Toward Understanding Users' Interactions with a Mental Health App: An Association Rule Mining Approach

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Abstract. Mental health apps are gaining increasing research attention. One reason for this is that many users find mental health apps a good alternative for self-management of mental conditions, especially in the last two years when access to physicians was limited because of the COVID-19 pandemic. Despite the existence of several mobile apps targeting mental health, studies show the need to explore and enhance existing mobile health (mHealth) apps to better serve patients and health practitioners. This work aims at analyzing data generated from users of a mobile app to enhance mHealth apps for improving mental health. Particularly, this paper aims to extract knowledge about the relationship between different activities (e.g., sport, home, school, etc.) that affect users' moods. To achieve this goal, an association rule mining technique was applied on a dataset collected in the wild from 232 users of a mental health app called the FeelingMoodie app. They used the app from September 2021 to May 2022. Our results revealed interesting associations between various daily life activities. Based on these association rules, we provide insights and recommendations for building better mHealth apps and a more personalized user experience.

Keywords: Mental health · Mobile health app · mHealth · Mood tracker · Mobile app · Association Rule Mining

1 Introduction

Recent years have witnessed significant adoption of technology in the health domain [4, 26]. Advanced technologies are nowadays an essential tool in the toolset of health service providers and patients. These technologies allowed for the delivery of health care services on a larger scale and with more efficiency. Among these technologies are mobile health (mHealth) apps, which are defined as "medical or public health practice supported by mobile devices" [20]. mHealth apps have shown strong evidence in supporting conventional health systems by augmenting diagnosing and treatment processes and increasing individuals' participation in managing their mental health. They have been shown to be useful for a wide range of health areas. Due to its importance, mental health apps comprise about one-third of disease-specific mHealth apps [29].

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Despite their prevalence, existing studies have shown that to be effective, mHealth apps need to be explored and enhanced so that they provide the best assistance for patients and health practitioners. For instance, existing studies show that mHealth apps need to be personalized, interactive, and easy to use. The available mHealth apps collect a significant amount of data, which can be explored to generate insights that can be used to advance these apps. Various data analytic approaches for processing data and generating insights from data have been explored by knowledge discovery and data mining (DM) researchers. Knowledge Discovery (KD) is defined as the process of analyzing and discovering interesting knowledge and patterns from a large amount of data [19]. Data Mining (DM) is the core process of knowledge discovery from databases [6]. It is used to extract meaningful information and infer relationships among variables, through classification, clustering, and association rule mining [5]. Association Rule Mining (ARM), which is of special importance for this study, is one of the most common techniques of data mining. It was introduced in the early 1990s [1], and it aims to infer interesting correlations and associations, and frequent patterns among sets of items in the data. ARM is widely used in different domains, including market, risk management, medical diagnosis, bio-medical literature, protein sequences, and inventory control [35].

This work aims to use existing data to enhance mHealth apps for improving mental health. Particularly, the goal of this research is to extract knowledge about the relationship between different activities that affect users' moods. To achieve this goal, ARM techniques were applied on a dataset generated by users of a mental health app, called the *Feeling Moodie* (*Moodie* for short) app [3, 22]. Users used the *Moodie* app to log their moods along with associated activities that users believe affect their mood. The app allows users to select moods that belong to five main categories (Good, Mad, Sad, Rad, and Neutral). Then, users can select one or more activities (e.g., family, event, friends, sports) that might have affected their moods. The data contains 2336 records collected from 232 users from September 2021 to May 2022, and it contains several features, including moods and activities, which are related to our study.

This work is part of ongoing research toward developing an adaptive and evidence-based mental health app. Identifying the relationship between moods and environmental aspects can help understand what factors (both negative and positive) and patterns impact people's moods and wellbeing. As a first step in designing an AI-based adaptive mental health app, this work aims to explore the relationship between factors affecting moods and how this relationship varies based on users' moods to inform the design of better mental health apps. To achieve our goal, we adopt the association rule mining concepts and applied them to uncover the relationships between activities. ARM explores the relationship between unrelated data. For instance, a supermarket can use data about customers' purchases and ARM to identify which products are frequently bought together. Association rules are if/then statements that identify the relationship between data elements [24], and they are used to identify the objects that frequently happen (or used) together. In this work, we used the same technique to uncover the relationship between different activities (or factors) that may affect users' moods. That is, we explore the relationship between the activities that lead the user to be in a particular mood.

The quantitative analysis of the data revealed that Home-, Work-, Relaxation-, and Family-related activities are the most common factors that affect users' moods, and Chill emerged as the most common mood. The current work adds to the ongoing efforts to understand how technology can be used to enhance positive wellbeing and how humans interact with mood-tracking apps for improving mental wellness. The analysis also revealed several association rules that describe the relation and association between different activities. This research contributes to the ongoing efforts to understand how self- and mood-tracking apps can be used to change negative to positive moods, as well as restore positive moods while reducing negative ones. This research also provides insights and recommendations for designing adaptive user-centric mental health apps.

2 Background and Related Work

This section introduces association rule mining and its applications. Then, it discusses related work on mHealth apps.

2.1 Association Rule Mining

Association Rule Mining (ARM) is an effective data mining technique that uses rule-based machine learning methods to discover relations between items in a dataset [2, 5]. Given transactions with a variety of items, ARM is meant to explore the rules that determine how certain items are connected. Association rules were firstly defined in the early 1990s by Agrawal et al. [1], as follows: let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of items, where items could be literals, shopping items, images, etc. Any subset $X \in I$ is called itemset. Let R be a table with a set of transactions t involving elements that are a subset of I. An association rule is an expression of the form $X \rightarrow Y$, where X and Y are itemsets and $X \cap Y = \emptyset$. X is called the antecedent (or body) of the rule, and Y is the consequent (or head) of the rule. An ARM algorithm usually mines several rules. The number of the mined association rules depends on the size of the dataset, and two essential measures: *Support* (S), and *Confidence* (C) [1], which are defined as follows [34]. *Support* is the percentage of transactions (or records) that contain X and Y to the total number of transactions $|X|$. *Confidence* is the percentage of the number of transactions that contain X and Y to the total number of records that contain X. Confidence shows the strength of the association rules. For instance, if the confidence of the association rule $X \rightarrow Y$ is 0.8, it means that 80% of the transactions that contain X also contain Y [35].

The process of mining association rules involves finding rules that satisfy minimum support and minimum confidence. These thresholds are domain-dependent, they are specified by the user, and they are used to drop less interesting and less important rules. Sometimes even the association rules generated from not so frequent itemsets (low support value) are still important. For instance, some items are not purchased so often because they are very expensive, consequently, they are not purchased as often as the threshold required. However, the association rules between those expensive items are as important as other frequently bought items to the retailer. Once the list of the most important rules is identified, it can be ordered based on *Lift* value (a measure of the importance of a rule), which helps select rules with high predictive power [34]. For example, the lift of α for the association rule $X \rightarrow Y$ tells us that Y is α times more likely to be bought by the customers who also buy X compared to the default likelihood sale of Y. Many algorithms for generating association rules were presented over time, such as Eclat, FP-Growth, and Apriori algorithms [6]. The most commonly used approach for finding association rules is based on the Apriori algorithm [35].

ARM is one of the most important data mining tasks. It has been extensively studied and applied in marketing, where it is known as the "market basket analysis". For instance, in a bookstore, association rules discovered from the transaction database can be used to rearrange the presentation of books on the shelves such that books that are found to be bought together are placed close to each other. Also, association rules are used for building marketing strategies. For instance, if the ARM process revealed that item Y is bought with item X 60% of the time, it indicates that promoting X can increase the sales of Y. In addition to this typical use of ARM, it has been also introduced to a wide array of applications, such as: classifying the student based on their performance in academics [6], to find the best combination of courses based on users' enrolment data [9], classifying text documents in associating terms of text categories [27, 39], and in transportation domain to explore the causes of accidents and maintenance issues [2, 28].

In addition, ARM techniques can be applied in the health domain (which is the focus of our research) to achieve various goals. For instance, Ribeiro et al., [34] proposed a method based on association rule-mining to enhance the diagnosis of medical images. Pan et al., [32] presented a solution using association rules to relate objects and categories of brain tumors. Wang et al., [38] investigated using ARM techniques to discover patterns of interest in a dataset containing digital mammographic images and textual reports of radiologists. Other researchers [30] deployed ARM and heart disease data to predict healthy and sick heart. Several researchers have also explored the use of ARM for disease and health issues [10, 25], such as cardiac diseases [31], diabetes [15, 16], cancer analysis [33], and explore epidemic and pandemics (e.g., dengue fever [11, 37] and virus outbreaks such as Ebola virus [18], and COVID-19 [23, 36]).

2.2 Mental Health Apps

The use of mental health apps has been shown to improve health behaviours and help with the regulation of moods. A recent review of the literature on mHealth apps that foster emotion regulation, positive mental health, and wellbeing found that although there is emerging evidence showing the benefits of these apps for improving mental health and wellbeing, very few apps are targeted at promoting emotion regulation. The researchers concluded that future mHealth apps may consider the inclusion of features that promote emotion regulation. One of the aims of the present research study is to make it easier for users to identify connections in their moods and help with emotion regulation, and coping with the ups and downs of life.

There has also been research on how people's moods are correlated with activities of daily living [the fundamental skills required to independently care for oneself such as eating, shopping, housecleaning, and communication with others. For example, Chan et al. [13] investigated the relationship between daily mood changes and one's personal characteristics, demographic factors, and daily health behaviours. For 30 days, 130 users completed a program called "ClickDairy" which allows users to enter their daily health-related behaviours. Results showed that a user's mood can be associated with health behaviours and daily life activities. The same conclusion has also been demonstrated by other researchers [3, 12]. Results also showed that users experience better moods on the weekends and users who perform more exercise experience better moods compared to users who do not perform an exercise. The quality of sleep was also related to mood fluctuations from day to day – better-quality sleep leads to the experience of a more positive mood the following day. In a different study, Bakker and Rickard [17] evaluated a self-reflection focussed app called "MoodPrism" for improving one's mental health and wellbeing. Results showed that users who had more positive and engaging experiences using the app experienced greater decreases in depression and anxiety. Results also showed that users who already had knowledge of mental health issues were more likely to use MoodPrism over the longer term.

More recently, Huberty et al. [21] examined the effectiveness of the "Calm" app for reducing stress and improving mindfulness and self-compassion among college students. Results showed that the use of the Calm app helped reduce stress, and self-compassion, and improve sleep quality. However, results did not show any association between the use of the app and changes in health-related behaviours such as alcohol consumption, physical activity, or healthy eating. The researchers concluded that there is a lack of research evaluating the impact of mindfulness mediation mobile apps on health behaviour outcomes and the short- and long-term effects.

Similarly, Cho et al. [14] conducted a 1-year pilot study to evaluate the effectiveness of a smartphone app called "Circadian Rhythm for Mood" for helping patients with mood disorders prevent the reoccurrence of mood episodes. Results showed that the total number of mood episodes was fewer and shorter for patients who used the app. Positive changes in health behaviour were observed and the app was found to be effective in preventing the reoccurrence of mood disorders, improving prognosis, and promoting better health behaviours.

Finally, Athanas et al. [8] investigated the effects of immediate and long-term use of a guided meditation and mindfulness app called "Stop, Breathe & Think (SBT)" on users' emotional states. To explore the long-term effects, the changes in the user's basal emotional state were assessed before they completed the guided meditation activity. Results showed repeated engagements with the SBT app are associated with an improvement in users' emotional states over time. Results also showed that after using the app for an extended period, users who felt sad at the beginning of the intervention became happier. The researchers concluded that repeated use of the SBT app can change a user's emotional state from negative to positive and suggest that more elaborate studies are needed to better understand the potential benefits of these apps to reduce the cost of healthcare services.

While there are many studies on the use of mHealth apps for reducing stress and improving health and wellbeing, and how moods are associated with people's daily life activities, there is a lack of work on using association rule mining to uncover how different activities are associated, the result of which could be used to inform the development of mHealth apps that are more adaptive, and easy to use. In this paper, we describe how we adopted the ARM concepts to identify relationships between activities that affect users' moods.

3 Method

This section discusses the research method we used to achieve our goals. First, it describes the *Moodie* app and its features. Then, it discusses the implementation of the Apriori algorithm (the association rule mining algorithm we used in our study).

3.1 The Moodie Mental Health App

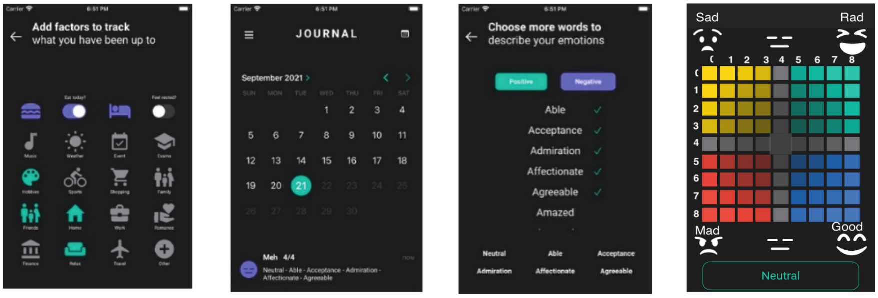
The *Feeling Moodie* (or *Moodie*) app [22] is a mental health app that tracks mood and health-related information. It is a HIPPA (Health Insurance Portability and Accountability) [7] and PIPEDA (Personal Information Protection and Electronic Documents Act) [40] compliant. The app allows users to track their moods by reporting their moods and associated activities (Family, Events, Friends, Sports, Travel, Romance, Finance, Shopping, Exam, Relax, Hobbies, Music, Work, Sleep, Home, Food, Weather, and Other). These activities are the most common activities, and they were selected based on an exploration of related apps. Users can identify their moods using a mood grid designed around four moods dimensions: Great (Happiness or good mood), Chill (being in a calm state, or to relax completely or being relaxed), Meh (indifference, boredom, or a lack of enthusiasm), and Sad (feelings of unhappiness and low mood). These four moods were selected as general moods representing a wide range of sub-moods. To make sure that these moods are clear, the app present the wide range of submoods as a grid, which makes moods clearer to users. The sub moods explain the general moods and provide more fine-rained categories. The Moodie app also allows users to enter free-text journaling entries to talk about their moods and associated activities.

Moodie app has four main features: (1) *Mood Tracking* where users can enter their moods and associated activities, (2) *Mind* Fitness Plan, which provides assistance for users to change their mood to a better state using cognitive behavioral therapy [11] treatment, (3) Journaling, which allows users to track events and situations that might affect their mood and (4) Visualization where users can see historical data and track their moods, which help users' and health care practitioners to recognize emerging trends and respond rapidly. Figure 1 depicts screenshots of the *Moodie* app.

3.2 Implementation

To analyze the association between different activities that affect users' moods, we applied the *Apriori* algorithm, a well-known and one of the most widely used ARM algorithms. It is mainly used for finding frequent items over transactional data sources [27]. Apriori algorithm takes a set of itemsets and tries to find the most common subsets. To do so, Apropri algorithm uses a "bottom up" approach where frequent subsets are extended one item at a time in a step known as candidate generation, which is based on the minimum support value. Apriori uses breadth-first search and a tree structure to count candidate itemsets efficiently. We used Apriori algorithm because it is easy to implement, and works efficiently in relatively small dataset [5]. So, it is suitable for our study.

All our experiments were executed in a laptop with Intel Core i7 CPU, at 2.1 GHz (4CPUs), and Windows 10 as the operating system. Python 3.7 (64-bit) was used to



(a) Activity tracking. (b) Journaling. (c) Emotion tracking. (d) Mood grid.

Fig. 1. Main features of the Moodie App[1]

implement the ARM algorithm. We set the minimum support (0.2) and the minimum confidence (0.8), to obtain all frequent itemsets and filter out the strong association rules based on confidence. Then, the lift value was considered to sort the rules based on their importance.

3.3 Dataset

The data set used in this study was obtained from users who used the Version II of the *Moodie* app. The data contains several features, including moods and activities, which are related to our study. Due to privacy concerns, users demographics were not collected and, therefore, it is not considered in our study. As mentioned above, users can use the *Moodie* app to log their moods along with associated activities that users believe that they affect their entered mood. The app allows users to select moods that belong to five main categories (Good, Mad, Sad, Rad, and Neutral). Then, users can select one or more activities that might have affected their moods. Particularly, eighteen different activities were provided to users: family, events, friends, sports, travel, romance, finance, shopping, exam, relax, hobbies, music, work, sleep, home, food, weather, and others. The data contains 2,336 records collected from 232 users from September 2021 to May 2022. Users logged their moods and activities as they wished and at the convenience of their schedule. According to previous studies [5], most of the research in ARM for health informatics uses small to medium datasets, containing less than 2,000 records. So, the number of records available in our dataset is adequate to mine association rules.

4 Results

This section discusses the results based on the data collected using the *Moodie* app. First, it shows a descriptive analysis of mood and activities distribution based on the overall data (including all the moods and activities). Then, it represents the association rule analysis of the overall data, followed by association rules per mood.

[1] AppAdvice: https://appadvice.com/app/feeling-moodie/1581336127.

4.1 Descriptive Analysis

A cross-tabulation of moods and activities is shown in Table 1, where the columns show moods, and the rows represent activities. The bolded-text between brackets values indicate the least frequent activity for each mood, while the bolded-text without brackets are the most frequent activities. As shown in Table 1, Finance is the least frequent activity for Rad, Neutral, and Sad; Travel is the least frequent activity for Good and Neutral; and Shopping is the least frequent for Mad. On the other hand, Food is the most frequent activity for all moods according to users' self-reports. This means that Food is the most frequent activity overall, as it is depicted in Fig. 2, which shows the overall frequency for each activity in the whole dataset. As Fig. 2 shows, Food is the most frequently selected activity, followed by Sleep, Home, and Relax. In contrast, Travel is the least frequently selected activity, while Finance and Shopping is the second and third least frequently selected activities, consequently.

Table 1. Frequency of moods and activities

Activity	Rad	Good	Neutral	Mad	Sad
Family	132	214	78	19	73
Event	40	67	23	5	26
Friends	107	168	68	19	61
Sprots	77	113	43	7	38
Travel	18	**(17)**	**(16)**	5	12
Romance	73	136	45	7	46
Finance	**(13)**	25	**(16)**	7	**(12)**
Shopping	43	31	17	**(2)**	17
Exams	71	133	82	16	100
Relax	133	272	93	10	71
Hobbies	59	71	27	4	22
Music	75	107	43	13	56
Work	100	171	91	43	101
Sleep	293	427	164	44	118
Other	45	54	31	16	63
Home	177	319	146	33	122
Food	**348**	**604**	**267**	**85**	**245**
Weather	88	117	58	18	48

4.2 Association Rule Mining

This section shows the association rules mined by the Apriori algorithm, setting the minimum support to (0.2) and minimum confidence (0.8) in order to filter the most significant rules. After getting the most significant rules, we sorted them based on the lift value, which measures the importance and interestingness of the rule [6]. For clarity purposes, the results presented in this section show the ten most important rules. A complete list of the rules can be provided as a supportive material.

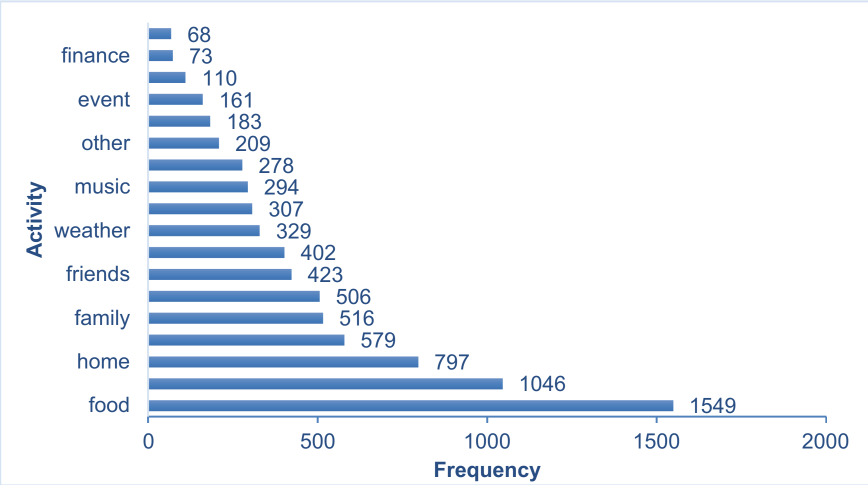


Fig. 2. Frequency of activities over all data

Overall Data Analysis

This section presents the association rules for the whole dataset. The total number of rules generated was 63 with confidence >80%. Table 2 shows the top ten association rules. As the table shows, the top rule indicates that moods that are affected by Romance- and Sport-related activities, are more likely affected by Family-related activities. It also shows that Sleep is associated with six itemsets. This is not surprising given that Sleep is the second most common activity (as shown in Fig. 2).

Mood-Based Analysis

This section presents the association rules for each mood. Tables 3, 4, 5, 6 and 7 depict the association rules per mood. That is, each table represents the association rules mined using only the records of the corresponding mood. Table 3 shows the association rules for Neutral mood. Our analysis revealed a total of 100 rules related to Neutral mood. The top rules show that Romance-related activities are highly associated with Weather, and Hobbies activities. This rule has (8.34) lift value with high confidence, which means that whenever Weather- and Hobbies-related activities made users be in a neutral mood, then there is a very high chance that a Romance-related activity is also affecting their

Table 2. Association rules based on the whole dataset

#	Rule	Confidence	Lift
1	{'Romance', 'Sports'} → {'Family'}	0.808	3.655
2	{'Shopping', 'Relax'} → {'Sleep'}	0.923	2.061
3	{'Shopping', 'Food'} → {'Sleep'}	0.882	1.968
4	{'Hobbies', 'Sports'} → {'Sleep'}	0.873	1.948
5	{'Shopping', 'Home'} → {'Sleep'}	0.841	1.876
6	{'Music', 'Hobbies'} → {'Sleep'}	0.806	1.799
7	{'Music', 'Romance'} → {'Sleep'}	0.803	1.793
8	{'Shopping', 'Sleep'} → {'Food'}	0.965	1.454
9	{'Friends', 'Sleep'} → {'Food'}	0.948	1.429
10	{'Hobbies', 'Sleep'} → {'Food'}	0.944	1.423

Table 3. Association rules for "Neutral" mood

#	Association Rule	Confidence	Lift
1	{'Weather', 'Hobbies'} → {'Romance'}	0.900	8.340
2	{'Hobbies', 'Sports'} → {'Friends'}	0.900	5.519
3	{'Shopping', 'Friends'} → {'Family'}	1.000	5.346
4	{'Weather', 'Romance'} → {'Friends'}	0.867	5.315
5	{'Romance', 'Work'} → {'Friends'}	0.846	5.189
6	{'Shopping', 'Family'} → {'Friends'}	0.833	5.110
7	{'Romance', 'Sports'} → {'Friends'}	0.813	4.983
8	{'Romance', 'Sleep'} → {'Friends'}	0.808	4.953
9	{'Hobbies', 'Sleep'} → {'Friends'}	0.800	4.906
10	{'Friends', 'Weather'} → {'Family'}	0.905	4.837

moods. Although As Fig. 2 shows, Food is the most frequently selected activity, followed by Sleep, Home, and Relax. In contrast, Travel is the least frequently selected activity, while Finance and Shopping is the second and third least frequently selected activities, consequently.

4.3 Association Rule Mining

This section shows the association rules mined by the Apriori algorithm, setting the minimum support to (0.2) and minimum confidence (0.8) in order to filter the most significant rules. After getting the most significant rules, we sorted them based on the lift value, which measures the importance and interestingness of the rule [6]. For clarity

Table 4. Association rules for "Good" mood

#	Association Rule	Confidence	Lift
1	{'Exams', 'Hobbies'} → {'Food'}	1.000	1.377
2	{'Music', 'Hobbies'} → {'Food'}	1.000	1.377
3	{'Other', 'Sleep'} → {'Food'}	1.000	1.377
4	{'Shopping', 'Sleep'} → {'Food'}	1.000	1.377
5	{'Hobbies', 'Sleep'} → {'Food'}	0.980	1.349
6	{'Romance', 'Hobbies'} → {'Food'}	0.957	1.318
7	{'Exams', 'Sleep'} → {'Food'}	0.953	1.313
8	{'Friends', 'Sleep'} → {'Food'}	0.951	1.310
9	{'Other', 'Family'} → {'Food'}	0.947	1.305
10	{'Shopping', 'Home'} → {'Food'}	0.947	1.305

Table 5. Association rules for "Sad" mood

#	Association Rule	Confidence	Lift
1	{'Event', 'Sports'} → {'Friends'}	0.900	6.374
2	{'Exams', 'Sports'} → {'Friends'}	0.867	6.138
3	{'Romance', 'Sports'} → {'Friends'}	0.846	5.992
4	{'Romance', 'Sports'} → {'Family'}	1.000	5.918
5	{'Family', 'Sports'} → {'Friends'}	0.800	5.666
6	{'Event', 'Sports'} → {'Family'}	0.900	5.326
7	{'Friends', 'Sports'} → {'Family'}	0.842	4.983
8	{'Event', 'Romance'} → {'Exams'}	0.917	3.960
9	{'Event', 'Friends'} → {'Exams'}	0.833	3.600
10	{'Music', 'Work'} → {'Sleep'}	0.833	3.051

purposes, the results presented in this section show the ten most important rules. A complete list of the rules can be provided as a supportive material.

Although Table 1 shows that Friends-related activities are not among the most common activities related to Neutral mood, the ARM results show that Friends-related activities are associated with seven itemsets, with high lift values, as shown in Table 3 (Rules 2, and 4 to 9). This means that whenever any of these seven itemsets made the user be in a Neutral mood, then it is almost five times more probable that their moods have also been affected by Friends-related activities.

With regards to the Good mood, Table 4 shows the top ten rules among a total of 54 association rules. Surprisingly, all the top ten association rules show the relation

Table 6. Association rules for "Mad" mood

#	Association Rule	Confidence	Lift
1	{'Friends', 'Hobbies'} → {'Relax'}	1.000	14.300
2	{'Exams', 'Family'} → {'Music'}	1.000	11.000
3	{'Romance', 'Sleep'} → {'Music'}	1.000	11.000
4	{'Weather', 'Sleep'} → {'Music'}	0.857	9.429
5	{'Exams', 'Music'} → {'Family'}	1.000	7.526
6	{'Finance', 'Home'} → {'Family'}	1.000	7.526
7	{'Friends', 'Music'} → {'Family'}	1.000	7.526
8	{'Family', 'Romance'} → {'Friends'}	1.000	7.526
9	{'Friends', 'Romance'} → {'Family'}	1.000	7.526
10	{'Music', 'Work'} → {'Family'}	1.000	7.526

between an itemset and Food activity. Also, we notice that the confidence values of these association rules are very high (>94%), with 100% confidence of the top four rules.

A total of 51 association rules were found in the Sad-related data. Table 5 shows the top association rules related to Sad mood. The top three rules show that if the users' mood is Sad because of {'Event', 'Sports'}-, {'Exams', 'Sports'}, or {'Romance', 'Sports'}-related activities, then it is highly likely that Friends-related activities have also affected users' moods and made them feel sad.

Table 6 summarizes the top association rules among 63 rules related to the Mad mood. It can be noticed that these rules have a very high confidence (100% for most of them). Also, the lift values for these rules are high. For instance, Relax activity is 14.3 times more likely to cause a Mad mood if Friends and Hobbies related activities also made users feel Mad.

Finally, the ARM revealed a total of 141 rules related to Rad mood. The top ten rules are shown in Table 7. The table shows that Music and Sports are 5.76 and 5.61 times, consequently, more likely to make users feel Rad if Exams- and Hobbies-related activities made them Rad. It also shows that Family is the consequent of five antecedent itemsets (rules 4–8). These five associations indicate that Family is an important activity that leads to Rad mood. Although it is not the most common activity in rad mood (as shown in Table 1).

5 Discussion and Future Work

In the previous section, we presented the results obtained from our ARM analysis. These rules can be used to develop mHealth apps that are more adaptive, and easy to use. Particularly, the benefits of these association rules can be summarized as follows:

Better Understanding of Users. The mined association rules allow designers of mHealth apps and researchers to better understand factors that are associated with users' moods by

Table 7. Association rules for "Rad" mood

#	Association Rule	Confidence	Lift
1	{'Exams', 'Hobbies'} → {'Music'}	0.846	5.765
2	{'Exams', 'Hobbies'} → {'Sports'}	0.846	5.615
3	{'Shopping', 'Music'} → {'Weather'}	0.923	5.360
4	{'Shopping', 'Friends'} → {'Family'}	1.000	3.871
5	{'Shopping', 'Music'} → {'Family'}	0.846	3.276
6	{'Romance', 'Sports'} → {'Family'}	0.824	3.188
7	{'Shopping', 'Weather'} → {'Family'}	0.813	3.145
8	{'Exams', 'Weather'} → {'Family'}	0.810	3.134
9	{'Shopping', 'Sports'} → {'Home'}	0.917	2.646
10	{'Shopping', 'Relax'} → {'Home'}	0.909	2.625

discovering more activities that might affect the user's mood but are not mentioned by the user. For example, based on the association rules ({'Romance', 'Sports'} → {'Family'}) mentioned in Table 2, if the user mentioned that Romance- and Sport-related activities only, the system understands that the user's mood could also be affected by Family-related activities. Therefore, the app may recommend interventions related to family activities as well.

Enhancing Credibility and Usability. The rules can be used to reduce the steps and inputs required from users. For example, instead of asking the user to continuously enter as many activities as possible, the system may ask for 2–4 inputs. Based on these inputs, the system can predict other activities of various kinds based on the provided rules. For instance, suppose that the user selected {Romance, Sport, and Hobbies} as the activities that caused their mood. If we look at Table 2, searching for the rules that have at least two of these three activities, we will find 3 rules. Accordingly, the system can infer that in addition to these three activities, Sleep, and Family are most likely affecting the user's mood as well. Adding these capabilities to the apps will increase their credibility and usability.

Personalization and Adaptation. The app can also use our results to personalize the list of activities and make it more adaptive. For instance, the order of the activities in the list can be changed based on their importance (how they are related) to the activities selected by users, or the activities can be presented as groups. This adaptability will in turn enhance the usability and credibility of the app.

As shown in Sect. 4.2, the results revealed interesting patterns that can inform the development of an adaptive AI-based mental health app. APPENDIX 1 summarizes the results presented in the previous section and acts as a reference for designers and researchers. Below is a summary of the key observations and recommendations/guidelines for designing mHealth apps:

- Food, Sleep, and Home are the most common activities, while Travel, Finance, and Shopping, events are the least common activities. It seems that the COVID-19 pandemic has had an impact on users' selections since, during the pandemic, people spent more time at home because of isolation and work from home. Also, during that time shopping activities were limited, and many people switched to delivery service options. To best understand the impact of the context on users' selection of activities, our data collection is continuing.
- Food is the most common activity in the overall dataset. Considering this observation in isolation reveals that a mental health app should emphasize food-related activities. However, the ARM results (Sect. 4.2) revealed that Food activities are associated with other activities. For instance, the association rules of the overall data (Table 2) shows that {'Shopping', 'Sleep'}, {'Friends', 'Sleep'}, and {'Hobbies', 'Sleep'} are all associated with Food activities. Also, other activities are associated with Food. For instance, Table 2 shows that if the user selected 'Shopping' and 'Food' activities, then it is more likely the user will select 'Sleep' activity to be associated with their moods. Therefore, designers should not focus only on the absolute popularity of the activities, but also consider the associated activities.
- Overall, Travel is the least frequent activity. Also, the top association rules did not reveal any association between Travel and other activities. However, it is important to mention that the data collection was done during the COVID-19 pandemic when travel was limited in most countries. So, users' activities during this time might be affected, and therefore their selection of activities. It will be important to do further studies as the pandemic situation shifts to an endemic.
- Friend-related activities are associated with neutral mood, although it is not among the most common activities related to neutral mood. Our results (see Table 3) indicate that Friends-related activities are associated with seven of the top itemsets (with a lift value of more than 5). This means that whenever the users indicate that any of these seven itemsets made the user feels Neutral, then it is almost five times more probable that their moods have also been affected by Friends-related activities.

5.1 Limitations and Future Work

Despite the interesting results and insights revealed by this study, this study is based on data collected in the wild, demographical information was not collected due to privacy reasons. Also, it is worth mentioning that the data were collected during the COVID-19 pandemic, we believe that it might have affected users' daily life activities (e.g., travel). Therefore, as a future work, we will conduct a subsequent study to expand on this study, investigate, and compare the association rules after the pandemic. Again, although, Mad-related association rules has a very high confidence (100%). However, Mad is the least frequent mood in the dataset (only 353 records). So, we need to collect more data related to this mood and repeat the analysis.

6 Conclusion

This paper presented our ongoing effort toward providing adaptive and personalized mental health apps. In this research, we used a dataset containing 2,336 records collected from 232 users of a mental health app in the wild, from September 2021 to May 2022. The mental health app is called the *FeelingMoodie* app. We used this data to extract knowledge about the relationship between different daily life activities that affect individuals' moods. To achieve our goals, we applied the association rule mining techniques on the dataset. Our results revealed interesting associations between various daily life activities, and these associations vary based on mood. The paper also shows how to use these rules to enhance mental health apps and provides insights and recommendations for building better mHealth apps and a more personalized user experience.

APPENDIX 1. Summary of the Association Rules

Rule		Mood
Antecedent	Consequent	
{'Romance', 'Sports'}	{'Family'}	Overall
{'Event', 'Friends'}	{'Exams'}	Sad
{'Event', 'Romance'}	{'Exams'}	Sad
{'Event', 'Sports'}	{'Family'}	Sad
	{'Friends'}	Sad
{'Exams', 'Family'}	{'Music'}	Mad
{'Exams', 'Hobbies'}	{'Food'}	Good
	{'Music'}	Rad
	{'Sports'}	Rad
{'Exams', 'Music'}	{'Family'}	Mad
{'Exams', 'Sleep'}	{'Food'}	Good
{'Exams', 'Sports'}	{'Friends'}	Sad
{'Exams', 'Weather'}	{'Family'}	Rad
{'Family', 'Romance'}	{'Friends'}	Mad
{'Family', 'Sports'}	{'Friends'}	Sad
{'Finance', 'Home'}	{'Family'}	Mad
{'Friends', 'Hobbies'}	{'Relax'}	Mad
{'Friends', 'Music'}	{'Family'}	Mad

(*continued*)

(*continued*)

Rule		Mood
Antecedent	Consequent	
{'Friends', 'Romance'}	{'Family'}	Mad
{'Friends', 'Sleep'}	{'Food'}	Good
	{'Food'}	Overall
{'Friends', 'Sports'}	{'Family'}	Sad
{'Friends', 'Weather'}	{'Family'}	Neutral
{'Hobbies', 'Sleep'}	{'Food'}	Good
	{'Friends'}	Neutral
	{'Food'}	Overall
{'Hobbies', 'Sports'}	{'Sleep'}	Overall
	{'Friends'}	Neutral
{'Music', 'Hobbies'}	{'Food'}	Good
{'Music', 'Hobbies'}	{'Sleep'}	Overall
{'Music', 'Romance'}	{'Sleep'}	Overall
{'Music', 'Work'}	{'Family'}	Mad
	{'Sleep'}	Sad
{'Other', 'Family'}	{'Food'}	Good
{'Other', 'Sleep'}	{'Food'}	Good
{'Romance', 'Hobbies'}	{'Food'}	Good
{'Romance', 'Sleep'}	{'Friends'}	Neutral
	{'Music'}	Mad
{'Romance', 'Sports'}	{'Family'}	Sad
	{'Family'}	Rad
	{'Friends'}	Neutral
	{'Friends'}	Sad
{'Romance', 'Work'}	{'Friends'}	Neutral
{'Shopping', 'Family'}	{'Friends'}	Neutral
{'Shopping', 'Food'}	{'Sleep'}	Overall
{'Shopping', 'Friends'}	{'Family'}	Neutral
	{'Family'}	Rad
{'Shopping', 'Home'}	{'Sleep'}	Overall
	{'Food'}	Good
{'Shopping', 'Music'}	{'Family'}	Rad
	{'Weather'}	Rad
{'Shopping', 'Relax'}	{'Home'}	Rad

(*continued*)

(*continued*)

Rule		Mood
Antecedent	Consequent	
	{'Sleep'}	Overall
{'Shopping', 'Sleep'}	{'Food'}	Good
	{'Food'}	Overall
{'Shopping', 'Sports'}	{'Home'}	Rad
{'Shopping', 'Weather'}	{'Family'}	Rad
{'Weather', 'Hobbies'}	{'Romance'}	Neutral
{'Weather', 'Romance'}	{'Friends'}	Neutral
{'Weather', 'Sleep'}	{'Music'}	Mad

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