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PAPER

Effects of Social Media Use on Adolescent Psychological Well-Being: A Systematic Literature Review

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ABSTRACT

This study aims to explore the intricate relationship between social media use and the overall well-being (WB) of young people. Previous research has presented conflicting findings, indicating both positive and negative effects of online platforms. Issues such as excessive use, reduced face-to-face interactions, social isolation, heightened stress levels, and disrupted sleep patterns have been identified as potential concerns. However, studies have also highlighted that moderate and mindful use of social media can enhance WB by facilitating social connections and support. It is crucial to consider the vulnerabilities of young individuals when examining this complex topic and provide them with age-appropriate guidance. This research project aims to address gaps in the existing literature and inform strategies for promoting positive online experiences and safeguarding the WB of young people by investigating the association between social media use and affective WB. The review process involved systematically searching for relevant research and evaluating its quality and relevance. The analysis encompassed 111 articles and reviews published between 2013 and 2023. The dataset comprised articles with an average age of 2.76 years and an average of 40.45 citations per article, sourced from 78 journals and other publications. Several variables were examined, including authors, publishers, affiliations, countries, and keywords used in the research articles. The discourse surrounding the benefits and drawbacks of social media use was found to be ongoing. Concerns were raised regarding the potential negative consequences of excessive use, including diminished face-to-face interactions, social isolation, increased stress levels, and sleep disturbances. However, it was also observed that moderate and mindful social media use could positively impact WB by promoting social support and connection. Given the complex nature of the relationship between social media use and WB, it is important to acknowledge the vulnerabilities of young people and provide appropriate assistance and guidance tailored to their age group.

KEYWORDS

social media, psychological well-being (WB), young people, adolescents, online platforms, affective WB

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1 INTRODUCTION

In recent times, there has been a growing discourse among scholars regarding the advantages and disadvantages associated with the adoption of online social media platforms [1]. Specifically, there is an ongoing debate concerning the potential positive or negative consequences of engaging with social networking sites and other similar online platforms [2]. However, a cursory examination of existing scholarly works indicates that prior endeavors in this field have yielded more inquiries than concrete resolutions [3]. A recent comprehensive evaluation investigating the correlation between online communication and the psychological well-being (WB) of adolescents highlights a plethora of conflicting evidence, which suggests both detrimental and advantageous aspects of internet-based social media [4]. Despite the potential for social media to facilitate new forms of social interaction and communication, initial apprehensions arose regarding the excessive amount of time young individuals dedicated to online platforms [5]. Notably, there were concerns that increased social media usage was linked to reduced face-to-face interaction, heightened social isolation, elevated levels of stress, feelings of sadness, and disruptions in sleep patterns [6]. Furthermore, it was suggested that social media platforms fostered an environment conducive to engaging in inappropriate behaviors, thereby posing a threat to mental well-being.

In addition, there has been a lot of research done on the effect that social media use has on young people's WB [7]. While there are arguments for the potential advantages of online platforms, worries have also been expressed about the possible drawbacks [8]. Due to the intricacy of this subject, research on the connection between social media use and WB has shown contradictory results [9]. According to [10], using social media in moderation and with awareness can improve WB by, for example, encouraging social connection and support. On the other hand, inappropriate online behavior and excessive usage have both been associated with negative mental health results [11]. However, young people are more likely than adults to exhibit the behavior of excessive social media use and the difficulties that go along with it [12]. According to [13], there are several reasons why social networking site use affects how long people sleep. First off, because these platforms are interactive, users may spend extended amounts of time staring at screens while still being exposed to interesting and exciting information.

Furthermore, the best way to address how social media affects young people's WB is to consider their vulnerabilities and offer them age-appropriate assistance and direction [14]. Studies investigating the connection between different forms of social network usage and subjective WB paint a clearer picture than studies examining total levels of social network utilization [15]. Most of the research, although not all, has found a favorable correlation between actively using social networking sites and subjective WB [16]. In addition, there isn't enough in-depth study on this subject, so it's unknown how social media use affects adolescents' emotional WB [17]. Prior research has mostly examined the relationships between social media use and conceptualizations of WB that are trait-like and reflect people's average WB over certain time periods [18]. However, there hasn't been much research done on how social media affects adolescents' affective WB, which is a fleeting emotional state [19]. Moreover, youngsters' subjective evaluations of their moods, emotions, and feelings—which might change from moment to moment—are referred to as their affective WB [20]. It is vital to comprehend how social media use connects to this facet of WB since it sheds light on the teens' present-day emotional experiences in the context of their online lives [21].

With an emphasis on understanding young people's current emotional experiences in the context of their online interactions, the goal of this study is to examine the link between social media use and young people's affective WB. It also considers both the advantages of online platforms and worries about potential negative impacts and improper behaviors as you weigh the potential advantages and disadvantages of social media use on young people's WB. This study aims to contribute to a deeper understanding of the complex relationship between social media use and WB by addressing these research objectives and offering insights that can guide future interventions and policies promoting positive online experiences and protecting the WB of youngsters.

2 RESEARCH METHODOLOGY

The review process was conducted in accordance with the established guidelines for a systematic literature review [22–24], encompassing several sequential stages. Initially, a review protocol was formulated to outline the methodology and objectives of the study. Subsequently, explicit criteria were established for the inclusion and exclusion of relevant articles based on predetermined standards. Following this, an extensive search was undertaken to identify relevant research literature pertaining to the topic of interest. The identified articles were then critically evaluated to assess their quality and relevance to the research question. The process involved extracting pertinent data from the selected articles and synthesizing the findings to derive meaningful conclusions. The specific details and procedures employed during each stage of the review process are elaborated upon in the subsequent subsections.

The initial phase of the review process involved the development of a comprehensive protocol that defined the primary research question, guided the synthesis methodology, outlined the search strategy, and established the criteria for the inclusion and quality assessment of relevant publications. Specifically, the research question under investigation was: "What is the relationship between a youngster's utilization of social media and their psychological WB?" This question served as a foundation for identifying the relevant subject areas and selecting appropriate publications and resources for the review.

Moving forward, the second step involved applying the predetermined inclusion and exclusion criteria to the Scopus database to identify and select materials that were pertinent to the research question. We used the criteria to ensure the selection of materials that met the specific requirements and objectives of the review, aligning with the aim to comprehensively explore the connection between a youngster's use of social media and their psychological WB. In the third stage, our search technique was to create search strings, which were then concatenated to create keywords. To limit the number of search strings, we also used wildcard symbols throughout the search. When the terms "social media use" AND "psychological well-being" were combined, 225 results were returned. These findings were then examined. Keywords were looked for in the publications' titles, abstracts, and keyword sections. Additionally, we selected the topics of accounting, business, management, human behavior, psychology, social sciences, and the humanities. For the current study, only article and review publications were included after the findings were reduced to 167. Additionally, we selected the published records and English-language documents for the study. A total of 111 articles and reviews were included in the preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement filtration. Figure 1 depicts the PRISMA statement inclusion and exclusion criteria in detail below.

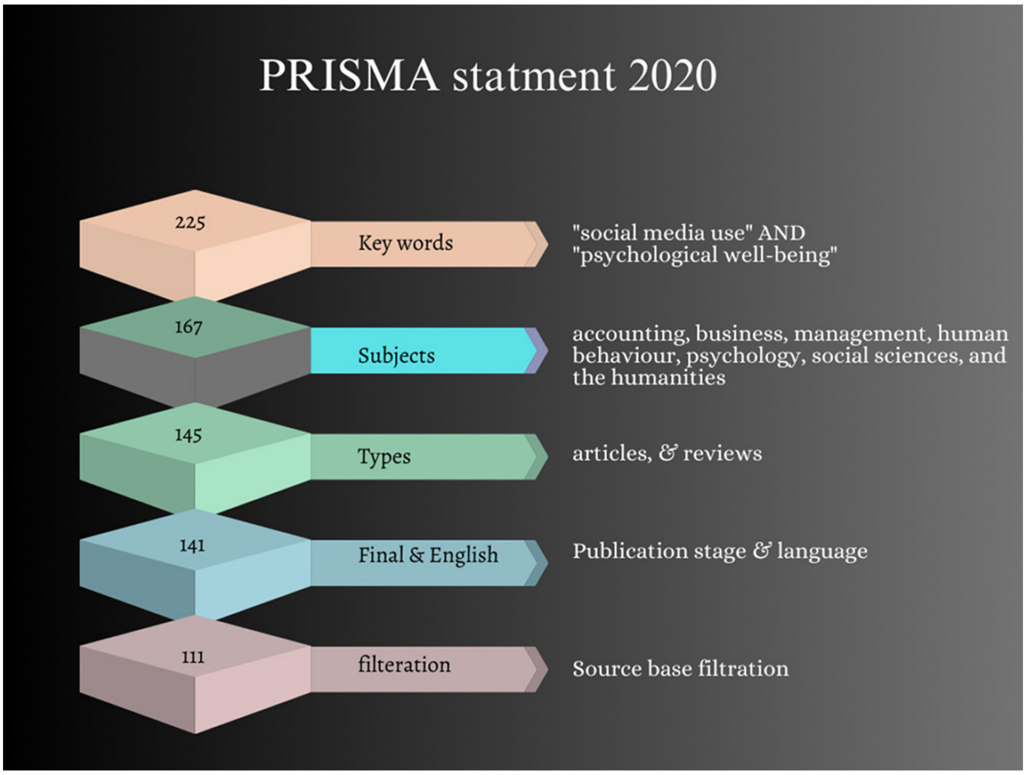

Fig. 1. The PRISMA reporting guideline statement

3 DESCRIPTIVE STATISTICS

3.1 Results

The Bibliometrix RStudio-4.2.1-win software was used in the descriptive analysis research in this bibliometric investigation. The most widely used R package, bibliometrics, is being utilized in an increasing number of papers [25]. Users of R can import a Scopus bibliography database using bibliometrics. A special tool called Bibliometric was created using statistical computing and the R programming language in accordance with a logical bibliometric process. System R is recognized as the de-facto standard platform for statistical algorithm creation and is one of the dynamic software tools used for data analysis and visualization (view of mapping research on using Biblioshiny) [26]. The analysis of the data takes the form of the publishing year, author, publisher, organization, nation, and keywords utilized in the research paper.

Table 1 below provides important facts and findings on the dataset utilized in the study. It gives a general overview of the data sources, the time covered, the number of documents examined, and other metrics pertaining to the document contents, authors, author cooperation, and document types. The "Main Information about Data" section lists 2013 to 2023 as the dataset's timeframe. The data come from 78 journals, books, and other pertinent publications. The collection has 111 documents and an 18.59% yearly growth rate. The documents have a 2.76-year average age and an average of 40.45 citations per document. The collection has 7015 references in total. The "Document Contents" section lists the keywords that were employed in the papers. There are 688 keywords designated as "Keywords Plus (ID)" and 351 as "Author's Keywords (DE)."

The 465 authors who contributed to the dataset are highlighted in the "Authors" section. It also notes the presence of seven papers with a single author in the collection. Information about author cooperation within the dataset is provided on the "Authors Collaboration" page. The average number of co-authors per document is 4.36, while there are seven documents that are single-authored. Furthermore, 31.53% of the co-authorships were from outside the United States. The "Document Types" section describes how different document types are distributed across the dataset. There are 12 reviews and 99 articles, according to the data.

Table 1. Summary of data characteristics and results

Description	Results
Timespan	2013:2023
Sources (Journals, Books, etc.)	78
Documents	111
Annual Growth Rate %	18.59
Document Average Age	2.76
Average citations per doc	40.45
References	7015
Keywords Plus (ID)	688
Author's Keywords (DE)	351
Authors	465
Authors of single-authored docs	7
Single-authored docs	7
Co-Authors per Doc	4.36
International co-authorships %	31.53
Article	99
Review	12

In addition, it presents citation metrics for academic publications published between 2013 and 2022, which are its main goals. The number of published papers, the average number of citations per year, and the length of citability are among the citation metrics considered. For evaluating the effectiveness and impact of scientific publications, several measures are crucial. Table 2 identifies several intriguing trends. The number of total citations per article was highest in 2016 (259.5), an indicator of the publications published in that year's substantial influence and recognition. The lowest average total number of citations per article, 9.8, was found in the year 2022, indicating a weaker overall effect. The number of publications published grew over time, going from 2 in 2013 to 30 in 2022, demonstrating an increase in scholarly production. The average number of citations each year varied greatly, from 18.64 in 2013 to 4.90 in 2022. This data points to fluctuations in the pace of citations and possible alterations in the effect of research over time. Additionally, from 11 years in 2013 to 2 years in 2022, the period of citability showed a reduction in time.

Table 2. Annual citable report: Analysis of citation metrics for academic years 2013–2022

Year	Mean TC Per Art	N	Mean TC Per Year	Citable Years
2013	205	2.00	18.64	11
2014	31.25	4.00	3.12	10
2015	8	1.00	0.89	9
2016	259.5	4.00	32.44	8
2017	66.8	5.00	9.54	7
2018	42	3.00	7.00	6
2019	58.78	9.00	11.76	5
2020	61.16	19.00	15.29	4
2021	19.96	23.00	6.65	3
2022	9.8	30.00	4.90	2

Furthermore, Figure 2 illustrates that out of a total of 30, 2022 saw the most articles published. This data points to a large rise in scholarly production, which may indicate more research and academic contributions in the area. The least number of papers were published, with just one, in the year 2015. This finding could be the result of a significantly lower level of research production or a particular academic trend that year. The number of articles published is generally increasing, although there are sporadic variations from year to year. With 19 publications published in 2020, the year stands out as having a much higher output of research than the years before. This conclusion might be explained by several variables, including new fields of investigation.

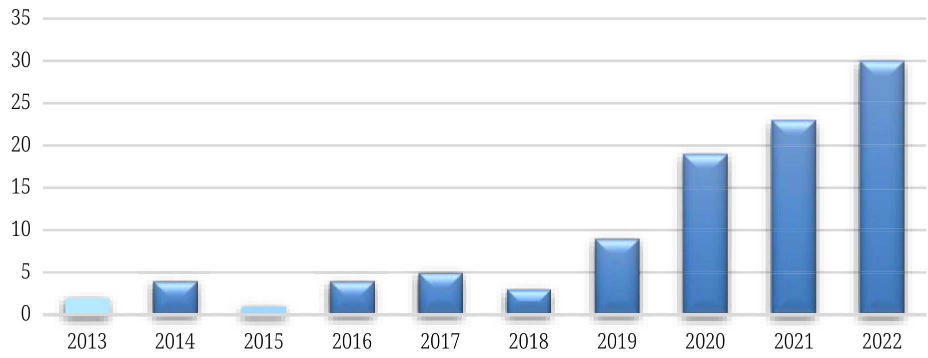

Fig. 2. Analysis of annual article publications for the period 2013–2022

Figure 3 presents the findings and lists the sources and the number of articles that cited each source. The distribution of sources highlights differences in the frequency of citation, indicating the predominance of sources in academic literature.

The research identifies several interesting trends. With eight articles citing it, “Computers in Human Behaviour” appears as the most often used source. This statistic shows that the journal or publication has a strong reputation among academics and is a significant source of knowledge for the subject. Six and five papers, respectively, from “Cyberpsychology, Behaviour, and Social Networking” and “International Journal of Environmental Research and Public Health” are cited next.

The journals “Frontiers in Psychology,” “Journal of Medical Internet Research,” and “Frontiers in Psychiatry” are also cited in four articles apiece. Considering that these sources occur often in the dataset under analysis, they are also likely to have a significant effect within their respective fields.

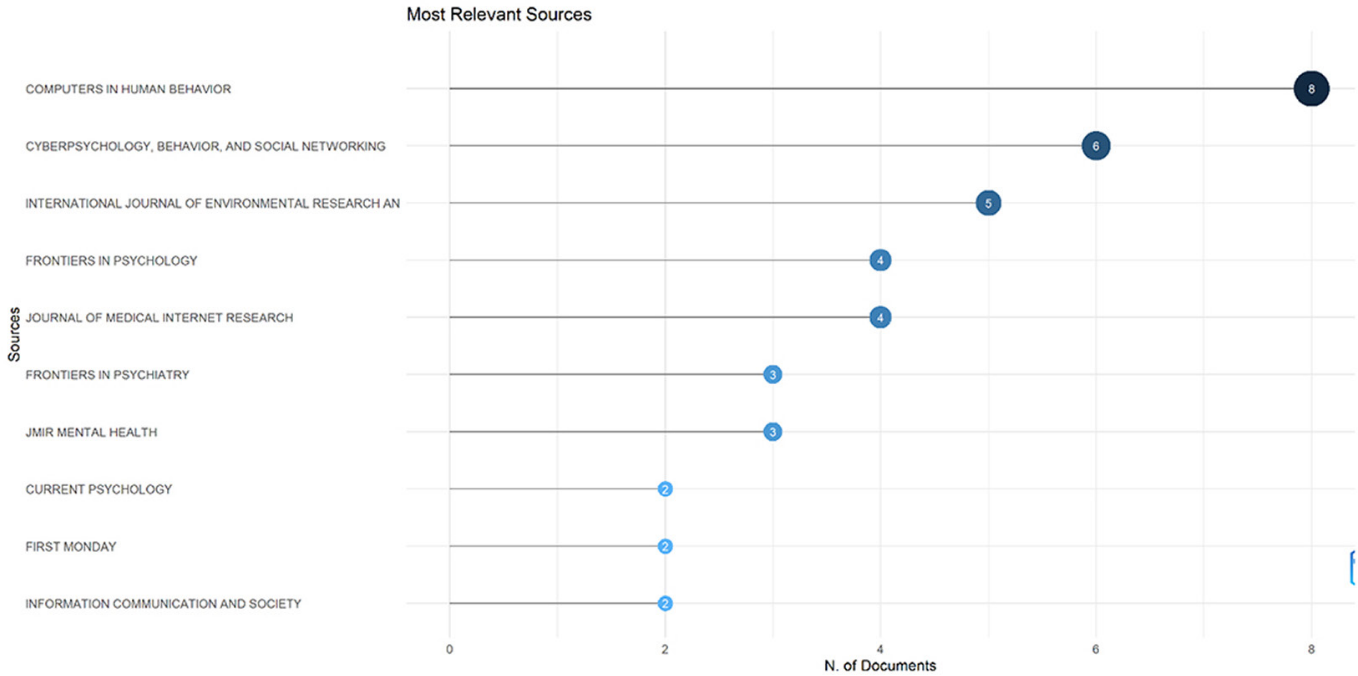

Fig. 3. Analysis of source distribution in academic articles

Furthermore, the findings are shown in Table 3, which charts the evolution of source citations over time. The research identifies several interesting trends. None of the chosen sources earned any citations in the early years, which ran from 2013 to 2015. This finding shows that during that time period, these sources were not often cited in the dataset under analysis.

The number of publications mentioning the chosen sources has been steadily rising since 2016. The number of citations for "Computers in Human Behaviour" and "Cyberpsychology, Behaviour, and Social Networking" starts to rise with time. The "International Journal of Environmental Research and Public Health" also began to earn citations in 2018 and saw a slow rise in popularity over the following years. A distinct trend may be seen in the sources "Frontiers in Psychology" and "Journal of Medical Internet Research." Although "Frontiers in Psychology" began to earn citations in 2018, its frequency is still rather low when compared to other sources. The "Journal of Medical Internet Research," on the other hand, started to get cited in 2019 and noticeably gained popularity in 2020 and 2021.

Table 3. Dynamics of source citations over time in academic articles

Year	Computers in Human Behavior	Cyberpsychology, Behavior, and Social Networking	International Journal of Environmental Research and Public Health	Frontiers in Psychology	Journal of Medical Internet Research
2013	0	0	0	0	0
2014	0	0	0	0	0
2015	0	0	0	0	0
2016	1	1	0	0	0
2017	2	2	0	0	0
2018	3	3	1	0	0

(Continued)

Table 3. Dynamics of source citations over time in academic articles *(Continued)*

Year	Computers in Human Behavior	Cyberpsychology, Behavior, and Social Networking	International Journal of Environmental Research and Public Health	Frontiers in Psychology	Journal of Medical Internet Research
2019	4	3	1	0	1
2020	5	3	3	1	3
2021	6	4	3	3	4
2022	7	5	4	3	4
2023	8	6	5	4	4

Moreover, Figure 4 presents the findings and shows the breakdown of scholarly paper citations by nation. The data highlights the research output and influence of various nations within the academic community by revealing variances in citation counts and average citation rates.

The research identifies several interesting trends. With a total of 1,173 citations, the United States of America (USA) emerges as the most referenced nation. This conclusion suggests that the research has had a substantial influence on the academic community. With 530 citations, Canada comes in second place, showing strong research output with an average of 106 citations per publication.

With 496 and 483 citations, respectively, the Netherlands and the United Kingdom (UK) also exhibit outstanding research performance. Average citation rates for these nations are 99.20 and 60.40 per article, respectively, showing significant impact. With just 338 total citations, Iraq stands out; nonetheless, with an average of 338 citations per article, it has the highest average citation count among the listed nations. This finding implies that research from Iraq has a considerable influence, maybe as a result of extremely significant and influential works.

Comparable citation numbers are shown by China, Luxembourg, and Hong Kong, with 288, 217, and 125 citations, respectively. These nations each have an average of 41.10, 217.00, and 125.00 article citations. Various results imply that various nations' levels of research production and influence differ.

With 95 and 67 citations, respectively, Korea and Germany had significantly lower citation counts. However, the average number of citations per article for both nations is 19, whereas it is 33.50, showing a moderate research impact within the academic community.

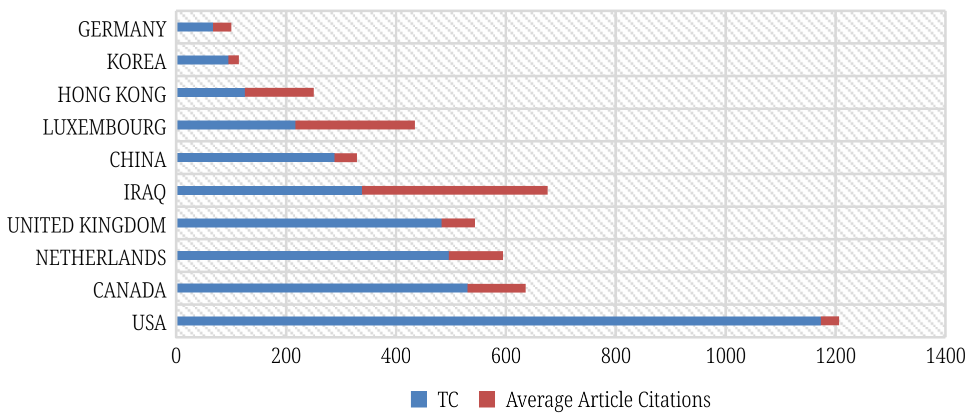

Fig. 4. Analysis of country-wise article citations

4 LITERATURE CLUSTERING

A systematic two-stage strategy was used in this work to perform a thorough literature review. The objective was to guarantee the authenticity, correctness, and completeness of the data that was collected. PRISMA, a widely used and acknowledged systematic review approach, was used in the first stage. The PRISMA architecture made it easier to pull pertinent information from diverse sources, guaranteeing thorough coverage of the literature.

On the retrieved data, descriptive and scientometric analyses were then performed. The literature's essential traits and trends were summarized through descriptive analysis, which also offered insights into the literature's subjects, techniques, and publishing trends. The centrality and co-occurrence of terms were investigated in order to better investigate the connections and linkages between various study topics. The R programming language was used for this study, allowing for the identification of significant research clusters and the visualization of their linkages.

Each research cluster found by the analysis was then subjected to content analysis. In order to compile pertinent literature unique to each study field, a thorough analysis of the data that had been obtained within each cluster was required. To better comprehend the study subjects and themes, content analysis categorizes, organizes, and synthesizes the data.

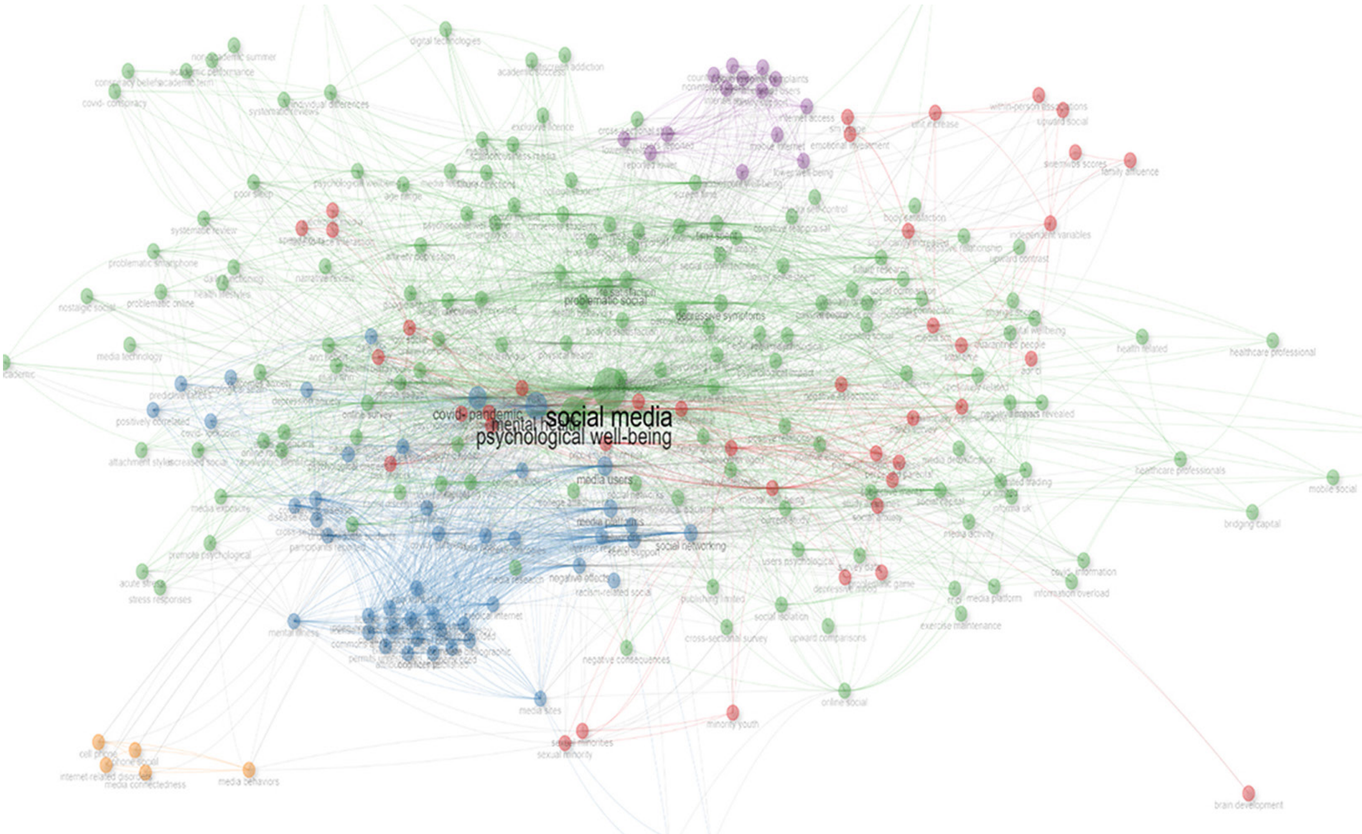

Fig. 5. Thematic map

According to [27], they emphasize in their study that a list of keywords might be used to summarize a particular research subject. The density and centrality criteria, which may be used for any study topic, are included in this list.

The degree of similarity between all terms in the list is referred to as density, and the degree of similarity between one subject and others is referred to as centrality [28].

A thematic map or strategic diagram is used to visually display the thematic linkages created from these keywords (see Figure 5). The themes are divided into four quadrants on this map, depending on the importance and density of the topics. Within the study theme, each quadrant represents a different thematic cluster. The study article's Figure 6 illustrates the presence of different traits in each of the four quadrants. These characteristics, which reflect certain facets or sub-themes within the broad study topic, are obtained from the examination of the keywords. Researchers may see the prevalence and linkages of various sub-themes within the study topic by mapping the keywords onto the thematic map.

Researchers may use this strategy as a useful tool to obtain an understanding of the primary areas of attention within a study subject and to spot any gaps or areas that could need more investigation. Researchers can prioritize their inquiry and concentrate on locations that display high relevance and density by looking at the distribution of keywords throughout the quadrants.

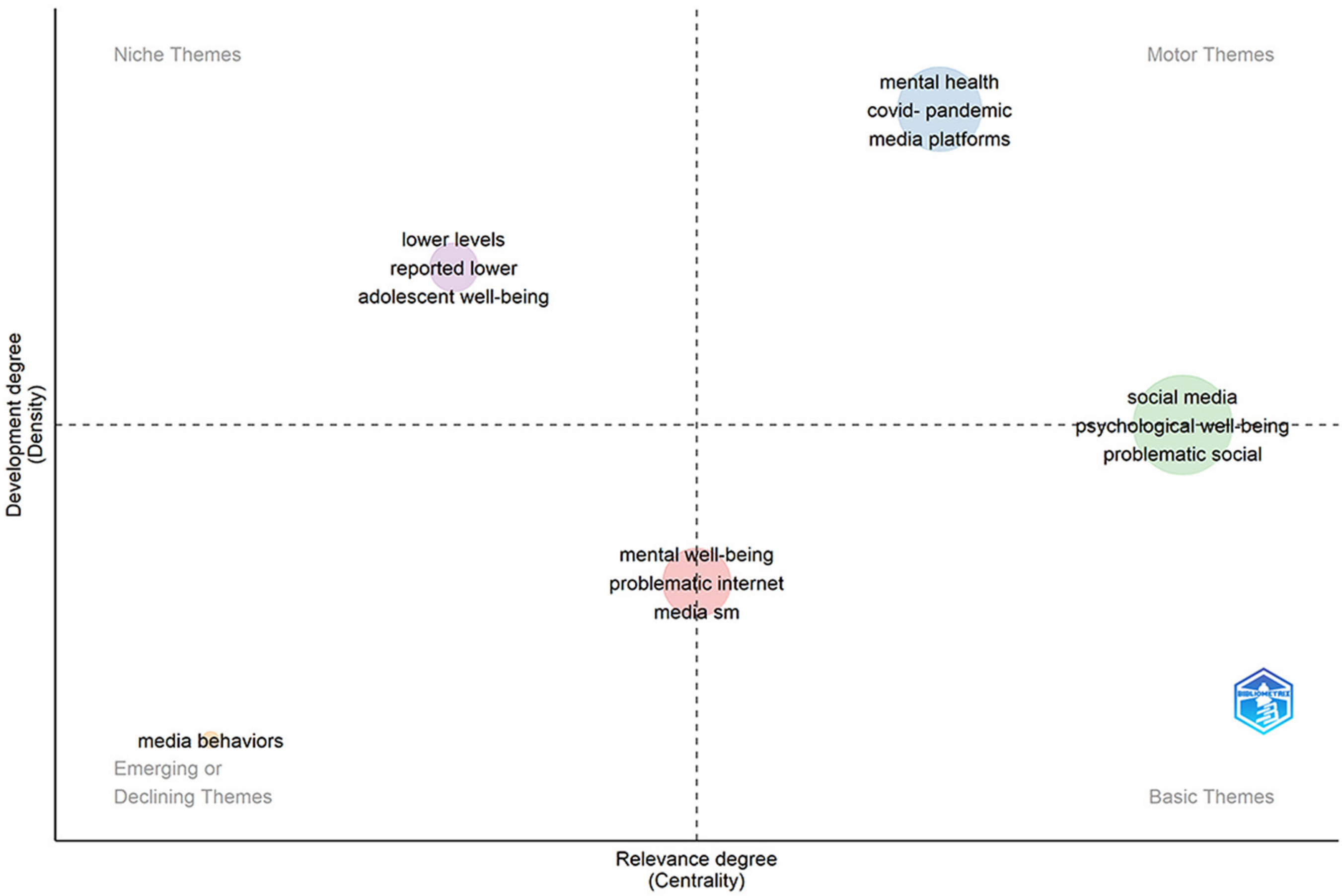

Fig. 6. Thematic evolution

An examination of clusters within a particular research field is shown in Table 4. Based on Callon centrality, Callon density, rank centrality, rank density, and cluster frequency, the clusters are assessed. These measurements shed light on each cluster's importance, density, and frequency within the study subject. With a Callon centrality of 8.01771164, the "mental well-being" cluster shows a modest level of relevance within the study topic. The Callon density for this cluster is 75.44312169, indicating that there is a disproportionately high concentration of phrases related to mental health. This cluster is rated second and third, respectively, among all the clusters in terms of rank centrality. The term "mental well-being" has a cluster frequency of 70, which indicates that it appears often in the examined publications.

A higher Callon centrality of 15.48282818 for the "mental health" cluster indicates that it is more significant within the study topic. This cluster has a Callon density of 194.7796484, which indicates a rather high density of linked words. This cluster is ranked fourth and fifth, respectively, for rank centrality and rank density. "Mental health" has a cluster frequency of 208, which indicates a greater prevalence than other clusters.

With a Callon centrality of 20.28935852, the "social media" cluster stands out as being quite prominent within the study subject. A significant density of phrases related to social media is shown by the cluster's Callon density of 85.36438092. This cluster is ranked third in terms of rank density and fifth in terms of rank centrality. With a frequency of 589, the cluster frequency for "social media" is the highest of all the clusters. With a Callon centrality of 2.298611111, the "lower levels" cluster is less significant in terms of the study subject. With a Callon density of 98.61111111, this cluster has a modest density of related words. This cluster is ranked second and fourth, respectively, for rank centrality and rank density. "Lower levels" have a cluster frequency of 18, which denotes a lesser incidence when compared to other clusters.

The "media behaviors" cluster has the least relevance within the study subject, as indicated by its lowest Callon centrality of 0.375. The cluster's 50-Callon density indicates a modest number of linked phrases. This cluster is ranked first and first, respectively, in terms of rank centrality and rank density.

Table 4. Analysis of clusters in a research topic

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
mental well-being	8.01771164	75.44312169	3	2	70
mental health	15.48282818	194.7796484	4	5	208
social media	20.28935852	85.36438092	5	3	589
lower levels	2.298611111	98.61111111	2	4	18
media behaviors	0.375	50	1	1	2

5 LOWER LEVELS AND MEDIA BEHAVIOR CLUSTERS

The frequency of keywords and their centrality scores within various clusters are shown in Table 5 below. The labels for the clusters reflect the relevant thematic focus. The centrality measurements, which reveal information about the weight and influence of the terms inside their respective clusters, include betweenness centrality, proximity centrality, and PageRank centrality.

The "lower levels" keyword cluster lies under niche themes that include phrases such as "users reported," "internet access," "lower levels," "reported lower," "adolescent well-being," "lower well-being," and "mobile internet." These keywords appear somewhere between two and four times. In addition, the "lower levels" cluster's keywords have betweenness centralities that range from 44.7367433 to 188.1144658, demonstrating how important it is for the network to link these keywords. The closeness centrality, which runs from 0.001776199 to 0.002079002, indicates how closely the terms are related to one another inside the cluster. According to the importance and significance of the terms in the overall network structure, the PageRank centrality ranges from 0.002883419 to 0.004631361.

Keywords such as "media behaviors" are found in the emerging or declined theme titled. This keyword appears two times. The "media behaviors" keyword has a betweenness centrality of 15.46272662, which highlights its significance in tying together various network nodes. As indicated by the closeness centrality of 0.001438849, it is near other terms in the cluster. The PageRank centrality, which measures how influential and dominant a node is within the broader network structure, is 0.002169954.

Table 5. Occurrences and centrality measures of keywords in clusters

Words	Occurrences	Cluster Label	Btw Centrality	Clos Centrality	Page Rank Centrality
users reported	2	lower levels	55.6878832	0.0019084	0.00329615
Internet access	2	lower levels	44.7367433	0.0019084	0.00311536
lower levels	4	lower levels	114.048129	0.00192678	0.00462752
reported lower	3	lower levels	188.114466	0.002079	0.00463136
adolescent well-being	3	lower levels	150.876525	0.00207039	0.00400662
lower well-being	2	lower levels	56.2974117	0.0017762	0.00328027
mobile internet	2	lower levels	50.1563051	0.00189753	0.00288342
media behaviors	2	media behaviors	15.4627266	0.00143885	0.00216995

6 MENTAL WELL-BEING CLUSTER

In addition, the "mental well-being" cluster's keyword occurrences and centrality metrics are shown in Table 6. The keywords in this cluster are those that are concerned with mental health and exist in the basic theme and decline theme in Figure 6 of thematic evolution. The table offers insightful information on the significance, interconnection, and effect of various terms within the cluster.

In the cluster, the keyword "mental well-being" appears 10 times, suggesting its frequency and importance. With a betweenness centrality of 776.8759055, this term plays a major role in tying together various areas of the network. As indicated by the closeness centrality of 0.002087683, it is near other terms in the cluster. The PageRank centrality, which measures how influential and prominent a node is within the broader network structure, is 0.008423216. The results of this study help us comprehend the thematic makeup and popularity of keywords associated with mental health. The linkages and dynamics within the "mental well-being" cluster may be further explored and analyzed using these findings, which will further our understanding of this field of study.

Table 6. Occurrences and centrality measures of keywords in the "mental well-being" cluster

Words	Occurrences	Btw Centrality	Clos Centrality	Page Rank Centrality
mental well-being	10	776.875906	0.00208768	0.00842322
problematic internet	6	212.881271	0.00190114	0.00520233
sexual minorities	2	34.2321147	0.00171821	0.0019248
adolescent mental	4	159.607835	0.00199601	0.00479662
sexual minority	2	34.2321147	0.00171821	0.0019248
total time	2	64.2006708	0.00189394	0.00222394
media sm	6	232.315436	0.00204082	0.005035
risk factors	3	91.5107536	0.00191571	0.00391134
adolescents mental	3	92.9881073	0.00197239	0.0037644
adolescents aged	4	350.961472	0.00206186	0.00475068
family affluence	2	8.82025409	0.00161031	0.00152503
health behaviors	2	58.1826959	0.00193424	0.00302981
low social	2	53.2924986	0.00190114	0.00303599
negative association	4	112.08542	0.00195695	0.00392106
panel survey	4	145.392978	0.00197628	0.00424117
significantly increased	2	37.1761204	0.00175747	0.00236466
social anxiety	2	4.58565639	0.0015625	0.00223356
unit increase	2	35.3832268	0.0017452	0.00233238
health risk	2	46.671476	0.00198413	0.00303795
independent variables	3	86.8023213	0.00173611	0.00282901
nationally representative	3	108.016887	0.00197239	0.00305684

7 SOCIAL MEDIA

Table 7 displays a cluster analysis of social media-related terms together with the appropriate centrality scores. In addition, a social media cluster is present in Figure 6 at the basic themes and motor themes. Additionally, this collection of words' cluster label is "social media." Each word in the cluster's frequency distribution is shown in the table along with three centrality metrics: betweenness centrality, proximity centrality, and PageRank centrality.

The importance of a word in tying together other words in the cluster is indicated by its betweenness centrality. Social media in this instance has the greatest betweenness centrality (3146.101547), indicating that it is extremely important in connecting other terms in the cluster. Based on the quantity and quality of connections a term has, its PageRank centrality reveals its significance. Social media is highly linked and influential inside the cluster, as indicated by its low PageRank centrality of 0.078997167. Also, "psychological well-being," "problematic social," "screen time," "time spent," "life satisfaction," and more are other terms in the cluster. These terms add to the broader cluster and are also connected to social media.

The cluster analysis emphasizes the significance of the phrase "social media" and its connections to many psychological and wellbeing variables. The findings highlight the relevance of social media in research and conversations about psychological health and social behavior by highlighting its prominence within the context of the data that was analyzed.

Table 7. Occurrences and centrality measures of keywords in the "social media" cluster

Words	Occurrences	Btw Centrality	Clos Centrality	Page Rank Centrality
social media	110	3146.10155	0.00229885	0.07899717
psychological well-being	64	2979.19317	0.00234742	0.04688973
problematic social	14	1207.46259	0.00226757	0.01175398
screen time	6	332.45421	0.0019802	0.00567642
time spent	10	757.103333	0.0021692	0.00845111
life satisfaction	10	827.411897	0.00218818	0.00899854
university students	9	641.360316	0.00207039	0.00753846
social comparison	6	337.203502	0.0020202	0.00544929
depressive symptoms	10	874.634035	0.00217865	0.00951492
health outcomes	6	345.318646	0.00209205	0.00734576
body image	5	146.736213	0.0020202	0.0045955
online survey	12	406.46193	0.00207469	0.00922353
social capital	5	163.922003	0.00191205	0.0040026
online social	5	71.1079189	0.00183824	0.00325971
physical health	5	185.99637	0.00199203	0.00506206
media exposure	2	54.8624544	0.0018797	0.00307188
structural equation	10	278.922509	0.00203666	0.00838545
undergraduate students	4	332.809931	0.00193424	0.00408649
anxiety depression	6	399.261395	0.002079	0.00653754
current study	6	259.237907	0.00202429	0.00552154
media usage	6	353.05876	0.00206612	0.00618722
physical activity	5	369.749967	0.0020202	0.00519834
social connection	2	14.6554837	0.00175747	0.00229155
body dissatisfaction	3	132.930148	0.002	0.00386385
future research	8	340.116949	0.00200401	0.00554659
negative affect	4	64.2526541	0.0019305	0.00399541
positively related	6	167.145002	0.00193798	0.0046877
public health	5	254.932884	0.00199601	0.00559221
equation modeling	7	261.529616	0.0020284	0.00604764

(Continued)

Table 7. Occurrences and centrality measures of keywords in the "social media" cluster *(Continued)*

Words	Occurrences	Btw Centrality	Clos Centrality	Page Rank Centrality
healthcare professionals	2	39.273861	0.00188679	0.0018612
mental wellbeing	5	165.401556	0.00200401	0.00421119
problematic smartphone	4	35.1822284	0.00170648	0.003037
social networks	2	24.8177012	0.0018315	0.0016826
ann liebert	6	81.5948896	0.00198807	0.0046559
mary ann	6	81.5948896	0.00198807	0.0046559
media llc	6	134.637942	0.00200401	0.00567367
mediating role	5	128.347321	0.0020284	0.00502494
mobile social	2	3.23128949	0.00142248	0.00166504
online communication	2	48.5452275	0.00194553	0.00201194
poor sleep	4	191.980097	0.00200803	0.0037631
psychological well-being	5	118.569938	0.00190476	0.00345499
racial discrimination	2	51.7277303	0.0019084	0.00307319
science business media	6	134.637942	0.00200401	0.00567367
social isolation	3	117.206708	0.00184843	0.00310783
study examined	6	450.033156	0.0020284	0.00602496
study examines	6	198.140791	0.00193798	0.0045861
systematic review	4	127.951738	0.00201613	0.0032815
analysis revealed	4	81.1961932	0.00194553	0.00344236
lower psychological	3	75.3424188	0.0019084	0.00309294
moderating role	4	69.4985047	0.00198413	0.00419159
perceived social	3	110.44774	0.00200803	0.00329696
publishing limited	5	30.3229574	0.00191205	0.00358121
study investigated	5	169.531717	0.00200401	0.00404903
users psychological	5	92.319871	0.00189753	0.00436907
digital media	2	12.1589803	0.00172414	0.00175054
future directions	4	84.6202711	0.00184162	0.0029927
health related	2	14.9662794	0.00171233	0.00173297
informa uk	4	39.1088253	0.00190476	0.00395718
information overload	2	8.17990933	0.00182815	0.00201302
limited trading	4	39.1088253	0.00190476	0.00395718
lower self-esteem	3	61.9913435	0.00189753	0.00289021
negative relationship	2	35.5073056	0.00183486	0.00212951
passive social	3	96.7481699	0.00195695	0.00314252

Finally, Table 8 illustrates the mental-health cluster in the motor theme. In addition, the statistical analysis findings for the "mental health" cluster are presented in Table 8. Each term or phrase in this cluster is listed in the table along with its cluster number, occurrences, label, betweenness centrality, proximity centrality, and PageRank centrality values. The phrase "mental health" is mentioned in the analyzed data 27 times, followed by "covid-pandemic" (17 times), "social support" (8 times), and other terms with varied frequency. The betweenness centrality metric gauges a term's significance in tying together other words in the network. The phrase "mental health" in this instance has the greatest betweenness centrality score (1769.985422), demonstrating its critical importance in tying together other terms in the mental health cluster. How tightly a phrase is related to other terms in the network is determined by its closeness and centrality. The phrase "mental health" is quite near other terms in the cluster, as indicated by its closeness centrality of 0.002298851.

The phrase "mental health" is a central and important term within the examined data, according to these centrality indicators. It has strong relationships with other terms in the cluster, contributes significantly to the connections between terms, and has considerable overall significance within the network. Other phrases in the cluster with modest degrees of centrality include "covid-pandemic," "social support," and "media platforms," all of which are pertinent to discussions of mental health. Their centrality scores, meanwhile, are considerably lower than those of "mental health."

Table 8. Occurrences and centrality measures of keywords in the "mental health" cluster

Words	Occurrences	Btw Centrality	Clos Centrality	Page Rank Centrality
mental health	27	1769.98542	0.00229885	0.02660898
covid-pandemic	17	1167.95909	0.00222717	0.01713292
social support	8	498.331137	0.00204918	0.00712479
media platforms	12	347.229165	0.00207039	0.01127296
college students	6	364.068347	0.00204499	0.00562668
media users	10	968.192566	0.00220264	0.01066993
social networking	9	657.928378	0.00223214	0.00840282
covid-outbreak	5	413.93883	0.00205339	0.00649643
negative effects	8	235.590871	0.00197239	0.00864916
networking sites	6	374.869856	0.00212314	0.00592845
coping strategies	3	136.510652	0.00187266	0.00380352
depression anxiety	4	77.3857329	0.00183486	0.00395673
Internet research	4	116.150593	0.00185874	0.00598802
participants reported	4	122.209504	0.00192308	0.00518358
psychological distress	3	34.1710718	0.00184502	0.00323139
medical internet	3	19.3377734	0.00177936	0.00512705
coronavirus disease	4	144.020067	0.00197239	0.00546464
daily life	4	146.035391	0.00200401	0.00426018
daily lives	3	271.982974	0.00215054	0.00424101

(Continued)

Table 8. Occurrences and centrality measures of keywords in the "mental health" cluster *(Continued)*

Words	Occurrences	Btw Centrality	Clos Centrality	Page Rank Centrality
disease covid-	4	144.020067	0.00197239	0.00546464
online questionnaire	4	294.831124	0.00199203	0.00537869
positively correlated	3	65.0827454	0.0018797	0.00302838
predictive factors	2	45.5007438	0.00191205	0.00264921
article distributed	3	12.6511322	0.00186567	0.00584219
attribution license	3	12.6511322	0.00186567	0.00584219
bibliographic information	3	12.6511322	0.00186567	0.00584219
commons attribution	3	12.6511322	0.00186567	0.00584219
complete bibliographic	3	12.6511322	0.00186567	0.00584219
covid-lockdown	2	20.8135612	0.00186567	0.00266781

8 DISCUSSION

To give a full study of the dataset, the review procedure employed bibliometric analysis, which combined bibliometrics with R. This dataset included several research publications, authors, publishers, organizations, nations, and keywords connected to the study topic [29]. Thematic keyword mapping enabled researchers to find and comprehend several sub-themes within the study issue, hence improving understanding, identifying research gaps, and planning future investigations. The usage of online social media platforms has sparked heated academic discussion, with researchers debating the benefits and drawbacks of such platforms [26]. Several studies have looked at the relationship between online communication and psychological WB in teenagers, but the results have been inconsistent, leading to more questions than solid answers [25]. The purpose of this article is to shed light on the complicated link between social media use and young people's WB, including both possible advantages and risks [20].

One of the early worries about social media was the excessive amount of time young people spent on internet platforms. This highlighted concerns about less face-to-face interaction, increased social isolation, increased stress, melancholy, and sleep problems. There were also concerns about how social media platforms can develop an environment favourable to improper behavior, posing a hazard to mental health [18].

While some studies have revealed the potential benefits of utilizing social media, there are also concerns about potential disadvantages [10]. Using social media in moderation and with awareness has been shown in studies to increase WB by increasing social connection and support [14]. Excessive usage and improper Internet behavior, on the other hand, have been linked to detrimental mental-health outcomes, particularly in young people who are more vulnerable to such behaviors [30]. The study also highlights the necessity of taking into account young people's vulnerabilities and providing age-appropriate information and help. It emphasizes the significance of distinguishing between different types of social media usage and subjective WB, as well as comprehending teenagers' affective WB, which refers to their transient emotional emotions.

9 CONCLUSION AND FUTURE RESEARCH

In conclusion, the discussion over how social media use affects young people's WB is still complicated and nuanced [31]. Previous studies have shown contradictory results, demonstrating both possible benefits and drawbacks related to online platforms. Social media can encourage new types of social connection and engagement, but there have been concerns voiced about its overuse, decline in in-person interaction, social isolation, rise in stress, and detrimental impacts on sleep hygiene.

The results of previous studies have been inconclusive, underscoring the need for more research into the connection between social media use and WB. Use of social media in moderation and with knowledge has been linked to better health, including social support and connection. However, there is evidence linking excessive consumption and improper Internet behavior to poor mental-health outcomes, especially in young people who are more susceptible to these behaviors [32].

Understanding the intricacies of this issue necessitates considering young people's vulnerabilities and offering them age-appropriate counsel and assistance. According to [33], the types and extents of social network usage have different effects on social media's influence on subjective WB. Active use of social networking sites has been linked favorably to subjective WB, but research on teenagers' affective WB, which relates to their fleeting emotional emotions, is scant [34]. This study examines the link between youths' usage of social media and their affective WB to close the knowledge gap. The goal of the study is to offer insightful information that can guide future treatments and policies by concentrating on participants' current emotional experiences as they relate to online interactions. It emphasizes how crucial it is to weigh the possible advantages and hazards of social media use in order to encourage pleasant online experiences and protect the WB of young people. Furthermore, a deeper comprehension of the intricate relationships between social media use and WB can ultimately be attained through thorough research and analysis, which will lead to evidence-based tactics for promoting positive online conduct and promoting young people's emotional well-being.

10 REFERENCES

[1] H. H. Soo Kim, "The impact of online social networking on adolescent psychological well-being (WB): A population-level analysis of Korean school-aged children," *International Journal of Adolescence and Youth*, vol. 22, no. 3, pp. 364–376, 2016. https://doi.org/10.1080/02673843.2016.1197135

[2] M. Merolli, K. Gray, and F. Martin-Sanchez, "Health outcomes and related effects of using social media in chronic disease management: A literature review and analysis of affordances," *J. Biomed Inform.*, vol. 46, no. 6, pp. 957–969, 2013. https://doi.org/10.1016/j.jbi.2013.04.010

[3] I. Mustapha, N. Khan, and M. I. Qureshi, "Is technology affecting the way our minds operate? Digital psychology of users in the era of digitalization," *Advanced Structured Materials*, vol. 174, pp. 71–92, 2022. https://doi.org/10.1007/978-3-031-01488-8_8

[4] M. Khan, N. Khan, S. Begum, and M. I. Qureshi, "Digital future beyond pandemic outbreak: Systematic review of the impact of COVID-19 outbreak on digital psychology," *Foresight*, 2023. https://doi.org/10.1108/FS-02-2021-0044

[5] M. O'Reilly, N. Dogra, N. Whiteman, J. Hughes, S. Eruyar, and P. Reilly, "Is social media bad for mental health and wellbeing? Exploring the perspectives of adolescents," vol. 23, no. 4, pp. 601–613, 2018. https://doi.org/10.1177/1359104518775154

[6] E. Staksrud, K. Ólafsson, and S. Livingstone, "Does the use of social networking sites increase children's risk of harm?" *Comput. Human Behav.*, vol. 29, no. 1, pp. 40–50, 2013. https://doi.org/10.1016/j.chb.2012.05.026

[7] H. T. Tseng, F. Ibrahim, N. Hajli, T. M. Nisar, and H. Shabbir, "Effect of privacy concerns and engagement on social support behaviour in online health community platforms," *Technol. Forecast Soc. Change*, vol. 178, p. 121592, 2022. https://doi.org/10.1016/j.techfore.2022.121592

[8] H. Bruggeman, A. Van Hiel, G. Van Hal, and S. Van Dongen, "Does the use of digital media affect psychological well-being? An empirical test among children aged 9 to 12," *Comput. Human Behav.*, vol. 101, pp. 104–113, 2019. https://doi.org/10.1016/j.chb.2019.07.015

[9] E. Kross, P. Verduyn, G. Sheppes, C. K. Costello, J. Jonides, and O. Ybarra, "Social media and well-being: Pitfalls, progress, and next steps," *Trends Cogn. Sci.*, vol. 25, no. 1, pp. 55–66, 2021. https://doi.org/10.1016/j.tics.2020.10.005

[10] V. Schønning, G. J. Hjetland, L. E. Aarø, and J. C. Skogen, "Social media use and mental health and well-being among adolescents—A scoping review," *Front. Psychol.*, vol. 11, p. 1949, 2020. https://doi.org/10.3389/fpsyg.2020.01949

[11] M. O'Reilly, N. Dogra, N. Whiteman, J. Hughes, S. Eruyar, and P. Reilly, "Is social media bad for mental health and wellbeing? Exploring the perspectives of adolescents," *Clinical Child Psychology and Psychiatry*, vol. 23, no. 4, pp. 601–613, 2018. https://doi.org/10.1177/1359104518775154

[12] J. C. Levenson, A. Shensa, J. E. Sidani, J. B. Colditz, and B. A. Primack, "The association between social media use and sleep disturbance among young adults," *Prev. Med. (Baltim)*, vol. 85, pp. 36–41, 2016. https://doi.org/10.1016/j.ypmed.2016.01.001

[13] Maciej Serda *et al.*, "Synteza i aktywność biologiczna nowych analogów tiosemikarbazonowych chelatorów żelaza," *Uniwersytet śląski*, vol. 7, no. 1, pp. 343–354, 2013. https://doi.org/10.2/JQUERY.MIN.JS

[14] Z. Jin, M. A. Griffith, and A. C. Rosenthal, "Identifying and meeting the needs of adolescents and young adults with cancer," *Curr. Oncol. Rep.*, vol. 23, no. 2, pp. 1–10, 2021. https://doi.org/10.1007/s11912-020-01011-9

[15] G. K. Perez, J. M. Salsman, K. Fladeboe, A. C. Kirchhoff, E. R. Park, and A. R. Rosenberg, "Taboo topics in adolescent and young adult oncology: Strategies for managing challenging but important conversations central to adolescent and young adult cancer survivorship.," *Am. Soc. Clin. Oncol. Educ. Book*, vol. 40, no. 40, pp. 1–15, 2020. https://doi.org/10.1200/EDBK_279787

[16] P. Verduyn, O. Ybarra, M. Résibois, J. Jonides, and E. Kross, "Do social network sites enhance or undermine subjective well-being? A critical review," *Soc. Issues Policy Rev.*, vol. 11, no. 1, pp. 274–302, 2017. https://doi.org/10.1111/sipr.12033

[17] C. Berryman, C. J. Ferguson, and C. Negy, "Social media use and mental health among young adults," *Psychiatric Quarterly*, vol. 89, no. 2, pp. 307–314, 2018. https://doi.org/10.1007/s11126-017-9535-6

[18] I. Beyens, J. L. Pouwels, I. I. van Driel, L. Keijsers, and P. M. Valkenburg, "The effect of social media on well-being differs from adolescent to adolescent," *Scientific Reports 2020*, vol. 10, no. 1, pp. 1–11, 2020. https://doi.org/10.1038/s41598-020-67727-7

[19] P. M. Valkenburg, "Social media use and well-being: What we know and what we need to know," *Curr. Opin. Psychol.*, vol. 45, p. 101294, 2022. https://doi.org/10.1016/j.copsyc.2021.12.006

[20] A. Durayappah, "The 3P model: A general theory of subjective well-being," *J. Happiness Stud.*, vol. 12, no. 4, pp. 681–716, 2011. https://doi.org/10.1007/s10902-010-9223-9

[21] A. O. Kusier and A. P. Folker, "The satisfaction with life scale: Philosophical foundation and practical limitations," *Health Care Analysis*, vol. 29, no. 1, pp. 21–38, 2021. https://doi.org/10.1007/s10728-020-00420-y

[22] Nohman Khan, I. Mustapha, and Muhammad Imran Qureshi, "Review paper on sustainable manufacturing in ASEAN countries," *Systematic Literature Review and Meta-Analysis Journal*, vol. 1, no. 1, pp. 7–29, 2020. https://doi.org/10.54480/slrm.v1i1.4

[23] H. Sikandar, Y. Vaicondam, N. Khan, M. I. Qureshi, and A. Ullah, "Scientific mapping of Industry 4.0 Research: A bibliometric analysis," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 18, pp. 129–147, 2021. https://doi.org/10.3991/ijim.v15i18.25535

[24] I. Mustapha, N. Khan, M. I. Qureshi, A. A. Harasis, and N. T. Van, "Impact of Industry 4.0 on healthcare: A Systematic Literature Review (SLR) from the Last Decade," *International Journal of Interactive Mobile Technologies*, vol. 15, no. 18, pp. 116–128, 2021. https://doi.org/10.3991/ijim.v15i18.25531

[25] H. Majiwala and R. Kant, "A bibliometric review of a decade' research on industry 4.0 & supply chain management," *Mater. Today Proc.*, vol. 72, pp. 824–833, 2023. https://doi.org/10.1016/j.matpr.2022.09.058

[26] B. Buyamin *et al.*, "The influence of war and global economy on article publication (Bibliometric Analysis using Biblioshiny-R)," *Research Square*, 2023. https://doi.org/10.21203/rs.3.rs-2680363/v1

[27] M. J. Cobo, A. G. López-Herrera, E. Herrera-Viedma, and F. Herrera, "Science mapping software tools: Review, analysis, and cooperative study among tools," *Journal of the American Society for Information Science and Technology*, vol. 62, no. 7, pp. 1382–1402, 2011. https://doi.org/10.1002/asi.21525

[28] B. Ayan, E. Güner, and S. Son-Turan, "Blockchain technology and sustainability in supply chains and a closer look at different industries: A mixed method approach," *Logistics*, vol. 6, no. 4, p. 85, 2022. https://doi.org/10.3390/logistics6040085

[29] I. Mustapha, M. Ali, N. Khan, and H. Sikandar, "The impact of industry 4.0 on innovative organisations, a thematic review using the PRISMA statement 2020," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 17, no. 09, pp. 88–105, 2023. https://doi.org/10.3991/ijim.v17i09.39465

[30] N. Khan, M. I. Qureshi, I. Mustapha, S. Irum, and R. N. Arshad, "A systematic literature review paper on online medical mobile applications in Malaysia," *International Journal of Online and Biomedical Engineering*, vol. 16, no. 1, pp. 63–82, 2020. https://doi.org/10.3991/ijoe.v16i01.12263

[31] Ahmed Ejaz, Abrar Ullah, Huma Sikandar, Nohman Khan, and Muhammad Hassan, "Mapping the literature of social network ties in business and management field: A bibliometric study," *Journal of Management Info*, vol. 9, no. 3, pp. 330–346, 2022. https://doi.org/10.31580/jmi.v9i3.2688

[32] R. Bhat, V. K. Singh, N. Naik, C. R. Kamath, P. Mulimani, and N. Kulkarni, "COVID 2019 outbreak: The disappointment in Indian teachers," *Asian J. Psychiatr.*, vol. 50, p. 102047, 2020. https://doi.org/10.1016/j.ajp.2020.102047

[33] S. M. Y. Arafat, S. K. Kar, M. Marthoenis, P. Sharma, E. Hoque Apu, and R. Kabir, "Psychological underpinning of panic buying during pandemic (COVID-19)," *Psychiatry Res.*, vol. 289, p. 113061, 2020. https://doi.org/10.1016/j.psychres.2020.113061

[34] S. Singh, D. Roy, K. Sinha, S. Parveen, G. Sharma, and G. Joshi, "Impact of COVID-19 and lockdown on mental health of children and adolescents: A narrative review with recommendations," *Psychiatry Res.*, vol. 293, p. 113429, 2020. https://doi.org/10.1016/j.psychres.2020.113429

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