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A Decision Support System for Determining the Level of Digital Addiction Among College Students Using the TOPSIS Method

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Abstract

Excessive smartphone use among college students has the potential to lead to digital addiction, which can negatively impact academic performance, mental health, and the quality of social life. This issue requires a systematic and objective approach to accurately identify the level of digital addiction. This study aims to develop a decision support system using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to determine the level of digital addiction among students based on five criteria: daily smartphone usage duration, frequency of accessing social media, sleep disturbances caused by gadget use, the impact of smartphones on study focus, and the frequency of gadget use during lectures beyond academic needs. Data were collected via a questionnaire distributed to 30 active students. The results of the TOPSIS calculations showed that 63.3% of students fell into the moderate category, 23.3% into the high category, 10.0% into the low category, and 3.3% into the very high category, with an average preference value of 0.4210. These findings indicate that digital addiction is a real and fairly widespread problem among students. The TOPSIS-based decision support system has proven capable of producing objective and measurable classifications, making it an effective tool for educational institutions in designing targeted intervention programs to address student digital addiction.

***Keywords**: Digital Addiction, Decision suppot system, TOPSIS, University Students*

1. Introduction

Information technology is evolving at a rapid pace and undergoing dynamic changes over time. Over the past two decades, information technology has evolved from a simple communication tool into an essential necessity that supports various activities of modern society. This development is marked by the emergence of digital products such as smartphones, social media platforms, streaming services, and artificial intelligence-based applications, which continue to grow and interconnect to form a complex digital ecosystem. This revolution has occurred not only due to technological advancements alone but also because of rapid adoption across various aspects of life [1].

In the digital age, smartphones have emerged as a popular device because they can support a wide range of user needs in a single practical, flexible, and efficient device. Smartphones are used for communication, accessing information, education, and entertainment [2]. According to the 2024 State of Mobile report from data.ai, Indonesia ranks among the countries with the highest average daily smartphone usage globally, at approximately 5.4 hours per day. Additionally, data from the Central Statistics Agency indicates that 68.65% of Indonesia's population uses mobile phones. This high level of smartphone usage demonstrates that digital devices have become an integral part of daily life, particularly for students.

The existence of smartphones offers a number of tangible benefits that cannot be ignored. Access to information is much faster and more extensive, the learning process is more flexible thanks to e-learning platforms, long-distance communication is easier and cheaper, and workplace productivity has increased thanks to the growing number of supporting apps. For students in particular, smartphones have become a powerful academic tool, ranging from accessing scientific journals and participating in online study groups to managing schedules and assignments in real-time. However, behind all these conveniences, there are often risks that go unnoticed at first. Intensive use, combined with apps deliberately designed to keep users engaged for as long as possible, gradually creates conditions conducive to the development of addictive behavior. These conditions can heighten the risk of serious threats to users.

Excessive use of digital technology can lead to digital addiction. Digital addiction is a form of behavioral dependence characterized by the continuous use of digital technology without time limits, including the internet, computers, smartphones, video games, and social media [3][4]. Among college students, this condition is generally characterized by prolonged smartphone and social media use, which can disrupt academic activities, reduce focus on studying, and negatively impact academic performance [5]. Excessive smartphone use can have negative effects on students, including mental, psychological, physiological, sociological, and educational impacts [6].

In terms of psychology, digital addiction is viewed as a form of behavioral addiction characterized by a strong urge to repeatedly use a smartphone without being able to control the duration of use. According to King et al. in [7], individuals experiencing digital addiction tend to feel restless, anxious, or uncomfortable when away from their smartphones or the internet. Digital addiction is also associated with impaired self-control, poor time management, and a high need for social validation through digital media. In the long term, these conditions can trigger stress, anxiety, depression, and even impair students' mental health. Therefore, an approach is needed that can accurately identify the level of digital addiction so that preventive measures and interventions can be implemented as early as possible.

One approach that can be implemented to assist in identifying the level of digital addiction is a decision support system (DSS). A decision support system is a computerized system used to store, process, and analyze structured and semi-structured information to serve as a basis for decision-making within an organization [8]. In this context, the DSS is used to determine the level of digital addiction based on a number of predetermined criteria, such as duration of smartphone use, frequency of social media access, sleep disturbances, and self-control. The use of a DSS is considered capable of providing more objective, systematic, and measurable assessment results compared to manual assessment [9]. One method that can be used in decision support systems is the TOPSIS method. TOPSIS is a multi-criteria decision-making method for ranking selected alternatives [8]. This method was chosen because it is rational, intuitive, and relatively easy to understand [10].

The effectiveness of the TOPSIS method in decision support systems has also been demonstrated in several previous studies. Research by Khorsandi and Li [11] on video game addiction analysis using the AHP and TOPSIS methods showed that the TOPSIS method is capable of ranking addiction levels effectively and systematically. Research by Ramadhan and Eliyen [12] on the implementation of the TOPSIS method in decision support systems showed that the TOPSIS method produces more objective assessments than manual assessments. Additionally, the study by Tuluba et al. [5] on the relationship between digital addiction and academic achievement indicates that digital addiction negatively impacts students' concentration and academic performance. The study by Saputra et al. on classifying the impacts of social media addiction among students using SVM and K-means clustering demonstrates that clustering methods are highly effective as a basis for risk labeling [13].

Based on several previous studies, there remains a research gap regarding digital addiction among college students. Previous studies have generally focused only on analyzing gaming addiction, the relationship between digital addiction and academic performance, or the application of the TOPSIS method to various decision-making scenarios. Furthermore, no study has specifically implemented a decision support system using the TOPSIS method to determine the level of digital addiction among college students based on an integrated set of digital behavior indicators. This study is expected to serve as an alternative to assist in the decision-making process regarding the identification of digital addiction levels in a more effective and systematic manner. Therefore, this study aims to develop a decision support system using the TOPSIS method to assist in the objective and measurable identification of students' digital addiction levels.

2. Literature Review

2.1. Digital Addiction

Digital addiction is a condition in which a person uses digital technology compulsively, repeatedly, and uncontrollably, including the internet, computers, smartphones, video games, and social media [3][4]. Individuals who are addicted to something exhibit several symptoms, such as salience (excessive preoccupation with digital activities), mood modification (changes in mood due to digital use), tolerance (an increasing need for time spent using digital devices), withdrawal symptoms (restlessness when not using digital devices), conflict (the emergence of conflicts with the surrounding environment), and relapse (a tendency to return to old habits despite efforts to stop) [7].

Digital addiction is on the rise alongside the rapid development of information and communication technology. Young (2010) defines internet addiction as a syndrome characterized by prolonged internet use and an inability to control one's online behavior [14]. Over time, forms of digital addiction have expanded beyond the internet to include social media addiction, online gaming addiction, and streaming content addiction. Research by Kuss and Griffiths (2011) indicates that excessive social media use can trigger addiction symptoms similar to substance addiction, particularly among adolescents and young adults. The impacts of digital addiction include reduced productivity, sleep disturbances, social isolation, declining academic performance, and mental health issues such as anxiety and depression [2][15].

2.2. Decision Support System

A Decision Support System (DSS) is a computer-based system used to assist decision-makers in solving semi-structured and unstructured problems [16]. It fulfills this function by providing the ability to store, process, and analyze data that assists managers in the decision-making process [17]. The main components of a DSS involve problem-solving, system functions, and documentation functions.

The application of DSS in various fields has been proven to significantly improve the quality and efficiency of decision-making. Effendi (2021) demonstrated that a DSS using the TOPSIS method produces more detailed, practical, and effective evaluations compared to manual evaluations that lack weighted priority criteria, and the developed system passed black-box testing, making it suitable for implementation [18]. Ramadhan and Eliyen (2022) implemented a TOPSIS-based DSS for student evaluation based on academic and non-academic achievements, and the results showed objective rankings because the weights and calculations were performed in accordance with the applicable methodological principles [12]. Dafitri (2023) developed a TOPSIS-based DSS for selecting student housing, yielding the highest preference score of 0.8017 among 10 alternatives, demonstrating the system's reliability in addressing multi-criteria problems [8]. Suherwin (2025) expanded the application of the TOPSIS DSS to the domain of geospatial-based social assistance distribution, demonstrating that the flexibility of the DSS allows it to be adapted to various domains, including the identification of addictive behavior among students [19].

2.3. TOPSIS

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-criteria decision-making method developed by Hwang and Yoon in 1981 [18]. This method is well-known for its ability to determine the best alternative by considering relative proximity to the positive ideal solution and the negative ideal solution [17]. Additionally, this method has several advantages, including sensitivity to differences in criterion weights and scales, the ability to handle uncertainty and complexity in alternative selection, as well as resource availability and ease of implementation. The TOPSIS method was selected for this study because identifying students' levels of digital addiction involves numerous criteria with varying weights such as duration of use, withdrawal symptoms, disruption of activities, and psychosocial impacts which require a method capable of integrating them simultaneously and producing objective, measurable rankings. The steps for the TOPSIS calculation are as follows:

a. Creating a normalized decision matrix

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad (1)$$

Where I = 1, 2, ..., m; and j = 1, ..., n, Notes:
r_{ij} = normalized decision matrix [i][j]
X_{ij} = decision matrix [i][j]

b. Creating a weighted normalized decision matrix.

$$Y_{ij = W_i} \times r_{ij} \qquad (2)$$

Notes:
Y_{ij} = result of the normalization matrix
W_i = weight of criterion i
r_{ij} = normalized matrix

c. Identifying positive and negative ideal solutions, where A^+ represents the positive ideal solution and A^- represents the negative ideal solution.

$$A^+ = (y1^+, y2^+, \ldots\ldots, y_i^+); \qquad (3)$$
$$A^- = (y1^-, y2^-, \ldots\ldots, y_i^-);$$

Conditions:
A value will be $y1^+$ if the maximum of y_{ij} has a benefit nature, and the minimum has a cost nature. An item will have a value of $y1^-$ if at most y_{ij} has a cost attribute, and at least one has a benefit attribute [20].

d. Determine the distance between the value of each choice and the positive ideal solution matrix D_i^+ and the negative ideal solution matrix D_i^-

$$D_i^+ = \sqrt{\sum_{i=1}^{n} (y_i^+ - y_{ij})} \qquad (4)$$

Notes:
D_i^+ = The distance between alternative Ai and the positive ideal solution.
y_i^+ = Components forming at position [i][j].
y_{ij} = the normalized matrix weighted at position [i][j].

$$D_i^- = \sqrt{\sum_{i=1}^{n} (y_i^- - y_{ij}} \qquad (5)$$

Notes:
D_i^- = The distance between alternative Ai and the positive ideal solution.
y_i^+ = Components forming at position [i][j].
y_{ij} = the normalized matrix weighted at position [i][j].

e. Determination of the preference values (Vi) for each alternative.

$$V_i = \frac{D_i^-}{D_i^- + D_i^+} \qquad (6)$$

Note:
A higher Vi value indicates that alternative Ai is preferred.

3. Research Method

This study employs a research methodology that serves as a guide to ensure a clear and structured research process. The stages of the research are presented in Figure 1.

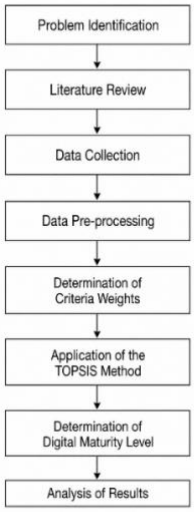

Fig. 1: Reaserch stages

3.1. Problem Identification

In this stage, the researcher will identify issues related to digital addiction among college students. The purpose of problem identification is to clearly define the scope of the problem so that the research can be directed toward appropriate solutions.

3.2. Literature Review

The literature review stage is used to establish a strong theoretical foundation to support the research process. The literature review involves collecting and analyzing relevant sources, including scientific journals, books, and previous studies related to digital addiction, decision support systems, and the TOPSIS method.

3.3. Data Collection

Data collection for this study was conducted by distributing a questionnaire. The questionnaire was used to obtain data regarding students' levels of digital addiction based on several criteria, including smartphone usage duration, frequency of social media access, sleep disturbances, and self-control. The questionnaire was distributed to 30 active students who use smartphones in their daily activities.

3.4. Data Preprocessing

In this stage, the collected data undergoes preprocessing before entering the calculation process. This stage aims to ensure the data used is clean, complete, and valid. The data preprocessing process includes checking data completeness, data cleaning, and converting the data into a format suitable for processing using the TOPSIS method.

3.5. Determination of Criterion Weights

In this stage, weights are determined for each criterion used in the decision-making process. Criterion weights reflect the relative importance of each criterion regarding the decision to be made. The determination of weights is based on a literature review and considerations from experts in the field of digital addiction, ensuring that the established weights are objective and scientifically justifiable.

3.6. Application of the TOPSIS Method

Once the criterion weights have been determined, the next step is to apply the TOPSIS method. This stage involves a series of calculations, including the normalization of the decision matrix, the weighting of the normalized matrix, the determination of the positive and negative ideal solutions, the calculation of the Euclidean distance of each alternative from the ideal solutions, and the calculation of the preference values for each alternative. The result of this process is the preference values used as the basis for ranking the level of digital addiction for each respondent.

3.7. Determination of Digital Addiction Levels

Based on the preference values obtained from the TOPSIS method calculations, the level of digital addiction is determined for each respondent. Digital addiction levels are classified into several categories based on the generated preference values, allowing each respondent's addiction level to be identified objectively and measurably. This classification serves as the primary output of the decision support system developed in this study.

3.8. Analysis of Results

The final stage is the analysis of results. In this stage, the results of the digital addiction level classification are interpreted and discussed. The analysis is conducted comprehensively by comparing the obtained results with relevant previous studies. Additionally, in this stage, the research conclusions and recommendations are formulated, which can serve as input for developers

4. Result

In this study, a decision support system was tested and developed using the TOPSIS method. The calculation process for the 30 sample data points was conducted in stages to ensure there were no errors during the process and that the results obtained were accurate. This process began with determining the criteria and continued through calculating the preference values for each predefined alternative. The criteria used to determine the level of digital addiction are shown in Table 2.

Table 1. List of Digital Addiction

Criterion	Description
C1	Daily Smartphone Usage Duration
C2	Daily Frequency of Social Media Use
C3	Sleep Disturbances Due to Gadget Use
C4	Impact of Smartphones on Study Focus
C5	Frequency of Gadget Use During Lectures Beyond Academic Needs

Table 1. Shows the indicators that may lead to digital addiction. Each criterion is rated on a 1–5 Likert scale based on its level of importance.

Table 2. Criteria Rating Scale

Score	Description
1	Very low
2	Low
3	Moderate
4	High
5	Very High

Table 2 shows the rating scale used in this study to convert qualitative data into quantitative data to facilitate calculations using the TOPSIS method. The use of this scale aims to simplify the process of measuring students' levels of digital addiction based on each criterion used in the study. The higher the score given, the higher the level of digital addiction behavior demonstrated by the respondents.

The weighting of each criterion was derived from a literature review of articles and journals.

Table 3. Criteria Values for Smartphone Usage Duration

Smartphone Usage Duration	Value
≤ 2 hours	1
3–4 hours	2
5–6 hours	3
7–8 hours	4
> 8 hours	5

Table 3 shows the rating scale for criterion C1, namely daily smartphone usage duration. This criterion is categorized as a "cost" criterion, meaning that the longer the duration of smartphone use, the higher the potential for digital addiction experienced by students. Smartphone use of two hours or less is assigned a value of 1, indicating a very low level of addiction, while use exceeding eight hours per day is assigned the highest value, 5, indicating a very high potential for addiction.

Table 4. Criteria values for Frequency of Social Media Use

Frequency of Social Media Use	Value
1–5 times	1
6–10 times	2
11–20 times	3
21–30 times	4
> 30 times	5

Table 5 shows the rating scale for criterion C2, which is the frequency of social media use per day. This criterion falls under the cost category, as the more frequently students access social media, the higher the potential for digital addiction. Respondents who access social media 1–5 times per day are assigned a score of 1, indicating a very low risk of addiction, while those who access social media more than 30 times per day are assigned a score of 5, indicating a very high risk of addiction. The frequency of social media access was selected as one of the indicators because it reflects the intensity of an individual's interaction with the digital environment in daily life. Excessive social media use can reduce productivity, lower concentration during study, and increase the tendency toward compulsive behavior in smartphone use.

Table 5. Criteria values for Sleep Disorder

Level of Sleep Disturbance	Value
Never	1
rarely	2
Sometimes	3

Often	4
Very often	5

Table 5 shows the rating scale for criterion C3, which is sleep disturbance caused by smartphone use. This criterion is a cost factor because the more frequently a person experiences sleep disturbance due to gadget use, the higher their level of digital addiction.

Table 6. Criteria values for impact on study focus

Impact on study focus	Value
No impact	1
Slight impact	2
Moderate impact	3
Significant impact	4
Major impact	5

Table 6 shows the rating scale for criterion C4, namely the impact of smartphone use on students' ability to focus on their studies. This criterion is also classified as a "cost" criterion because the greater the negative impact of smartphones on students' ability to focus, the higher the level of digital addiction experienced. The impact of smartphones on students' ability to focus is a highly relevant indicator in the context of this study because the research subjects are college students who should prioritize academic activities. Research by Tülübaş et al. shows that digital addiction, particularly smartphone addiction, is significantly and negatively correlated with students' academic achievement through the mechanisms of attention disruption and increased cognitive load [3].

Table 7. Criteria values for gadget usage frequency during lectures

Frequency of Gadget Usage During Lectures	Value
Never	1
Rarely	2
Sometimes	3
Often	4
Very often	5

Table 7 shows the rating scale for criterion C5, namely the frequency of gadget use during lectures beyond learning needs. This criterion is a cost factor because gadget use that is not relevant to lecture activities indicates uncontrolled digital usage behavior.

After the questionnaire data was collected, the values were converted using the rating scale in Table 3. This process was carried out to facilitate the TOPSIS method calculation. The following decision matrix data, converted using a 1–5 Likert scale, is presented in Table 8.

Table 8. Decision Matrix

Code	C1	C2	C3	C4	C5
A1	5	2	3	2	3
A2	5	4	3	2	2
A3	3	1	2	5	4
A4	3	2	4	3	2
....	....	....	....	....	....
A27	4	3	2	2	3
A28	4	4	3	3	3
A29	5	5	4	3	3
A30	4	4	2	2	2

These weights were determined based on an in-depth review of the scientific literature on the determinants of digital addiction, in which the duration and frequency of digital device use are consistently cited as the most influential key indicators for identifying digital addiction in individuals, as shown in Table 9.

Table 9. Type and Weight of Criteria

Criteria	Type	Weight
Smartphone Usage Duration	Cost	5
Frequency of Social Media Use	Cost	4
Level of Sleep Disturbance	Cost	3
Impact on study focus	Cost	3
Frequency of Gadget Usage During Lectures	Cost	2

Steps in calculating the TOPSIS method:

1. Construct a normalized decision matrix.
   a). Squaring each value in the matrix is the first step in normalization. The squares of each matrix element are then taken to the root according to the criteria from the 30 data points are shown in Table 10.

Table 10. First Stage of the Normalized Matrix

Kode	C1	C2	C3	C4	C5
A1	25	4	9	4	9
A2	25	16	9	4	4
A3	9	1	4	25	16
A4	9	4	16	9	4
....	....	....	....	....	....
A27	16	9	4	4	9
A28	16	16	9	9	9
A29	25	25	16	9	9
A30	16	16	4	4	4
Total	524	378	312	317	269
square root	22,891	19,442	17,664	17,804	16,401

b). Dividing each element of the decision matrix X_{ij} by the square root of each criterion constitutes the second stage of normalization. The results of dividing each element by the square root of the criterion for the 30 available data points are shown in Table 11.

Table 11. Normalized Matriks

	C1	C2	C3	C4	C5
A1	0.2184	0.1029	0.1698	0.1123	0.1829
A2	0.2184	0.2057	0.1698	0.1123	0.1219
A3	0.1311	0.0514	0.1132	0.2808	0.2439
A4	0.1311	0.1029	0.2265	0.1685	0.1219
.....	....	....	....	....	....
A27	0.1747	0.1543	0.1132	0.1123	0.1829
A28	0.1747	0.2057	0.1698	0.1685	0.1829
A29	0.2184	0.2572	0.2265	0.1685	0.1829
A30	0.1747	0.2057	0.1132	0.1123	0.1219

2. The next step is to create a normalized decision matrix with weights. This step is known as the Weighted Normalized Matrix. The procedure for this step involves multiplying the normalized decision matrix by the criterion weights listed in Table 10. The results of the weighted normalized decision matrix are presented in Table 12.

Table 12. Weighted Normalized Matrix

	C1	C2	C3	C4	C5
A1	1.0921	0.4115	0.5095	0.3370	0.3658
A2	1.0921	0.8230	0.5095	0.3370	0.2439
A3	0.6553	0.2057	0.3397	0.8425	0.4878
A4	0.6553	0.4115	0.6794	0.5055	0.2439
A27	0.8737	0.6172	0.3397	0.3370	0.3658
A28	0.8737	0.8230	0.5095	0.5055	0.3658
A29	1.0921	1.0287	0.6794	0.5055	0.3658
A30	0.8737	0.8230	0.3397	0.3370	0.2439

3. Determine the positive and negative ideal solutions by performing calculations based on the characteristics of each criterion, using formula (3) as shown in Table 13.

Table 13. Determining the Positive and Negative Ideal Solutions

	C1	C2	C3	C4	C5
Positive	0.2184	0.2057	0.1698	0.3370	0.2439
Negative	1.0921	1.0287	0.8492	0.8425	0.4878

4. Use the positive and negative ideal solution matrices to determine the distance of each alternative.

a). The first step in calculating the distance to the ideal solution is to square the difference between the weighted normalization matrix and the positive and negative ideal solutions. The results of squaring the positive ideal solution are presented in Table 15.

Table 14. Squaring the Positive Ideal Solution

	C1	C2	C3	C4	C5
A1	0,7634	0,0423	0,1154	0	0,0149
A2	0,7634	0,3810	0,1154	0	0
A3	0,1908	0	0,0288	0,2555	0,0595
A4	0,1908	0,0423	0,2596	0,0284	0
A27	0,4294	0,1693	0,0288	0	0,0149
A28	0,4294	0,3810	0,1154	0,0284	0,0149
A29	0,7634	0,6772	0,2596	0,0284	0,0149
A30	0,4294	0,3810	0,0288	0	0

b. Squaring the ideal negative solution

Table 15. Squaring the Negative Ideal Solution

	C1	C2	C3	C4	C5
A1	0	0.3810	0.1154	0.2555	0.0149
A2	0	0.0423	0.1154	0.2555	0.0595
A3	0.1908	0.6772	0.2596	0	0
A4	0.1908	0.3810	0.0288	0.1136	0.0595
......	....	....	......	....	....
A27	0.0477	0.1693	0.2596	0.2555	0.0149
A28	0.0477	0.0423	0.1154	0.1136	0.0149
A29	0	0	0.0288	0.1136	0.0149
A30	0.0477	0.0423	0.2596	0.2555	0.0595

c). The next step is to calculate the square of the sum of the positive and negative ideal solution values for each alternative to determine the ideal solution distance shown in Table 16. This value will then be used to calculate the preference score for each respondent.

Table 16. Calculation of the Distance Between the Positive and Negative Ideal Solutions

Positive	negative
0.967441	0.87563
1.122362	0.687541
0.731222	1.061934
0.721924	0.879592
....	....
0.80151	0.864308
0.984372	0.577804
1.320411	0.396586
0.916072	0.815263

5. Calculate the preference scores for each respondent using the TOPSIS method. These preference scores are used to classify respondents according to their level of digital addiction. A score close to 0 indicates a low level of digital addiction. while a score close to 1 indicates a very high level of addiction.

Table 17. Calculation of Preference Values

Code	Preference
A1	0.48
A2	0.38
A3	0.59
A4	0.55
......	....
A27	0.52
A28	0.37
A29	0.23
A30	0.47

Based on the reference values in Table 17. each respondent's level of digital addiction was then classified into four categories according to the established preference values.

Table 18. Classification of Digital Addiction Levels

Range	Category
0 - 0.25	Low
0.26 – 0.50	Medium
0.51 – 0.75	High
0.76 – 1	Very High

Based on the classification ranges in Table 18. each respondent's score was then grouped into the categories of low. moderate. high. and very high. The results of the classification of respondents' addiction levels are shown in Table 19.

Table 19. Levels of Digital Addiction

Code	Preference	Tingkat kecanduan
A1	0.48	Medium
A2	0.38	Medium
A3	0.59	High
A4	0.55	High
A5	0.27	Medium
A6	0.30	Medium
A7	0.85	Very High
A8	0.00	Low
A9	0.57	High
A10	0.41	Medium
A11	0.57	High
A12	0.51	High
A13	0.28	Medium
A14	0.43	Medium
A15	0.45	Medium
A16	0.31	Medium
A17	0.41	Medium
A18	0.45	Medium
A19	0.44	Medium
A20	0.30	Medium
A21	0.41	Medium
A22	0.53	High
A23	0.42	Medium
A24	0.46	Medium
A25	0.45	Medium
A26	0.22	Low
A27	0.52	High
A28	0.37	Medium
A29	0.23	Low
A30	0.47	Medium

Based on the results of the TOPSIS method calculations presented in Table 17 and the classification in Table 18. all 30 student respondents were successfully grouped into four categories of digital addiction levels. The distribution of results in Table 19 shows that the majority of students fall into the moderate category. namely 19 students or 63.3% of the total respondents. followed by the high category with 7 students (23.3%). the low category with 3 students (10.0%). and the very high category with 1 student (3.3%). The average preference score for all respondents was 0.4210. which falls within the moderate category range. The dominance of the moderate category reflects that the digital usage patterns of most students have exceeded reasonable limits but have not yet reached a stage that significantly disrupts daily functioning. Nevertheless. this condition warrants caution because. without appropriate intervention. students in the moderate group concentrated in the preference score range of 0.40 to 0.48 have the potential to escalate their addiction levels to higher categories. From a behavioral addiction perspective. the moderate phase is often a condition in which individuals have not yet realized that their behavioral patterns are beginning to shift toward compulsive behavior [7].

Upon closer examination by category. respondents in the high category include A3. A4. A9. A11. A12. A22. and A27. with preference scores ranging from 0.51 to 0.59. The digital behavior profile of this group indicates high smartphone usage intensity across nearly all criteria. particularly in criterion C4. which suggests that smartphone use has actively interfered with the quality of the learning process. This finding aligns with Hsieh's [2] research. which demonstrates that high smartphone usage frequency is significantly negatively correlated with students' academic performance. On the other hand. one respondent. A7. received the highest preference score of 0.85 and fell into the very high category. indicating that their digital behavior pattern most closely resembled the most severe addiction profile among all respondents. Conversely. the three respondents in the low category A8. A26. and A29 with preference scores of 0.00. 0.22. and 0.23. respectively. demonstrated good self-regulation skills. did not experience significant sleep disturbances. and were able to maintain their focus on studying without being excessively distracted by their smartphones [3].

Overall. the findings of this study have significant implications from both academic and practical perspectives. From an academic standpoint. these results reinforce the argument that digital addiction is a multidimensional phenomenon that cannot be reduced to a single indicator alone; thus. a multi-criteria approach using the TOPSIS method has proven capable of producing a more comprehensive and objective classification. From a practical perspective. the proportion of students in the high and very high categories. reaching 26.6%. is a concerning figure within the academic context and requires a response from educational institutions. Intervention programs such as digital literacy initiatives. technology usage counseling. or more structured policies regarding gadget use in classroom activities should be considered as concrete preventive measures. As emphasized by Ramadhan and Eliyen [11]. a decision support system-based approach offers added value because it can identify specific individuals who require further attention. thereby enabling the management of digital addiction to be carried out in a more targeted and efficient manner.

5. Conclusion

Based on the research results. the application of the TOPSIS method in this decision support system is capable of classifying students' levels of digital addiction according to the established criteria. The results of the study on 30 respondents indicate that the majority of students fall into the moderate digital addiction category. accounting for 63.3%. followed by the high category at 23.3%. the low category at 10%. and the very high category at 3.3%. The average preference value obtained was 0.4210. indicating that students' digital addiction levels generally fall into the moderate category. The TOPSIS method provides objective. systematic. and measurable assessment results in identifying students' digital addiction levels based on several indicators of smartphone usage behavior.

uture research is recommended to expand the sample size and scope of the study to ensure that the results are more representative. In addition. future studies could include psychological indicators such as anxiety levels. self-control. and withdrawal symptoms to make the identification of digital addiction more comprehensive. The development of a web-based system or mobile application could also be pursued to facilitate the automatic and real-time identification of digital addiction levels.

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