1. INTRODUCTION

Digital technology plays an important role in daily life. Social Networking Sites (SNSs) have become an incredibly popular type of communication through which groups of people virtually meet and interact with others who share similar interests [1]. The use of SNSs continues to dramatically increase. Unfortunately, some people spend too much time on them, especially in potentially deleterious ways. Excessive SNS usage can cause such negative consequences as relational, performance, health-related, and emotional problems, including the risk of addiction [1].

This research is conducted to assess the symptoms of excessive SNS usage by studying user behavior in SNSs. We designed and developed a data collection application as a tool for gathering data from questionnaires and SNSs by APIs from 177 volunteers at the Thai-Nichi Institute of Technology (TNI), Thailand. This paper introduces the analysis results of questionnaire data to find the factors associated with SNS addiction. Our analytic results identified potential candidates for the key components of SNS addiction.

2. LITERATURE SURVEY

2.1 Negative consequences of excessive SNS usage

Many studies have argued that excessive SNS usage causes various negative consequences. People who spend too much time on SNSs are less involved in their real life communities [1]. Students who use Facebook have lower grades than those who do not because the former are easily distracted and exercise poor time management [1]. J. Al-Menayes et al. [4] concluded that Kuwaiti university students who spend time on SNSs instead of studying have lower grades. In Thailand, many teenagers suffer from such negative effects of excessive SNS usage as lack of sleep, reduced academic performance, inappropriate manners, negative emotional expressions, impairment of family and social functions, and mental health problems [5]. Excessive SNS usage delays bedtimes and reduces sleep quality [6].

Regarding those research outcomes, excessive SNS usage causes relational, performance, health-related, and emotional problems, including the risk of addiction [1].

2.2 SNS addiction

The excessive and compulsive use of SNSs has been linked to behavioral addictions [6]. SNS addiction also shares similarities with other behavioral addictions [1,6]. Kuss and Griffiths [1] argued that its symptoms resemble those of other addictions.
Internet addiction is one type of behavioral addiction. Young [7, 8] identified five types of internet addiction: computer addiction, information overload, net compulsion, cyber-sexual addiction, and cyber-relationship addiction. SNS addiction falls in the last category [1]. Since Facebook has become one of the world’s most commonly used Internet sites, addiction to it may be a specific form of Internet addiction [8].

The huge increase in the amount of SNS usage has attracted many researchers who are interested in SNS addiction. Using a survey-based method, Poh et al. [9] explored the factors that lead to SNS addiction and analyzed the relationship between two factors: social networking dependency and mood modification. They found that among Malaysian undergraduates both factors had significant correlations with SNS addiction. J. Khumsri et al. [10] determined Facebook addiction and related factors among Thai high school students using self-administrative questionnaires to reduce detrimental impacts. Another study [11] conducted a paper-based survey to determine Facebook addiction among Turkish university students and found a relation between loneliness levels and time on Facebook.

Regarding such studies of SNS addiction, even though researchers were drawn to the emerging phenomenon of SNS addiction and relationships with others such as SNS usage pattern, interpersonal relationship, and other addictions, only a few have addressed the prevention of SNS addiction. Therefore, this research is conducted to assess the symptoms of excessive SNS usage by studying user behaviors. Our analytic results will be applied for developing prevention strategies to increase the awareness of the risks of excessive SNS usage.

2.3 Measurement of SNS addiction

Several screening questionnaires of SNS addiction have appeared in the literature [12]. In this study, we measured SNS addiction with two tests: the Internet Addiction Test (IAT) and the Bergen Facebook Addiction Scale (BFAS).

1) Internet Addiction Test:

The Internet addiction test (IAT) [7] is a 20-item questionnaire that measures the characteristics and behaviors associated with compulsive Internet use. It is scored on a 6-point Likert scale that ranges from rarely to always and includes not applicable. The scores of compulsive use range within the following four levels: none (0-30), normal Internet user; mild (31-49), sometimes online too long but able to control usage; moderate (50-79), experiences frequent problems; and severe (80-100), significant impact on daily life. Each IAT question reflects the following symptoms:

1) Salience: feeling preoccupied with the Internet, hiding such behavior, and feeling bored or depressed without it;
2) Excessive use: compulsive usage and an inability to control time online;
3) Neglecting work: decreased performance and productivity due to the amount of time spent online;
4) Anticipation: thinking about future online use;
5) Lack of control: has trouble managing online time;
6) Neglecting social life: forming new relationships with online users to cope with problems and/or reduce mental tension and stress.

2) Bergen Facebook Addiction Scale:

The Bergen Facebook Addiction Scale (BFAS) [6], a six-item questionnaire that assesses Facebook addiction in epidemiology studies and clinical trials, is scored on a 5-point Likert scale from very rarely (0) to very often (4). The total addiction score ranges from 0 to 24 points. The cut-off score for excessive users is 12 points (e.g., scoring 3 or above on at least four of the six items). The items are representative of the following six core addiction components [13]:

1) Salience: behavioral, cognitive, and emotion preoccupation with SNS usage;
2) Mood modification: SNS engagement that modifies/changes emotional states;
3) Tolerance: increased amount of time spent on SNSs;
4) Withdrawal: unpleasantness when SNS use is restricted;
5) Conflict: usage that causes relationship problems with family and friends;
6) Relapse: failure to avoid use.

2.4 Data collection

Understanding user behavior on SNSs has attracted great interest in such research fields as sociology, marketing, and healthcare. Researchers have studied it by collecting the data of SNS usage behaviors as a first step [9,14-18]. Many types of data and collection methods exist. Abdesslem et al. [16] summarized the existing data collection methods as follows:

1) Self-reported data:
   This approach gathers difficult to obtain or expensive data and also saves time. It can be implemented on such large samples as web questionnaire systems [17]. However, some research in human behavior areas has argued that self-report measures are less accurate that actual behavior [19].
2) SNS measurement:

The most common way to directly retrieve data from SNSs uses the application programming interfaces (APIs) provided by the SNSs themselves. Some studies employ automated script that automatically scans and crawls content from websites using HTTP requests/responses [14]. Other researchers collect data through a social network aggregator [14,18] or by tracing network traffic from Internet service providers (ISPs) [16]. However, some of the data available on SNSs cannot be collected with this approach.

3) Application deployment:

This application monitors records and logs the operations and activities of users while they are using computers or smartphones and provides flexibility and privacy for data access [16]. Unfortunately, researchers need to install applications on user devices and manually get the data.

Regarding such existing data collection methods, they are all useful to capture user behaviors, even though they have some limitations. Abdesslem et al. [16] believe that “more reliable data can be obtained by using a new methodology based on the combinations of existing methods: this way, the data collected come from different sources and describe better users’ behaviors.” Therefore, we employed self-reported and SNS measurement approaches and designed and developed a web-based application as a tool for aggregating data from questionnaires and SNSs by APIs [2,3]. We analyzed the obtained data to clarify the characteristics of SNS usage and relationships with SNS addiction. In this paper, we introduce our analysis results of data obtained from questionnaires to find the factors associated with SNS addiction.

3. METHOD

This study explores the key components of SNS addiction by clarifying the characteristics of SNS usage and their relationships. We experimentally collected data from Thai undergraduates at the Thai-Nichi Institute of Technology (TNI) to determine SNS usage variables and the relationships between them and SNS addiction.

3.1 Data collection application

We designed a data collection application and developed a tool for collecting SNS data from questionnaires and SNSs by APIs [2,3]. Its architecture design is shown in Figure 1. The methods for retrieving the data were previously described [3,20,21].
3.3 Experimental procedure

The following steps describe our experimental procedures:

1. The instructor explained an overview of the research and the data collection application.
2. She distributed the instruction documents and explained the experiment’s procedure.
3. Participants accessed the application by a web browser and followed the procedures in the document.
   a. Participants completed the Twitter and/or Facebook quizzes, based on which account they used.
   b. Participants answered questionnaires.

They also read and accepted the terms of agreement before they did the quizzes and answered the questionnaires.

4. RESULTS

4.1 Descriptive statistics

1) Participants:

We did our experiment with 177 undergraduate volunteers from the faculty of Information Technology, the Thai-Nichi Institute of Technology. 155 (87.57%) answered the questionnaires: 101 males and 54 females. Their ages ranged from 17 to 26 (x̄=21.17, SD=1.64), and their cumulative grade point averages (GPAs) ranged from 1.22-4.00 (x̄=2.64, SD=0.62). 92.9% were familiar with computers and the Internet. An overwhelming majority (83.2%) had been using SNSs for more than five years.

2) SNS usage:

The questionnaire results are summarized in Table 1. In terms of the frequency of use, all of the participants visited SNSs every day. We divided them into two frequency groups based on their usage: low or high. The low frequency group (47.74%) visited SNSs at most twice a day, and the high frequency group (52.26%) visited SNSs every two hours.

Figure 3 summarizes the SNS accounts and the usage of the participants. They had 5.26 accounts. Most were Facebook users (x=3.58).

3) SNS addiction:

We used the modified IAT and BFAS tests to determine the SNS addiction of the participants. Their internal consistency and reliability were verified with a Cronbach’s alpha of 0.93 and 0.80, respectively.

Table 2 shows the IAT and BFAS levels. For IAT, there are four levels. No participant fell into the severe level. BFAS has just two levels. 54.84% of the participants were excessive users, and the others were normal users.
4.2 Correlation between IAT and BFAS

We used Pearson’s correlation analysis to clarify the relationship between IAT and BFAS. As shown in Table 3, there were significant positive correlations between IAT and BFAS. The IAT scores had a strong positive correlation with the BFAS scores ($r = 0.773$, $p < 0.01$). The IAT levels also had a positive correlation with the BFAS levels ($r = 0.574$, $p < 0.01$). Moreover, there were significant positive correlations between the IAT scores and each BFAS question. BFAS_5 had the strongest correlation with the IAT score ($r = 0.635$, $p < 0.01$), while BFAS_1 had the weakest correlation with the IAT score ($r = 0.421$, $p < 0.01$).

4.3 Differences between excessive and normal users

Based on the definition of the original IAT level, we named participants as excessive users if their scores appeared in all three levels of Internet addiction (mild, moderate, and severe) and the others as normal users. The original BFAS also classified users this way.

1) Gender:

We used a Chi-square test to examine the differences between genders. The analytic results indicated no significant differences between genders for both IAT ($\chi^2 = 0.032; p > 0.05$) and BFAS ($\chi^2 = 3.309; p > 0.05$).

2) Academic performance:

We used cumulative GPA to compare the academic performances of excessive and normal users. The test for the equality of variances indicated that excessive and normal users had no significant differences. T-test results also indicated that GPA was significantly different between excessive and normal users for both IAT ($t = 2.260; p < 0.05$) and BFAS ($t = 2.160; p < 0.05$).

3) SNS usage:

We constructed discriminant analysis and decision trees for both IAT and BFAS to find effective SNS usage variables from questionnaires (Table 1) for differentiating excessive from normal users.

A. Discriminant analysis: The analysis results showed the variables for differentiating excessive from normal users.

For IAT, the following variables differentiated excessive from normal users:

- Frequency of use;
- Time spent;
- Length;
- Period of use: 09:00-12:00 and 18:00-24:00;
- Purpose: making new friends;
- Location: school/university and on vehicles;
- Activity: posting, commenting, and messaging.

For BFAS, the following variables differentiated excessive from normal users:

- Period of use: 18:00-24:00;
- Location: school/university;
- Activity: messaging.

B. Decision tree: The tree structures showed that the following variables influenced the differentiation of excessive from normal users:

- For IAT (Figure 4), excessive users commented several times a day and messaged daily.

Table 2: IAT and BFAS Levels

| IAT     | BFAS | Total  |
|---------|------|--------|
| None    | 54 (34.84%) | 19 (12.26%) | 73 (47.10%) |
| Mild    | 15 (9.67%)  | 35 (22.58%)  | 50 (32.5%)  |
| Moderate| 1 (0.65%)  | 31 (20.00%)  | 32 (20.65%) |
| Severe  | 0 (0%)     | 0 (0%)      | 0 (0%)      |
| Total   | 70 (45.16%) | 85 (54.84%) | 155 (100.0%) |

Table 3: Correlation Matrix between IAT and BFAS

| Variables | IAT score | IAT level | BFAS score | BFAS level | BFAS_1 | BFAS_2 | BFAS_3 | BFAS_4 | BFAS_5 | BFAS_6 |
|-----------|-----------|-----------|------------|------------|--------|--------|--------|--------|--------|--------|
| IAT score | 1         |           |            |            |        |        |        |        |        |        |
| IAT level | .893**    | 1         |            |            |        |        |        |        |        |        |
| BFAS score| .773**    | .703**    | 1          |            |        |        |        |        |        |        |
| BFAS_1    | .619**    | .574**    | .744**     | 1          |        |        |        |        |        |        |
| BFAS_2    | .421**    | .425**    | .646**     | .413**     | 1      |        |        |        |        |        |
| BFAS_3    | .550**    | .500**    | .758**     | .427**     | .560** | 1      |        |        |        |        |
| BFAS_4    | .525**    | .470**    | .741**     | .527**     | .349** | .494** | 1      |        |        |        |
| BFAS_5    | .564**    | .508**    | .736**     | .628**     | .354** | .418** | .431** | 1      |        |        |
| BFAS_6    | .635**    | .552**    | .777**     | .634**     | .313** | .515** | .506** | .507** | 1      |        |
| BFAS_7    | .613**    | .553**    | .600**     | .541**     | .193** | .249** | .308** | .390** | .482** |        |

** Correlation is significant at 0.01 level (2-tailed).
• For BFAS (Figure 5), excessive users did not use SNSs between 18:00-24:00 or 09:00-12:00. Based on the decision tree results for BFAS, we compared each period of use for BFAS and found that during the 18:00-24:00 period, excessive users used SNSs less than normal users (Figure 6). We also compared each period of use for the participants who did not use SNSs during the 18:00-24:00 period and found that during the 09:00-12:00 period, excessive users used SNSs less than normal users (Figure 7).

5. DISCUSSION AND CONCLUSION

This research is conducted to assess the symptoms of excessive SNS usage by studying user behavior in SNSs. We designed and developed a data collection application as a tool for collecting SNS user behavior data. In this study, we experimentally collected data from undergraduate students in Thailand by questionnaires and statistically analyzed them to clarify SNS usage behaviors and factors associated with SNS addiction.

We employed IAT and BFAS for measuring SNS addiction. A literature survey defined SNS addiction as a sub-type of Internet addiction [1]. Since Facebook is one of the most common SNSs on the Internet, we modified IAT and BFAS for measuring the characteristics and behavior associated with the compulsive use of SNSs by retaining our original concepts and cut-off scores. The results observed from the modified IAT and BFAS scores showed similar results: over half of the participants were excessive users. Since our finding also indicated a positive correlation between the modified IAT and BFAS scores, we can use them for measuring SNS addiction.

Moreover, the analytic results indicate some candidates of effective variables for SNS addiction. A discriminant analysis for both IAT and BFAS indicated the variables...
that differentiate excessive from normal users. All of the variables that influenced BFAS also influenced IAT. This finding also resembled the decision tree results. Based on this study’s results, the following are the candidates for the key components of SNS addiction:

- SNS activities:
  - commenting (+)
  - messaging (+)
- Period of use:
  - from 09:00-12:00 (+)
  - from 18:00-24:00 (-)

The (+) sign indicates that excessive users engaged in more SNS activities than normal users. The (-) sign indicates that excessive users did fewer SNS activities than normal users.

According to our finding, SNS usage is a factor related to potential SNS addiction. Empirical research has suggested gender, generation and cultural differences in many aspects of SNS usage [1].

As for gender, some studies have found that males tend to have higher potential to develop addictive behaviors than females [10, 11], whereas others reported that there were no gender differences in SNS addiction [23, 24]. The results are different according to circumstances. For our results (4.3, 1)), there were no gender differences in SNS addiction. Even we employed the same test, our finding still was different from [10] which found that young Thai males have higher potential to develop addictive behaviors. Therefore, we continue to pay attention to gender for our future work.

As for generation, younger people tend to be more likely to engage in SNSs [1, 25]. They are the majority of SNS users that we should find factors related to SNS addiction. Therefore, we firstly targeted our participants to be younger people.

As for culture, SNS usage has been found to differ across cultures [1]. However, this study was limited to Thai SNS users for exploring the factors that correlate with SNS addiction. Further studies will include participants from other areas.

In this study, we explained the method we used to analyze and obtain factors related to SNS addiction. The method can be applied for further research. In addition, our results are similar to the survey of Thai SNS users with a random sample of 16,661 participants in Thailand in term of usage [26] and the report of global SNS users [25]. Therefore, there is a possibility that the results obtained from this study are broadly applicable to SNS users in general.

6. FUTURE WORK

Further studies will employ the data obtained by SNS APIs, including a combination with questionnaire data to improve data analysis for identifying the factors associated with SNS addiction. Finally, we will apply our analytic results for detecting the symptoms of excessive SNS usage and employ our research’s outcome for developing prevention strategies to increase the awareness of the risks of excessive SNS usage.

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