Exploring Links Between Social Media Habits, Loneliness, and Sleep: A Formal Concept Analysis Approach

Fernanda M. Gomes[a], Julio C. V. Neves[b], Luis Enrique Zárate Gálvez[c] and Mark Alan Junho Song[d]

Instituto de Ciências Exatas e Informática, Pontifícia Universidade Católica de Minas Gerais, Brazil
fernanda.gomes.1117337@sga.pucminas.br, juliocesar.neves@gmail.com, {zarate, song}@pucminas.br

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Abstract: Social media platforms have reshaped personal interactions, allowing engagement with diverse audiences. However, growing evidence suggests that these platforms may also contribute to mental health challenges. This paper investigates the associations between social media usage patterns, loneliness, and sleep quality, using Formal Concept Analysis (FCA) on data from a sample in Bangladesh. The dataset includes information on social media habits, loneliness, anxiety, depression, and sleep disturbances, using metrics from validated psychological scales. Through FCA, this study extracted implication rules that describe how specific social media usage behaviors relate to feelings of loneliness and sleep issues. Findings show that individuals with high levels of social media engagement report shorter sleep durations and heightened symptoms of loneliness. FCA is used in this study to uncover non-obvious relationships within complex datasets, making it a valuable approach for analyzing patterns between social media behaviors and mental health outcomes.

1 INTRODUCTION

Social media are online platforms in which individuals can engage with others and present themselves in a chosen manner. These platforms allow for interaction with a range of audiences, from small groups to vast networks, providing value through content created by users and the feeling of social connection (Carr and Hayes, 2015).

This research aims to uncover links between loneliness, social media usage, and sleep patterns by applying Formal Concept Analysis (FCA) to a publicly available dataset from Bangladesh. The data provided include information on Social Networking Sites (SNS) usage and validated mental health scales. FCA was introduced in 1982 by Rudolf Wille as a derivation of concept hierarchy from a set of objects and their properties (Wille, 2009). FCA has received significant interest in fields such as health, software engineering, and data mining.

Previous studies, such as Marttila's (Marttila et al., 2021), suggest that "increased problematic social media use (PSMU) predicts increased individuals loneliness over time, as well as that increased loneliness predicts decreased life satisfaction". It is interesting to note the hypothesis that "in some cases, PSMU might initiate a cycle of social comparison, isolation, and decreased life quality, happiness, and life satisfaction".

Furthermore, Alonzo (Alonzo et al., 2021) notes that "longitudinal studies suggest poor sleep quality and frequent sleep disturbances may partially explain the association between excessive social media use and poor mental health outcomes."

Examining these relationships through Formal Concept Analysis enable us to move beyond simple correlations and to explore the interplay between social media behaviors and mental health outcomes. Understanding these dynamics is essential for public health interventions, developing responsible platform design, and empowering individuals to cultivate healthier relationships with social media.

This paper is structured as follows: Section 2 introduces the background of the study; Section 3 is about related work; Section 4 describes the methodology; Section 5 presents and discusses the results and Section 6 outlines the conclusion and future work.

[a] https://orcid.org/0009-0005-5607-1689
[b] https://orcid.org/0000-0002-0520-9976
[c] https://orcid.org/0000-0001-7063-1658
[d] https://orcid.org/0000-0001-7315-3874

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2 BACKGROUND

2.1 Social Network - Mental Health

Over the past decade, the extensive use of Social Networking Sites (SNS) like Instagram, Facebook, and Twitter has fundamentally transformed how we interact, communicate, and process information. The broad adoption of these platforms in our everyday lives has influenced multiple aspects of modern society, including advertising, education, public relations and political campaigning As a result, social media has become a fundamental element of contemporary society.

The World Health Organization highlights psychological health issues as a major contributor to declining global mental health. Rising rates and severity of mental illnesses emphasize the need for prioritizing mental health planning, despite often being overlooked. Mental illnesses are among the top causes of disability for individuals aged 15 to 44, with many other disabilities also linked to mental health challenges (Kumar et al., 2024).

Among mental health concerns, loneliness has emerged as a pressing issue in the digital age, with its implications far-reaching across demographics and social contexts. The widespread adoption of SNS has reshaped social interactions, enabling connections but sometimes heightening feelings of isolation. Although these platforms are intended to enhance connectivity, their impact on users' mental health is complex.

2.2 Formal Concept Analysis

Formal Concept Analysis (FCA) is a method used to identify patterns by employing association rules and their implications (Ganter and Wille, 2012). It operates on the principle that concepts are formed through the relationships between objects and attributes, which allows for the development of conceptual hierarchies and facilitates a deeper understanding of associations between significant terms. As such, FCA proves especially valuable for organizing and extracting insights from data sets.

This technique is often applied in studies that examine domains represented as binary tables of objects and attributes. While longitudinal studies investigate a group of individuals with specific traits over multiple time periods (referred to as waves), FCA differs in that it concentrates on analyzing the semantic structure of data at a single point in time, without accounting for temporal changes. Therefore, FCA is particularly useful when the goal is to understand the underlying structure of data at a given moment.

At the core of FCA is the concept of a formal context, represented as a triple $K = (G, M, I)$, where G is a set of objects, M is a set of attributes, and $I \subseteq G \times M$ is the incidence relation, meaning that $(g, m) \in I$ indicates that object g has attribute m.

Table 1: Formal Context Example.

	Attribute 1	Attribute 2	Attribute 3	Attribute 4
object 1	**X**			
object 2		**X**		**X**
object 3	**X**	**X**		**X**
object 4			**X**	

Table 1 exemplifies a formal context. In this example, objects correspond to lines, attributes to columns, and the relationship of incidence represents whether or not the object has an specific characteristic. An $'X'$ is present in the table if the object possesses the corresponding characteristic.

For a set of objects $A \subseteq G$, the set of common attributes shared by the objects in A is denoted as $A' = \{m \in M \mid \forall g \in A : (g, m) \in I\}$. Similarly, for a set of attributes $B \subseteq M$, the set of objects sharing these attributes is $B' = \{g \in G \mid \forall m \in B : (g, m) \in I\}$.

Building on this foundation, a formal concept in a formal context $K = (G, M, I)$ is defined as a pair (A, B), where A is called the extension (the set of objects) and B the intention (the set of attributes). For a pair (A, B) to qualify as a concept, it must satisfy the conditions $A = B'$ and $B = A'$. The set of all formal concepts in context K is denoted as $\beta(K)$.

As an example, using Table 1, objects A = $\{object2, object3\}$, when submitted to the operator ($'$) described above, will result in $A' = \{attribute2, attribute4\}$. So $\{\{object2, object3\}, \{attribute2, attribute4\}\}$ is a concept. All concepts found from Table 1 are displayed in Table 2.

In Table 2 there is a concept with an empty attribute set and a concept with an empty object set. They are called *infimum* and *supremum*, respectively.

Furthermore, FCA supports the generation of association rules that help highlight relationships within the data. Rules are dependencies between elements of a set obtained from a formal context.

Given the context (G, M, I) the rules of implication are of the form $B \to C$ if and only if $B, C \subset M$ and $B' \subset C'$. A rule $B \to C$ is considered valid if and only if every object that has the attributes of B will also have the attributes of C.

Given a rule r and parameters s and c, one can denote:

$$s = suppr(r) = \frac{|A' \cap B'|}{|G'|} \tag{1}$$

Table 2: Existing concepts in the formal context of Table 1.

Objects	Attributes
{object 1, object 2, object 3, object 4}	{}
{object 4}	{attribute 3}
{object 1, object 3}	{attribute 1 }
{object 2, object 3}	{attribute 2, attribute 4}
{}	{attribute 1, attribute 2, attribute 3, attribute 4}

- known as the support of the rule r, and

$$c = conf(r) = \frac{|A' \cap B'|}{|A'|} \quad (2)$$

- referred to as confidence.

These are key metrics for evaluating association rules. Support (s) represents the proportion of transactions in which both attributes $A \cup B$ appear, relative to the total number of transactions. It indicates how often a rule is applicable within the dataset. Confidence (c), on the other hand, measures the likelihood that if a transaction contains A (the antecedent), it will also include B (the consequent), expressed as a percentage or fraction.

3 RELATED WORK

Formal Concept Analysis (FCA) has been recognized for its ability to handle complex data and extract meaningful relationships.

In (Škopljanac Mačina and Blašković, 2014) the authors provide an overview of FCA's theoretical foundations and its applications across various fields, including computer-aided learning, information retrieval and machine learning. Their work shows how FCA can uncover patterns and hierarchies within large datasets, making it a valuable tool for knowledge representation and analysis in different domains, including education and e-learning systems.

FCA has also proven to be a versatile tool across multiple fields of study (Poelmans et al., 2013). A comprehensive survey of FCA applications was conducted, highlighting its usage in areas like text, web and software mining, life sciences and ontology engineering.

(Lana et al., 2022) perform a longitudinal analysis of a COVID-19 database using triadic formal concept analysis. The study presents implication rules that describe the evolution of the COVID-19 pandemic across different points in time.

A longitudinal study provides valuable insights into the evolution of psychological behaviors, especially during the COVID-19 pandemic. (Coutinho et al., 2024) applied triadic analysis, based on Formal Concept Analysis (FCA), to examine a longitudinal dataset capturing individuals' attitudes and reactions throughout the pandemic. By deriving rules, the work illustrates how various factors interact under different pandemic conditions, revealing stress levels associated with disease prevention measures. The findings emphasize how these stress-related behaviors evolved, offering a nuanced view of psychological responses across different pandemic scenarios.

(Song et al., 2024) applied triadic formal concept analysis (FCA) to characterize infant mortality across different regions of Minas Gerais, Brazil. Key factors identified included birth weight, gestation period, and APGAR scores. The findings revealed associations among these variables, underscoring the significance of maternal education and prenatal care consultations.

Furthermore, FCA has been recognized as an effective tool for analyzing complex, unstructured data, and has demonstrated its value in both theoretical and practical applications, such as gene expression analysis and evaluating chemical compound properties.

By leveraging FCA, the present study focuses on extracting meaningful patterns and associations within the selected dataset, contributing to the ongoing exploration of FCA's applicability in health-related domains.

While traditional FCA is based on a dyadic structure, consisting of objects and attributes, Triadic Concept Analysis (TCA) introduces a third element-conditions, forming triadic contexts (Wille, 1995).

These triadic structures are mathematically represented as complete trilattices, allowing for more complex relationships between the three components to be explored. TCA enables the comprehension of sets of concepts within a three-dimensional context, offering a framework for data analysis in fuzzy environments (Lehmann and Wille, 1995).

4 METHODOLOGY

This section details the methodology, including the tool employed for Formal Concept Analysys, the dataset selected and the data preprocessing steps applied. The complete process is represented in Figure 2.

4.1 Database

The database used in this paper is the *Data set concerning the use of social networking sites and mental health problems among the young generation in Bangladesh*, publicly available on Science Direct (Islam et al., 2021). The study was conducted by researchers from the University of Asia Pacific in Dhaka between February and March 2021, using Google Forms.

Initially, the survey received 826 responses, however, 35 were excluded due to partial or incomplete information. This resulted in a final sample of 791 adults from Bangladesh, aged between 15 and 40 years. The study included participants from different education levels, economic statuses, and occupations, ensuring that the analysis captures varied perspectives.

The survey aimed to explore the relationship between social networking site (SNS) use and four dimensions of psychological distress: depression, anxiety, loneliness, and sleep disturbances.

It was divided into sections focusing on sociodemographic information, SNS usage patterns and assessments of mental health problems using internationally validated scales - UCLA Loneliness Scale, PHQ-9 (depression), GAD-7 (anxiety) and PSQI (sleep quality).

The UCLA Loneliness Scale is a tool assess subjective feelings of loneliness and social isolation. The scale consists of 20 items rated on a 4-point scale, ranging from “never” to “often” (Russell, 1996).

The PHQ-9 is a self-administered tool used to screen for depression and measure its severity. It consists of 9 questions that align with the diagnostic criteria for major depressive disorder in the DSM-IV. Each item is scored from 0 (not at all) to 3 (nearly every day), with a total score ranging from 0 to 27. Higher scores indicate more severe levels of depressive symptoms.

Moreover,the GAD-7 is a brief self-report questionnaire used to identify generalized anxiety disorder (GAD). The survey includes 7 items, each scored from 0 (not at all) to 3 (nearly every day), with a total score ranging from 0 to 21. Scores of 10 or higher suggest the presence of GAD.

Finally, the Pittsburgh Sleep Quality Index (PSQI) is a self-report questionnaire that measures sleep quality over a one-month period. It has 19 items that generate seven component scores: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction. They are then combined to create a global score that reflects overall sleep quality, with higher scores indicating worse sleep outcomes (Buysse et al., 1989).

4.1.1 Data Preprocessing

Originally, the dataset had 51 attributes spanning demographics, social media usage habits and health-related information.

For this study, sixteen attributes were selected according to their direct relevance to studying the relationships between social media usage, loneliness, and sleep patterns . Of these, five were created based on the original survey by turning specific responses into binary variables.

Table 3 provides a full list of the selected attributes, while the newly created binary variables and their coding criteria are detailed below:

- **A:** Main purpose of social media usage is social communication.

  For the question “What is your main purpose for using social media?”, the response indicating “To stay connected with people” was coded as 1 and all other purposes were coded as 0.

- **B:** Uses social media at anytime of day.

  For the question “When do you usually use social media?”, the response “Frequently at anytime” was coded as 1 and the other responses as 0.

- **C:** Sleeps for less than 7 hours.

  For the question “How many hours of actual sleep do you get at night?”, responses 4-6 hours and “Less than 4 hours” were coded as 1, indicating less than the recommended 7 hours of sleep. Other responses as 0.

- **F:** More than 3 hours of social media per day.

  For the question “How much time do you spend daily in social media?”, the responses were categorized in two groups: “More than 5 hours” and “3-5 hours” were coded as 1, the rest as 0.

- **H:** Trying to reduce or stop the use of Social Media.

  For the question “Are you trying to control that thing and trying to reduce the use of social media?”, responses “Trying to stop the use” and “Trying to reduce the use” were coded as 1, others as 0.

To further prepare the dataset for Formal Concept Analysis (FCA), binarization rules were applied to all

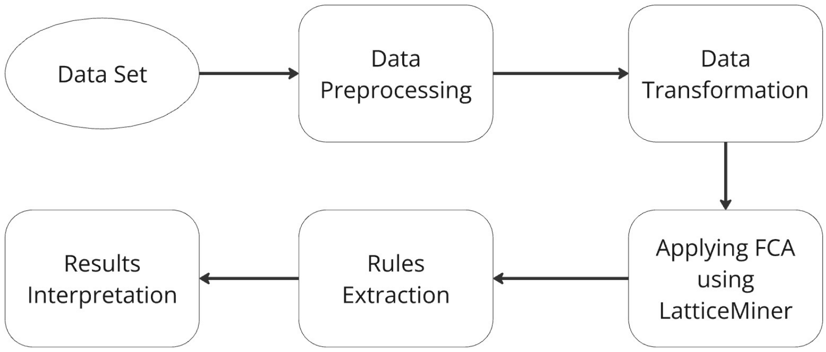

Figure 2: Methodology Diagram.

Table 3: Attributes Selected.

Attribute	Caption
A	Main purpose of social media usage is social communication.
B	Uses social media at any time of day.
C	Sleeps for less than 7 hours.
D	Has experienced peer pressure due to social media.
E	Feels like people are around them but not with them in the last 30 days.
F	Uses social media for more than 3 hours per day.
G	Feels isolated from others in the last 30 days.
H	Trying to reduce or stop the use of social media.
I	Thinks mental well-being would improve without social media.
J	Trouble concentrating on things in the last 30 days.
K	Feels left out in the past 30 days.
L	Feels like people are around them but not with them in the past 30 days.
M	Feels a lack of companionship in the past 30 days.
N	Feels tired or has little energy in the last 30 days.
O	Worries too much about different things in the last 30 days.
P	Feels like there is no one they can turn to in the last 30 days.

categorical variables. The full binarization schema is presented in Table 4.

Table 4: Rules applied to the dataset.

Original Value	Binarized Value
Never, Rarely	0
Sometimes, Often	1
Not at All, Several Days	0
Half Days, Nearly Everyday	1
No	0
Yes	1

4.2 Lattice Miner

Lattice Miner 2.0 is a public domain Java tool developed by Kevin Emamirad under the supervision of Rokia Missaou at the Université du Québec en Outaouais.

It enables the representation and manipulation of input data, concept lattices, and association rules, being a powerful tool for data analysis (Missaoui and Emamirad, 2017).

In the context of this work, Lattice Miner was used for extracting association rules between mental health concerns, sleep patterns and SNS usage.

5 RESULTS

When applying FCA, the minimum thresholds for support (sup) and confidence (conf) were set at 20%. As previously discussed, support is the proportion of transactions with both the antecedent and the consequent. Confidence, on the other hand, measures the likelihood that if a transaction includes A it will also include B.

With these thresholds, 389 implication rules were generated in the format $A \rightarrow B$, in which A represents the antecedent and B the consequent. The selected rules will be discussed in detail within this section.

5.1 Social Media Usage Patterns

Both rules presented in Table 5 highlight the potential addictive nature of SNS. Despite the intention to cut back or awareness of potential mental health benefits from reduced usage, users frequently struggle to limit their time on these platforms.

Table 5: Rules related to Social Media usage patterns.

Index	Rule	Support	Confidence
01	$H \rightarrow F$	27%	47%
02	$I \rightarrow F$	29%	47%

Rule 01 suggests that even among users actively trying to reduce or stop social media usage (H), nearly half still spend more than three hours daily on SNS (F).

Similarly, for *Rule 02*, among those who believe their mental well-being would benefit from reduced social media usage (I), a significant portion (47%) continues to engage heavily, with over three hours of daily use (F).

Studies show that the use of Social Networking Sites can lead to addictive behaviors, characterized by excessive use, withdrawal symptoms, and difficulty in controlling time spent on these platforms.

Heavy usage is often motivated by a need for social connection and a fear of missing out, leading users into a cycle of continued engagement even when they recognize potential benefits of reducing screen time (Kuss and Griffiths, 2017).

These results suggest a potential addictive pattern in SNS use, where users, despite efforts to limit usage, continue to engage heavily, indicating possible dependency behaviors

5.2 Social Media as a Social Communication Tool

Rules displayed in Table 6 show that social motivations can be a factor that leads to heavy, unrestricted and potentially detrimental SNS use.

Table 6: Rules associated to individuals that use SNS as a social communication tool.

Index	Rule	Support	Confidence
03	$A \rightarrow B$	39%	69%
04	$A \rightarrow F$	28%	50%
05	$A \rightarrow C$	31%	56%

Rule 03 implies that 69% of individuals who primarily use Social Media for Social communication (A) tend to access these platforms at any given time (B).

Furthermore, *Rule 04* demonstrates that within the same group, half of the users spend more than three hours daily on SNS (F).

Finally, *Rule 05* shows that of all the individuals who primarily use social media for social communication (A), 56% report less than seven hours of sleep (C).

5.3 Social Media Usage and Sleep

Table 7: Rules that reveal patterns between SNS use and sleep.

Index	Rule	Support	Confidence
06	$B \rightarrow C$	36%	58%
07	$F \rightarrow C$	30%	64%
08	$C \rightarrow J$	20%	31%

As shown in Table 7 there was a significant relationship between high SNS use and reduced sleep duration.

According to the National Sleep Foundation, the minimum appropriate sleep duration for young adults and adults is seven hours (Hirshkowitz et al., 2015).

Sleep deprivation impairs perception, concentration, vision, and reaction time. It also leads to poor memory, rigid thinking, poor decision-making, and emotional issues (Orzeł-Gryglewska, 2010).

For *Rule 06*, a support level of 36% alongside a confidence level of 58% suggests that individuals who access social media frequently at any time (B) are more likely to report sleeping less than seven hours per night (C).

Likewise, *Rule 07* indicates that those who spend over three hours daily on SNS (F) are more likely to experience shorter sleep durations (C).

Longitudinal studies have found that frequent social media use was a risk factor for both poor mental health and poor sleep outcomes (Alonzo et al., 2021).

As for the consequences of the lack of sleep, *Rule 08*, with a support level of 20% and a confidence of 31%, implies that individuals who state sleeping less than seven (C) hours per night are also more likely to experience difficulties concentrating on tasks, such as reading or watching television (J).

These insights align with research suggesting that limiting screen time could play a crucial role in improving sleep quality and, consequently, mental health outcomes (Exelmans and Van den Bulck, 2016).

The findings show a significant association between high SNS engagement and reduced sleep duration, aligning with previous research that links screen time to impaired sleep quality.

5.4 Social Media and Loneliness

Rules shown in Table 8 reveal a relationship between extended Social Media usage and indicators of loneliness , outlining a complex connection between these factors.

Table 8: Rules that demonstrate a duality between SNS use and loneliness.

Index	Rule	Support	Confidence
09	$F \rightarrow L$	26%	54%
10	$F \rightarrow M$	24%	50%
11	$F \rightarrow K$	23%	48%
12	$F \rightarrow G$	23%	48%
13	$L \rightarrow F$	26%	53%
14	$M \rightarrow F$	24%	53%
15	$K \rightarrow F$	23%	54%
16	$G \rightarrow F$	23%	51%

Rules 09-12 indicate that people that spending more than three hours on Social Media daily (F) is associated with several loneliness-related symptoms:

- Feeling that people are around but not with them (L);
- Lacking companionship (M);
- Feeling left out (K);
- Experiencing isolation from others (G).

Conversely, *Rules 13-16* reveal that feelings of loneliness (L, M, K, G) often lead individuals to spend more time on social media (F). This duality suggests that while social media may initially seem like a remedy for loneliness, frequent use can deepen those same feelings, creating a cycle where the pursuit of social connection ultimately reinforces a sense of isolation.

Supporting research shows that lonely individuals turn to social media to fill the gap left by limited in-person relationships, yet they often do not find the support they seek online. Additionally, loneliness is frequently associated with problematic social media usage patterns (O'Day and Heimberg, 2021; Song et al., 2014), and this excessive engagement with SNS has been linked to heightened feelings of loneliness (Marttila et al., 2021).

This cyclical pattern suggests that while social media can temporarily address feelings of loneliness, frequent use may exacerbate isolation, creating a self-reinforcing loop that can contribute to poor mental health outcomes.

6 CONCLUSION AND FUTURE WORK

The present study used FCA to further investigate the associations between Social Media use, sleep patterns and feelings of loneliness among a sample of young adults in Bangladesh.

Among fifty one attributes, the sixteen more relevant to the study were selected and binarized. In sequence, Lattice Miner, a public domain Java tool, was used to extract the implication rules.

From 389 extracted rules, sixteen were selected for in depth analysis, highlighting significant links such as the association between extended social media use and disrupted sleep, and the cyclical relationship between loneliness and increased social media use. Here are the main outcomes:

- Users who attempt to reduce their time spent on Social Media, often find it challenging to do so. Even when individuals recognize potential benefits of limiting their online time, the appeal of ongoing engagement with SNS endures;
- Those who primarily use SNS as a means of social communication tend to spend significant time online, often engaging without restriction, which can lead to reduced sleep duration;
- Frequent social media users, especially those who access platforms at all hours, are more likely to experience shorter sleep time, which can contribute to cognitive challenges, such as difficulties with concentration.
- High SNS engagement correlates with feelings of isolation, while loneliness, in turn, motivates increased social media usage.

The study findings reinforce concerns that while SNS can serve as a medium for social connection, frequent or prolonged use might aggravate feelings of isolation and impair sleep quality, impacting overall well-being.

It is important to note that FCA turned out to be an efficient and useful approach to find aspects not easily identified at first.

Future research could employ longitudinal data to track changes over time, further validating the impact of social media on mental health. Additionally, studies could incorporate diverse demographic datasets to examine whether cultural differences influence these behaviors.

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