

ISSN:

e-ISSN : 2718-0794 - Print ISSN : 2757-5861

ABOUT US

Journal of Theory and Practice in Healthcare, an independent academic publication, is a peer-reviewed journal published three times a year in January, May and September

Publication Type

National (Local) Academic Journal, 3 Issues Per Year

Publisher

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SAGE Yayıncılık Rek. Mat. San. Tic. Ltd. Şti Tel: (312) 341 00 02

SAĞLIKTA METİN MADENCİLİĞİ: TEORİ VE UYGULAMA



DR. SEMA DÖKME YAĞAR
DOÇ. DR. ÇAĞDAŞ ERKAN AKYÜREK

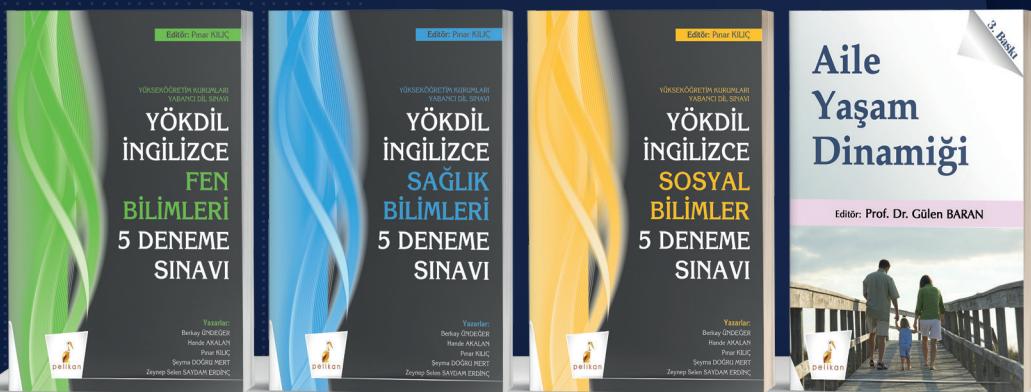


Digital Health Searches After the February 6, 2023 Earthquakes: An Analysis Based on Google Search Volume Data

Ferda IŞIKÇELİK

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ARTICLE INFO	ABSTRACT
Article Type: Research Article	
Keywords: Earthquake, Natural Disaster, Hospital, Access to Healthcare, Health	
Corresponding Author(s) Ferda IŞIKÇELİK	<i>This study aims to examine the Turkish public's digital search behaviour for healthcare needs in the 30 days following the 6 February 2023 earthquakes, using Google Trends data. This descriptive cross-sectional study examined trends in searches related to healthcare access, institutional responses, and psychological impacts. In this context, the following terms were searched for: 'earthquake emergency service', 'earthquake hospital', 'earthquake stress', 'earthquake 112', 'earthquake emergency aid', 'Kızılay', 'National Medical Rescue Team (UMKE)', 'field hospital', 'Disaster and Emergency Management Authority (AFAD)', 'health teams', 'earthquake anxiety', 'earthquake trauma', 'earthquake stress', 'earthquake fear', and 'earthquake psychology'. Google Trends data shows the relative popularity of search terms at a specific time and in a specific region, using a Search Volume Index (SVI) ranging from 0 to 100. In this study, SVI values were analysed as a time series. Line graphs show the daily and weekly SVI changes for each keyword between 6 February and 8 March 2023. Pearson correlation analysis and paired t-tests were applied to examine public online search behaviour after the earthquake and determine relationships between themes. The results revealed that the terms 'earthquake fear', 'earthquake hospital', and 'AFAD' had high search volumes. While searches for 'earthquake hospital' rose rapidly in the early days before declining quickly, 'earthquake fear' declined gradually. Interest in 'AFAD' was steadier and longer-term. The study found that digital searches accurately reflected the public's needs. It is recommended that public digital search behaviour be taken into account when developing plans for the provision of health services in disasters.</i>
Article Application Date: 03.09.2025	
Article Acceptance Date: 08.12.2025	



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Health Workers Attitudes Toward Affiliation and the Effect of Affiliation on Job Satisfaction

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ARTICLE INFO	ABSTRACT
Article Type: Research Article	
Keywords: Affiliation, Health professionals, Job satisfaction	
Corresponding Author(s) 1. Hamit Özgür SÜNGER 2. Turgut UZUNÇAKMAK 3. Serap DURUKAN KÖSE	<p><i>In recent years, healthcare systems have undergone significant transformation due to cost pressures, rising patient expectations, and the need for institutional restructuring. In this context, hospitals have increasingly adopted strategies such as mergers, acquisitions, and affiliation agreements to ensure economic and organizational sustainability. Affiliation stands out as a strategic collaboration model based on workforce, training, and resource sharing between institutions. The aim of this study is to identify healthcare workers' attitudes toward the affiliation process and examine the effect of these attitudes on job satisfaction. The research was conducted between April and July 2023 with 342 voluntary healthcare workers employed at Muğla Sıtkı Koçman Training and Research Hospital. Independent samples t-test was used to compare two groups, while one-way ANOVA with Bonferroni post-hoc analysis was applied for comparisons among three or more groups. Pearson correlation analysis and multiple linear regression were used to examine relationships between variables. Data were collected using the Affiliation Attitude Scale and the Minnesota Job Satisfaction Questionnaire. The main hypothesis was that positive attitudes toward affiliation would increase job satisfaction, whereas negative attitudes would reduce it.</i></p> <p><i>Findings show that positive affiliation attitudes increase job satisfaction, while negative attitudes decrease it. Factors such as monthly income and work experience influence these attitudes, whereas gender and marital status do not show significant effects. Bachelor's degree holders and Ministry of Health employees tend to approach affiliation more critically, while physicians perceive negative impacts to a lesser extent. In the literature, affiliation is described as a strategic model that enhances service quality and educational processes, with different implementations observed in Europe and the United States. The study highlights the significant effects of affiliation on managerial processes and employee satisfaction and offers recommendations such as developing institution-specific affiliation models, informing employees, and utilizing international experiences.</i></p>
Article Application Date: 13.10.2025	
Article Acceptance Date: 12.12.2025	



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The Effect of Healthcare Environment on Health-Seeking Behavior: A Study on Students of the Faculty of Applied Sciences at Tarsus University

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ARTICLE INFO	ABSTRACT
<p>Article Type: Research Article</p> <p>Keywords: Healthcare services, health-seeking behavior, health literacy, healthcare environment</p> <p>Corresponding Author(s) 1. Aysu LALE 2. Şükrü Anil TOYGAR</p> <p>E-mail: 1. aysulale03@gmail.com 2. saniltoygar@tarsus.edu.tr</p> <p>Article Application Date: 13.10.2025</p> <p>Article Acceptance Date: 18.12.2025</p>	<p><i>This study aims to examine the effect of the physical environment of healthcare services on the health-seeking behavior of university students. The descriptive and cross-sectional study was conducted with 360 undergraduate students studying at the Faculty of Applied Sciences of Tarsus University. Data were collected using a questionnaire containing socio-demographic characteristics, the "Healthcare Environment Scale," and the "Health-Seeking Behavior Scale." The reliability coefficients of the scales were found to be 0.926 and 0.752, respectively. Parametric tests were used in the analysis of the data. According to the results, significant differences were found between the gender variable and the sub-dimensions of health-seeking behavior. No significant differences were found between age, chronic disease, and general health status variables and health-seeking behavior. Significant differences were determined between groups according to the frequency of physician visits. The findings suggest that perceptions of the physical environment of healthcare services may be associated with individuals' health-seeking behaviors.</i></p>

SAĞLIKTA METİN MADENCİLİĞİ: TEORİ VE UYGULAMA



DR. SEMA DÖKME YAĞAR
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AI-Based Analyses of Associations Between Social Media Usage (SMU), Sleep Duration, and Mental Health

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ARTICLE INFO	ABSTRACT
<p>Article Type: Research Article</p> <p>Keywords: AI, Machine Learning, Mental Health, Social Media Use (SMU), Sleep Duration, Young Adults</p> <p>Corresponding Author(s) 1. Hatice ULUSOY 2. Volkan GÖREKE</p> <p>E-mail: 1. hulusoy@cumhuriyet.edu.tr 2. vgoreke@cumhuriyet.edu.tr</p> <p>Article Application Date: 21.10.2025</p> <p>Article Acceptance Date: 08.12.2025</p>	<p><i>Aim:</i> Advanced AI methods are rarely applied to analyze SMU's complex effects on sleep and mental health. This study explored the associations between SMU, sleep duration, mental health and romantic relationships in youth using statistical and AI-based methods.</p> <p><i>Method:</i> A publicly available dataset from 705 students across 27 countries was analyzed using correlation analysis, Multiple Linear Analysis, and machine learning models including Bayesian Ridge, Random Forest, and XGBoost. Principal Component Analysis and K-means clustering were utilized for behavioral profiling, and threshold analysis was conducted to identify critical usage limits.</p> <p><i>Results:</i> Significant strong negative correlations were found between daily SMU and mental health scores ($r = -0.80, p < 0.001$) as well as sleep duration ($r = -0.81, p < 0.001$). Regression analysis showed that each additional hour of SMU reduced mental health scores by 0.57 points ($\beta = -0.5666, p < 0.001$), while each additional hour of sleep increased scores by 0.19 points ($\beta = 0.1939, p < 0.001$). The model accounted for 65.6% of variance in mental health outcomes. A critical SMU threshold of 4.67 hours/day was identified, beyond which negative effects on sleep intensified. Clustering revealed three user profiles: low-risk (32%, 3.81 hours/day), moderate-risk (41%, 4.98 hours/day), and high-risk (27%, 6.43 hours/day). Among AI models, XGBoost achieved the highest predictive accuracy ($R^2 = 0.954$), and Bayesian Ridge showed superior generalization ($CV R^2 = 0.784$).</p> <p><i>Conclusion:</i> SMU exceeding 4.67 hours/day marks a critical threshold for poor sleep and mental health. AI models may aid early risk detection and targeted interventions.</p>

1. INTRODUCTION

Social media has become an indispensable component of daily life, particularly among young adults. According to recent global digital reports, approximately 5.24 billion individuals—representing 63% of the global population—are active social media users (Kemp 2025). Young users aged 16 to 24 report the highest daily usage, spending more time on platforms than any other demographic group (Ahmed et al. 2024). Increasing evidence suggests that youth mental health is closely linked to social media usage (SMU), with impacts largely shaped by the nature of users' interactions (Weigle & Shafi 2024).

Valkenburg et al., (2022) define SMU “as active (e.g., posting) or passive (e.g., browsing), occurring either privately or publicly across platforms such as Instagram, Facebook, WhatsApp”. Although social media promotes social connectivity and mental health literacy, excessive use has been associated with adverse outcomes. In the literature, social media addiction (SMA), or “problematic social media use” (PSMU) is described as irrational and excessive use of social media to the extent that it detrimentally affects daily functioning [Pellegrino et al., 2022; Griffiths 2012]. It is associated with addiction symptoms and impaired self-regulation—factors strongly linked to diminished mental health. The existing body of knowledge is predominantly derived from studies conducted within the last three years (Eichenberg, 2025).

1.1. Sleep as a Mediating Factor

Among the mediators proposed in the SMU-mental health relationship, sleep quality has emerged as a key factor. Prior studies highlight strong associations between social media use and disrupted sleep patterns ((Ahmed et al., 2024; Garrett et al., 2016; Alonso et al., 2021; Berard et al., 2023; Han et al., 2024; Yu et al., 2024). Sleep quality is a well-established predictor of both physical and psychological well-being. Garrett's study with 197 university students revealed a link between SMU and decreased sleep quality. Similarly, Xie and Wang (2025) reported positive correlations between excessive use, depressive symptoms, and insomnia in a sample of 644 college students.

1.2. Mental Health Implications

Beyond sleep disturbances, SMA has been negatively associated with various aspects of mental health (Ahmed et al., 2024; Galanis et al., 2025; Huang 2017). While general SMU shows weak correlations with depression and anxiety, SMA is significantly linked to poor well-being across platforms. Galanis et al., 2025 found that problematic TikTok use among young adults correlates with poor sleep, emotional dysregulation, narcissism, and distress intolerance. While Garcia and Cooper (2024) identified relationships between SMA, self-control failure, elevated stress, and poor sleep, it is also found that adolescents using social media more than three hours daily are at increased risk for internalizing symptoms (Riehm et al., 2019). A recent study found that depression, anxiety, fear of missing out, loneliness, and mindfulness had a direct effect on social media addiction (Meynadier et al., 2025). Santini et al., (2025) showed that SMA was associated with an elevated risk for depression and negatively with mental wellbeing and an elevated risk of loneliness and negatively with social network size.

1.3. Impact on Romantic Relationships

Emerging literature indicates that PSMU may also affect romantic relationships (Meynadier et al., 2025; Arikewuyo et al., 2022). Abbasi (2019) identified increased jealousy, mistrust, and infidelity as key pathways through which SMA negatively impacts romantic partnerships. A Turkish study involving university students (ages 18-29) revealed that SMA elevated levels of depression, anxiety, and stress, thereby reducing relationship satisfaction (Satici et al., 2023). Similarly, Kolhar et al. (2021) reported that 59% of a sample of 300 female university students aged 17 to 29 indicated that excessive social media use adversely affected their familial and social relationships, as well as their ability to engage in face-to-face communication.

1.4. Research Gaps and AI Applications

Although existing studies have documented the negative effects of PSMU, there remains a lack of research exploring mediating mechanisms—particularly sleep—and identifying behavioral thresholds. Berard et al., 2023 and Lee et al., 2023 highlighted sleep's mediating role between SMU and depression in adolescents. It is also found that sleep quality mediated the impact of problematic mobile phone use on mental health among 4624 university students (Zou et al., 2019).

To the best of our knowledge no prior research has utilized artificial intelligence (AI) methodologies to model the SMU and mental health relationship including sleep patterns among young people. Understanding this connection is essential for developing effective public health interventions aimed at promoting balanced usage and preventing psychological harm.

1.5. Aims of the Present Study

In the present study, we utilize a publicly available dataset provided by Shamim (2025), accessible via Kaggle. Dataset is suitable for both statistical analyses and AI-based machine learning applications. We employ multidimensional statistical and AI-based analyses to examine the effects of social media use on sleep and mental health. The specific objectives are to;

1. explain the relationship between social media usage duration and mental health
2. assess the moderating effect of sleep duration on this relationship
3. identify the impact of social media-related conflicts on romantic relationships
4. determine the critical usage threshold for social media addiction
5. evaluate the predictive power of AI-based models in these domains.

2. METHOD

2.1. Dataset and Participants

The dataset includes responses from 705 students aged 16–25 across 27 countries including the United States, Germany, the United Kingdom, Austria, India, Canada, Brazil, South Korea, Japan and Turkey. Participants were enrolled in high school, undergraduate, or postgraduate programs. Data were collected via an online self-report survey during Q1 of 2025. All data were anonymized, with no identifying information included.

2.2. Variables

Key variables drawn from the dataset include:

- **Demographics:** Age, gender, education level
- **Social Media Usage:** Average daily usage in hours, most-used platform
- **Health and Lifestyle:** Average sleep hours per night
- **Mental and Social Health:**
 - Mental health score (1–10; 1 = poor, 10 = excellent)
 - Conflict in romantic relationships due to social media use (Conflicts_Over_Social_Media)
 - Social media addiction score (Addicted_Score, 1–10; 1= low, 10=higher = indicating greater addiction)

2.3. Data Preparation and Statistical Analyses:

Outliers with Z-scores > 3 were removed, missing data were checked, and derived variables such as sleep efficiency were created.

Spearman correlation, partial correlation, and Multiple Linear Regression (MLR) were employed.

AI Models: Bayesian Ridge, Random Forest, and XGBoost models were used, with performance evaluated using R^2 , RMSE, and cross-validation.

Clustering and Dimension Reduction: Principal Component Analysis (PCA) and K-Means clustering analyses were conducted.

Moderator and Threshold Analysis: Independent samples t-tests and Partial Least Squares (PLS) regression were applied.

3. RESULTS

3.1. Correlation and Causality Analyses

Table 1. Relationship between social media usage duration and mental health

N	r	CI95%	p-value
705	-0.7998	[-0.82, -0.77]	1.62e-157

Table 1 presents the relationship between social media usage duration and mental health. Findings show a strong negative correlation between social media usage duration and mental health. This statistically significant result ($p = 1.62e-157$) indicates that increased time spent on social media is associated with lower mental health scores.

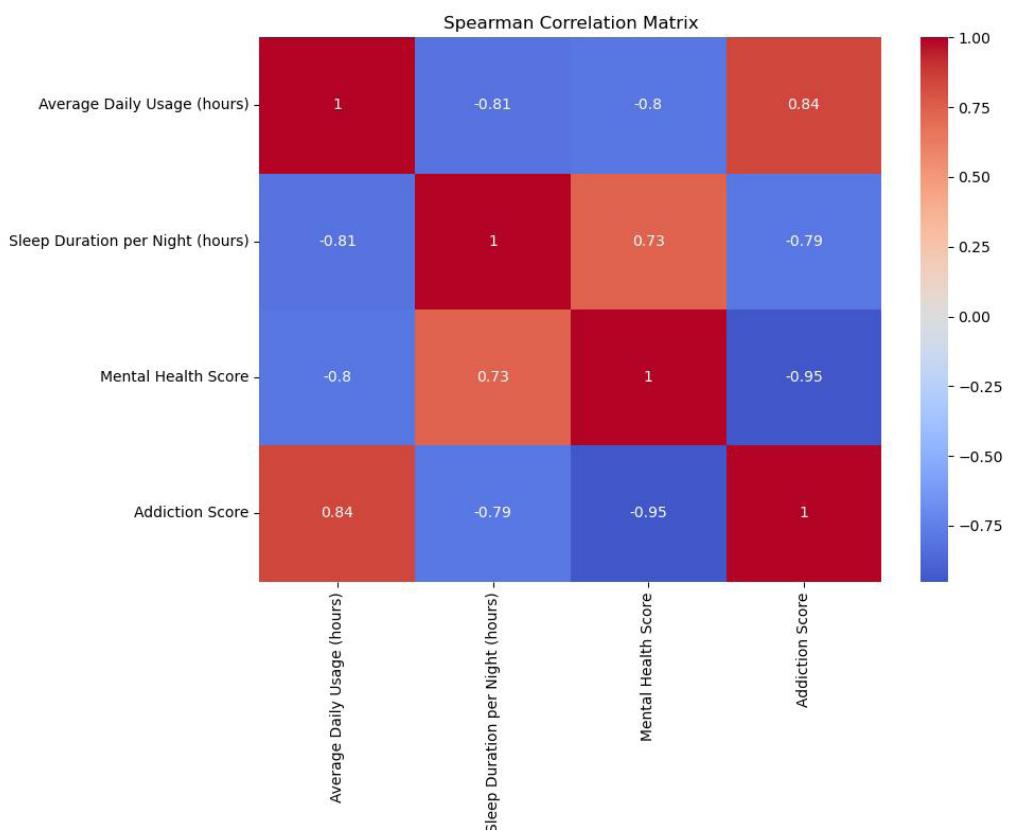


Figure 1. Spearman Correlation Matrix Between Variables

Figure 1 presents the Spearman correlation matrix visualizing the strength and direction of monotonic relationships between variables (Culyer 2019). Key findings include:

- **Social Media and Mental Health:** A very strong negative correlation ($r = -0.80$) exists between average daily usage duration and mental health score, indicating that as students' SMU increases, their mental health levels decrease.
- **Social Media and Sleep:** A similarly very strong negative relationship ($r = -0.81$) is observed between usage duration and nightly sleep hours, meaning that as social media usage duration increases, sleep duration significantly decreases.
- **Sleep and Mental Health:** A strong positive correlation ($r = 0.73$) exists between sleep duration and mental health score, indicating that as sleep duration increases, mental health status also improves.
- **Social Media Addiction Score:** The addiction score shows very strong correlations as expected, positive with usage duration ($r = 0.84$) and negative with sleep duration and mental health ($r = -0.79$, $r = -0.95$, respectively).

Partial correlation analysis was conducted to investigate whether demographic variables such as age and gender affect the relationship between social media use and mental health. Results indicated that demographic factors do not influence this relationship.

3.2. Multiple Linear Regression (MLR) Analysis

Table 2. Multiple Linear Regression (MLR) Results Estimated by Ordinary Least Squares (OLS)

Variable	Coefficient	Std. Error	t-value	p-value
Constant	7.6823	0.380	20.221	<0.001
Avg_Daily_Usage_Hours	-0.5666	0.032	-17.845	<0.001
Sleep_Hours_Per_Night	0.1939	0.035	5.472	<0.001

Note: Model $R^2 = 0.656$, $p < 0.001$

MLR was conducted using the Ordinary Least Squares (OLS) estimation method, with mental health score as the dependent variable and social media use plus sleep duration as predictors. MLR analysis was conducted to examine the effects of social media use and sleep on mental health (Table 2). The model was estimated using the Ordinary Least Squares (OLS) method, which minimizes the sum of squared errors to obtain the best-fitting regression line. This approach is widely used to evaluate the linear associations between one dependent variable and multiple independent predictors, providing estimates of direction, magnitude, and statistical significance (Zdaniuk 2023). The model explained 65.6% of the variance in mental health outcomes, which is considered high for social science research. The results indicate that increased social media use is significantly associated with lower mental health scores, whereas longer sleep duration is associated with higher mental health scores. Based on this, the analysis of the findings indicates that;

- **Causal Effect of Social Media:** The model shows that when other variables are held constant, each 1-hour increase in daily social media use causes an average 0.57-point decrease in mental health score ($\beta = -0.5666$, $p < 0.001$). This effect is statistically highly significant and clinically important.
- **Protective Role of Sleep:** In contrast, each 1-hour increase in sleep duration provides an average 0.19-point improvement in mental health score ($\beta = 0.1939$, $p < 0.001$). This finding indicates that sleep plays a potential buffering or protective factor role against the negative effects of social media.

3.3. Performance of AI Models and Variable Importance Levels

Table 3. Performance Comparison of Machine Learning Models

Model	R ²	RMSE	CV R ² (Mean)
Bayesian Ridge	0.835	0.449	0.784
Random Forest	0.945	0.259	0.697
XGBoost	0.954	0.238	0.615

Note: R²: Explained Variance, RMSE: Root Mean Square Error, CV R²: Cross-Validation Mean R²

In Table 3, the performance of three different machine learning models developed to predict mental health scores is compared. Accordingly;

- **Predictive Power:** The XGBoost model ($R^2 = 0.954$) showed the highest performance in explaining variance in the current dataset, indicating that the model learned the relationships in the dataset very precisely. However, high R² values do not directly inform about the model's generalization capacity (Kumar et al., 2025).
- **Generalization Capacity and Overfitting:** Model success is measured not only by how well it explains current data but also by how well it will perform on new and unseen data. Cross-validation (CV R²) scores are critically important here. The Bayesian Ridge model has the highest CV R² score (0.784), offering the best generalization capacity. The large difference between R² and CV R² values for Random Forest and XGBoost models indicates these models tend to memorize data and carry "overfitting" risk (Roelofs 2019). This issue is particularly pronounced in

complex models (e.g., RF, SVM), where random cross-validation (R-CV) may lead to overly optimistic estimates of model performance (Aliferis & simin 2024). Therefore, the Bayesian Ridge model is expected to make the most stable predictions on new data.

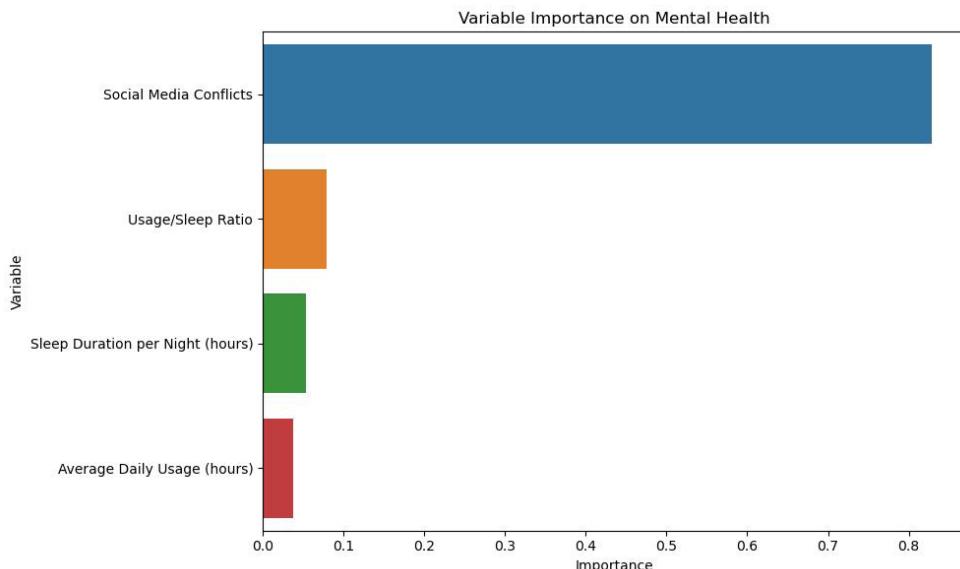


Figure 2. Effects of Variables on Mental Health (Feature Importance)

Figure 2 shows the variable importance analysis obtained from the Random Forest model, presenting the hierarchy of factors affecting mental health: Based on this, the analysis of the findings indicates that;

- **Most Important Factor:** The analysis shows that “conflicts on romantic relationship due to social media use” is more important than all other factors. This finding may indicate that interpersonal stress and conflict created by social media can be a stronger predictor of mental health than pure usage duration.
- **Other Factors:** The conflict variable is followed by “Usage/Sleep Ratio,” “Sleep Duration,” and “Daily Usage Duration,” respectively. The lower importance of usage duration alone compared to other factors may suggest that “how” and “with what consequences” social media is used may be more critical than “how long” it is used.

3.4. Clustering and Threshold Analysis

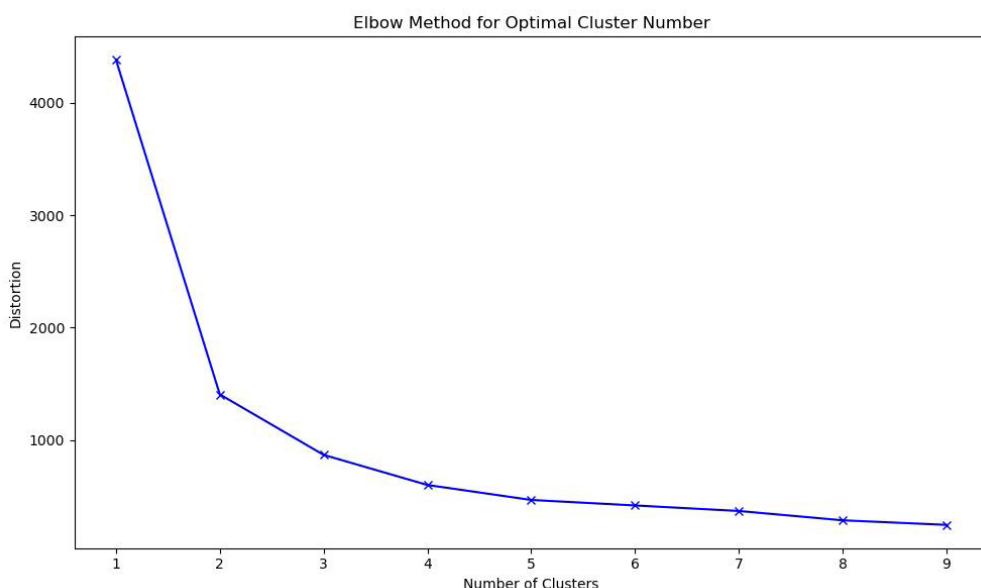


Figure 3. Elbow Method Plot for Determining the Optimal Number of Clusters

The Elbow method is employed to determine the optimal number of natural groupings (clusters) within a dataset (Herdiana et al., 2025). The graph (Fig.3) shows a sharp decrease in variance as the number of clusters increases from 1 to 3. After the point k=3 on the graph, the impact of adding an additional cluster on reducing variance becomes marginal, and the curve begins to flatten, forming an “elbow.” This indicates that the optimal number of clusters for separating students in the dataset based on their behavioral profiles is 3. The Elbow Method analysis statistically confirms that the optimal number of clusters is k=3, as adding more clusters beyond this point contributes only marginally to the total explained variance.

3.5. Role and Purpose of Clustering Analysis in the Study

1. Determining Student Behavioral Profiles

Clustering analysis was used to divide students into homogeneous groups according to their social media usage habits, sleep patterns, and mental health status, enabling:

- Identification of student groups with different risk profiles
- Revelation of unique characteristics of each group
- Development of targeted intervention strategies

2. Risk Classification and Early Warning System

As seen in Table 4, Clustering results revealed three different risk groups:

- **Low Risk Group (Cluster 0):** Average 3.81 hours usage, high mental health score (7.39)
- **Moderate Risk Group (Cluster 1):** Average 4.98 hours usage, moderate mental health score (5.87)
- **High Risk Group (Cluster 2):** Average 6.43 hours usage, low mental health score (5.01)

3. Exploration of Multidimensional Data Structures

Cluster analysis, when integrated with Principal Component Analysis (PCA), has revealed latent structures within the dataset. Through dimensionality reduction, this approach has facilitated the extraction of more interpretable and distinguishable clusters in high-dimensional spaces. In datasets involving multivariate relationships—such as those encompassing social media use, sleep patterns, and mental health indicators—clustering algorithms applied to PCA-derived components (e.g., K-means or Spectral Clustering) have enhanced the visualization and interpretation of intricate relational patterns (Ramos et al 2023).

Specifically, clustering combined with PCA has enabled the following:

- Visualization of complex interdependencies among social media use, sleep behavior, and mental health outcomes.
- Identification of subgroup dynamics that remain undetectable through conventional correlational analyses alone.

4. Subgroup Identification for Clinical and Educational Applications

Cluster analysis serves several practical purposes in educational and clinical settings:

- **Personalized Intervention:** Tailored prevention and intervention programs can be developed for each identified subgroup.
- **Resource Optimization:** Limited resources can be more efficiently allocated by prioritizing high-risk clusters.
- **Monitoring and Evaluation:** Longitudinal tracking of students' cluster transitions enables monitoring of improvement or deterioration over time.

5. Enhancing AI Models

Clustering outcomes contribute to the development and refinement of AI-driven predictive models by:

- Enabling advanced feature engineering grounded in discovered patterns.
- Serving as proxy target variables in supervised learning contexts.
- Establishing reference groups for anomaly detection and model calibration.

6. Implications for Policy and Program Development

Findings from clustering analysis provide actionable insights for university administrators and public health policymakers:

- Provides insights into the size and prevalence of high-risk groups.
- Guides the planning and implementation of campus mental health services.
- Enables user segmentation for the targeted design of digital health interventions.

Accordingly, cluster analysis in this study functions not merely as a descriptive tool, but as a strategic analytical tool aimed at generating **actionable insights** with practical relevance.

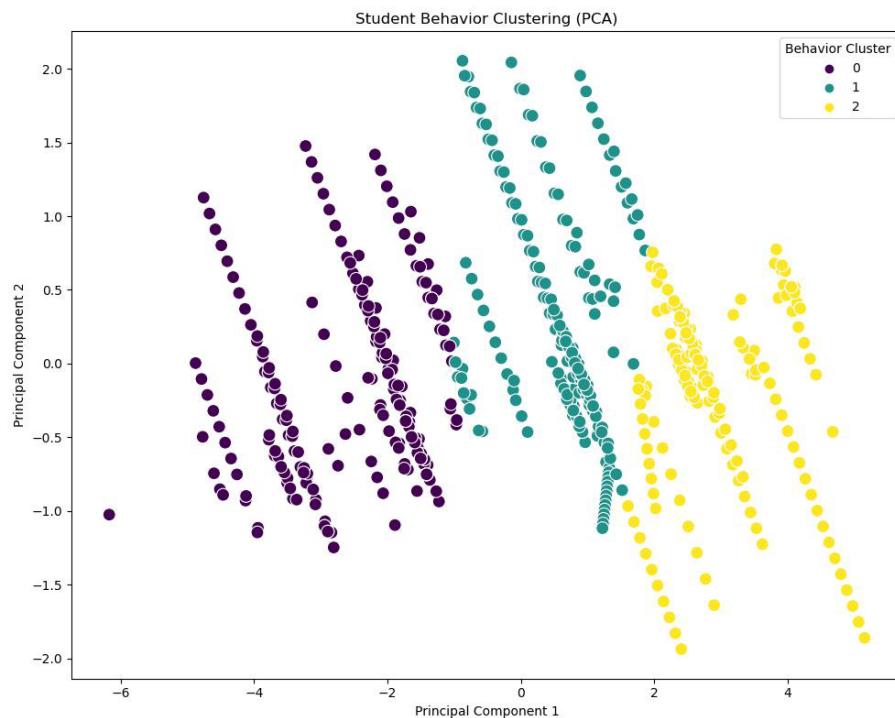


Figure 4. Student Behavior Clustering (2D Visualization with PCA)

Table 4. Comparison of Cluster Profiles

Cluster	Risk Group	Average Usage (hours)	Average Sleep (hours)	Mental Health Score	Population Ratio
0	Low Risk	3.81	7.2	7.39	32%
1	Moderate Risk	4.98	6.8	5.87	41%
2	High Risk	6.43	6.1	5.01	27%

Note: Data compiled from clustering analysis results.

When Figure 4 and Table 4 analyses are examined, PCA-based K-Means clustering analysis divided students into three distinct and homogeneous groups according to their social media use, sleep habits, and mental health status:

- **Cluster 0 - Low Risk Group (32%):** This group has the lowest social media use with an average of 3.8 hours per day, the highest sleep duration (7.2 hours), and the best mental health score (7.39). This profile represents a healthy student group with balanced digital habits.
- **Cluster 1 - Moderate Risk Group (41%):** The most populous cluster, this group exhibits a profile close to the critical threshold value with approximately 5 hours of daily use. Significant decreases are observed in mental health scores (5.87) and sleep duration (6.8 hours). This group represents a “transition” group in the process of transitioning to risky use.
- **Cluster 2 - High Risk Group (27%):** With usage exceeding an average of 6.4 hours per day, the shortest sleep

duration (6.1 hours), and the lowest mental health score (5.01), this group defines a “high-risk” profile where problematic use and negative health outcomes are seen together.

3.6. Critical Threshold Analysis

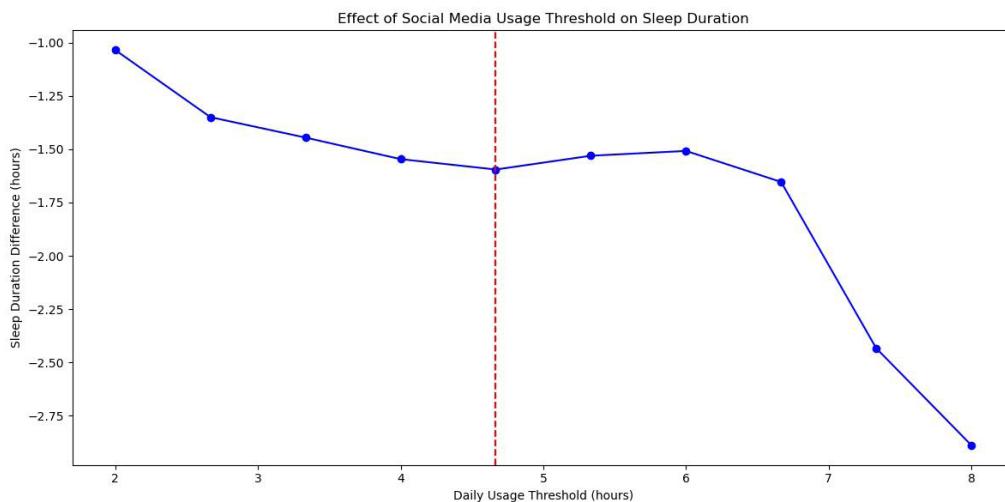


Figure 5. Graph of the Effect of Social Media Usage Threshold on Sleep Duration

Figure 5 presents the analysis conducted to determine at what point the negative effect of social media use on sleep becomes critical. Accordingly;

- As the daily usage threshold value increases, it shows how the average sleep duration difference between users above and below this threshold changes.
- The analysis reveals that **the critical threshold value for social media use is 4.67 hours/day**. This value can be interpreted as the “tipping point” where the negative effect of social media use on sleep duration begins to increase significantly and statistically meaningfully when it exceeds approximately 4.5 hours per day.
- Exceeding this threshold may trigger circadian rhythm disruptions through increased blue light exposure and cognitive arousal. This finding may offer concrete daily usage limit recommendations for preventive interventions and digital health applications.

3.7. Moderator Analysis

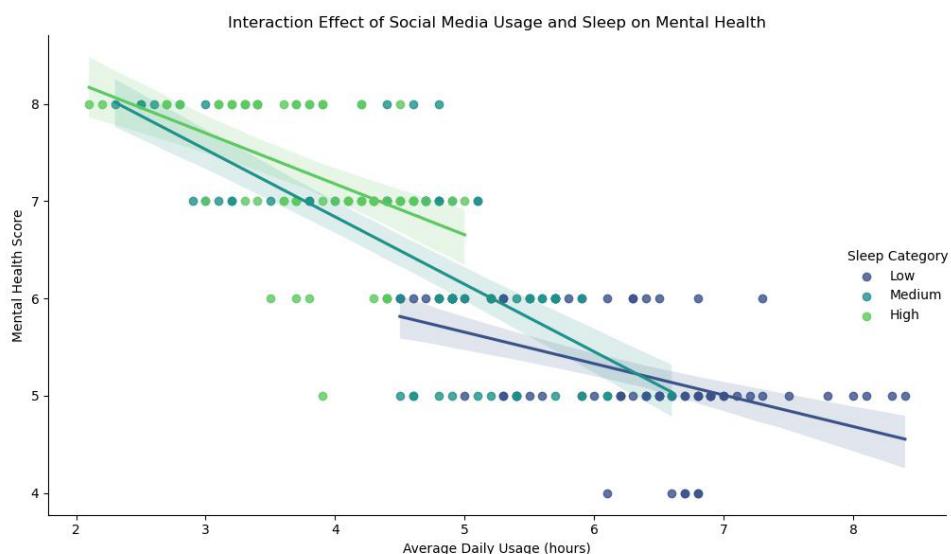


Figure 6. Effect of the Interaction Between Social Media Use and Sleep on Mental Health (Moderator Analysis)

Figure 6 visualizes the results of PLS regression analysis, clearly revealing sleep's moderator role in the social media use-mental health relationship. The graph examines the relationship between social media use and mental health in three separate groups according to students' sleep levels (Low, Moderate, High). When the findings obtained from the graph are analyzed;

- **Basic Findings:** In all three groups, mental health scores decrease as social media use increases. However, the slope of this decrease differs significantly depending on sleep duration.
- **High Sleep Group:** In students who sleep adequately (>7.5 hours), the regression line has the smallest slope. This shows that sleep significantly buffers the harmful effects of social media and weakens the negative impact.
- **Low Sleep Group:** In students with insufficient sleep (<6.5 hours), the regression line has the steepest slope. This situation suggests that sleep deprivation multiplies the negative effect of social media on mental health.
- **Clinical Inference:** This interaction effect ($p < 0.001$) strongly demonstrates that in combating the harms of social media, not only reducing usage duration but also improving sleep hygiene should be a fundamental intervention strategy.

4. DISCUSSION

The present study provides robust statistical and machine learning evidence that social media use is strongly associated with mental health outcomes among students in the 16-25 age group. By integrating traditional statistical approaches such as MLR with advanced AI models, this research makes an important contribution to the growing literature on digital health and psychosocial well-being.

4.1. The Protective Role of Sleep

One of the most salient findings of the present study is the robust positive correlation observed between sleep duration and mental health status ($r = 0.73$), suggesting that longer sleep duration is associated with improved mental well-being. This relationship aligns with existing literature emphasizing the pivotal role of sleep in emotional regulation and cognitive performance. Notably, this finding underscores the protective function of adequate sleep in sustaining mental health. In this context, it may be posited that sufficient sleep serves as a moderating factor, mitigating the potential deleterious effects of excessive social media use on mental well-being. Previous research has shown that excessive screen time disrupts circadian rhythms and reduces sleep quality [Garett et al., 2016; Han et al., 2024; Yu et al. 2024]. Although Ahmed et al. (2024) reported that PSMU was linked to sleep disturbances but not necessarily to sleep duration, our analysis quantitatively demonstrates that each additional hour of sleep contributes positively to mental health, buffering against the harmful impacts of social media. These findings resonate with mediation studies showing that sleep quality mediates the relationship between problematic technology use and depressive symptoms (Berard et al., 2023; Lee et al., 2023; Zou et al. 2019). Our study identified a **critical threshold at 4.67 hours/day** further advances the field by offering concrete, evidence-based guidelines for healthy digital habits.

4.2. Social Media Use and Mental Health

The SMA score showed strong correlations including a robust positive relationship with usage duration ($r = 0.84$), and strong negative associations with both sleep duration ($r = -0.79$) and mental health score ($r = -0.95$). Our findings align with a growing body of evidence indicating that PSMU is associated with poorer mental health outcomes, including poor sleep quality, elevated stress, anxiety, and depressive symptoms [Ahmed et al., Alonzo et al., Galanis et al., Huang 2017]. The present study demonstrates that each additional hour of daily social media use is significantly associated with a decline in mental health scores. This is consistent with Riehm et al. (2019), who reported that adolescents using social media more than three hours daily are at increased risk for internalizing symptoms. Importantly, our results highlight that these effects are not trivial: the magnitude of the regression coefficients demonstrates both statistical and clinical significance. However, Huang's (2017) meta-analysis showed that correlations between time spent on social networking sites and negative mental health indicators such as loneliness and depression were weak, with no significant moderation by platform, measurement scale, or demographic variables. This discrepancy may be attributed to the temporal context in which Huang's study was conducted, as the prevalence of social media use at that time was considerably lower than current levels."

4.3. Conflicts in romantic relationships due to SMU

Our variable importance analysis indicated that conflicts within romantic relationships resulting from social media use emerged as the most salient predictor among all examined factors. This finding supports prior research (Meynadier et al., 2025; Abbasi 2029; Arkewuyo et al 2022; Karaman & Arslan 2024). Importantly, our analysis moves beyond conventional metrics such as usage duration, demonstrating that interpersonal conflicts linked to social media engagement are more predictive of adverse mental health outcomes than time-based measures alone. These results contribute to a conceptual shift in the literature—from a predominant focus on “time spent” on social media to a more nuanced understanding of the “quality and consequences of use,” which is largely shaped by the nature of youth engagement with these platforms, as increasingly emphasized by recent literature (Weigle & Shafi 2024).

4.4. Methodological Strength: Combining Statistics and AI

A further strength of this study lies in its methodological innovation. By combining OLS-based regression analysis with state-of-the-art AI models such as Bayesian Ridge, Random Forest, and XGBoost, the research demonstrates both explanatory and predictive power. While regression clarified causal associations, machine learning provided accurate prediction and risk stratification, with XGBoost achieving high predictive accuracy ($R^2 = 0.954$) and Bayesian Ridge showing superior generalizability. This dual approach addresses limitations noted in recent methodological critiques regarding overfitting in complex models (Kumar et al., 2025; Roelofs 2019). Such an integration of traditional and modern methods is rare in the digital health field and strengthens the reliability and applicability of the results.

4.4. Implications for Policy and Practice

The practical implications of this research are substantial. The identification of distinct behavioral risk clusters via PCA-based clustering suggests opportunities for personalized interventions. For example, students in the high-risk cluster (average 6.4 hours of daily use and the lowest mental health scores) may benefit from targeted digital health programs and sleep hygiene education. Universities and policymakers could use these insights to design early-warning systems and digital well-being apps that monitor usage thresholds and promote healthier habits. Furthermore, the integration of AI models suggests a scalable approach to mental health monitoring, which could complement traditional clinical screening.

4.5. Contribution to Literature

In summary, this study extends prior work in three key ways:

1. It provides strong quantitative evidence of a critical threshold for social media use that impacts both sleep and mental health.
2. It highlights the moderating and buffering role of sleep.
3. It demonstrates the value of AI-enhanced prediction in psychosocial health research, paving the way for data-driven prevention strategies.

By addressing these gaps, the study not only confirms but also expands upon existing literature, offering actionable insights for researchers, clinicians, and policymakers.

5. CONCLUSIONS & RECOMMENDATIONS:

- The duration of SMU has a statistically significant and strong negative effect on mental health.
- Sleep duration serves a protective and buffering role against the harmful effects of SM.
- An average SMU of **4.67 hours/day** represents a critical threshold at which negative health outcomes begin to emerge.
- AI-based models can be used to identify at-risk students based on behavioral data

It is recommended that future research focus on longitudinal studies examining the relationship between SMU patterns and mental health outcomes over time. Additionally, the development and validation of AI-based intervention systems, as well as analyses of the moderating roles of cultural and demographic variables in these relationships, are suggested

as critical areas for further investigation. Digital literacy and awareness programs that encourage conscious and limited social media use should be organized for students. The ability of AI models, particularly Bayesian Ridge, to successfully predict mental health scores with high generalization capacity presents important potential for developing digital early warning systems that can identify at-risk students early on.

Study Limitations:

Self-report measures may be subject to bias. Cultural variations across the 27 countries were not specifically analyzed.

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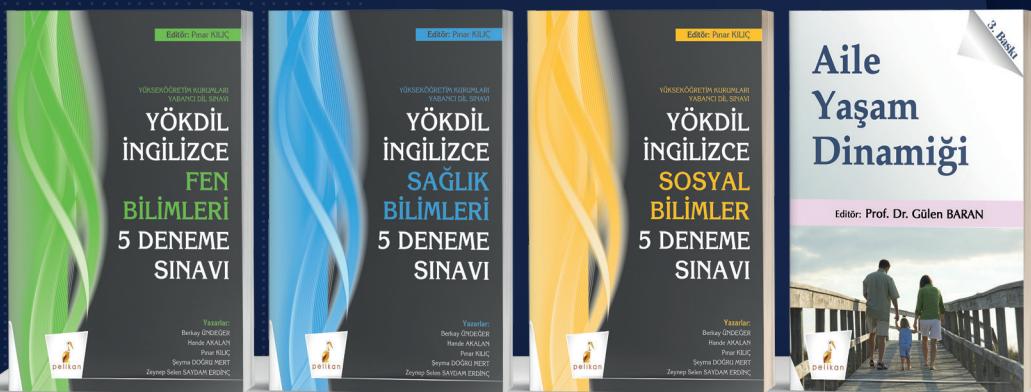
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Midwifery Students' Views and Attitudes Towards Fertility and Having Children

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ARTICLE INFO	ABSTRACT
<p>Article Type: Research Article</p> <p>Keywords: Midwifery, fertility, child, attitude, opinion</p> <p>Corresponding Author(s)</p> <ol style="list-style-type: none"> 1. Burcu Tuncer Yılmaz 2. Özlem Koç 3. Yasemin Hamlacı Başkaya <p>E-mail:</p> <ol style="list-style-type: none"> 1. tunburcu@51gmail.com 2. ozlemkoc@tarsus.edu.tr 3. yaseminhamlaci@gmail.com <p>Article Application Date: 25.10.2025</p> <p>Article Acceptance Date: 16.12.2025</p>	<p>Purpose: The research was conducted to evaluate the knowledge, opinions and attitudes of senior midwifery students regarding fertility and having children.</p> <p>Method: This study is descriptive, cross-sectional, and correlational in nature, and was conducted between January and May 2023 using an online survey with 407 university students in their final year of midwifery programs in Turkey. The data was obtained with a personal information form and the "Attitudes Toward Fertility and Childbearing Scale (AFCS)".</p> <p>Results: The average age of the students participating in the research is $22,28 \pm 1,67$ and 96,1% are single. 80,6% of the students stated that they planned to have children in the future and 74,4% stated that they planned to have their first child between the ages of 25-29. 38,6% of the students correctly identified the 20-24 age range as the most fertile age for women, while only 5,2% correctly identified the 25-29 age range when female fertility begins to decline. Again, 76,9% of the participants stated that they wanted to have children with assisted reproductive techniques in case of possible infertility. In the study, the mean scores for the sub-dimensions of the AFCS "1. Importance of Fertility for the Future"; "2. Viewing Having Children as an Obstacle" and "3. Expectations and Planning" are (1) $41,20 \pm 10,91$; (2) $37,91 \pm 9,05$ and (3) $22,81 \pm 2,67$ respectively. Cronbach's Alpha internal reliability coefficient was found to be (1) 0,91; (2) 0,91; (3) 0,77 in the sub-dimensions respectively.</p> <p>Conclusion: In the study, it was determined that midwifery students' views and attitudes towards fertility and having children were positive. However, it has been observed that the information regarding the change in female fertility according to age is not sufficient. It is recommended that midwifery students, whose profession is of paramount importance in fertility regulation, receive more emphasis on fertility awareness in their education, and that more research be conducted on this topic.</p>



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Socioeconomic Inequalities in Chronic Kidney Disease Research: A Bibliometric Analysis

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ARTICLE INFO	ABSTRACT
<p>Article Type: Research Article</p> <p>Keywords: Bibliometric analysis, inequality, chronic kidney disease, socioeconomic inequalities</p> <p>Corresponding Author(s) 1. İrem ŞENGÜN 2. Vahit YİĞİT</p> <p>E-mail: 1. iremsengunn@gmail.com 2. vahityigit@sdu.edu.tr</p> <p>Article Application Date: 30.11.2025</p> <p>Article Acceptance Date: 16.12.2025</p>	<p><i>Chronic Kidney Disease (CKD) is a global public health problem with an increasing disease burden due to socioeconomic, cultural, and political disparities in access to diagnosis, treatment, and care services. These inequalities, which negatively affect the course of the disease in low-income and disadvantaged groups, increase global morbidity and mortality. The aim of this study is to map the scientific literature produced on CKD and socioeconomic inequalities globally using bibliometric analysis methods and to determine research trends. Within the scope of the study, the Web of Science (WoS) database was used to search for studies published up to February 3, 2025, without any start date restriction. A search using keywords examining the interaction between CKD and socioeconomic inequalities yielded 1,341 studies. After applying the inclusion criteria, the remaining 1,260 articles were analyzed using the RStudio-based Biblioshiny module. The analyses show that the number of publications on the subject has been steadily increasing since 1985, and that the topic has become prominent on the global health agenda, particularly in the last decade (2015-2025). The United States of America (USA) leads in the number of publications. However, it was found that contributions to the literature from low- and middle-income countries with a high disease burden remain limited. Keyword analyses revealed that the concepts of "mortality," "access," and "racial disparities" were prominent. While studies focusing on socioeconomic determinants in CKD research are increasing, the geographic distribution of this increase is disproportionate to the global disease burden. Increasing academic collaborations targeting regions with high disease burden but low research output is critical for the development of health policies.</i></p>