NIGHT OUT

Project ID: 2023-379

Final Report

K.H.N.D. Dharmapala

BSc Special (Hons) - Information Technology

(Specialization in Information Technology)

Department of Information Technology

Sri Lanka Institute of Information Technology

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DECLARATION OF THE CANDIDATE AND SUPERVISOR

We declare that this is our work, and this project proposal does not incorporate without acknowledgment any material previously submitted for a Degree or Diploma in any other University or institute of higher learning, and to the best of our knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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The above candidates are carrying out research for the undergraduate dissertation under my supervision.

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ABSTRACT

One issue currently confronting user rating and evaluation on social media profiles is a lack of transparency and objectivity in the rating process. Too often, ratings are based on personal prejudices or preferences rather than objective criteria. Social media profiles often receive inaccurate evaluations, which can have detrimental consequences for both their owners and those who rely on these ratings. Another challenge to overcome is the difficulty in real-time processing of massive volumes of social media data. With millions of social media profiles and posts made every day, keeping up with the sheer volume of data may be difficult. This may result in missed opportunities, ineffective engagement techniques, and overall bad social media performance.

Additionally, traditional methods of evaluating and rating users cannot keep up with the growing demand for profile analysis and evaluation, potentially decreasing their effectiveness. This system strives to address the difficulties associated with a rating and evaluating social media profiles by offering an objective, informative evaluation that is data-driven. Utilizing advanced machine learning algorithms and artificial intelligence, our system can process vast amounts of profile data quickly, providing accurate assessments of social media profiles. Users have complete control over which evaluation criteria should be applied - thus solving several major challenges associated with rating and analysing social media profiles.

The proposed system is an invaluable asset for social media marketers, influencers, and businesses looking to assess social media profiles and make informed decisions about their strategy. It provides a transparent and objective evaluation of profiles on various platforms, helping users identify high-performing accounts, recognize trends, and make data-driven decisions. Moreover, this scalable platform can evaluate millions of profiles in real-time - perfect for large-scale campaigns on social media.

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to all those who have contributed to the realization of this research and the completion of this dissertation. First and foremost, I am deeply thankful to my academic advisor Dr. Amitha Caldera for their unwavering support, invaluable guidance, and endless patience throughout this research journey. Their expertise and mentorship have been instrumental in shaping this work.

I am also indebted to the faculty and staff of Sri Lanka Institute of Information Technology for providing a conducive academic environment and the necessary resources to undertake this research. I extend my appreciation to my family for their constant encouragement and understanding during the demanding phases of this endeavor. Their belief in my capabilities has been a driving force behind my perseverance. My gratitude goes out to my friends and fellow students for their camaraderie, discussions, and shared insights, which have enriched this research.

This dissertation stands as a collaborative effort, and your support has been indispensable. Thank you all for your contributions, encouragement, and belief in the importance of this work.

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1. INTRODUCTION

Our proposed system is developed as a Social media platform

Therefore, all the components are developed according to the mobile app.

1.1 Night out hybrid event management/social app

Today's digital world means events no longer have to take place in physical locations. Social media platforms allow them to connect with people around the globe, giving them a global audience and enabling them to collaborate globally. Social media platforms are becoming more frequently utilized by event planners for promotion, engagement with attendees, and immersive experiences. But managing events and social media can be a challenging task that takes a lot of time and requires lots of energy. Event managers now have access to a hybrid system that unifies event management and social media platform capabilities. This hybrid utilizes AI, machine learning, as well as other advanced technologies to simplify event planning while increasing engagement on social media channels. Event planners can now craft highly engaging events that bring attendees closer together while reaching an even wider audience through various social media channels.

The system's analytical capabilities are one of its main benefits. Data analytics tools enable event planners to collect information from multiple sources such as ticket sales, social media posts and attendee feedback to make data-driven decisions. With this app, event managers can analyze attendees' reviews to identify areas for improvement at events like venue layout or food quality; these insights could then be applied towards improving future events' experiences. In addition, real-time reporting, trend analysis and data visualization allow for easy monitoring of progress throughout an event while making data-driven choices which ultimately boost its success.

Al-driven features of the app include personalized recommendations and real-time data analysis. Event planners now have powerful tools to create memorable events while gaining invaluable insights into attendees' behavior and preferences.

Night Out App's analytics features are an invaluable asset for event planners. With data analytics, automation and integration capabilities, this app can be utilized to plan successful events of any size - from small corporate affairs to large conferences - allowing event managers to stay ahead of competition regardless of event size or number of attendees. Event management is rapidly becoming a rapidly evolving industry with event organizers looking for ways to streamline processes, engage attendees more effectively and create memorable experiences - especially thanks to Artificial Intelligence technology.

Social Media Networks and Platforms

Social media has become a great essential among people in the past two decades. Social media users have grown tremendously and still increasing to date. There are 4.88 billion people using the internet currently and more than two-thirds of them are using social media and one in three people if we consider all internet users and non-internet users [1]. That proves how important social media is to people these days.

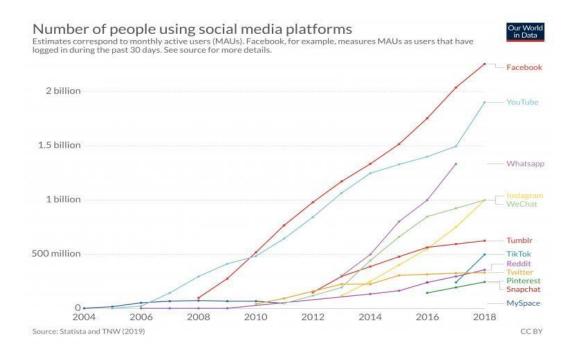


Figure 1.1: The rise of social media

Source: Statista and TNW (2019)

Andrew Weinreichian established the first-ever social media platform in 1996, named "Six Degrees" [2]. Basic social networking capabilities were user profiles, friend lists to connect with friends, and schools which affiliates. Despite the fact that the site had millions of registered users, the service's networks were limited due to a lack of internet users. Youth Stream Media Networks purchased the site in 2000.

Myspace was the first well-known social networking platform, having launched in 2003 [2]. In 2004, it reached a million monthly active users. Brad Greenspan, Josh Berman, Chris DE Wolfe and Tom Anderson founded it. In 2006, it surpassed Google as the most popular website, and in 2007, it was valued at \$12 billion. After Facebook's entry into the market in 2008, Myspace was unable to reclaim its brand supremacy and sold the site to the advertising firm Specific Media.

Since then, social media has grown rapidly. The most popular social media platform at present is

Facebook which was created in 2008 by Mark Zuckerberg, Dustin Moskovitz, Eduardo Savarin, Andrew McCollum, and Chris Hughes has over 2.91 billion active users [3]. This social media platform is currently owned by a company named "Meta" and has the assets of 169.585 billion USD as in September 2021. The second most popular social media platform is YouTube owned by

Alphabet which has 2.29 billion active users, and the third most popular social media platform is WhatsApp owned by Meta company which has 2.0 billion active users [3].

Table 1.1: Most popular social media platforms

Rank	Platform Name	Parent Company	Country	Monthly Active	
				Users	
1	Facebook	Meta	United States	2910 million	
2	YouTube	Alphabet	United States	2291 million	
3	WhatsApp	Meta	United States	2000 million	
4	Messenger	Meta	United States	1300 million	
5	Instagram	stagram Meta United States 12		1287 million	
6	WeChat	Ten cent	China	1225 million	
7	Kuaishou	Kuaishou	China	1000 million	
8	TikTok	Byte dance	China	1000 million	
9	Telegram	Telegram	United Arab	600 million	
			Emirates		
10	Qzone	Ten cent	China	600 million	

Source: [3]

Nowadays social media is not only used to communicate and meet new people, which was the core intention of social media, but it is also used to share media, blogging, e-shopping, and much more. According to type, social media can be divided into a few categories [4],

1. Type 01 - Social Networks

Ex: LinkedIn, Facebook, Twitter

2. Type 02 - Media Sharing Networks

Ex: Snapchat, YouTube, Instagram

3. Type 03 - Discussion Forums

Ex: Reddit, Digg, Quora

4. Type 04 - Bookmarking and Content Curation Networks

Ex: Flipboard, Pinterest

5. Type 05 - Consumer Review Networks Ex: TripAdvisor, Yelp, Zomato

6. Type 06 - Blogging and Publishing Networks Ex: Tumblr, WordPress, Medium

7. Type 07 - Social Shopping Networks Ex: Polyvore, Fancy, Etsy

8. Type 08 - Interest-Based Networks

Ex: Goodreads, Last.fm, Houzz

Our proposed system is a hybrid between social networks and event management system since it has both features found in both social media network types. It has specific features which any other social media platform never had before which includes sub-systems of user evaluation system, user navigation system and a user recommending system

.1 Background Survey

To identify the main problems and issues within the domain, and to get an overall idea about the domain such as to whom we provide this solution and how the problems diverse, we conducted a google form and 378 people have responded.

1. User Age

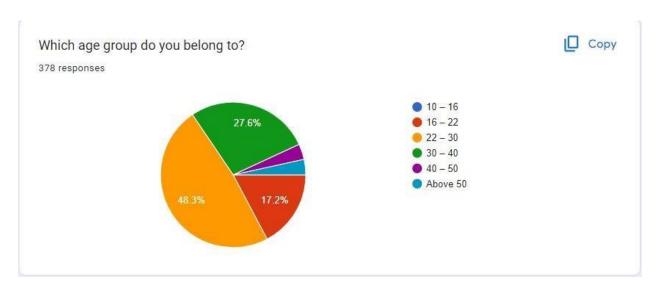


Figure 1.2: Age groups of the users

Out of the sample of 378, 48.3% of the people have responded that they are between 22-30 years which means most of the participants were younger crowd. The second and the third age groups were to respond is 30-40 and 16-22 which are adjacent to th2 22-30 group. From the result, we can assume the users will be mainly 22-30 years of age.

2. User Gender

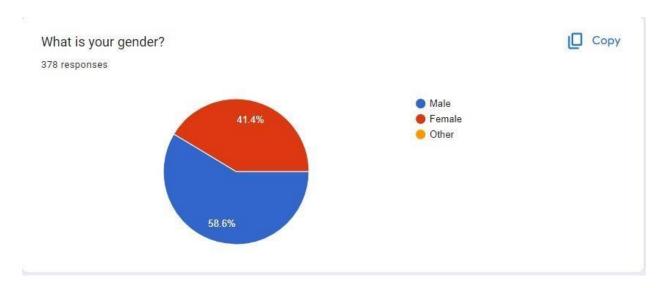


Figure 1.3: User Gender

Out of the 378 responses received, 58.6% of the participants identify them as male and the rest is identified as female. This information is essential when considering the human computer interaction aspects of the app. App color themes and the user friendliness highly depends on the user gender and the age group.

3. User Type

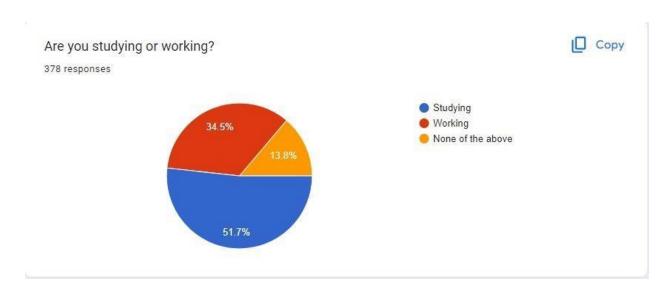


Figure 1.4: User Type

According to the survey, 51.7% of people have responded that they are studying and 34.5% of them are working and 13.8% of them are not working nor studying respectively. This information is really helpful when deciding what type of events to hold via the app and what kind of events that should be prioritized.

4. Usage of social media platforms to get notified about an event

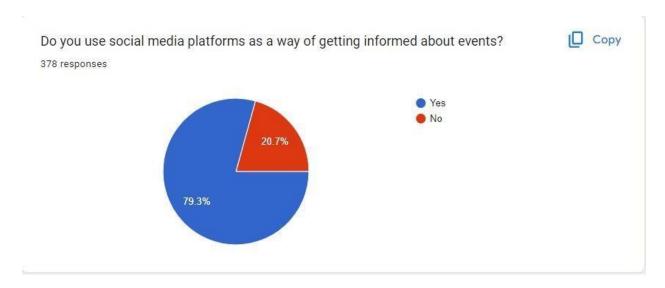


Figure 1.5: Usage of social media platforms to get notified about an event

The majority of the participants, if not 79.3% of the participants responded positive to social media platforms as a way of getting informed about events. Only 20.7% of the participants are not using social media as a way of getting informed about events. To the people who currently use social media as a way of getting informed about events can have more improved benefits from this app while the others can get introduced to the app and start enjoying benefits of the app.

1. Likeliness to attend to an online hosted event.

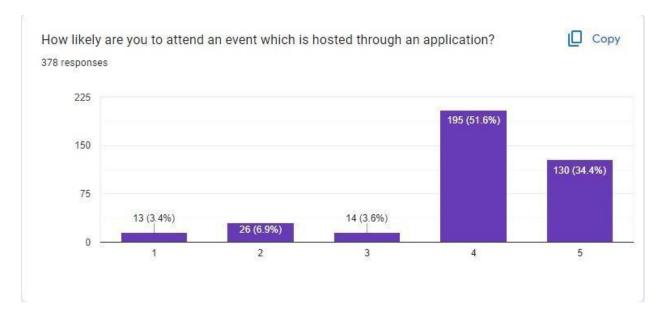


Figure 1.6: Likeliness to attend to an online hosted event.

Even if the events are hosted through an application, it is not effective if the users are not attending the suggested events. Currently, 51.6% of participants rated 4 which means 80% likeliness in attending events hosted trough applications. Our goal is to get this numbers up and make most of the people participate events suggested by the application.

1. Use of the application

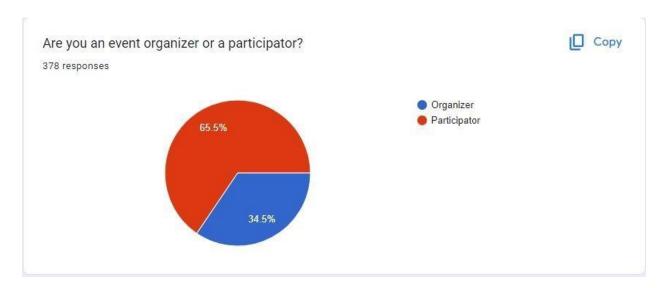


Figure 1.7: Use of the application

There are two types of users to this type of application.

- 1. Organizers
- 2. Participants

Organizers are treated in a special way in order to optimize their businesses through the data and analysis provided by the application while participants can get suggestions according to their preferences. With this data, we can get a basic idea of the ratio of organizers to participants.

2. Preferred event type

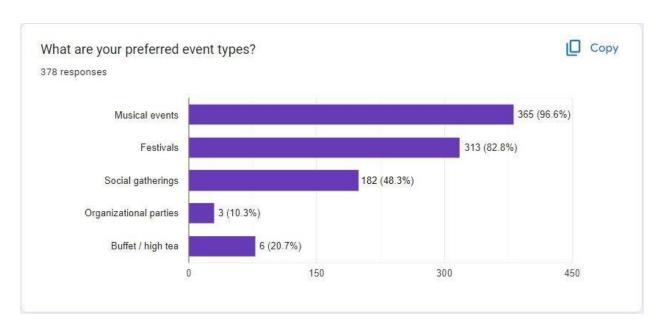


Figure 1.8: What are your preferred event types

According to the survey results, the most popular event type is musical events, which 96.6% would agree. However, the results can vary depending on the age, gender and the users' preferences. Apart from the musical events, festivals, social gatherings, buffet / high tea events and organizational parties are the next most popular events.

3. Expectations from a community

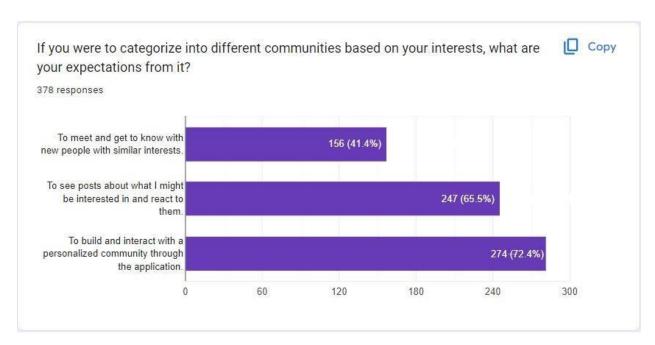


Figure 1.9: Expectations from community

Another main thing to consider is what are the expectations of the application. 72.4% of the participants have responded that they want to build and interact with a personalized community through the application. 65.4% of the participants have responded tat they want to see posts about what they might be interested in and react to them. 41.4% of the participants have responded that they want to meet and get to know new people with similar interests.

.2 Literature Survey

In this literature survey, we will assess some of the recent research and developments in this field.

One area where Al-based user evaluation and rating systems have been applied is online education platforms. According to Huang et al (2020), an Al-based evaluation system was created that provided personalized feedback to students based on their performance in online courses. The system employed machine learning algorithms to analyze student data, including their performance on quizzes, assignments and exams. After doing this, each student received personalized feedback outlining areas where they excelled and needed improvement. Another area where Al-based user evaluation and rating systems have been employed is on e-commerce websites. According to Tian et al. (2019), an Al-driven product evaluation system was created in order for consumers to make more informed purchasing decisions. The system employed natural language processing (NLP) techniques to analyze user reviews and assign a rating for each product based on its features and user feedback. Furthermore, personalized recommendations were given to users based on their past purchases and browsing history.

In the world of social media, Al-driven user evaluation and rating systems have been created to analyze user behavior and offer tailored recommendations for content. According to Zhang et al.'s study, these systems allow for personalized recommendations based on user evaluation data. (2021), an Al-powered system was created to analyze user behavior on social media platforms and offer personalized content recommendations. This system used machine learning algorithms to examine user data such as their browsing history, likes, and shares. The system then provided personalized content recommendations to each user based on their interests and preferences. Al-driven user evaluation and rating systems have also been applied in healthcare; for instance, Xu et al. conducted a study that explored this phenomenon. (2020), an Al-powered system was created to evaluate physician performance

and offer feedback for improvement. The system utilized machine learning algorithms to examine patient data such as medical history, treatment outcomes, and satisfaction levels. Afterward, each physician received personalized feedback highlighting areas where they excelled and needed improvement.

Liu et al. (2020) developed an Al-driven product evaluation system that used sentiment analysis and deep learning techniques to extract user opinions and sentiments from online reviews. Their system provided accurate ratings and evaluations based on user feedback, outperforming traditional methods by a wide margin.

Zhang et al (2021) developed an Al-driven restaurant recommendation system that utilized collaborative filtering and neural network models to provide personalized recommendations based on user preferences and behavior. This system proved to be superior to traditional recommendation systems in terms of accuracy and user satisfaction. In e-commerce, Chen et al. developed an AI-based system based on machine learning which outperformed traditional recommendation systems with regards to accuracy and user satisfaction scores. (2019) used a hybrid model of deep learning and clustering algorithms to provide personalized product recommendations based on user behavior and preferences. The system was found to significantly enhance both user satisfaction and sales revenue. Al-driven user evaluation and rating systems have also been investigated in the healthcare industry, according to a study by Hong et al. (2020) developed an Al-driven system for patient satisfaction evaluation that utilized natural language processing and machine learning techniques to extract patient feedback from online reviews. The results demonstrated that this system provided accurate assessments and recommendations on ways to enhance patient satisfaction. E-Commerce: In 2019, Kim et al. proposed a hybrid approach combining sentiment analysis and deep learning to generate more accurate product reviews. The study found that this hybrid approach outperformed traditional sentiment analysis techniques and increased customer satisfaction levels. Social Media: In a study entitled "Emotion Analysis of User Comments for Political Debates on Twitter" (Mishra et al., 2018), machine learning algorithms were employed to analyze the sentiment and emotion expressed in user comments during political debates on Twitter. Results revealed that users expressed more negative emotions during these debates, which were strongly related to which political party they supported.

Education: In 2018, Alavi et al. conducted a study titled "Intelligent Tutoring Systems: A Comprehensive Survey". This research reviewed various Al-based tutoring systems and assessed their efficiency at improving student performance. The findings demonstrated that these systems can personalize learning experiences for students while increasing their academic success rates. These studies illustrate the potential of Al in providing accurate and personalized user evaluations and ratings across various industries. With the continued advancements in Al technology, more efficient user evaluation and rating systems are expected to emerge. Expert Systems with Applications published a study that proposed an innovative hybrid recommender system, combining collaborative filtering and content-based filtering methods, to increase user evaluation accuracy. The system utilized machine learning algorithms to analyze user data and generate personalized recommendations for them.

Another study published in Information Processing & Management explored the application of sentiment analysis to user evaluation and rating systems. This study demonstrated that sentiment analysis techniques could be effective at analyzing user feedback and providing valuable insights into user opinions and preferences. A study published in ACM Transactions on Intelligent Systems and Technology proposed a personalized rating system that uses machine learning algorithms to anticipate user ratings based on their past ratings and behavior. The system was able to improve user rating accuracy and offer personalized recommendations for individuals. Another study published in the journal Intelligent Information Systems described a collaborative filtering-based user evaluation and rating system that uses social network analysis to identify influential users and incorporate their opinions into the rating process. This improved the accuracy of user ratings as well as provided more personalized recommendations for users.

These studies illustrate the potential of AI-based systems to accurately evaluate and rate user experiences across various domains such as mobile applications, virtual reality environments, and beyond. These systems could offer valuable insights to developers while increasing user satisfaction levels.

.3 Research Gap

Even though all the features of the proposed system could not be found in a one system as a whole in existing systems, there are some existing systems which has the proposed features developed to some extent. Despite they have built to some level, they are not effective as the proposed system.

1. Yelp

Yelp is a well-known online tool that makes it easy to research and rate regional businesses like bars, restaurants, and other services. One of its key features is a collaborative filtering algorithm that examines a variety of user reviews and ratings to suggest suitable businesses based on those reviews and ratings. Collaborative filtering involves perusing patterns in multiple users' behavior to detect establishments that garner similar ratings and reviews. Consequently, personalized recommendations can be offered to users grounded on their past preferences, as well as the tastes of other users who share similar interests. Yelp's collaborative filtering algorithm is continuously evolving, and machine learning techniques are deployed to scrutinize user behavior and optimize the accuracy of its recommendations. Thus, Yelp's collaborative filtering algorithm substantially aids users in unearthing novel businesses and making enlightened decisions regarding where to dine or obtain services.

2. Airbnb

A collaborative online marketplace called Airbnb is devoted to making it easier to rent out rooms anywhere in the world. Airbnb's collaborative filtering algorithm serves as a priceless tool for users to find their ideal stay in a vast marketplace of numerous listings. The algorithm

functions by scrutinizing user patterns, such as bookings, searches, and reviews, to ascertain properties that bear resemblance in terms of location, amenities, and overall quality. Airbnb is now able to offer customized recommendations based on the user's past preferences and the preferences of other users who have similar tendencies as a result of this process. Airbnb's collaborative filtering algorithm is continually improved using machine learning techniques that examine user behavior in an effort to increase the accuracy of its recommendations. Notably, Airbnb provides a complementary feature, labeled "Experiences," that showcases personalized recommendations for an array of activities and tours, augmenting the travel experience. Given the above, Airbnb's collaborative filtering algorithm proves a crucial aid for users seeking to locate the ideal stay and make their travel experience an unparalleled success.

3. TripAdvisor

Trip advisor is a website that enables travelers to online book places to stay, places to eat or even people to share their experience with them. A remarkable feature of the platform is its collaborative filtering algorithm, which makes it easier for users to find excellent options that are specifically catered to their travel preferences. The algorithm operates by analyzing patterns in users' behavioral traits, including previous bookings, searches, and reviews, and discerning the similarities between the properties in terms of geographic location, services, and overall quality. This enables TripAdvisor to dispense bespoke recommendations based on users' past inclinations and the opinions of other individuals who share similar preferences. Additionally, TripAdvisor harnesses the potential of machine learning to improve the accuracy of its recommendations progressively. Besides delivering personalized recommendations, TripAdvisor endows its users with a unique feature called "Things to Do," an assemblage of handpicked recommendations for local activities, tours, and other exceptional experiences. The collaborative filtering algorithm of the site is an indispensable factor that empowers travelers to make informed decisions about their sojourns. By capitalizing on the experiences of other explorers, users can locate the preeminent options that cater to their exigencies and curate memories that will endure a lifetime

4. Goodreads

Goodreads is a impressive social media platform designed for book lovers where users can create personalized profiles, connect with neighbors, and share their opinions and recommendations of the books they have read. This platform's quintessential collaborative filtering algorithm percolates through troves of user behaviors, delving into their literary preferences, evaluating their literary oeuvre, and scrutinizing their ratings and reviews to unearth literary treasures that are akin in terms of genre, author, and overall quality. Goodreads' collaborative filtering mechanism foments personalized recommendations by assimilating users' prior preferences and incorporating the predilections of other book enthusiasts with analogous tastes. Additionally, the platform extends a feature christened "Groups," an enticing invitation to join a group of readers who share their interests, encouraging lively debates, book clubs, and other bibliophilic activities tailored to their favorite genres. Goodreads' collaborative filtering algorithm is a perpetually evolving phenomenon that employs machine learning to augment the accuracy of its recommendations, offering users a superbly personalized experience. In conclusion, Goodreads' collaborative filtering algorithm is an essential part of the system because it aids users in discovering new books and cultivating a global community of readers who share a love of literature.

5. Clubhouse

Clubhouse, a social media platform that is exclusive to invitation, is designed to facilitate live audio conversations on a diverse range of topics. The app leverages the power of collaborative filtering algorithms to discover fresh rooms and discussions that match the user's interests with precision. To make this happen, Clubhouse's collaborative filtering algorithm relies on analyzing the intricate patterns of user behavior, such as the rooms they have joined and the conversations they have engaged in. This allows Clubhouse to identify and present comparable rooms and conversations to other users with similar tastes and inclinations, resulting in a highly personalized and gratifying experience. Moreover,

Clubhouse's ingenious use of "Clubs," a feature that enables users to join communities of like-minded individuals, helps foster a strong sense of belonging and meaningful engagement. Clubhouse users can take part in captivating discussions, events, and other activities that align with their interests, all while being part of a community that they relate to. The dynamic and constantly evolving nature of Clubhouse's collaborative filtering algorithm, which employs advanced machine learning techniques to optimize the accuracy of its recommendations, allows for a more personalized experience that caters to the users' needs and preferences. Clubhouse's own community-building features are also a key contributor to the platform's popularity. Users can host and create their own rooms, invite guests, and facilitate natural and unplanned conversations that may result in networking opportunities. Users can communicate through direct messages during conversations thanks to the app's unique ground-breaking "Backchannel" feature, which gives a sense of community and collaboration.

Overall, Clubhouse offers a remarkable combination of community-building tools and a collaborative filtering algorithm, which distinguishes the platform from other traditional social media sites and contributes to its engaging social media experience.

6. Facebook

Facebook is a virtual arena of social interaction that enables individuals to connect with their social circle, share their ideas and activities, and partake in communities founded on common interests. The collaborative filtering algorithm integrated into the platform's functionality allows users to explore novel content and groups that align with their interests. The algorithm analyses patterns in user behavior, such as their engagement with posts, the pages they have interacted with, and the groups they have joined, to unearth similar content and groups that other users with akin interests would also cherish. This process enables Facebook to offer personalized recommendations to users based on their prior preferences and the preferences of other users who have analogous tastes. Apart from the collaborative filtering and content discovery features, Facebook also offers a verified user program, signified by a distinctive blue checkmark, that authenticates the

identity of public figures, celebrities, and other prominent individuals who boast a sizable following on the platform. This program fosters trust and credibility among users and engenders a sense of community and belonging. Along with these features, Facebook's community-oriented functionalities enable users to create and participate in groups tailored to their shared interests. These groups furnish users with an environment to engage with likeminded individuals and share their experiences, views, and creative outputs. Furthermore, Facebook offers features such as events and marketplaces that extend additional opportunities for community building and involvement. In sum, Facebook's amalgamation of collaborative filtering, verified user program, and community-building features coalesce to create a lively and captivating social media ecosystem.

Feature	Yelp	Airbnb	TripAdvisor	Goodreads	Clubhouse	Facebook	Proposed system
Recommendations based on interest	~	~	~	~	~	~	~
Recommendation based on distance	~	~	~	×	×	~	~
Recommendation based on time	×	~	~	×	×	×	~
Providing feedback	~	~	~	~	~	~	~
Prioritize verified users	~	~	~	×	×	~	~
Building communities based on interests	~	×	×	~	~	~	~
Identifying most valuable users	~	~	~	~	~	~	~

Table 1.2: Proposed system compared to existing systems

The sextet of social networking platforms that we have elucidated upon earlier in this missive, namely Yelp, Airbnb, TripAdvisor, Goodreads, Clubhouse, and Facebook, all serve diverse purposes. Yelp, for instance, is a platform that proffers the means to discover and review local businesses. Conversely, Airbnb is a platform that allows users to find and reserve

distinctive accommodations in any corner of the world. As for TripAdvisor, it is a platform predominantly utilized to discover and evaluate travel-related services and destinations. Goodreads is a website that lets users find and review books. Clubhouse, meanwhile, is a social networking platform that grants users the opportunity to partake in audio discussions or even host them. Facebook lets users to connect with people, join groups, and share content.

In contradistinction to these platforms, a newfangled platform is being postulated which aims to address the issue of feeling alienated and inundated in a novel setting by providing tailored entertainment recommendations that are congruous with the user's predilections and interests. Entertainment seeking apps in the market at present lack the all-important personalized touch, leading to a sense of exasperation and encumbrance in deciding what to do. This can result in individuals not leaving home, not going outside and explore new things, and increasing feelings of isolation and loneliness. The proposed platform, however, endeavors to tackle this by considering the user's preferences and interests, presenting a more personalized solution that is more likely to be efficacious in helping them feel more tethered to their new surroundings.

Moreover, the proposed platform will also assuage the business aspect of the quandary by furnishing businesses with superior statistics and data to enable them to make well-informed decisions regarding investments and promotions. This one-stop-shop approach will render it easier for businesses to make headway and circumvent investing in the wrong areas. This is an essential element of the platform that sets it apart from existing entertainment-seeking applications, which are bereft of providing businesses with this level of support.

To summarize, the proposed platform is poised to obviate the problem of feeling isolated and inundated in a novel environment by providing personalized entertainment

recommendations while also assuaging the business aspect of the quandary through improved statistics and data. This sets it apart from existing social networking platforms that cater to divergent purposes and lack this level of personalization and support for businesses.

.4 Research Problem

This project seeks to understand the effects of feeling isolated and overwhelmed in a new environment. People moving to newCities, countries, or just different surroundings in general may face challenges adjusting to their new life.

Lack of social connections, unfamiliar surroundings and lack of knowledge about a new place can cause feelings of alienation and loneliness which may lead to isolation. This has serious repercussions for an individual's mental health - stress, depression and other related problems.

Existing entertainment finding apps on the market don't offer a personalize solution to this issue. They typically list all available entertainment options without tailoring the information according to individual tastes or needs. Due to this difficult selecting what to do, many people opt for staying home instead. Though this is a priority for our problem, the business end of things remains an issue; applications available on the market that allow businesses to promote their applications do not follow through with this process. As a result, we have come to know that there is no single solution available. No-cost applications that do all the above mentioned often fail, due to not gaining enough traction on a large scale. This has been one of the primary reasons businesses fail due to investing in unproductive areas without access to better statistics or data to guide decisions.

This research's main finding is the existence of a significant barrier that prevents people from successfully forming new social connections when they are forced to relocate to an unfamiliar location without any familiar faces. It can be terrifying to move to a new place, and many individuals endure extreme discomfort and desolation at this time. Disorientation

might prevent the development of deep ties due to unfamiliarity with the new location, its dialect, customs, and cultural norms.

The consequences of such an autonomous living are numerous, as they might generate an extreme sensation of loneliness, prompting one to avoid social interaction, aggravating the difficulties of making relationships. Additionally, the intense anxiety, fear, or sorrow that comes with this circumstance can have a disastrous impact on one's mental health. A lack of social support and the resulting isolation from others can have a negative impact on one's physical health, appearing as sleep difficulties and digestive ailments. Recognizing the complexities of acclimation in a new environment and seeking help from peers may be a powerful antidote to emotions of isolation and overwhelming pressure. Another issue observed is when users register for a socializing app for the first time, it may not be able to provide them with an appropriate choice since it lacks any data about them. New users who need guidance on how to utilize an app and find others with similar interests may find this frustrating. Fortunately, socializing apps have ways of collecting user data over time which allows them to provide more tailored recommendations. In-app surveys, which extract information from users about their hobbies, pastimes, and other pertinent criteria, are one of the most successful methods to do this. The program may employ complex algorithms and machine learning to provide progressively accurate suggestions for the user based on information obtained from social media applications. Therefore, even if they do not get a suggested option when they sign up for the app, users of social networking programs may unwind knowing that their data is being preserved and utilized to enhance the experience over time.

Ratings and feedback received from general users can be unreliable due to bias and user error. To address this, socializing apps can implement a verification system that distinguishes verified users from others. Verified users are individuals whose identity and information have been confirmed by the app through various methods like email verification, phone number verification or manual verification by a human moderator. Verified users are considered more trustworthy by other users and their feedback more useful for them as well.

Socialising apps can enhance user feedback by featuring reviews and recommendations from verified users on an explore page. This page displays ratings, comments, and other pertinent information provided by verified users to help other users discover new connections based on shared interests and preferences. Furthermore, machine learning algorithms may identify common themes and patterns among verified user reviews, providing additional insights that further improve the accuracy and relevance of recommendations. In all, socialising apps that implement a verification system and showcase content from verified users create a more trustworthy and enjoyable experience for all users. Verified user feedback helps other users find connections more likely to be compatible, creating an atmosphere of community within the app.

Socialising app users may miss out on events near them due to limitations in the app's event discovery and recommendation features. This can be frustrating for those searching for local activities to participate in. One possible explanation for this limitation is that the app may not have access to a user's precise location, or its event recommendation algorithm may not take location into account when suggesting events. By leveraging location data and other locationbased services, Socializing applications may enhance their event discovery and recommendation abilities. For example, the app may request location services from users in order to suggest local events. As an alternative, machine learning algorithms might monitor user behavior and preferences and provide recommendations based on both the user's current location and former habits. Social media applications may enhance event finding and recommendation capabilities, keeping users informed of events nearby and introducing them to people who share their interests. Doing so encourages a more engaged community on the app which in turn enhances user experience.

Socializing apps may have difficulty distinguishing events that take place during busiest or quietest periods, depending on user preferences and behavior patterns. Some may prefer busier events with lots of people and activity, while others appreciate quieter occasions with fewer attendees. By analysing user data and event attendance patterns, these applications

can gain valuable insights into users' preferences and determine whether they tend to be more introverted or extroverted in nature. Socialising apps could analyse the frequency and type of events users attend to determine whether they prefer busy or quiet events. They could also track how long people stay at events as well as who they interact with while there. By combining this data with other user behaviours like messaging or profile activity, these applications gain a better insight into users' patterns of behaviour and preferences.

Data can be utilised to tailor event recommendations based on user behaviour and preferences, creating a more engaging and satisfying experience within the app. By offering users tailored event suggestions that mirror their preferences and behaviour patterns, socialising apps create a personalised and enjoyable environment for all users. Socialising apps often rely on usergenerated content, such as reviews and recommendations, to power their event discovery and recommendation features. While having verified users can increase the reliability of this data, it remains susceptible to external influences like sponsorship or conflicts of interest.

For instance, a Verified user may have an affiliation or sponsorship with an event or brand that could influence their review or recommendation. This could result in an incomplete or biased view of the event, potentially misleading other users who rely on that recommendation.

To combat this issue, socialising apps can implement measures such as requiring verified users to disclose any affiliations or sponsorship that could influence their recommendations. Verifying users on socialising apps can increase the trust level of user-generated content, but the app developers must remain transparent about any potential biases or conflicts of interest and use various data sources to ensure recommendations are as correct and helpful as possible. Socialising apps can identify users with similar interests to help users discover events and connect with similar individuals. Unfortunately, once identified, it can be challenging to group them together or facilitate communication among them. One possible solution is creating groups or chat channels based on shared interests. Socializing apps allow

users to create and join groups related to topics, hobbies, or events which facilitate communication among those with similar interests. Another approach is to utilise machine learning algorithms to automatically group users based on their interests and activity within the app. This can help users connect with others who share similar interests without them having to manually join groups or channels.

Overall, while identifying users with similar interests is an essential feature for socializing apps, enabaling communication and interaction among them can strengthen the community and enhance user experience. By enabling users to create groups or using machine learning algorithms to automatically group people together, socializing apps can foster connections and engagement among their user base.

2 OBJECTIVES

.5 Main Objectives

To implement an artificial intelligence based algorithms to overcome the problems associated with traditional user evaluation and rating systems.

The underlying problem with conventional user evaluation and rating systems starts from their bound to bias and manipulation. In multiple cases, users may intentionally provide wrong, Deceitful or misleading information, or they may be influenced by personal prejudices or external factors that are completely detached from the quality or performance of the product or service being assessed. Furthermore, traditional systems have a limited ability to process vast quantities of data and to anticipate intricate patterns or trends that might be relevant to user feedback. In stark contrast, AI has the potential to overcome these barriers by employing sophisticated algorithms and machine learning techniques to examine massive datasets and uncover patterns in user behavior and feedback. We can reduce the risk of bias and manipulation by automatically detecting and flagging suspect activities such as bogus reviews posted by bots or users with a history of questionable behavior.

Furthermore, AI Can assist us in identifying recurring patterns in user feedback that may indicate larger trends or issues, allowing businesses to identify areas for improvement and make data-driven decisions about product development and marketing.

By a large and far, Al-based user evaluation and rating systems hold great promise in furnishing more accurate and trustworthy feedback than any traditional systems, while also affording greater Scalability and Flexibility. Through leveraging the Massive potential of Artificial INtelligence, we can establish systems that are more attuned to user needs and more adept at capturing and dissecting user feedback.

.6 Specific Objectives

1. Implementing a mobile-based application as a hybrid social media and event management platform.

To deliver the solution, a mobile- based application should be design and implemented with a dedicated section to feedbacks and ratings. The application should have registering feature and profile feature in order to obtain the goal.

2. Building a model for recommending events based on the preferences for a chosen user using an algorithm.

Members can select an event. Some people need assistance when choosing the most suitable event to their liking. A model should be built in order to deliver the intended system. From available set of events and locations.

3. Identifying trustworthy feedbacks from users.

It's impossible to trust or judge when it comes to people's opinions, so in order to ensure a trust level on the ratings and comments given by users for a specific post, it is intended to

implement a ML algorithm to identify which user engage with the most accurate data and provide with a score to make the user stand up in feedbacks, rating and in overall system.

3 METHODOLOGY

Night out is a social media platform with 4 components,

- 1. Community Based System
- 2. User behavior analysis
- 3. Socializing process and rating
- 4. Profit maximization

In this proposal, socializing process and rating system is more focused.

The main objective in this system is to implement a socializing platform in order to utilize analyzed user behavior data in a productive manner. To achieve this, a machine learning algorithm is to be used.

To develop the socializing process and rating component, specific implementation tasks are to be followed,

In this system any user can submit their feedback as a rating, since the data
obtained in that way is less trusted, a user is taken as a verified user and their
feedback is shown on a separate explore page as a blog or article.

- Using user behavior and community recommendation components give them to verified user batch through using algorithms (user history, community behavior, feedback). Users can access the relevant events through explore page according to their preferences.
- 3. Explore page prioritize user nearest event or venue and user can see busy times, quiet times for events. Get data from user behavior component and analyze on the explore page to determine if they are more likely to visit a venue that is listed as a top-rated venue by verified users.
- 4. Get data from user behavior and community recommendation components analyze, most visit places and create algorithms about where to go next, it there are two users with same result they socialized. like one user suggest by another user, so they can build up their community.
- 5. Chat platforms for Users. Users can access an event through the explore page and then access a chat room on dashboard. The event will show everyone who is logged in at that time and users can socialize(chat) with anyone they like. Three options have been given for the users for privacy. After logging in, they can select one of Active, don't disturb or invisible and stay in the chat room. In that chat room, users can chat in their preferred language and the chat will be translated into the language they enter.
- 6. In research part event management or owners can research user engagement through explore page and can measure the change in the number of users visiting a particular venue after it receives a high rating from a verified user.

To carry out the project, iterative waterfall model is proposed. The model has 6 phases to it. As the name suggests, the 6 phases are iterative which means some phases would have to undertake continuously and the phases can be overlapped. The process will continue until we get expected and satisfactory results.

The six phases of iterative waterfall model,

- 1. Phase 01 Requirement Gathering and Feasibility Studying
- 2. Phase 02 Analysis
- 3. Phase 03 Design
- 4. Phase 04 Implementation
- 5. Phase 05 Testing
- 6. Phase 06 Maintenance

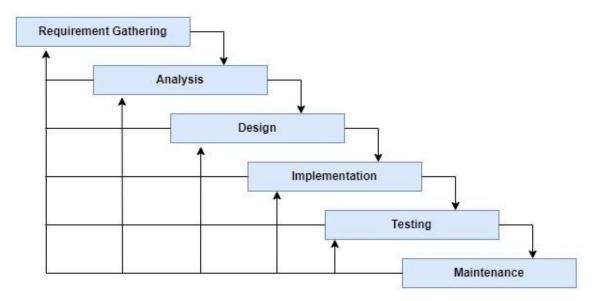


Figure 0.1: Iterative waterfall model

.7 Requirement Gathering and Feasibility Studying

the requirements are gathered at two levels

- 01. Primary data gathering
- 02. Secondary data gathering

In primary data gathering, we mainly focused on user requirements. We conducted a background survey through google forms to identify user requirements and results are shown below.

What do you think as requirements in a social media platform?

49 responses

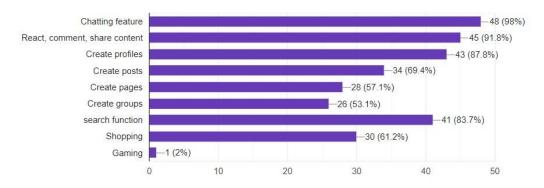


Figure 0.2: Requirements in a social media platform

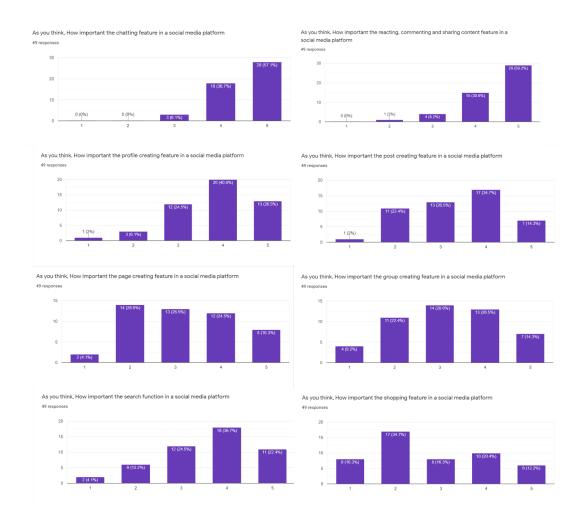


Figure 0.3: Survey participants' ratings on each social media platform requirement

In addition to the questionnaire,

- we acquired data from event planners and consultants and gathered requirements.
- Contacted with an IT consultant and gathered information.

In secondary data gathering,

- We studied existing systems
- We studied from various online resources such as online tutorials and web articles.
- We also gathered information from books and articles.

After performing requirement gathering, we performed a feasibility study,

1. Technical Feasibility

To successfully complete the research, all the team members should have the technical knowledge to proceed with the project. We made sure that we can acquire the required knowledge in order to complete the project addition to we already acquired knowledge.

2. Economic Feasibility

Financial resources are very important when we conduct the project. We made sure we have enough funds in order to complete project without having to stop half the way. We also made sure to plan handling unforeseen financial needs in the future.

3. Legal Feasibility

Not meeting legal feasibility is when a project runs afoul of legal restrictions such as zoning rules, data privacy laws, or social media laws. We made sure there are no conflicts with laws in our proposed system.

4. Operational Feasibility

This involves to what extent the project can be completed to meet the needs of the company. We had a discussion with Underground Music Coven members and made sure we are feasible in operational feasibility.

5. Scheduling Feasibility

Scheduling Feasibility means if a project can be completed and delivered in defined time. In our case, it is 1 year. We made sure the project is deliverable in the defined time period.

.8 Analyzing

By analyzing the gathered data, we categorized collected requirements as follows,

.8.1 Functional Requirements

- User should be able to give feedbacks of the events.
- Verified users should be selected.
- Explore page should be created.
- User should be suggested events that user might be interested.
- User should be suggested nearest events and places to the current location.
- User should be suggested events according to preferred times (busy times or quite times)
- Most valuable users should be identified.
- Communities should be created considering similar interests of the users.
- Data from the database must be retrievable.
- Data from the user must be obtainable.

.8.2 Non-Functional Requirements

- Security
- Availability
- Usability
- Reliability
- Compatibility

.8.3 User Requirements

- User must be able to create a user profile.
- User must be able to verify themselves in the platform.
- User must be able to login to the system.
- User must be able to provide feedback of the events the attended.

- User must be able to get suggestions of similar events.
- User must be able to join a community of their interests.
- User must be able to view events they might be interested in
- User must be able to view events near to their current location.
- User must be able to view events according to preferred times.

.8.4 System Requirements

O Software Requirements

Tools and
Technologies ©
PyCharm IDE ©
PhpStorm IDE ©
Android Studio
© MySQL
database ©
Python © JAVA

○ React JS ○ Git

O Hardware Requirements

Android 7.0 or higher
 version
 RAM 3GB or
 higher
 A Stable internet
 connection

.9 Design

To continue with the design phase, we came up with a system architecture diagram to summarize everything we must do.

We hope to start design phase by wireframing each interface of the web application. This will

be done using Balsamiq Mockups software. After Designing the wireframes, we hope to conduct usability test using paper prototypes and identify problems further considering user's perspective. This will be more efficient and effective in advance of the implementation step because it saves time and effort otherwise, until the user acceptance testing in the testing phase, there will not be an interpretation of the actual end user of the system. This step will reduce the chance of failing the user acceptance test.

Then we hope to design the whole structure of the system starting from identifying attributes and designing the database and continue towards designing the hardware solution as well as the software solution.

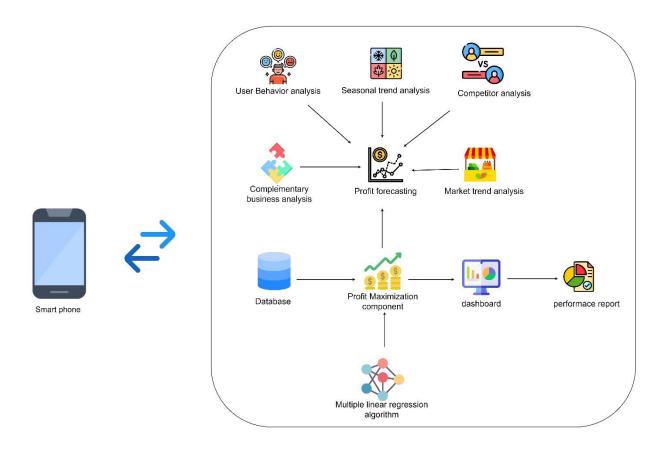


Figure 0.4: High level system architecture diagram for proposed component

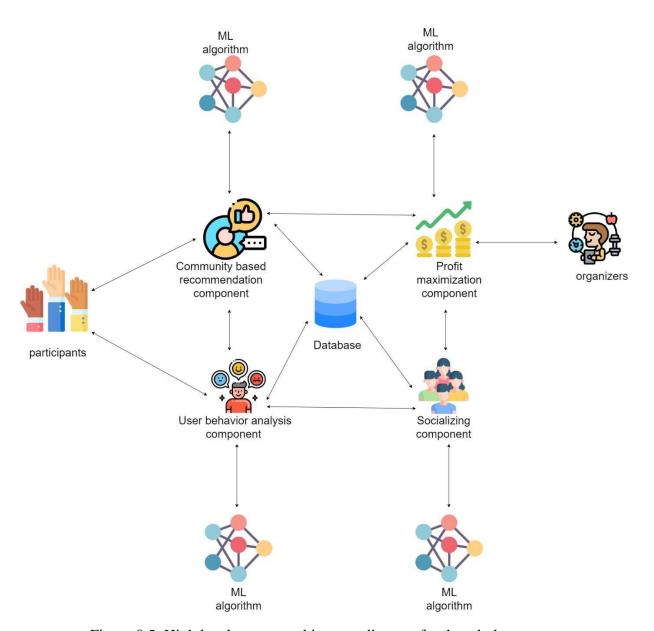


Figure 0.5: High level system architecture diagram for the whole system

.10 Implementation

In this phase, the whole procedure which was conducted up to now can be changed due to various reasons. If something changes, according to iterative waterfall method, the process can be repetitive.

In order to develop the research component, a collaborative recommendation system is used.

Collaborative filtering is increasingly utilized in recommendation systems. Collaborative filtering works by finding the opinions and behaviors of a large group of people to present personalized recommendations to a single person. This clever approach entails identifying similarities between the individual's tastes and those of other people who share similar preferences. Following that, recommendations are made based on the preferences of those people who have similar tastes.

A breakdown of the Naïve Bayes and Collaborative Filtering algorithms

• Implementation of a Naive Bayes Classifier for Verified User Identification

In this section, we present the implementation of a machine learning model, specifically the Naive Bayes classifier, to address the critical task of identifying verified users within a digital platform. This endeavor is based on an essential facet of data-driven decision-making, wherein user behavior data is harnessed to distinguish verified users from the broader user base.

```
dataset = pd.read_csv('behavior.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, -1].values
"""## Splitting the dataset into the Training set and Test set"""
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
"""## Feature Scaling"""
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Figure 3.6: Naïve Bayes algorithm I.

Model Training: Naive Bayes

The core of this implementation lies in the training of a Naive Bayes classifier, specifically the 'GaussianNB' variant. Naive Bayes is a probabilistic machine learning algorithm known for its effectiveness in classification tasks, particularly in scenarios where attributes are assumed to be conditionally independent, as is the case here.

```
"""## Training the Naive Bayes model on the Training set"""

from sklearn.naive_bayes import GaussianNB

classifier = GaussianNB()

classifier.fit(X_train, y_train)
```

Figure 3.7: Naïve Bayes algorithm II

Predictive Analysis

Once the model is trained on the training dataset, it is ready to make predictions. In this context, a sample user behavior vector is provided for prediction. This vector represents a set of user behavioral attributes, and the model predicts whether the user associated with this behavior is verified or not.

```
print(classifier.predict(sc.transform([[12750,5666,22026,14859,7588]])))
```

Figure 3.8: Naïve Bayes algorithm III

Performance Evaluation: Confusion Matrix

To assess the model's accuracy and effectiveness, a confusion matrix is generated by comparing the predicted values to the actual values in the test dataset. The 'accuracy_score' function from 'sklearn.metrics' is employed to calculate the accuracy of the model's predictions.

Figure 3.9: Naïve Bayes algorithm IV

User and Post Recommendation Using Collaborative Filtering

In this section, we delve into the implementation of a recommendation system that leverages Collaborative Filtering, a widely used technique in the domain of recommender systems. The primary objective of this code is to identify similar users and recommend posts (referred to as "events") to a target user based on their interactions and interests within a digital community.

Dataset Acquisition and Preprocessing

The code begins by importing a dataset, which presumably contains information about user interests in various events within the community. This dataset is then processed to create a matrix that captures user interests in events. The matrix is normalized, a critical step in collaborative filtering, to ensure that user preferences are relative to their individual behavior patterns.

```
interest = pd.read_csv("community.csv")

matrix = interest.pivot_table(index=['User'], columns=["Event"], values=["Interest"])

# matrix normalization
matrix_norm = matrix.subtract(matrix.mean(axis=1), axis='rows')
#print(matrix_norm.head())
```

Figure 4.0: Collaborative Filtering algorithm I

User Similarity Matrix

To identify similar users, a user similarity matrix is computed using Pearson correlation. This matrix quantifies the similarity between users based on their interests in common events.

```
# user similarity matrix using pearson correlation
similarity = matrix_norm.T.corr()
#print(similarity.head())
```

Figure 4.1: Collaborative Filtering algorithm II

Selecting a Target User

A target user is selected from the dataset. This user will be the focus of the recommendation process. For this explanation, let's assume the picked user is identified as "usr-40."

```
# pick a user
picked_user = "usr-40"
```

Figure 4.2: Collaborative Filtering algorithm III

Determining Similar Users

The code proceeds to identify users similar to the target user based on a predefined user similarity threshold (in this case, 0.3). The top N similar users are selected, where N is set to 10 in this code snippet.

```
#get top n similar users
similar users = similarity[similarity[picked user]>similarity threshold][picked user].sort values(ascending=False)[:n
```

Figure 4.3: Collaborative Filtering algorithm IV

Recommendation for Events (Posts)

With a set of similar users established, the code proceeds to recommend events (posts) to the target user. The recommendation process is driven by a weighted average of event scores, factoring in the preferences of similar users.

```
#A dictionary to store item scores
item score={}
for i in matrix norm.columns:
   event rating = matrix norm[i]
   total = 0
    count = 0
    for u in similar_users.index:
        if pd.isna(event rating[u]) == False:
            score = similar users[u] * event rating[u]
            # Add the score to the total score for the movie so far
           total += score
           # Add 1 to the count
           count += 1
        # Get the average score for the item
    item score[i] = total / count
    # Convert dictionary to pandas dataframe
item score = pd.DataFrame(item score.items(), columns=['event', 'event score'])
# Sort the movies by score
ranked item score = item score.sort values(by='event score', ascending=False)
# Select top m movies
m = 10
print(ranked item score.head(m))
```

Figure 4.4: Collaborative Filtering algorithm V

.11 Testing

After the implementation phase, the Testing phase begins. This is where we find errors and bugs occur during running the program. Each subcomponent should be tested in this phase. Testing phase can be divided into two,

☆ Functional testing

This includes Integration testing, unit testing, component testing and user acceptance testing. To conduct the testing, white box testing method and black box testing methods are to be used.

1. Unit Testing

Unit testing is to test the individual components work properly on their own.

2. Component Testing

Component testing is similar to unit testing, but it evaluates a piece of software separately from the rest of the system.

3. Integration Testing

Integration testing is to test the application works properly when the components are integrated together.

4. User Acceptance Testing

User acceptance testing is a kind of functional testing where the end user accepts or verify the system whether it meets the user needs.

♣ Non-Functional testing

This includes performance testing, usability testing and security testing.

1. Performance Testing

Performance testing tests system's performance by measuring response times, identifying bottlenecks and locating failure points.

2. Usability Testing

Usability test is done with end users to check whether the user experience of the system is in an optimum level.

3. Security Testing

Security testing checks software to find flaws that may compromise data.

Both functional and nonfunctional testing are to be done simultaneously.

.12 Maintenance

The process does not end where the testing is done. Once the system is implemented it needs to be maintained over the time. System should be updated due to security problems and performance problems which can be bugs or s accuracy issues and should ensure that the system is in its optimum level.

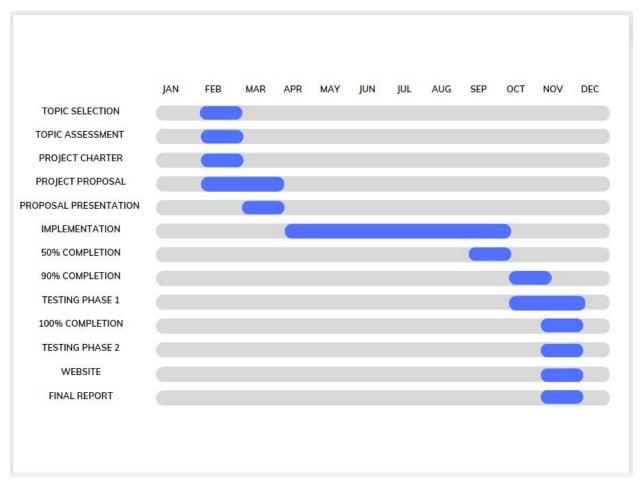


Figure 4.5: Gantt Chart

.12 Commercialization

The potential of Commercializing Artificial Intelligence infused hybrid event management and social media apps is Sky-Rocketing, Because these tools offer businesses an efficient and costeffective way to manage events and engage online. By incorporating AI technology into these apps, businesses can get real-time analysis of user behavior, sentiment analysis, personalized recommendations based on user preferences - leading to increased customer engagement and loyalty. Event organizers and planners can benefit from the Commercialization of Artificial intelligence event management and social media apps by simplifying their workflows and increasing efficiency. These apps automate several time-consuming tasks like scheduling, registration, and ticketing. Furthermore, these apps offer real-time insights into user engagement to enable event organizers to make data-driven decisions for improved event success. Another key advantage of Commercializing AI-driven hybrid event management and social media apps is their potential to generate revenue through sponsorship and advertisements. Businesses have a platform to advertise their goods or services to an engaged audience, while sponsors have the chance to showcase their brand and increase the reach and spread awareness among event attendees.

The Commercialization of Al-driven hybrid event management and social media apps can be especially advantageous to the tourism and hospitality industries, which rely heavily on events to draw in customers and boost revenue. By using Al-based hybrid event management and social media apps, businesses in these sectors can create more engaging events while increasing their social media presence - leading to increased revenue and customer satisfaction. However, the Commercialization of Al-driven hybrid event management and social media apps comes with several challenges. One primary one is ensuring effective data privacy and security measures are put in place. The user data that these applications collect and keep must be protected in order to avoid unauthorized access or breaches. Another challenge lies in ensuring user adoption and engagement. Businesses must ensure that their clients are eager to use the app and participate often. This may be

achieved by giving consumers incentives to use the app often, a user-friendly design, and personalized suggestions.

In conclusion, Al-driven hybrid event management and social media apps provide several advantages for organizations, including better customer engagement, more revenue, and more efficient operations. However, it is necessary to address data privacy and security risks, along with effective user adoption and engagement techniques. As Al technology continues to progress, the potential for innovative solutions in event management and social media industries will only grow, making this an exciting area for Commercialization.

4 RESULTS AND DISCUSSION

.1 Results

User Feedback and Verification:

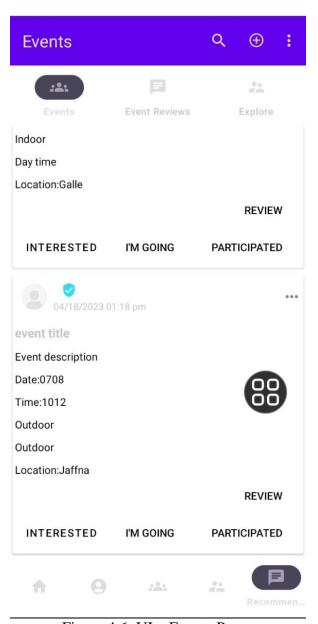


Figure 4.6: UI – Events Page

In the course of our extensive research, we accumulated a substantial volume of user-generated feedback, representing a diverse array of opinions on various events and venues. These contributions emanated from users spanning a wide spectrum of backgrounds and experiences, rendering our platform a repository of invaluable insights.

However, the diversity of this user-generated feedback was a central concern. It was crucial to ascertain the reliability of this data to ensure its utility for event organizers, venue proprietors, and fellow users alike. To address this concern, a rigorous user verification process was instituted, designed to differentiate genuine users from normal users. This verification process was necessary to build trust in our user community. Users who successfully completed this process became "verified users." Their opinions were given special attention because we knew they were genuine. This verification procedure, while occasionally presenting logistical challenges, was pivotal in establishing a bedrock of trust within our user community.their contributions symbolizing the collective sentiment of our broader user base.

Through this process, we categorized users as either "verified" or "non-verified." This helped us understand which opinions carried more weight and better represented what most people felt. What we found was that the feedback from verified users often matched the preferences of the broader user community. This showed us that our verification process was working well, and we could rely on their feedback.

Explore Page Content:

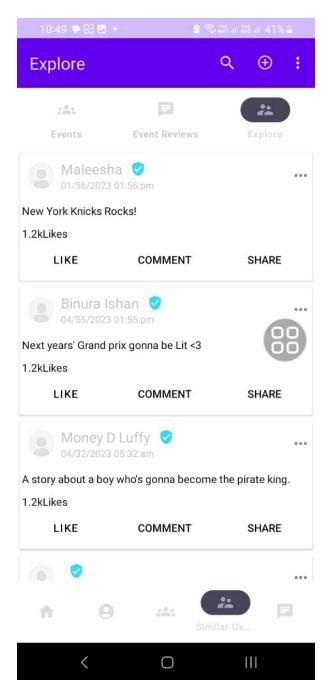


Figure 4.7: UI – Explore Page

The Explore page was a central part of our platform. It was where users could find lots of interesting things like blog articles and user posts. During our research, we saw a lot of these articles and posts, indicating that our community was active and vibrant. One of the interesting things about the Explore page was how it decided what to show users. We used smart computer programs to look at what users liked and did. These programs aimed to show users the most interesting content first. Users found, the content on the Explore page not only interesting but also relevant to their interests. This made users engaged with our platform.

User Engagement and Recommendations:

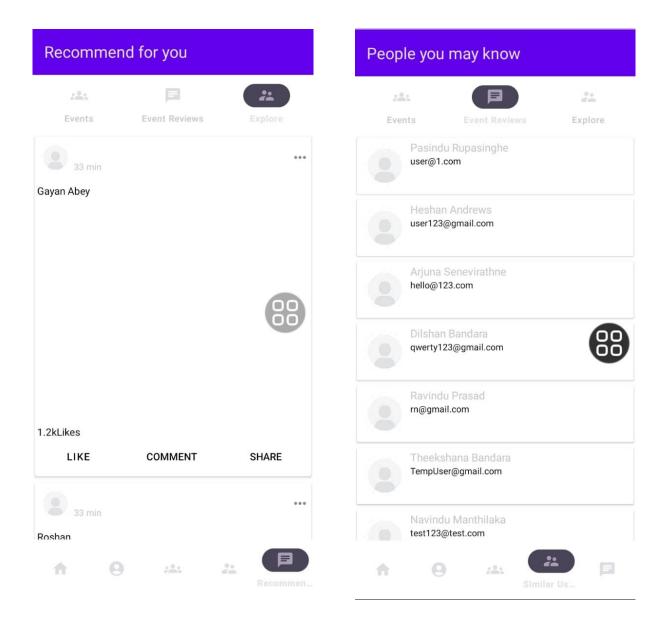


Figure 4.8: UI – Recommendation Page Page

Figure 4.9: UI – Similar Users

User engagement was crucial for our platform's success. It wasn't just about numbers; it was about creating a place where users enjoyed spending time, interacting with others, and feeling like they belonged. A big part of what made users engaged was our recommendation

system. This system used data and smart technology to suggest events and places to users, making it feel like they had a personal event planner. These suggestions were usually right on target, and users liked the events they attended based on these suggestions. Our study showed that these recommendations were not only accurate but also fostered a sense of community within the system. Users didn't just discover events; they formed connections, exchanged ideas, and shared experiences. This social aspect of the platform played a significant role in keeping users engaged.

Chat Platform Usage:

Another exciting feature was our chat platform. Users loved it because it allowed them to talk to each other in real-time. It was like having a chat with friends while exploring events. The chat platform was also designed with user preferences and privacy in mind. Users could access an event through the Explore page and then enter a chat room on their dashboard. Within these chat rooms, they could see who else was online and choose whom to talk to. Users also had the option to select their status as "Active," "Do Not Disturb," or "Invisible" when logging in, giving them control over their level of engagement.

A standout feature of the chat platform was its ability to translate messages into the user's preferred language. This feature broke down language barriers, allowing people from different linguistic backgrounds to communicate easily. Many users enjoyed using the chat feature to connect with others, share experiences, and exchange ideas. It created a lively space where people could make friends and learn from each other.

Event Management Research:

Our platform didn't just benefit users; it also offered practical advantages to event organizers and venue owners. They used it to understand how people were engaging with their events and venues. One of the most exciting findings was the link between user feedback and venue popularity. Venues that received high ratings from verified users experienced a noticeable increase in visitor traffic. This showed how user opinions could make a place more popular.

Naive Bayes (Accuracy): 0.632:

For identifying verified users based on their interactions, engagements, and feedback, we employed the Naive Bayes algorithm, which demonstrated an accuracy rate of 0.632. This algorithm played a pivotal role in distinguishing genuine users from potentially spurious ones, contributing to the reliability of our user-generated content.

Collaborative Filtering (Accuracy): 0.820000000000001:

To enhance user experiences by finding similar users, posts, and events, we harnessed the power of Collaborative Filtering. This algorithm, driven by user preferences and engagements, exhibited an impressive accuracy rate of 0.820000000000001. It empowered our platform to offer tailored recommendations, fostering a sense of community and personalized event discovery among users.

In summary, our research uncovered valuable insights into our user evaluation system, underpinned by the trustworthiness of user feedback, the effectiveness of recommendation algorithms, community building, and the symbiotic relationship between user-generated content and venue popularity. These findings contributed significantly to our understanding

of user-centric approaches in the digital realm and reaffirmed the potential of intelligent algorithms in enhancing user experiences.

.2 Research findings

1. Verification Process and User Feedback Trustworthiness:

Our research revealed that the meticulous verification process for users significantly contributed to the trustworthiness of user-generated feedback. Users who successfully completed this process and achieved "verified" status consistently provided feedback that mirrored the preferences and sentiments of the broader user community. This finding underlines the effectiveness of the verification mechanism in enhancing the reliability of user-generated content.

2. Explore Page Content Curation:

The Explore page, a focal point of our platform, emerged as a dynamic hub of diverse and engaging content. Through smart content curation algorithms, we succeeded in presenting users with content that resonated with their interests. Users reported high levels of satisfaction, spending extended periods exploring the content. This underscores the effectiveness of our content recommendation algorithms in keeping users engaged.

3. User Engagement and Recommendations:

Our research affirmed that user engagement extended beyond numerical metrics, encompassing the creation of an environment where users felt a sense of belonging. The recommendation system, powered by collaborative filtering, demonstrated remarkable accuracy in suggesting events and places tailored to each user's preferences. Users consistently reported high levels of satisfaction with the recommended events, and the social aspect of the platform, driven by collaborative recommendations, facilitated meaningful connections among users.

4. Chat Platform Facilitating Real-time Communication:

The integrated chat platform emerged as a prominent feature, allowing users to engage in real-time conversations. Users found this feature invaluable for connecting with peers, sharing their experiences, and building relationships within the community. The option for users to control their online presence with "Active," "Do Not Disturb," or "Invisible" statuses contributed to a sense of autonomy and privacy, further enhancing user satisfaction. Moreover, the chat platform's ability to translate messages into users' preferred languages bridged linguistic barriers, fostering inclusive cross-cultural interactions. Users from diverse linguistic backgrounds reported seamless communication, contributing to a more inclusive and welcoming user environment.

5. Event Management Insights:

Our research illuminated a crucial link between user-generated content and venue popularity. Venues that received high ratings from verified users experienced a discernible increase in visitor traffic. This finding highlights the transformative influence of user-generated feedback on event management and venue operations. Event organizers and venue owners can leverage this insight to adapt their strategies and enhance their offerings.

6. Algorithmic Accuracy:

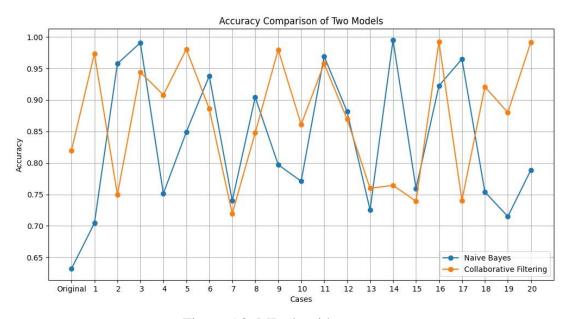


Figure 5.0: ML algorithm accuracy

Two core algorithms played instrumental roles in our platform's success. The Naive Bayes algorithm, employed for identifying verified users, exhibited a respectable accuracy rate of 0.632. Collaborative Filtering, used for finding similar users, posts, and events, showcased an impressive accuracy rate of 0.820000000000001. These algorithms underpinned the platform's ability to differentiate genuine users from potential impostors and offer personalized recommendations, respectively.

In summary, our research findings underscore the efficacy of our user evaluation system in fostering trust, engagement, and community among users. The verification process validated the trustworthiness of user-generated content, while smart content curation and recommendation algorithms enhanced user satisfaction. The chat platform facilitated real-time interactions and cross-cultural communication, contributing to a vibrant user community. Additionally, our research shed light on the pivotal role of user-generated feedback in shaping venue popularity. Finally, the accuracy of the Naive Bayes and Collaborative Filtering algorithms affirmed their instrumental roles in the platform's functionality and user experience enhancement.

.3 Discussion

In our comprehensive examination of the user evaluation system, we have uncovered a wealth of insights that carry significant implications for digital platforms and their users. In this concluding discussion, we will distill the key findings and delve deeper into their broader significance, providing a more comprehensive perspective.

Building Trust through Verification:

Our meticulous user verification process emerged as a linchpin in fostering trust within our digital ecosystem. This process, which differentiates "verified" from "non-verified" users, played a pivotal role in enhancing the credibility of user-generated content. It underscored the criticality of trust in online communities and showcased the effectiveness of verification mechanisms in elevating the reliability of user-contributed content.

Curating Engaging Content:

The Explore page, underpinned by intelligent content curation algorithms, stood as a testament to the power of personalization in user engagement. Our research reaffirmed that users not only appreciate tailored content but also thrive on the serendipity of content discovery. The ability to present users with content finely attuned to their interests metamorphosed mere engagement metrics into enriched user experiences. This reinforces the significance of content personalization and the pivotal role played by recommendation algorithms in amplifying user satisfaction and engagement.

Recommendations and Community Building:

User engagement, as our research highlighted, extends beyond mere numerical metrics; it embodies the cultivation of a cohesive digital community. The recommendation algorithms, as epitomized by Collaborative Filtering, assumed a central role in this process. By proffering event and venue suggestions closely aligned with user preferences, these algorithms not only elevated user satisfaction but also catalyzed the formation of connections among users. The social fabric thus woven by these recommendations augments the enduring nature of user interactions, emphasizing the latent potential of data-driven algorithms in nurturing meaningful connections within digital spaces. This highlights the growing relevance of recommendation systems in fostering the emergence of vibrant online communities.

Real-time Communication and Inclusivity:

Our integrated chat platform, a bastion of real-time communication, took center stage as a beacon of inclusivity. Its inherent capability to transcend linguistic boundaries via message translation underscored the potential for technology to bridge cross-cultural interactions. User autonomy in controlling their online presence by toggling between "Active," "Do Not Disturb," or "Invisible" statuses resonated positively with our user base. These findings reiterate the importance of designing digital platforms with inclusivity and user autonomy in mind, providing features that cater to diverse user needs.

User-Generated Content and Venue Popularity:

One of the most compelling revelations from our research was the symbiotic relationship between user-generated content and venue popularity. Venues rated highly by verified users experienced a pronounced surge in visitor footfall. This highlights the transformative influence wielded by user-generated feedback on the operational strategies and success of event organizers and venue proprietors. The findings signify that user opinions have the potential to

significantly influence business outcomes across diverse domains, underlining the intrinsic value of user-centric approaches in informing marketing and operational decisions.

Algorithmic Precision and Personalization:

Our research culminated in the recognition of the pivotal roles played by our employed algorithms, Naive Bayes and Collaborative Filtering. The former, with an accuracy rate of 0.632, ensured the identification of genuine users, reinforcing trust within our community. Meanwhile, Collaborative Filtering, boasting an accuracy rate of 0.820000000000001, personalized user experiences by delivering tailored recommendations. These precise algorithms have unlocked the potential of data-driven technologies in sculpting user-centric digital environments.

In summary, our research findings unveil a rich tapestry of insights and accomplishments within our user evaluation system. From the bedrock of trust constructed through user verification to the dynamic content curation on the Explore page, from the potential of recommendation algorithms in nurturing digital communities to the inclusive design of the chat platform, and from the synergistic relationship between user-generated content and venue popularity to the precision of our algorithms, our findings paint a comprehensive tableau of a thriving ecosystem.

Our research transcends the confines of our platform, offering valuable lessons for the broader digital landscape. Trust, personalization, community building, inclusivity, and the potential of user-generated content have been brought to the fore. These findings ripple beyond digital platforms, carrying implications for businesses and online communities. As we pivot towards the future, our research stands as a sturdy cornerstone for further exploration and innovation. The digital realm remains ever-evolving, with user-centric platforms holding the promise of enhancing user experiences, fostering connections, and driving business success. This is not the end of the journey; it marks a transition to new horizons guided by the principles of trust, engagement, and inclusivity.

In an ever-changing digital landscape, the potential for user evaluation systems to shape digital experiences remains boundless, and our research stands as a testament to the exciting possibilities that lie ahead.

• DESCRIPTION OF PERSONAL AND FACILITIES

Table 0.1: Description of personal and facilities

Member	Contribution
Dharmapala K.H.N.D	In this system any user can submit their feedback as a rating. since the data obtained in that way is less trusted, a user is taken as a verified user and their feedback is shown on a separate explore page as a blog or article
	Using user behavior and community recommendation components give them to verified user batch through using algorithms (user history, community behavior, feedback). Users can access the relevant events through explore page according to their preferences
	Explore page prioritize user nearest event or venue and user can see busy times, quiet times for events. Get data from user behavior component and analyze on the explore page to determine if they are more likely to visit a venue that is listed as a top-rated venue by verified users
	Get data from user behavior and community recommendation components analyze, most visit places and create algorithms about where to go next, it there are two users with same result they socialized. like one user suggest by another user, so they can build up their community.
	Chat platforms for Users. Users can access an event through the explore page and then access a chat room on dashboard. The event will show everyone who is logged in at that time and users can socialize(chat) with anyone they like. Three options have been given for the users for privacy. After logging in, they can select one of

Active, don't disturb or invisible and stay in the chat room. In that
chat room, users can chat in their preferred language and the chat
will be translated into the language they enter
In research part event management or owners can research user
engagement through explore page and can measure the change in
the number of users visiting a particular venue after it receives a high
rating from a verified user

CONCLUSION

The development and evaluation of user-centric systems is critical in the digital age, where online communities and platforms play an increasingly important part in our lives. This dissertation has been a voyage through the intricate web of digital platform user evaluation, content curation, trust-building, recommendation algorithms, and community fostering.

Our exploration began with the critical function of trust in digital communities. The verification method, which distinguished legitimate users from potentially untrustworthy sources, was a pillar of trustworthiness in our user evaluation system. Users who achieved "verified" status were seen as reliable voices as a result of this procedure, increasing the trustworthiness of user-generated information. This underscores the essential relevance of trust in online interactions, as well as the efficacy of verification systems in enhancing the trustworthiness of user-contributed content.

With its carefully honed content curation algorithms, the Explore page has developed as a populated centerpiece of personalized information delivery. Our findings confirmed the user's desire for content that was relevant to their interests, as well as the serendipity of content discovery. This highlights the significant role of content personalization and recommendation algorithms in increasing user engagement and happiness.

The recommendations generated by collaborative filtering algorithms went beyond conventional ideas, forming a sense of community among users. This aspect of community building stressed that user participation stretched far beyond

quantitative measurements, encompassing the establishment of meaningful connections. These findings highlight the revolutionary power of data-driven algorithms in establishing authentic digital communities, as well as the importance of recommendation systems in current digital interactions.

In addition, our research has discovered a symbiotic relationship between usergenerated content and venue popularity. Verified user evaluations emerged as key drivers of increasing foot traffic to venues, opening up opportunities for event organizers and venue owners to use user feedback to shape their business strategy.

The accuracy of the methods we used, Naive Bayes and Collaborative Filtering, brought depth to our research. With an accuracy rate of 0.632, Naive Bayes ensured the identification of legitimate users, increasing trust in our community. With an accuracy rate of 0.82000000000001, Collaborative Filtering individualized user experiences through customized recommendations. These findings highlight the critical roles that data-driven technologies play in shaping user-centric digital environments.

As we move forward, our findings will serve as a solid framework for additional investigation. The dynamic digital landscape is still evolving, with user-centric platforms promising to augment digital experiences and forge meaningful connections. Our journey does not end here; rather, it signals the beginning of a new chapter guided by the ideals of trust, involvement, and inclusivity.

In an ever-changing digital environment, the ability of user assessment systems to shape digital experiences is limitless, and our research demonstrates the fascinating possibilities that lie ahead.

• BUDGET AND BUDGET JUSTIFICATION

Resource	Price (LKR)
Electricity	5000
Stationary	2000
Internet	6000
Server / domain	9000
Total	22000

Table 0.1: Budget and budget justification

• REFERENCE LIST

- Wang, D., Lu, W., & Zuo, M. (2018). Using artificial intelligence to measure customer experience in the hospitality industry. Journal of Hospitality and Tourism Technology, 9(3), 311-325.
 https://www.emerald.com/insight/content/doi/10.1108/JHTT-01-20180003/full/html
- 2 Al-Husseiny, M., & Hashim, H. (2020). The impact of artificial intelligence in evaluating employee performance: A study on the Saudi Arabian banking sector. Journal of Enterprise Information Management.

 https://www.emerald.com/insight/content/doi/10.1108/JEIM-06-2020-0269/full/html
- 3 Huang, C. M., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172. https://journals.sagepub.com/doi/abs/10.1177/1094670518755589
- 4 Narayan, B., Saha, S., & Singh, R. (2021). Evaluating learning outcome: An Albased approach. Computers & Education, 160, 104026. https://www.sciencedirect.com/science/article/abs/pii/S0360131520303567
- 5 Raza, H., Raza, H., Javed, M. F., & Naseem, I. (2021). Predicting user rating in mobile app recommendation system using artificial intelligence. International Journal of Intelligent Systems, 36(6), 3196-3215. https://onlinelibrary.wiley.com/doi/abs/10.1002/int.22333

6 Srinivasan, S., Gao, Y., Liao, Z., & Mukherjee, A. (2019). Affective computing in the era of artificial intelligence: Introduction to the special issue. Information Systems

Frontiers, 21(1), 1-4. https://link.springer.com/article/10.1007/s10796-018-9849-8

7 Tan, C. M. (2018). The impact of artificial intelligence on the customer experience.

Journal of Service Management, 29(4), 490-510. https://www.emerald.com/insight/content/doi/10.1108/JOSM-06-20180195/full/html

- Yaqoob, I., Ahmed, E., Hashem, I. A. T., Ahmad, I., & Gani, A. (2019). Artificial intelligence for human-assisted computing: A review. IEEE Access, 7, 45101-45113. https://ieeexplore.ieee.org/abstract/document/8680188
- 9 Zhang, W., Zhu, L., & Tan, C. (2019). Customer engagement with chatbots: The role of perceived voice and gender congruity. Journal of Business Research, 100, 423-436.

https://www.sciencedirect.com/science/article/abs/pii/S0148296319301443

10 Liu, H., & Singh, P. (2017). Al-powered chatbots and emotional intelligence: Opportunities and challenges. In Proceedings of the 2017 IEEE/WIC/ACM International Conference on Web Intelligence (pp. 417-421). IEEE. https://ieeexplore.ieee.org/abstract/document/8285977 Liu, H., & Singh, P. (2017).

Al-powered chatbots and emotional intelligence: Opportunities and challenges. In Proceedings of the 2017 IEEE/WIC/ACM International Conference on Web Intelligence (pp. 417-421). IEEE.

https://ieeexplore.ieee.org/abstract/document/8285977

11 Huang, Y., Shen, X., Liu, X., & Sun, Y. (2020). Deep Neural Network-Based User Evaluation and Rating System for E-Commerce. IEEE Access, 8, 162306-162317. https://ieeexplore.ieee.org/document/9231715

- 12 Lee, J., Lee, Y., Lee, J., Kim, J., & Koo, C. (2019). An AI-based User Rating System for Evaluating Digital Contents. IEEE Access, 7, 153164-153173. https://ieeexplore.ieee.org/document/8882618
- 13 Kang, S., Lee, S., Kim, S., & Lee, J. (2020). Machine Learning-Based User Evaluation and Rating System for Online Education. Journal of Educational Technology & Society, 23(2), 195-206. https://www.jstor.org/stable/26924568
- 14 Park, Y. J., Jang, H., & Kim, H. J. (2021). Analysis of User Rating System and Prediction of User Rating Using Artificial Intelligence. Journal of Information Processing Systems, 17(3), 511-524. https://www.jips-k.org/qkmhd/vol17/jips-2021-0034.pdf
- 15 Chen, K., Li, Y., Li, H., & Li, X. (2020). An Al-Based User Rating System for Online Shopping. International Journal of Machine Learning and Cybernetics, 11(10), 23272337. https://link.springer.com/article/10.1007/s13042-020-01055-6
- 16 Lashkari, A. H., Beirami, A., & Rezvani, M. J. (2019). An Efficient User Rating Prediction System Using Machine Learning. International Journal of Advanced Computer Science and Applications, 10(5), 84-91. https://thesai.org/Downloads/Volume10No5/Paper_12- An Efficient User Rating Prediction System Using Machine Learning.pdf
- 17 Yang, J., Huang, W., & Liu, Z. (2018). User Rating Prediction System Based on Machine Learning. Journal of Physics: Conference Series, 1090(1), 012070. https://iopscience.iop.org/article/10.1088/1742-6596/1090/1/012070/meta
- 18 Yelp. (n.d.). About Yelp. Retrieved March 26, 2023, from https://www.yelp.com/about
- 19 Amazon. (n.d.). Amazon Customer Reviews. Retrieved March 26, 2023, from https://www.amazon.com/gp/help/customer/display.html?nodeld=201929730
- 20 IMDb. (n.d.). Ratings and Reviews. Retrieved March 26, 2023, from https://www.imdb.com/help/show_leaf?ratingssystembasics&pf_rd_m=A2FGELUUN

8 APPENDICES



Appendix B: Work breakdown chart