Reaffirming the Critical Role of Transformative Research and Knowledge Production in the Age of Post-Truth

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A Recommender System against Social Media Addiction among Adolescents

Adrian Rafael DC. Bernandino[1], Karl Dominic L. Rodrigo[1], and Shirley B. Chu[1*]
[1] *De La Salle University Integrated School (Manila)*
**corresponding author: shirley.chu@dlsu.edu.ph*

Abstract: Social media is a dominant and an ever-expanding platform for social interaction and communication. In its popularity, Social Media Addiction (SMA) emerged as an unintended consequence, affecting a handful of users. Recommender Systems (RS) have been proven to be useful in domains such as health and alcoholism prevention. This study develops a prototype RS against SMA using a user's personality dimensions and status of SMA. The prototype used a user-based collaborative filtering (CF) approach in recommending items. The prototype will also undergo an evaluation phase but this will not be included in the scope of this paper. The RS prototype accurately predicts an active user's similarity with his/her neighbors using their scores on TIPI (personality dimensions) and BSMAS (status of SMA) through cosine similarity. Although recommendations show bias towards certain items, they can neither be proven effective nor ineffective without further evaluation such as a User Acceptance Test (UAT). Future prototypes can improve the RS's information collection phase to reduce inaccuracies.

Keywords: recommender systems; social media addiction; collaborative filtering; personality; cosine similarity

1. INTRODUCTION

1.1 Background of the Study

Social Media has provided many advantages and benefits to its users, especially for adolescents who grew up with various networking platforms. "In the current information age, more and more people use social networking sites (SNS) for communication and entertainment" (Sun et al. 2021). Although its conveniences may have merit, various factors can lead to Social Media Addiction (SMA). Some emotional and psychological problems such as stress, anxiety, and depression are likely results of SMA (Hou et al., 2019).

Five factors of SMA were identified: Personality, Metacognition, Family, Culture, and Attachment Styles (Hawi & Samaha, 2018; Casale et al., 2018; Balıkçı et al., 2020; Turel and Serenko, 2020; Sun et al., 2021; Cheng et al., 2021; D'Arienzo et al., 2019). Basic demographic variables (primarily age and sex), self-esteem, and narcissism are also associated with the addictive use of social media (Andreassen et al., 2017). This research only factors personality as the variable of SMA. To assess personality, the Ten Item Personality Inventory (TIPI) which measures the big five personality dimensions, which are extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience is used (Gosling, Rentfrow, and Swann 2003).

Various studies have found multiple approaches to measure SMA. Five different instruments for measuring SNS Addiction have been assessed (Andreassen, 2015). The Bergen Social Media Addiction Scale (BSMAS), a modified generalized version of the Bergen Facebook Addiction Scale (BFAS) was the most popular assessment tool out of the five. BSMAS is used in this study.

Recommendation Systems (RS) are described as information filtering systems that use data mining and analytics to analyze user behavior, such as preferences and activities, to produce individualized recommendations, guide the user in a personalized way, or predict users' interests in information, products or services (Burke, 2011; Zhu et al., 2021). Previous studies on RS have applied the method to other practices; particularly in medical and health-related fields. For instance, Jayachandra (2020) discussed how the researchers created a mobile app called "Besober" which uses an RS which helps assist individuals with their alcohol addiction.

At present, no research has been conducted regarding the viability of recommender systems in the prevention and intervention of SMA, especially among adolescents. This study addressed this by developing a simple recommender system for adolescents to combat SMA.

1.2. Scope and Limitations

The recommendations or "items" suggested by the prototype is limited to data gathered during the first and second phase. Both surveys collected participant's age, sex, personality, and status of the participant's SMA. The participants of this study are adolescents aged 15 to 20 only. The prototype is based on a collaborative filtering (CF) recommendation system. CF recommends items highly rated by the active user's neighbors (users similar to the active user). The prototype used cosine similarity to determine an active user's similarity to his/her neighbors, and the dataset for recommendations is limited to the data gathered from the surveys. The intended users for the prototype are adolescents. Details about deployment and discussion of the User Acceptance Test (UAT) of the RS and its results are not included in this paper.

1.3. Significance of the Study

Recommender systems have been implemented in various fields — in medicine and health, online shopping, and through applications such as YouTube and TikTok. SMA is most prevalent in younger generations, specifically adolescents worldwide (Sun et al., 2021). This study contributes to society by introducing RS to the intervention of SMA. Interventions identified such as exercise, self-help, and mindfulness can prevent cases of SMA among SNS users (Andreassen, 2015). The research contributes to the academic community by collecting applicable recommendations and interventions against SMA for adolescents. This paper serves as a foundation for future research, particularly in developing RS against SMA.

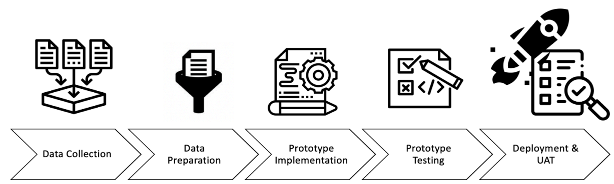
2. METHODOLOGY

2.1. Research Design

The study employs a mixed-method research design. Figure 1 shows the different stages of how the research is conducted, including data collection and preparation, prototype implementation, prototype testing, and the deployment of the prototype and UAT.

Figure 1

Research Design



Data Collection & Preparation

A total of 48 participated in the survey. In the initial data collection, quantitative evaluation methods, TIPI and BSMAS, are included to assess a participant's personality and status of SMA respectively. BSMAS items are rated by the participant on a scale of 1 (very rarely) to 5 (very often). TIPI for each personality dimension is measured by two 7-point Likert-type questions, ranging from 1 (strongly disagree) to 7 (strongly agree).

The survey has two phases. The first phase collects initial recommendations through short answers. The recommendations collected from the first survey were categorized and filtered by treating similar responses as duplicates. 30 distinct items were identified. The filtered recommendations were used in the second phase. Participants were tasked to rate these items through a 6-point Likert scale. Surveys in both phases include personality and SMA assessments and were conducted through Google Forms.

Prototype Implementation

The prototype is implemented in Python using a cosine similarity algorithm and a CF approach.\

Testing

The prototype was tested on the accuracy of the cosine similarity algorithm (test case 1), its rating prediction (test case 2), and its neighbor identification (test case 3). In test case 1, the prototype was tested in its ability to find five of the most similar users (neighbors) to the currently active user. To confirm whether the algorithm is accurate or not, the cosine similarity should be able to output a value of 1.0

(meaning an exact match) to the user with the same attributes. In test case 2, the prototype was tested on its ability to predict the active user's rating on items within the system. The system should be able to recommend five items that are rated highly by the active user's neighbors. In test case 3, two predetermined attributes were given, and the prototype should be able to identify five neighbors with the highest similarity score.

Deployment and User Acceptance Test

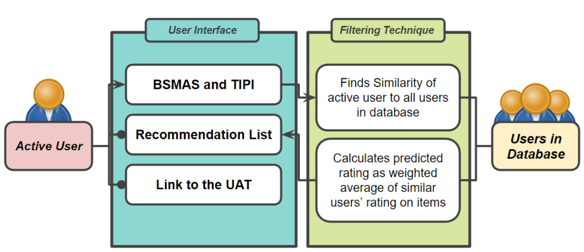
Once the prototype has been tested, it will be deployed simultaneously with the distribution of the User Acceptance Test (UAT) to 15 participants with the same demographic from the data collection. The UAT will be a newly designed survey that is based on other frameworks to evaluate the developed prototype.

2.2. Prototype Design

Isinkaye et al. (2015) identified three phases of the recommendation process: information collection, learning, and prediction/recommendation. Accordingly, the prototype follows the same recommendation process. Unlike other processes where the active user has to rate the recommended item, the only feedback needed from an active user is his/her scores on BSMAS and TIPI (Figure 2).

Figure 2

Diagram of Program Flow

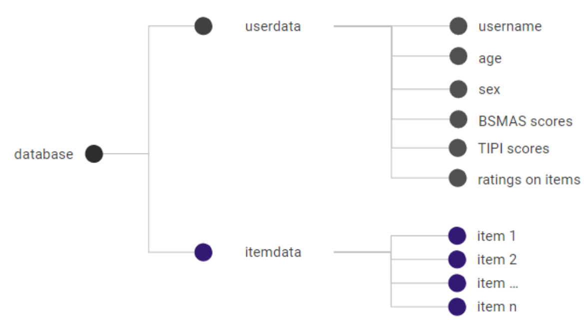


Information Collection Phase

The database consists of individuals who participated in phases 1 and 2 of the data collection. Data from those who were not able to participate in the second phase of the survey to rate the filtered items were excluded. These data are manually organized and prepared (Figure 3). *Userdata* contains all collected information including username, age, sex, BSMAS scores, TIPI scores, and ratings on each item. *Itemdata* consists of the filtered recommendations given by the participants from phase 1.

Figure 3

Database Structure



Learning Phase

An active user's data consists of his/her username, TIPI scores and BSMAS scores. To build a user profile, the personality attributes and status of SMA of users are converted to vector form, wherein the x component serves as their score in percentage form, and the y component as $100 - x$ (Figure 4). For instance, if a user scored 80% on extraversion, his/her extraversion score would be converted to the vector form [0.80, 0.20].

Figure 4

Profile Database Visualization

Username	Big Five Personalities Dimensions	Social Media Addiction	List of Ratings
user_1	*Each dimension, score in vector form [x, y]*	*Score in vector form [x, y]*	*Rating of user for items 1 to n in list form* *[r1, r2, …, rn]*
user_2	*user_2's personality dimensions*	*user_2's status of SMA*	*user_2's ratings on all items*
…	…	…	…
user_n	*user_n's personality dimensions*	*user_n's status of SMA*	*user_n's ratings on all items*

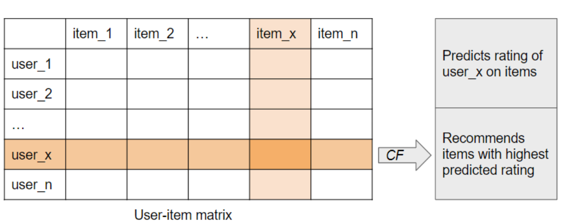
Note. The BFP dimensions are separated in the database. Each row represents a user.

Prediction/Recommendation Phase

The CF approach calculates the similarity between users and computes the predicted rating for an item by the active user as a weighted average of the ratings of the active user's "neighbors" in the profile database (Figure 5). Active user's neighbors are those whose weights are similar to the active user. (Isinkaye et al., 2015).

Figure 5.

Collaborative Filtering Process



The prototype compares the BFP dimensions and SMA score of the active user with those in *userdata* using cosine similarity. To get the overall similarity, the similarities for each personality dimension along with the similarity for their status of SMA are averaged. The similarity between each individual attributes of two users *a* and *b* can be defined as follows (Eq 1):

$$s(\vec{a}, \vec{b}) = \frac{\vec{a} \bullet \vec{b}}{|\vec{a}| * |\vec{b}|} = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2}\sqrt{\sum_{i=1}^{n} b_i^2}} \qquad \text{Eq. 1}$$

The system retains five neighbors with the highest similarity whose item-matrices are used as reference. To predict the rating of the active user on an item, the weighted average of the ratings of neighbors is computed (Eq. 2):

$$W = \frac{\textit{sum of value} * \textit{weights}}{\textit{sum of all weights}} = \frac{\sum_{i=1}^{n} x_i w_i}{\sum_{i=1}^{n} w_i} \qquad \text{Eq. 2}$$

The top five items with the highest predicted ratings are recommended to the user.

3. RESULTS AND DISCUSSION

3.1. Recommended Items

Thirty (30) distinct recommendations were given and rated by participants. These items were rated by the participants according to a 6 point likert scale, ranging from 0 to 5. Recommended activities for each category and their average rating are shown in Table 1.

Table 1.

Recommended activities per category

Category	Activities	Average Rating
Self Care	*Allot time for exercise/workout or any other form of physical activity*	*2.98*
	Have good quality rest and a regular sleep schedule	*2.86*

	Participate in meditation	*2.10*
	General self-care and self-improvement	*3.46*
Hobbies	*Play video games*	*3.58*
	Play an instrument (e.g. piano)	*1.40*
	Eat good food	*4.02*
	Take up cooking	*2.78*
	Go outside or go for a walk	*3.08*
	Play sports	*2.52*
	Find new hobbies that hone your personal skills and are interesting to you.	*3.96*
	Listen to your favorite bands (e.g. Twice, Itzy, New Jeans, Enhypen)	*4.06*
Time Management	*Restrict your social media time. Use apps to lock your phone at a certain time when necessary*	*2.52*
	Implement a schedule and stick to it (improve discipline). Compartmentalize	*3.48*
	Focus on and prioritize requirements, important tasks, academics, assignments and goals	*4.02*
	Allot time for social media detox and off-screen time	*3.19*
Social Media Usage	*Stop using or turn off your phones and/or gadgets*	*2.71*

Category	Activities	Average Rating
Social Media Usage	*Avoid short video type content (TikTok, Youtube Shorts) that encourage mindless scrolling*	*2.83*
	Make it a goal to reduce social media usage	*2.79*
	Be efficient at using social media to have a sense of control. Use it as a tool for light entertainment and information.	*3.23*
	Detach yourself from social media addiction. Take a cleanse and uninstall social media apps	*2.27*
Socialization	*Spend quality time with friends and/or family in real life. (e.g. talking, going outside)*	*3.65*
	Try to be more sociable and interact with others outside of your circle (e.g meet new friends, volunteer, go outdoors)	*2.71*
	Search for a support system (people who can provide you with practical or emotional support)	*3.77*
Mindset	*Hold accountability for your social media addiction*	*4.15*
	Avoid misinformation	*4.44*
	Be aware of the effects of social media addiction	*4.46*
	Convert your addiction into something positive or productive	*4.27*
	Keep in check with reality, enjoy the real world	*4.33*
Professional Intervention	*Seek professional help (Therapy and counseling)*	*3.00*

Table 2

Test Case Results

Description	Input	Expected Output	Test Result
Testing of cosine similarity	*User's attributes*	*1.0*	*Passed*

Testing of rating prediction	*User's attributes*	*Five recommended items*	*Passed*
Testing neighbor identification	*Two set Attributes*	*Five neighbors*	*Passed*

Note. User's attributes are structured as in Figure 3 "userdata".

Test case 1 used each user's attributes in the database as a test input. In all cases, the output was an exact match with a value of 1.0 which indicates that the inputs match the attributes in the database. Table 2 shows that the algorithm can accurately predict the similarity of an active user to his/her neighbors. Thus, the prototype was able to use personality as a profiling tool for recognizing similarities using the cosine similarity formula.

Test case 2 treated each user in the database as an active user. The prototype was able to recommend five items for each case. 48 test cases were executed and 240 recommendations were generated. Out of 30 items, only 17 were recommended, meaning certain items were left out despite being recommended by the participants. Items under the mindset category are the most frequently recommended (Table 3). These results may be related to the category's average rating from the recommended intervention.

Two sets of inputs for test case 3 were used. The most similar neighbors for each set were found, with similarity scores upwards of 0.95 (Figure 6). BSMAS scores are simply added and then compared. Hence, if the sum of its inputs is equal; the similarities should align as well.

Figure 6

Test case 3 results

```
INPUT VALUES:
{'age': 19, 'sex': 'M', 'tipi': [2, 5, 3, 5, 6, 6, 4, 5, 3, 4], 'bsmas': [5, 5, 4, 4, 4, 4]}
CLOSEST NEIGHBORS
{'TIPI Score': [2, 5, 3, 5, 6, 6, 4, 5, 3, 4], 'BSMAS Score': [5, 5, 4, 4, 4, 4], 'Similarity to User': 1.0}
{'TIPI Score': [3, 4, 1, 6, 7, 7, 5, 5, 4, 6], 'BSMAS Score': [4, 5, 3, 5, 2, 4], 'Similarity to User': 0.9848168333333334}
{'TIPI Score': [3, 5, 5, 6, 5, 5, 5, 5, 3, 3], 'BSMAS Score': [4, 4, 4, 4, 4, 3], 'Similarity to User': 0.9827426666666667}
{'TIPI Score': [4, 5, 4, 5, 5, 7, 6, 5, 5, 5], 'BSMAS Score': [5, 5, 5, 5, 4, 5], 'Similarity to User': 0.9771061666666666}
{'TIPI Score': [1, 2, 4, 5, 4, 7, 2, 3, 3, 3], 'BSMAS Score': [4, 4, 5, 4, 3, 2], 'Similarity to User': 0.9754798333333333}
INPUT VALUES:
{'age': 19, 'sex': 'M', 'tipi': [5, 5, 5, 3, 5, 4, 4, 2, 4, 4], 'bsmas': [4, 1, 4, 1, 3, 1]}
CLOSEST NEIGHBORS
{'TIPI Score': [5, 5, 5, 3, 5, 4, 4, 2, 4, 4], 'BSMAS Score': [4, 3, 2, 3, 1, 1], 'Similarity to User': 1.0}
{'TIPI Score': [5, 4, 7, 4, 5, 5, 4, 3, 5, 3], 'BSMAS Score': [5, 3, 2, 3, 3, 2], 'Similarity to User': 0.9888688333333334}
{'TIPI Score': [3, 6, 6, 3, 5, 4, 7, 2, 4, 3], 'BSMAS Score': [2, 3, 3, 2, 1, 2], 'Similarity to User': 0.9846143333333334}
{'TIPI Score': [6, 5, 7, 5, 5, 3, 5, 3, 4, 3], 'BSMAS Score': [4, 4, 5, 2, 1, 1], 'Similarity to User': 0.9816511666666665}
{'TIPI Score': [3, 6, 6, 3, 5, 3, 4, 2, 5, 4], 'BSMAS Score': [1, 1, 1, 2, 1, 1], 'Similarity to User': 0.9798153333333334}
```

4. CONCLUSIONS

This study developed a simple recommender system to combat SMA. The data for the profile database was collected from 48 participants through surveys conducted in Google Forms. The prototype utilized a user-based CF approach to determine the recommendations for an active user. The results of the study indicate that the cosine similarity algorithm was able to accurately find an active user's neighbors using their personality dimensions and SMA score. There are different methods to identify a person's personality and SMA, and the study only utilized TIPI and BSMAS as its assessment method. Although the prototype can recommend activities, the recommendations lean heavily towards items with higher average participant ratings. This may cause inaccuracies, such as certain activities not being recommended at all despite being useful to specific individuals. These inaccuracies may be primarily due to CF approach's dependence on the quantity and quality of data, and not on the algorithm itself. Future RS against SMA can use feedback, machine learning, and real-time data for the information collection phase. The prototype RS has not yet been evaluated by potential users. At the time of writing, it is not yet possible to determine whether the recommendations would be useful or effective to its users in lessening SMA. Based on the test results, recommendations lean heavily towards items under the mindset category. Future research may delve into how mindset affects the SMA of adolescents.

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