, measured and analysed the review results for a particular period. These software's provides easy-to-understand insights into an app using artificial intelligence algorithm tools and also provides a large number of data-mining and sentiment analysis features in categories such as Reviews, Sentiment, Words, Phrases, Topics, and Languages. Data Statistics from software's is collected till 7th Sept 2021. Therefore, all the reviews data until that date were included in our dataset.

In the NLP literature, automatic identification of the semantic tone of a given text is referred to as sentiment analysis. Sentiment analysis refers to the use of NLP to systematically quantify the affective state of a given text. A given text can have four types of sentiments: positive, negative, neutral, and mixed. A positive sentiment denotes that the text has a positive tone in its message. “Neutral” sentiment implies that there is no strong sentiment in the text, e.g., "I have used this app". A text is given the “mixed” sentiment when it is conflicting sentiments (both positive and negative). Our chosen data-mining tools AppBot and AppFollow support the above four types of sentiments for each given review: positive, neutral, mixed, and negative sentiment. To classify the sentiment for a given review, AppBot calculates and provides a sentiment score for each review (a value between 0-100percent).

Sentiment Analysis is vital for organizations to understand how users feel about their apps. Users’ feedback is important to the success of any product or service. AppBot helps in feedback analysis facilitating better, faster decisions about product or service roadmap, based on AI-powered near real-time sentiment analysis of real users. It uses natural language processing (NLP) to provide insight to the app owners about what users think of apps. It also offers actionable insights into the keywords, phrases, and topics that are driving sentiment in given app reviews with advanced text analytics. AppBot uses the Words tool to retrieve the most commonly used keywords in user reviews, use Topics to see what themes are popular with users from all countries from the Apple, Google Play, Amazon, and Windows app stores. AppBot and AppFollow web applications were used to analyse the NDLI data (reviews & feedback comments) to generate reports on user sentiment and review content. The report thus generated will help in identifying and understanding feature requests, bug and crash reports, and design/UX issues for the NDLI app (Android and iOS).

1. Results and Discussion:

The following table provides some key information and descriptive statistics of both platforms of the NDLI app. NDLI iOS has received 33 reviews and the android app has received 4527 reviews, as of 7th Sept 2021.

Table 11: Reviews of iOS and Android Google Play Store

Store/OS	Positive Sentiment	Score	Review Count	Average Review Stars	5 Star Count	4 Star Count	3 Star Count	2 Star Count	1 Star Count
iOS	21.42%	50	33	2.5	7	3	4	4	15
Google Play (Android)	54.03%	66	4527	3.3	1987	475	362	372	1331

Source: AppBot

Looking at all ratings, including those without a review, for Android, 43.9 % of the ratings were 5-star ratings and 29.40 % were 1-star ratings. The average was 3.3 stars. For iOS, 21.2 % of the ratings were 5-star ratings and 45.45 % were 1-star ratings. The average was 2.5 stars. For the ratings with reviews, 1-star ratings made up the largest proportion of the reviews, for iOS and 5-star ratings made up the largest proportion of the reviews, for Android.

Table 12: Star Rating

Star Ratings	No. of Reviews	No. of Reviews (%)	No. of Reviews Replied	No. of Reviews Replied (%)

★★★★★	1994	44	679	34
★★★★	478	10	202	42
★★★	366	8	138	38
★★	376	8	98	26
★	1346	30	242	18

Source: AppBot (Total Reviews 4560) on 7^{th} Sept 2021

The above table provides information about star ratings (from 1 to 5) with a number of reviews on that rating and the number of reviews replied to by the NDLI developers. 44% reviews (n=1994) are associated with 5-star ratings with 34% response rate (n=679). Similarly, 10% reviews (n=478) are associated with 4-star ratings with 42% response rate (n=202). Likewise, 8% reviews (n=366) are associated with 3-star ratings with 38% response rate (n=138), 8% reviews (n=376) are associated with 2-star ratings with 26% response rate (n=98) and 30% reviews (n=1346) are associated with 1-star ratings with 18% response rate (n=242). The statistics show that the number of reviews replied to reviewers of 1 and 2-star ratings were less as compared to 3, 4, and 5 star rating.

Table 13: AppBot data as on 7^{th} Sept 2021

Sentiments	iOS	Percentage (iOS)	Google Play	Percentage (Google Play)
Positive	6	18	2130	47
Neutral	2	6	293	6
Mixed	3	9	295	7
Negative	22	67	1808	40
Total	**33**	**100**	**4527**	**100**

AppBot uses an advanced method, based on artificial intelligence (AI) and Natural Language Processing (NLP), to assign one of the four types of sentiments for each given review: positive, neutral, mixed, and negative sentiment. The above table depicts the number and percentage of sentiments (Positive, Mixed, Neutral, and Negative) of iOS and Android. Positive comments contain mostly positive sentiments. Neutral comments lack strong sentiment, mixed comments have conflicting sentiment and negative comments contain mostly negative sentiments. The

Android apps have received more reviews compared to iOS apps. It seems that “Android users tend to participate more in reviewing their apps”.

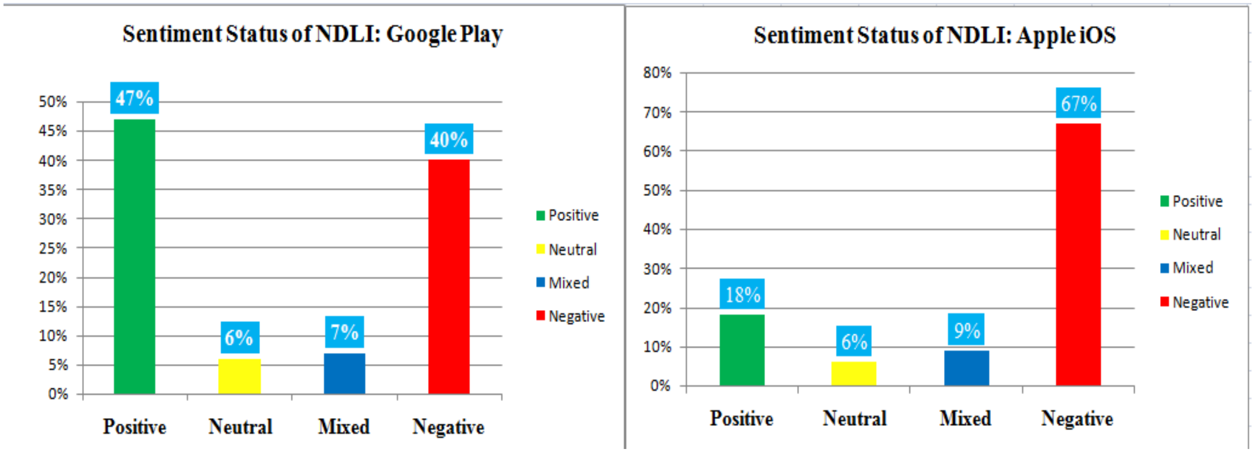

Figure 2: Breakdown Sentiment Status of Google play and Apple iOS

Source: AppBot (Sentiment Breakdown) (Total Reviews 4560)

The Sentiment breakdown chart in the above figure depicts the Comparison of the Sentiment breakdown that demonstrates the proportion of positive, Negative, Neutral, and Mixed Reviews of the NDLI app as mentioned in Google Android and Apple iOS platforms from July 10, 2008, to Sept 7, 2021. Our chosen data-mining tool (AppBot) supports the above four types of sentiments for each given review. To classify the sentiment for a given review, AppBot calculates and provides a sentiment score for each review (a value between 0-100%). This tool showed that app users are optimally positive with an Android app than an iOS app.

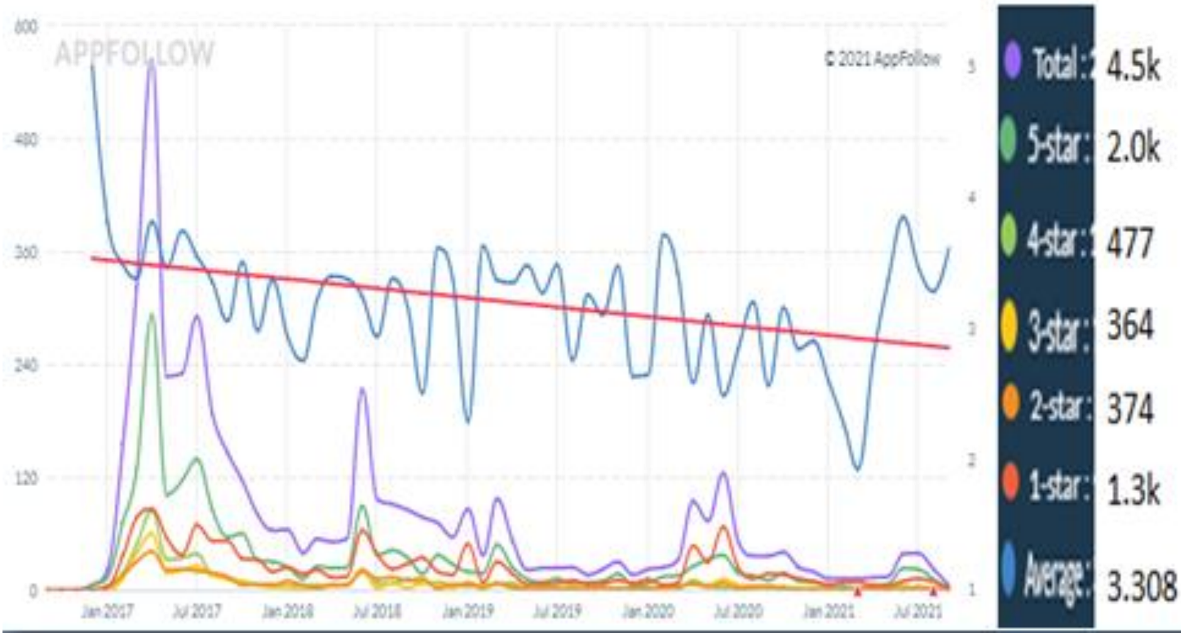

Figure 3: Reviews and Rating of Google play and iOS

The above graphics from AppFollow gives information about the total number of reviews and star ratings. Ratings were differentiated using different colours 5 star (dark green), 4 star (Light green), 3 star (yellow), 2 star (Orange), and 1 star (red) as shown in graphics. The reviews were collected from 2nd Sept 2016 to 7th Sept 2021. Ratings Spike, so one can keep an eye on increasing or decreasing ratings and user feedback. Ratings were differentiated using different colours as shown in graphics. The overall trend is declining. The peak is highest on 26 Feb and 2 March in the year 2017.

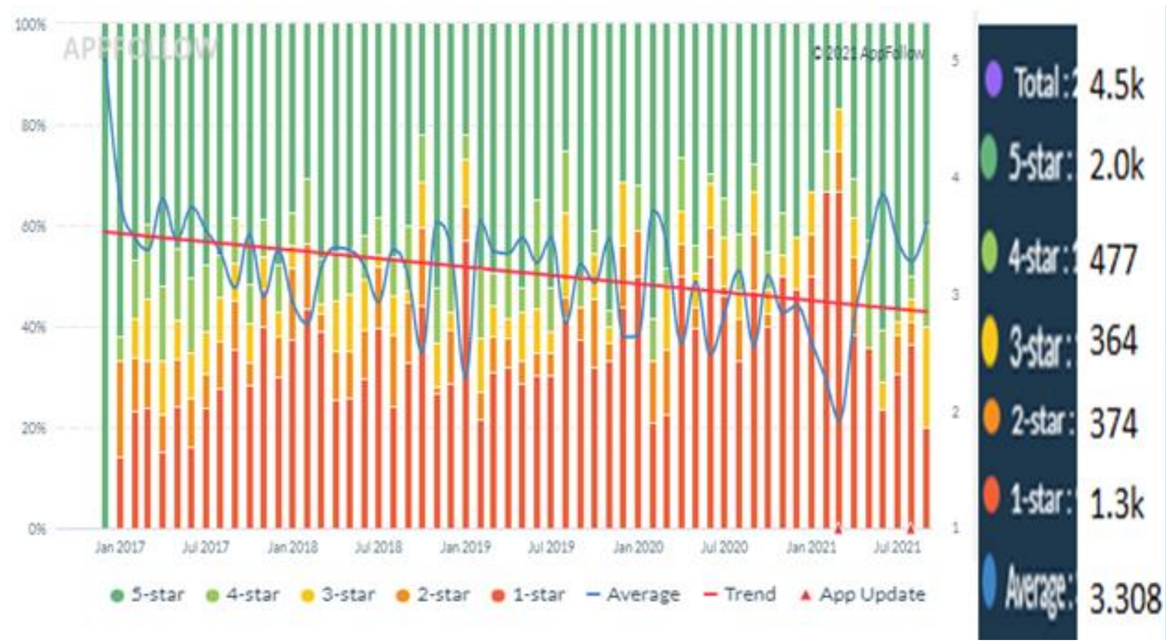

Figure 4: Monthly Reviews and Rating from Dec 2016 to Sep 2021

Source: AppFollow (2nd Sept 2016 to 7th Sept 2021)

It is interesting to see that, in all cases, the Android apps have received more reviews compared to iOS Apps. However, the review data that is fetched using our chosen analytics tool (AppFollow, as discussed in the next section) was until 2 September 2021. Ratings have color codes based on sentiment analysis: 5 star (dark green), 4 star (Light green), 3 star (yellow), 2 star (Orange), and 1 star (red).

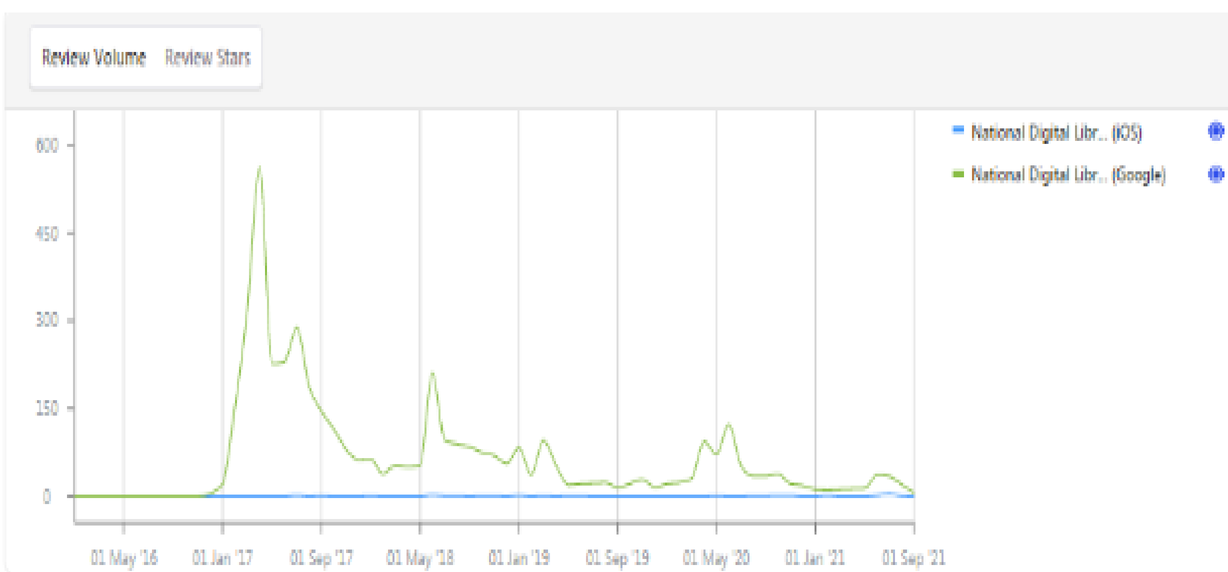

Figure 5: Sentiment timeline

The Sentiment Timeline helps to understand the trends. This is an interesting aspect of the review dataset that can found to be worth analysing the trends of review volumes and their sentiments over time. The AppBot tool again already has a feature to get such trend-charts easily. The above Figure shows a Review per month over the period Dec 2016 to Sep 2021. During the maintenance and evolution of the Google Play Store mobile app of NDLI, the overall user review sentiment of the period is abnormal. The overall trend is declining with certain peaks of the android curve. On 1 April 2017, the average per month reviews were 564, when it was at the highest peak. The overall trend is declining and review volume is also declining. The user's review is inconsistent.

On the other hand, iOS is getting a straight line and there is no fluctuation. There are no high and lows, rise and decline. It is almost constant. This can be accounted for by the fact the number of active installations and active users is very low in comparison to android.

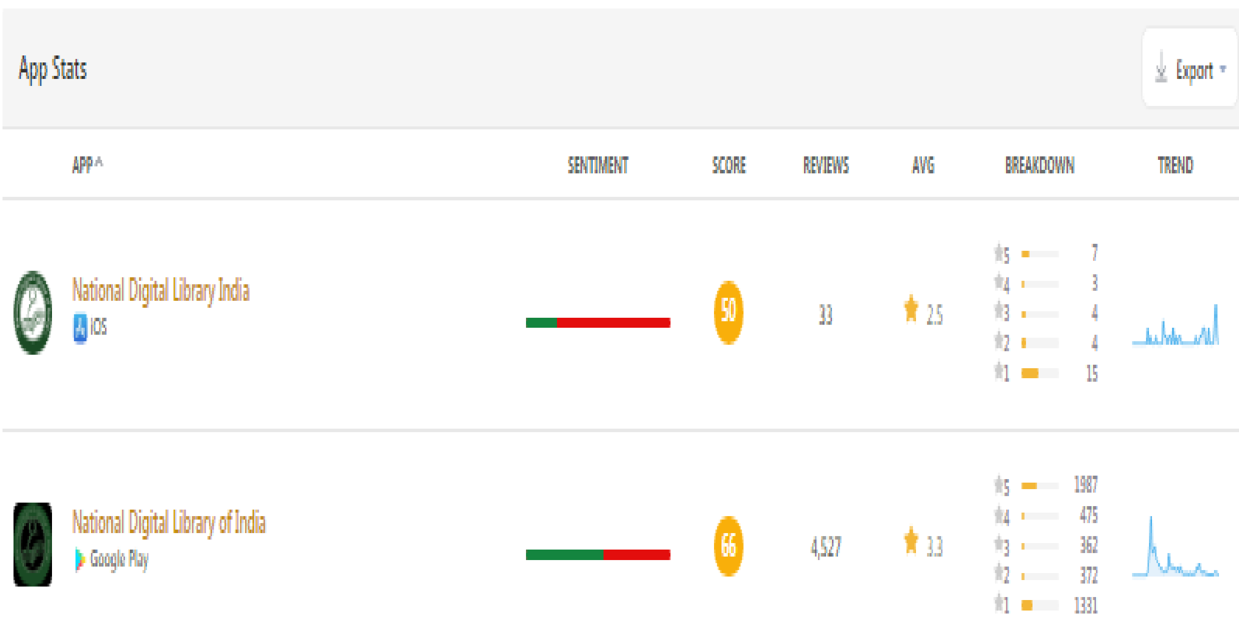

Figure 6: Comparison of App Stats

Source: AppBot

The above Summary provides the sentiment analysis, score, total reviews received, an average rating of total reviews, star ratings (from 1 to 5) and trend in review volume of a NDLI app on both Android and iOS. From above Figure, it is inferred that the android platform (4527) received more reviews in text than iOS (33). 1987 reviewers show positive feedback for the

Android version as compared to just 7 reviewers for the iOS version and the average rating shows a negative trend in iOS than Android with 2.5 and 3.3 ratings respectively.

Table 14: Most Popular words in NDLI App Reviews (Android and iOS)

Words	Occurrence	Percentage
Good	728	16.1
Books	624	13.8
Open	450	9.9
Useful	373	8.2
Great	361	8.0
Work	339	7.5
Initiative	297	6.6
Please	295	6.5
Download	290	6.4
Nice	283	6.3

The Above table shows the list of the top 10 most popular words, the number of times it occurred in reviews with their percentage. Some of the words can be used in both positive as well as negative contexts, for example, a review given is "The app is not good" or "The app is good." The word good alone does not suffice to interpret the sentiment of the review.

Phrases

2 Words		3 Words		4 Words	
Phrases	Mentions	Phrases	Mentions	Phrases	Mentions
Good Initiative	106	Server verification faied	61	Says server verification failed	12
Great initiative	99	Something went wrong	18	Shows server verification failed	10
Verification faied	65	Says server verification	13	Message server verification failed	5
Server verification	64	Manage phone calls	11	Sorry something went wrong	5
Please fix	49	Shows server verification	10	Says something went wrong	4
Working properly	46	Crashing every time	10	Shows something went wrong	3
Every time	45	Says something went	5	Like google play books	2
IIT kharagpur	34	Sorry something went	5	Need improvement please add	2
Great work	28	Login every time	4	Getting server verification failed	2
Please add	27	Please add books	4	Access server verification failed	2

Figure 7: AppBot Phrases

The "AppBot Phrases" tool analyzes all of the phrases in-app reviews. It presents data that shows how frequently each phrase appears, patterns, and a breakdown of the sentiment for reviews containing that phrase. The phrases tool analysis examined the 2 phrases, 3 phrases, and 4 phrases appeared in review results. From above figures for both the Android and iOS app results demonstrates the top 10 "2 phrases, 3 phrases, and 4 phrases" with its sentiment mentions. Further, Stats shows the individual results of each phrase. For example, the 'good initiative' phrase appeared in total of 105 reviews with a 3.9% average star rating with 69% positive feedback by users. Similarly in the iOS app, 'server verification failed' phrase shows 95% negative feedback by users with 1.6 average star rating. Analyzing these common phrases in reviews helps to identify the cause of poor star ratings faster so that action can be taken immediately.

5.1 Users' experience and their satisfaction with NDLI app

Our first exploratory analysis is to assess the ratios of users who, as per their reviews, have been happy or unhappy with the apps. To gauge satisfaction with an app, the built-in rubric of app stores is 'stars', a rating feature also used in many other online systems, such as Amazon. A user can choose between one and five stars when she/he submits a review as well as optionally provide text. Another more sophisticated way to derive users' satisfaction with an app is to look at the positive/negative 'sentiment' score of their textual reviews. Sentiment analysis refers to the use of natural language processing (NLP) to systematically quantify the affective state of a given text. Our chosen tool (AppBot) derives four possible types of sentiments for a given review text: positive, negative, neutral, and mixed sentiments. 'Neutral' reviews lack strong sentiment, for example, 'I have used this app'. 'Mixed' reviews have conflicting sentiments (both positive and negative).

NDLI m-app has received the average of 3.64 rating based on 11,861 reviews.

Star Ratings	**#Ratings**
★ ★ ★ ★ ★	6079
★ ★ ★ ★	1427
★ ★ ★	1048
★ ★	589
★	2715

Figure 8: AppBrain Star Ratings

Source: AppBrain

Versions of NDLI (2008-2021)

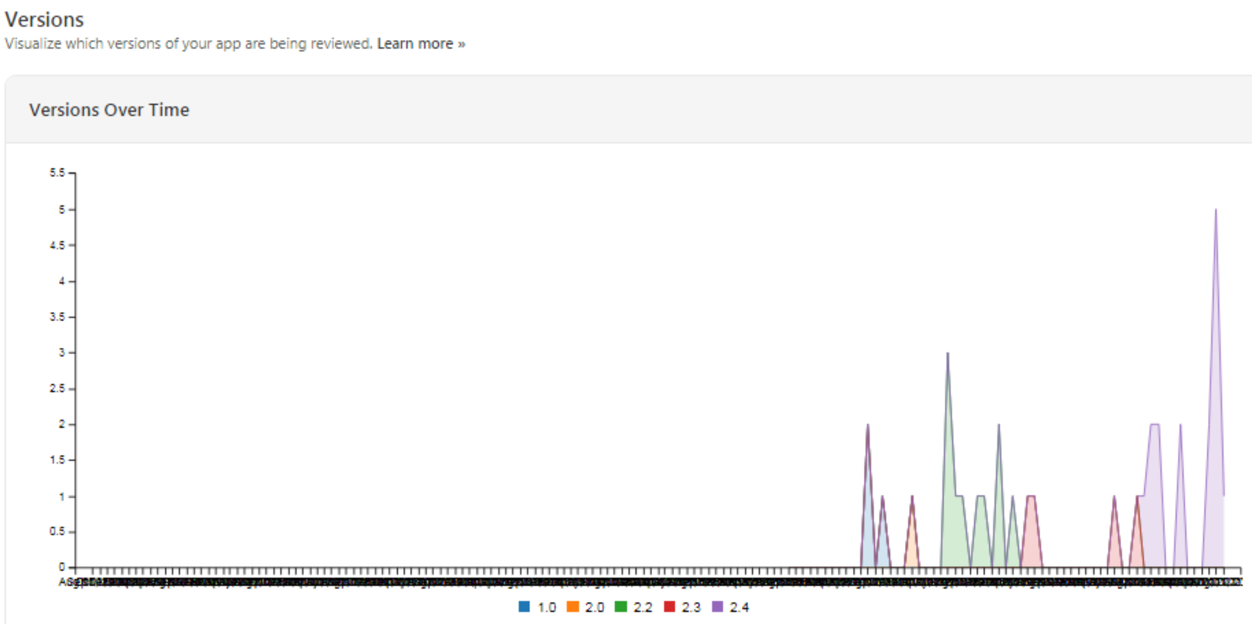

Figure 9: Version NDLI App Over time (Versions are only available for iOS apps)

The above figure shows the version of the NDLI App over time. AppBot's Version tool allows to easily compare the sentiment of different versions of any given app at a glance. It is designed to determine if a new version is a success, or if users are responding negatively to the changes that can be implemented. The latest version of the NDLI iOS app is 2.4. The first release date was July 2017 and the number of releases after that date until the data-extraction date of our study (Sep. 2, 2021). The figure shows version 1.0 with blue colour, version 2.0 with pink colour, version 2.2 with green colour, version 2.3 with red colour, and version 2.4 with purple colour.

Reviews by Versions Scanned 33 reviews

	VERSIONS ▲	AVE RATING	SENTIMENT	MATCHES	OVERALL REVIEWS	TREND
1	2.4 (Latest)	★ 2.5		15	45.5%	
2	2.3	★ 2.5		4	12.1%	
3	2.2	★ 2.1		10	30.3%	
4	2.0	★ 1.0		1	3.0%	
5	1.0	★ 4.0		3	9.1%	

Figure 10: Reviews of Versions

The above chart shows the period when reviews for each version grew and fell. It provides data on all the different versions of the app that have been released over time. Each version shows:

- average star rating,
- a measure of the positive to negative sentiment,
- how many reviews that particular version has received,
- what percentage of the overall reviews that version makes up and
- a timeline of review quantity.

Versions make it easy to understand how app users feel about each new update. It also shows increasing proportions of positive sentiment and rapid adoption for each new version. Slow adoption might indicate that poor reviews or word of mouth are deterring users from updating to the latest version.

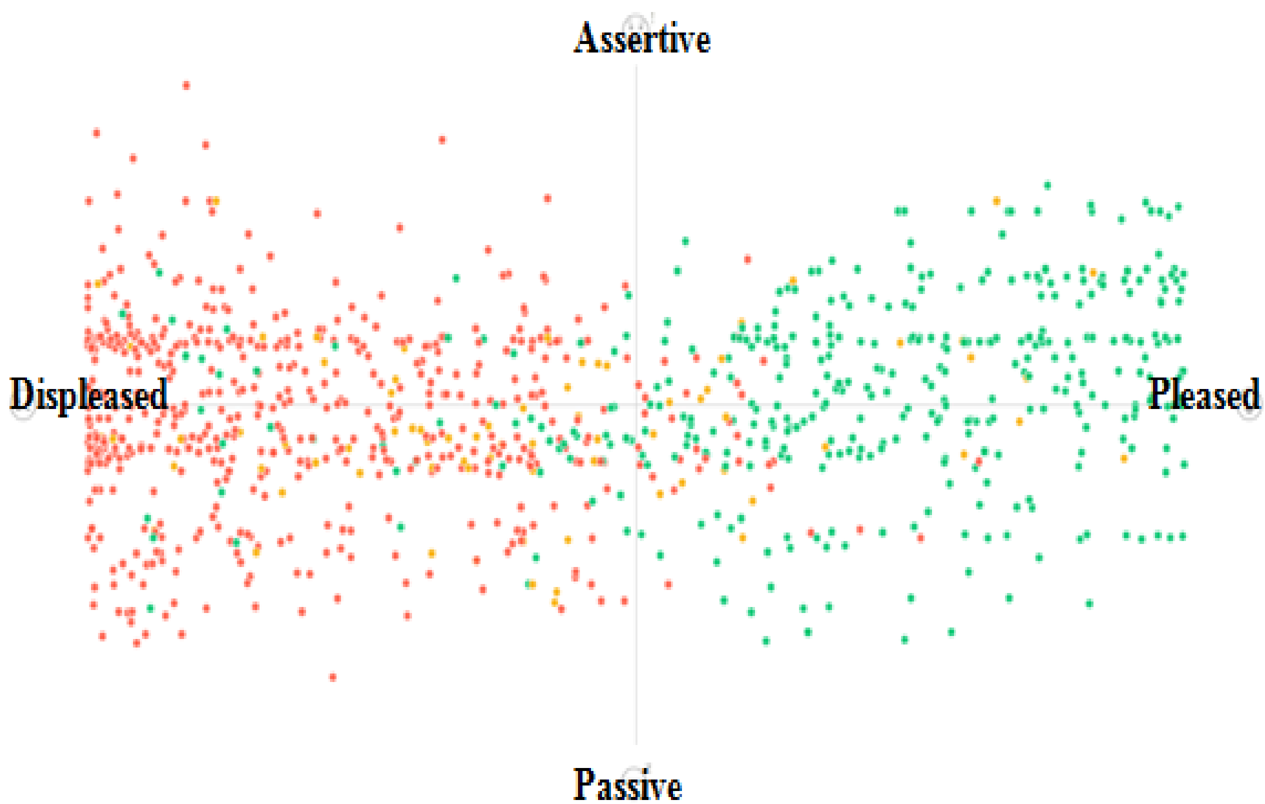

Figure 11: Emotional Visualizer

Source: Appbot

Colourful dots in the above graphics of "Emotional Visualizer" indicate sentiments of reviews. Green indicates positive sentiment; orange indicates neutral and red indicates negative sentiment.

X-axis: Pleased vs Displeased

The X-axis shows how pleased vs displeased a user appears to be. Most pleased users will be at the far right, neutral users in the centre, and most displeased users at the far left.

Y-axis: Assertive vs Passive

The Y-axis shows how strongly users feel about the comments they are making about the app. Users who feel strongly about what they are saying will appear at the Assertive end of the axis. Indifferent users will appear at the Passive end. It's less common for users to leave a review if they don't feel strongly about their experience, so it's not unusual for most of the reviews to be on the Assertive end of the scale. Hovering over any of the dots will display the specific review it relates to.

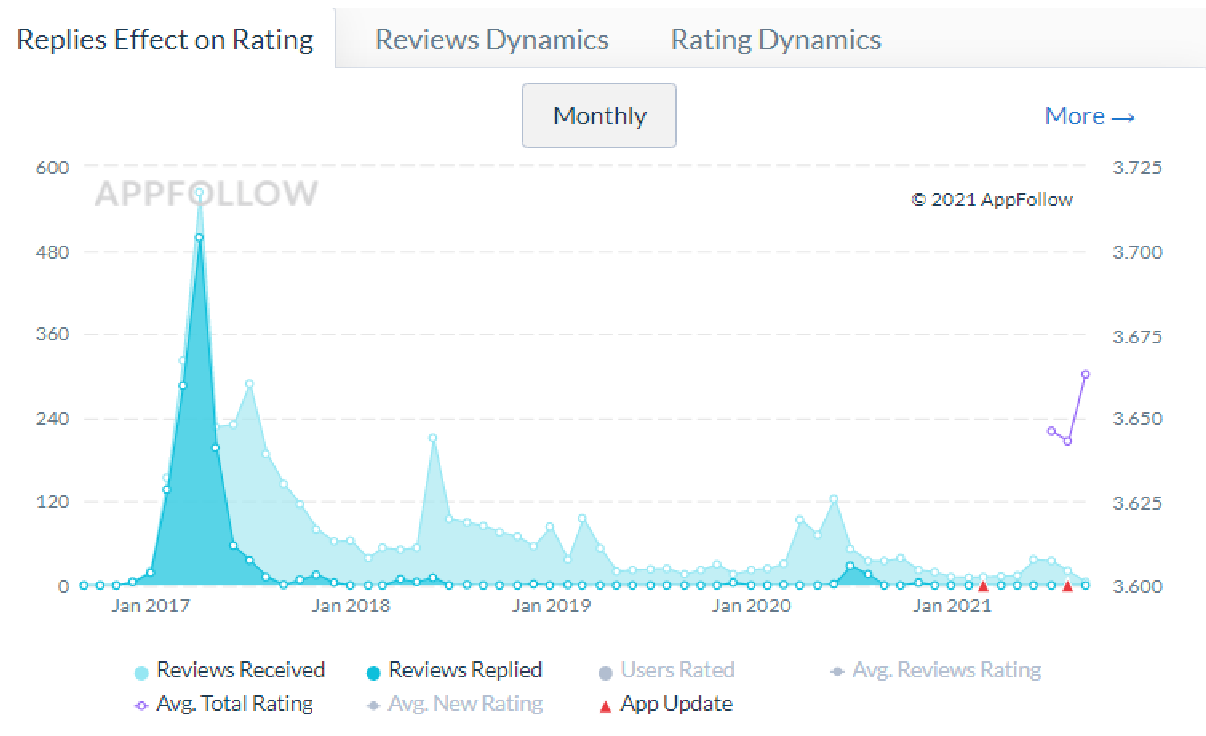

Figure 12: AppFollow Ratings & Reviews

Source :AppFollow

The above figure shows Replies Effects on Rating. It shows Reviews Received with light blue coloured circles, Reviews Replied with dark blue coloured circles and App Update with red coloured triangles.

Rating and Review of Google Public data

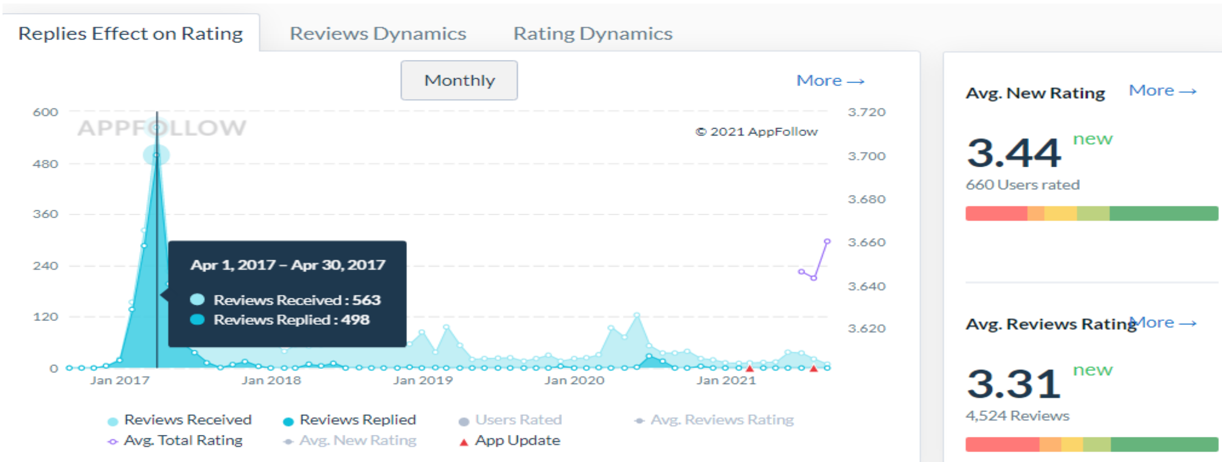

Figure 13: Replies Effects on Rating

Above figure shows the different dynamics with different colours. It also shows rise and decline with the help of certain peaks. The Peak was highest from April 1 to 30 March.

Reviews Dynamics

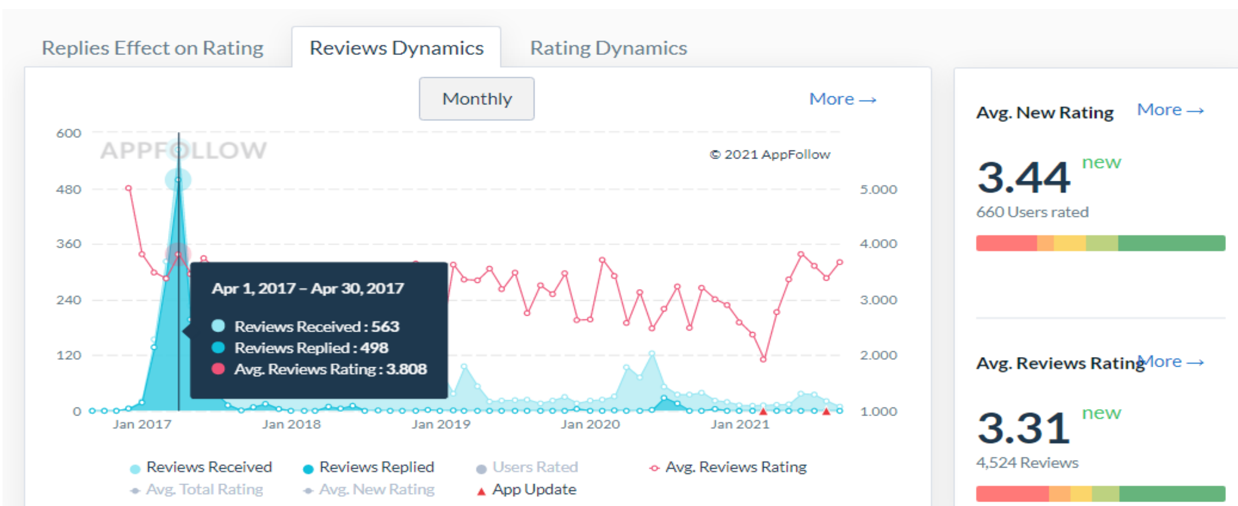

Figure 14: Using the "Review Dynamics" feature shows different dynamics of AppFollow as shown.

Figure 15: Rating Chart after update (Google App Store)

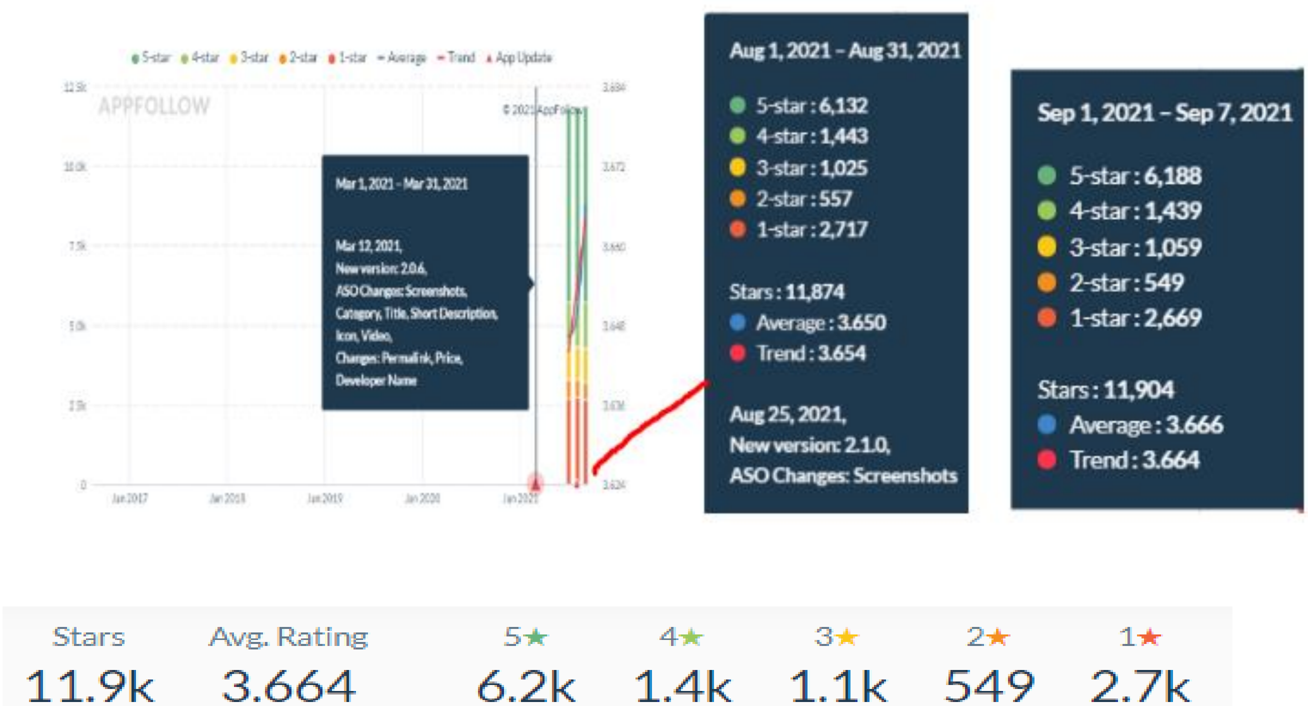

Figure 16: Rating Chart (iOS)

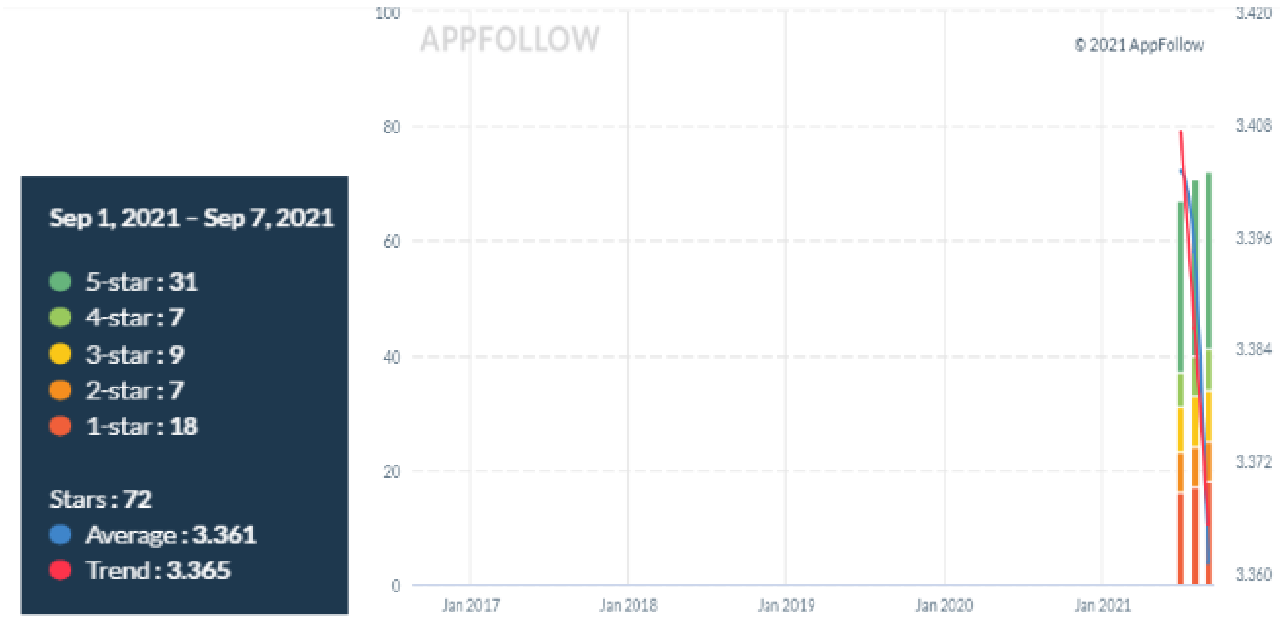

Figure 17: Rating Chart iOS

Figure 18: Google Play Store Reviews

With ratings being seen as key to the success of apps, it is important to understand the concerns and issues that lead users to most commonly complain or leave poor reviews. The above figures show the Rating chart of each Google play store and iOS version and then fed them into AppBot's sentiment analysis. AppBot data analyses show that the Google App reviews are more positive than iOS App reviews. AppBot provided a dataset composed of 4560 reviews of iOS (33) and Android (4527). It also shows Star Rating, iOS has 72 stars and Google App Store has 11,904 Stars.

Word Cloud

For generating word clouds based on reviews, AppBot provides six types of options to filter review subsets: interesting reviews, popular reviews, critical reviews, trending up reviews, trending down reviews, and new reviews. The Popular tab shows the 10 common words in reviews. This helps to identify the most common themes in app reviews; and the Critical tab is a quick way to identify strong negative sentiments in user reviews. This can help isolate bugs and crashes, enabling locating and fixing problems in the app faster. In Figure 19, words in a word cloud are coloured according to their sentiments in reviews. AppBot provides four types of sentiments: positive (green labels in the word cloud), negative (red), neutral (grey), and mixed (orange). Reviews related to a specific term can be listed by clicking on a particular word appearing in the word-cloud which provides a lot of insight including word sentiments. User sentiments are displayed visually with colour indications, each colour representing a sentiment type, the red being negative and green being positive sentiments.

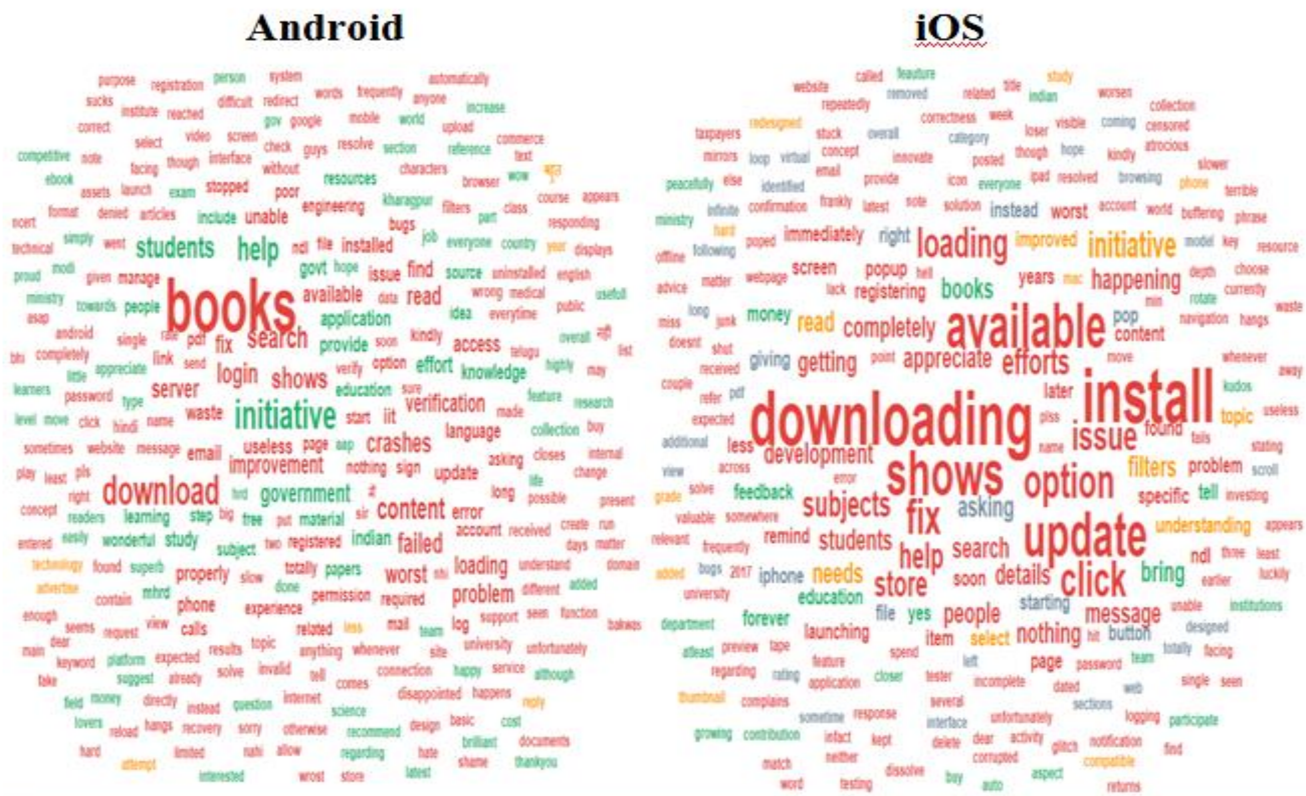

Figure 19: Word cloud of Google play and Apple iOS

Source: AppBot

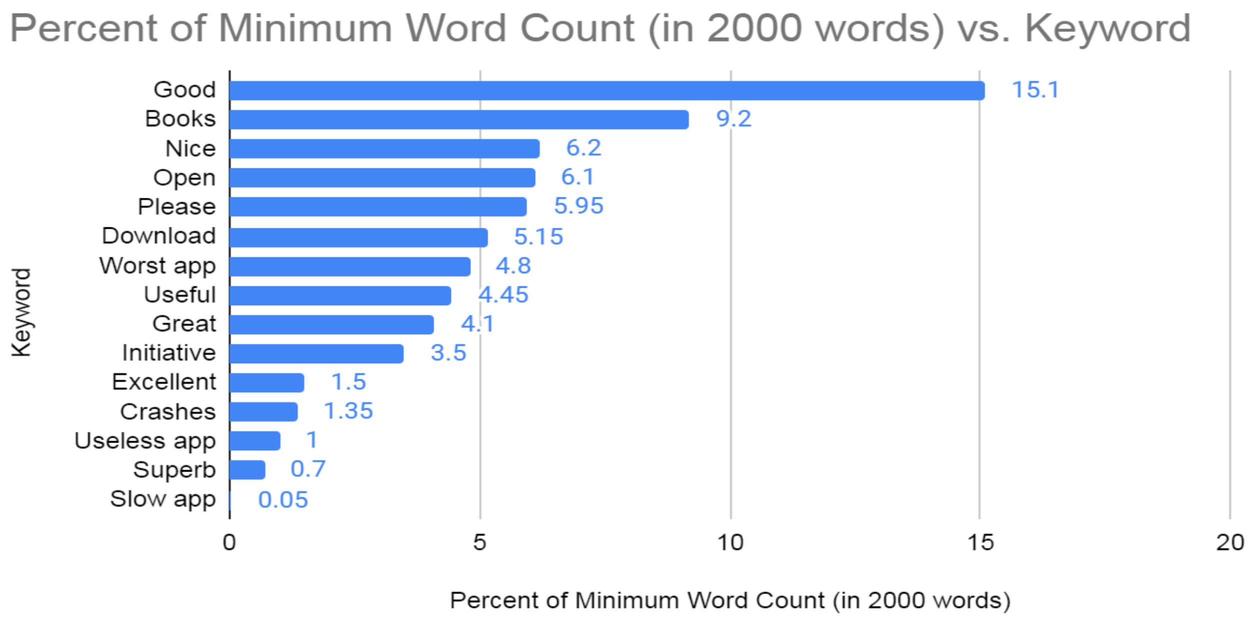

Figure 20: Percentage of minimum word count

This figure shows the most popular words used in reviews posted by users by order of occurrence.

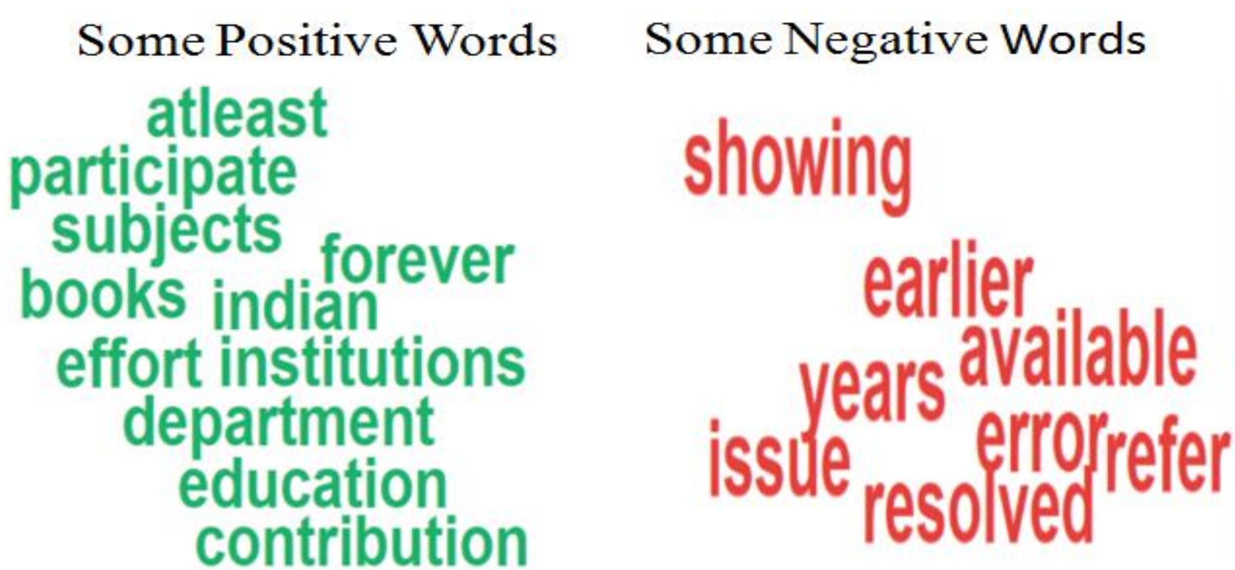

Figure 21: Positive words and Negative Words

Source: AppBot

It can be inferred from above figure that certain issues have varying degrees of sentiment (positive or negative) in different apps. Topics are ordered by the number of 'mentions' (occurrence) in reviews. For example, with the NHS app, 'design & UX' was widely discussed in negative sentiments by the users. A valuable feature of AppBot is that it groups the topics under similar groupings, for example, topics such as 'satisfied users', 'bugs', and design & UX.

More data in one snapshot

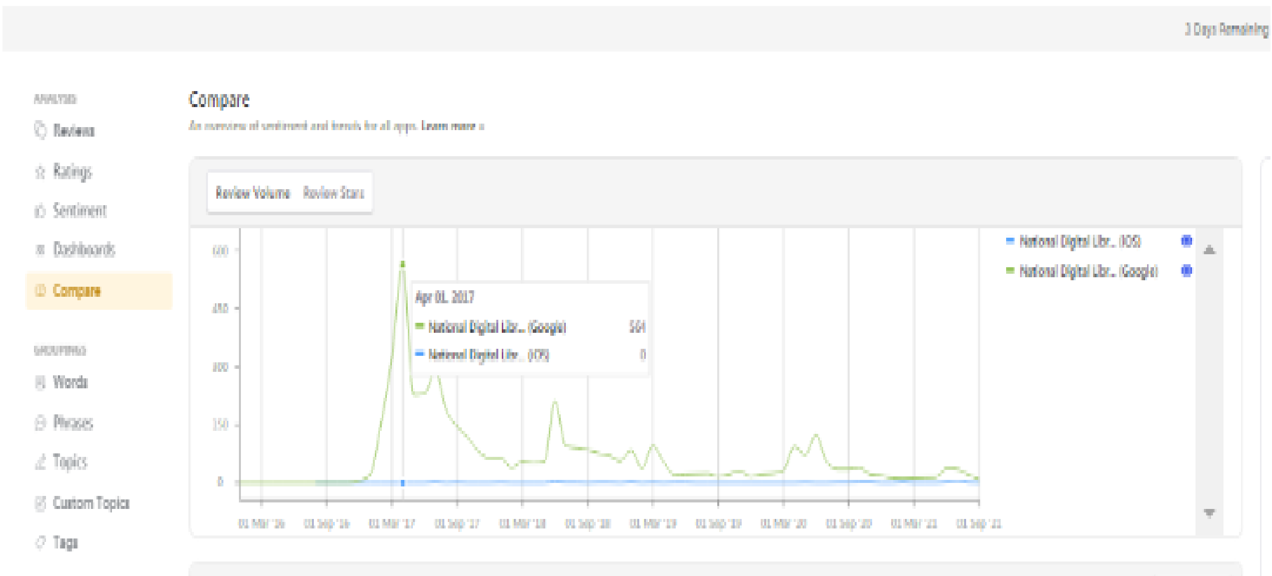

Figure 22: Comparison of Google play store and iOS (Source: AppBot)

Overall Sentiment

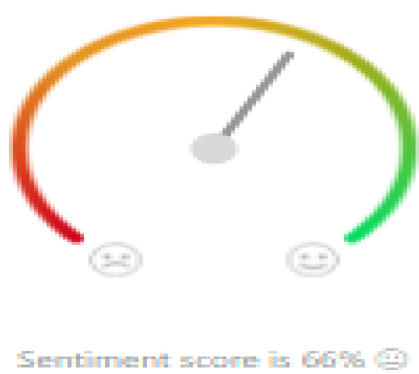

Figure 23: Sentiment Score

AppBot calculates and provides a sentiment score of each review (a value between 0-100%)

Major findings

NDLI is largely used by android users as compared to iOS. AppBot and Appfollow software were used to extract the data and to discover the emotions, feelings, sentiments of the users and sentiment analyse is applied to get the results of the study. Data collected with the AppBot tool revealed that Android users give more positive reviews as compared to iOS. Looking at all ratings, including those without a review, for Android, 43.9 % of the ratings were 5-star ratings and 29.40 % were 1-star ratings. The average was 3.3 stars. For iOS, 21.2 % of the ratings were 5-star ratings and 45.45 % were 1-star ratings. The average was 2.5 stars. NDLI iOS has received 33 reviews and the android app has received 4527 reviews, as of 7th Sept 2021. The development team of the NDLI app needs to be proactive in replying to user reviews. 1987 reviewers show positive feedback for the Android version as compared to just 7 reviewers for the iOS version and the average rating shows a negative trend in iOS than Android with 2.5 and 3.3 ratings respectively. This study proposes a sentiment-Statistical approach for detecting abnormal days during mobile app maintenance. It is observed that negative sentiment increases sharply in a particular period. The result shows that potential updates of the Android app brought up positive changes in the app reviews. AppBot calculates and provides a sentiment score of each review (value ranging between 0-100%). The overall sentiment score is 66%.

Conclusion:

NDLI serves as an all-digital library that stores information about different types of digital content including books, articles, videos, audio, thesis, and other educational materials relevant for users from varying educational levels and capabilities. It provides a single-window search facility so that learners can retrieve the right resources with the least effort in minimum time. NDLI is designed to hold the content of any language and provide interface support for the leading vernacular languages. It is available on all popular forms of access devices including mobile apps on Android and iOS platforms. End-users widely use mobile apps and give feedback in the form of reviews; hence, the need to infer how to utilize this feedback for further improvements. This act would help identify and derive substantial insights that can positively influence app maintenance and evolution. Online app stores are promoting and supporting a more dynamic way of distributing the software directly to users with mobile apps, where releases are managed through online app stores, such as the Apple App Store, Google Play Market, or Windows Phone App Store. The pressure for continuous delivery of apps is a constant in the mobile economy, in which users are demanding new and better features from the apps, and the ratings/reviews provided by the users are a strong mechanism to promote the apps in the market. Consequently, by analyzing ratings and reviews, development teams are encouraged to improve their apps, for example by fixing bugs or by adding commonly requested features. In this paper, sentiment analysis of users' reviews on the NDLI mobile application (iOS and Android) was undertaken on a dataset composed of 4560 reviews (iOS =33; Android =4527). The method was based on the analysis of text reviews, sentiment distribution, and the similarities between update description and review texts. The study findings will support future research on the topic. The results from this study are significant for learning apps development and maintenance to improve user satisfaction.

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Terminologies:

1. Machine learning: Machine learning is a form of artificial intelligence that uses and studies computer algorithms that improve and adapt automatically through analysis and identification of data patterns.
2. Natural language processing (NLP): Natural language processing (NLP) is the computer science application of artificial intelligence to train computers to understand the nuances of human communication through speech and written language.
3. Opinion mining: Opinion mining is an alternate name for sentiment analysis.
4. Polarity: In the field of sentiment analysis, polarity is the positive or negative value given to quantify the sentiment in the text being analysed.
5. Sentiment library: Sentiment libraries are lengthy lists (or lexicons) of specific adjectives (such as terrific, awful, good, bad) and phrases (such as great food, horrible service, fantastic product, dreadful show) that have been identified and manually scored positively or negatively by human coders.
6. Text analytics: Text analytics is the process of transforming written qualitative information into quantitative data points that can be measured for statistical analysis.