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ORIGINAL RESEARCH

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The influence of search volume for suicide on suicide rates: focusing on gender differences

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Abstract

Background: Suicide poses a significant public health challenge worldwide, with rising concerns during the COVID-19 pandemic, and despite global efforts to reduce suicide rates, predicting suicidal behavior remains challenging. This study aims to investigate the relationship between internet search volumes related to suicide and actual suicide rates in South Korea. **Methods**: Using data from Naver Data Lab and Statistics Korea covering January 2016 to April 2024, this study conducted regression analyses to investigate how search volumes for suicide-related terms correlate with monthly suicide counts. **Results**: Our findings indicate a significant positive correlation between overall search volumes for suicide and total suicide cases, particularly emphasizing the mediating role of searches related to depression. However, this association was statistically significant among females but not in males. **Conclusions**: This research highlights the potential of digital data to inform public health strategies and improve suicide prevention efforts in South Korea, underlining the importance of integrating mental health support into economic recovery policies.

Keywords

Suicide; Internet search behavior; Gender differences; Depression; Digital epidemiology

1. Introduction

Suicide poses a severe public health issue globally, with over 700,000 individuals losing their lives to suicide each year [1]. Consequently, international efforts aimed at suicide prevention have intensified. The United Nations' Sustainable Development Goals (SDGs) and the World Health Organization (WHO)'s Mental Health Action Plan highlight the reduction of global suicide mortality rates by one-third by 2030 as a critical mental health objective [1].

Researchers focused on suicide prevention have endeavored to analyze individuals at risk of suicide and the behaviors and conditions predicting suicidal tendencies. However, current suicide prediction models have been criticized for their low accuracy in forecasting actual suicides [2], and the tools used for assessing suicide risk in clinical settings often lack diagnostic clarity [3]. In screening processes conducted by mental health professionals, a limitation exists that individuals may not disclose their suicidal thoughts, plans or actions unless they choose to do so [4, 5]. This necessitates ongoing efforts to identify various factors that can capture and detect suicide risk.

One promising approach involves utilizing digital data as a significant resource reflecting human behavior. For instance, there is a growing possibility of using digital lifestyle-related data, such as that from social media, as tools for screening and early detection of suicide risk. However, this approach faces challenges due to age-related bias and the tendency for individuals to share data with consideration for others [6]. In contrast, search behaviors directly address individual concerns and interests, reflecting personal attitudes and intentions with descriptive and predictive qualities [7]. In fact, the big data accumulated from internet searches is regarded as a valuable resource for reflecting and predicting human behavior [8]. Research utilizing big data analytics, such as Google Trends, to predict individuals' current and future health-related behaviors is rapidly increasing [9, 10]. This trend has expanded into studies focused on predicting suicidality through internet search volumes. Considering the social contagion of suicide [11] and temporal characteristics [12], search volumes could effectively serve as indicators of suicide risk and societal concern on a macro level.

Indeed, studies have reported a relationship between search volumes for suicide-related terms and actual suicide rates [13–17]. These studies often focus on specific populations [13], examine search volumes of related terms [16, 17], or assess the influence on behaviors similar to suicide rather than suicide itself [14], thereby contributing to the inference of a close relationship between search volumes and suicidality. Conversely, some studies suggest that search volumes for suicide-related terms may not predict suicides [18, 19]. This discrepancy could arise from differences in the timing of search volume measurements and suicide rates or overly rigid restrictions in defining the keywords used in these studies.

In light of the diverse and sometimes contradictory findings

regarding the relationship between search volumes for suicide and actual suicides, this study aims to analyze the impact of internet search volume related to the keyword "suicide" on the actual suicide rates during the same period, using monthly data as the unit of analysis. Notably, this research will focus on South Korea, which has the highest suicide rate among Organisation for Economic Co-operation and Development (OECD) member countries. In 2020, South Korea recorded a suicide rate of 24.1 per 100,000 people, which nearly doubles the OECD average [20]. Furthermore, with an internet penetration rate of 98%, South Korea is recognized for its exceptional digital connectivity [21]. This makes it an ideal setting for investigating the relationship between internet-based searches and suicidality, thereby providing clearer insights into these variables.

This study will utilize data from Naver, Korea's leading search engine, which commands a market share of approximately 50–60%, followed by Google with 28–35% and Daum or MS Bing at about 2–5% [22]. Using data available from Naver Data Lab since 2016, we will longitudinally examine the relationship between search volumes for "suicide" and actual monthly suicide counts. Additionally, considering gender differences in both suicidal behavior [23, 24] and online search behavior [25], this study will also examine whether there are gender differences in the relationship between search volumes and suicide rates. Through this analysis, we aim to discuss the potential of web-based suicide prevention strategies.

Overall, this study seeks to provide valuable insights into the predictive power of internet search volumes regarding suicidality in South Korea and explore the implications for developing preventive measures leveraging digital data. By analyzing search volumes, especially within a prominently digital nation like South Korea, we anticipate that the findings will contribute significantly to understanding how digital behavior can serve as an indicator for suicide risk, thereby aiding the development of timely and effective interventions in public health strategies.

2. Material and methods

2.1 Research model

This study aims to examine the impact of monthly search volume for suicide-related terms on the number of suicides. To achieve the research objectives, the research model is illustrated in Fig. 1.

2.2 Data and measurement tools

To analyze the relationship between suicide-related search volumes and the number of suicides, this study collected monthly data from two primary sources. The analysis period spans from January 2016 to April 2024, with data extracted on 24 September 2024. The unit of analysis is organized by month, allowing for an exploration of how monthly search volumes for suicide influence the number of suicides in the corresponding month.

2.3 Dependent variable: number of suicides

The number of suicides was obtained from the "Causes of Death Statistics" provided by Statistics Korea [20]. Monthly data on causes of death from January 2016 to April 2024 were collected through the Korean Statistical Information Service (KOSIS) national statistical portal. This statistical data includes classifications based on causes of death, and in this study, the number of deaths classified as intentional self-harm (X60-X84) according to the 8th edition of the Korean Standard Classification of Diseases (KCD-8) was used as the dependent variable.

Data Characteristics: The number of suicides is compiled monthly and categorized by age, gender and region. This study analyzes total suicide counts across all age groups and genders to understand national trends.

Data Collection Process: Raw data were extracted from the KOSIS portal of Statistics Korea, the data were sorted and organized by month for analysis. A total of 1000 data points were derived from the monthly data spanning from January 2016 to April 2024.

The Causes of Death Statistics from Statistics Korea systematically record the causes of death occurring in South Korea and are widely utilized as valuable data for analyzing social issues. When addressing serious social problems such as suicide, these statistics are considered the most authoritative source and serve as essential reference material for policy formulation and research [20].

2.4 Independent variable: search volume for suicide

The search volume for suicide-related terms was obtained from data provided by Naver Data Lab. Naver Data Lab is a big data analytics service offered by Naver, a prominent portal site in South Korea, which tracks changes in search volume for specific keywords over time through search trend analysis. In this study, the search volume for the primary keyword was

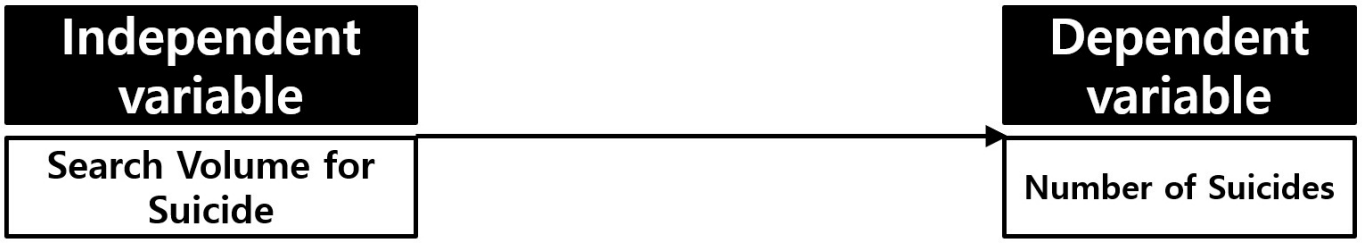

FIGURE 1. Research model.

"suicide".

Data Characteristics: Naver Data Lab reflects online interest in specific topics and is well-suited for measuring suicide-related search volumes, given that Naver is the most widely used search engine in South Korea. According to research by Nielsen Korea, Naver holds over 70% market share in the South Korean search market, providing meaningful data as a representative indicator of public interest [26].

Data Collection Method: Monthly search volume data from January 2016 to April 2024 were extracted using the "Search Trend" function of Naver Data Lab. The search scope included all age groups and genders, capturing search records from both Personal Computer (PC) and mobile devices using Naver. Search volumes were normalized so that the highest search volume on any given day was assigned a score of 100, with other days' search volumes presented as values between 0 and 100 in proportion. In this study, keywords such as "suicide", "methods of suicide" and "suicidal thoughts" were designated as search terms, and the monthly search volume data for these keywords were aggregated to create a composite indicator of suicide-related search volume.

2.5 Analysis method

Data collected from Naver Data Lab and Statistics Korea were downloaded as .xlsx files, merged according to the respective dates, and then converted into .sav files. For data analysis, SPSS version 22.0 (IBM Corp., Armonk, NY, USA) was utilized, and the specific process is outlined as follows. First, descriptive statistics were conducted for both the search volume related to suicide and the number of suicides. Second, to examine gender-based differences, independent sample *t*-tests were performed. Third, correlations among the primary variables were analyzed to detect potential multicollinearity before verifying causal relationships. Finally, linear regression analysis was conducted to assess the effect of suicide-related search volume on actual suicide rates. Regression analysis enables a clear numerical understanding of the direction and strength of relationships between variables and is well-suited for structured time-series data, such as monthly datasets. This statistical method aligns with the goals of the study. Whereas many previous studies have primarily focused on simple correlation analysis or visualizing time-series trends—often without fully accounting for demographic variables such as gender [27, 28]—the present study addressed this gap by stratifying the analysis by gender and applying a regression model. This approach allowed for a more precise examination of the structural relationship between search behavior and suicide rates.

3. Results

3.1 Descriptive statistics for key variables and differences by gender

Table 1 presents the descriptive statistics for the key variables and analyzes the differences in these variables by gender. Firstly, the average search volume for suicide was 60.43 (Standard Deviation (SD) = 11.30). The average search volume for suicide among males was 62.56 (SD = 11.35), which was significantly higher than the average for females at 53.09 (SD = 10.79). This difference was statistically significant ($t = 18.54$, $p < 0.001$).

The overall average number of suicides was 1113.97 (SD = 107.13). The average number of male suicides was 784.83 (SD = 79.48), which exceeded the average number of female suicides at 329.14 (SD = 39.29), and this difference was also statistically significant ($t = 69.97$, $p < 0.001$).

Fig. 2 aggregates the search volume for the keyword "suicide", setting the maximum search volume to 100, and presents the relative search volume during the analysis period, categorized by total, male and female. Initially, the search volume for suicide among females was relatively low; however, it gradually changed to display a pattern similar to that of the total and male search volumes. The period during which the "suicide" keyword was most frequently searched was found to be the same for both males and females.

Fig. 3 illustrates the monthly number of suicides categorized by total, male and female. It reveals that the number of male suicides is greater, with a significant fluctuation observed in the monthly suicide counts. In contrast, the monthly number of female suicides remains relatively lower, ranging from approximately 200 to 400, with smaller fluctuations compared to males.

3.2 Correlation among key variables

The results of the correlation analysis among key variables are presented in Table 2. The correlation between the search volume for the keyword "suicide" on Naver and the number of suicides was found to be 0.202 ($p < 0.05$) when considering the overall population, and 0.456 ($p < 0.001$) when focusing on females, indicating a statistically significant positive correlation in both cases.

3.3 Impact of search volume for suicide on suicide rates

To examine the effect of search volume for suicide on suicide rates, a regression analysis was conducted, the results of which are presented in Table 3. Firstly, Model 1 investigated the impact of total search volume for suicide on the overall number of suicides. The results indicated that the total search volume for suicide has a significant positive effect on the total number of suicides ($\beta = 0.202$, $p < 0.05$, $F = 4.17$).

In Model 2, the influence of male search volume for suicide on the number of male suicides was analyzed. The findings revealed that the search volume for suicide among males did not have a significant impact on the number of male suicides.

Model 3 examined the effect of female search volume for suicide on the number of female suicides. Similar to Model 1, the increase in female search volume for suicide was found to have a significant positive impact on the number of female suicides ($\beta = 0.456$, $p < 0.001$, $F = 25.70$).

These results indicate that as the overall search volume for suicide increases, the total number of suicides significantly rises. When analyzed separately for males and females, it is particularly evident that the increase in female search volume for suicide correlates with an increase in the number of female suicides.

TABLE 1. Descriptive statistics for key variables.

Variable	Min	Max	Mean	SD	*t*
Total Search Volume for Suicide	36.59	100	60.43	11.30	-
Male Search Volume for Suicide	39.83	100	62.56	11.35	18.54***
Female Search Volume for Suicide	32.59	100	53.09	10.79	18.54***
Total Number of Suicides	879	1409	1113.97	107.13	-
Number of Male Suicides	621	1021	784.83	79.48	69.97***
Number of Female Suicides	240	428	329.14	39.29	69.97***

*Note. Min: Minimum; Max: Maximum; SD: Standard Deviation; t: t-statistic. ***p < 0.001.*

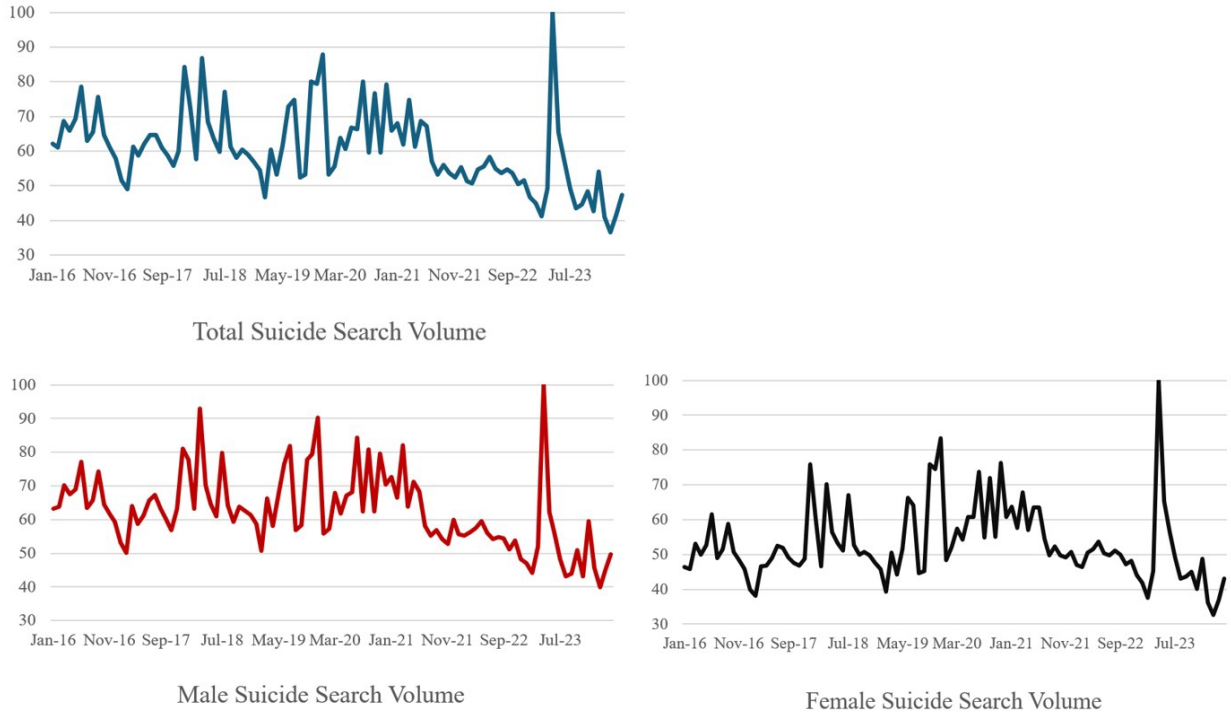

FIGURE 2. Monthly search volume for suicide.

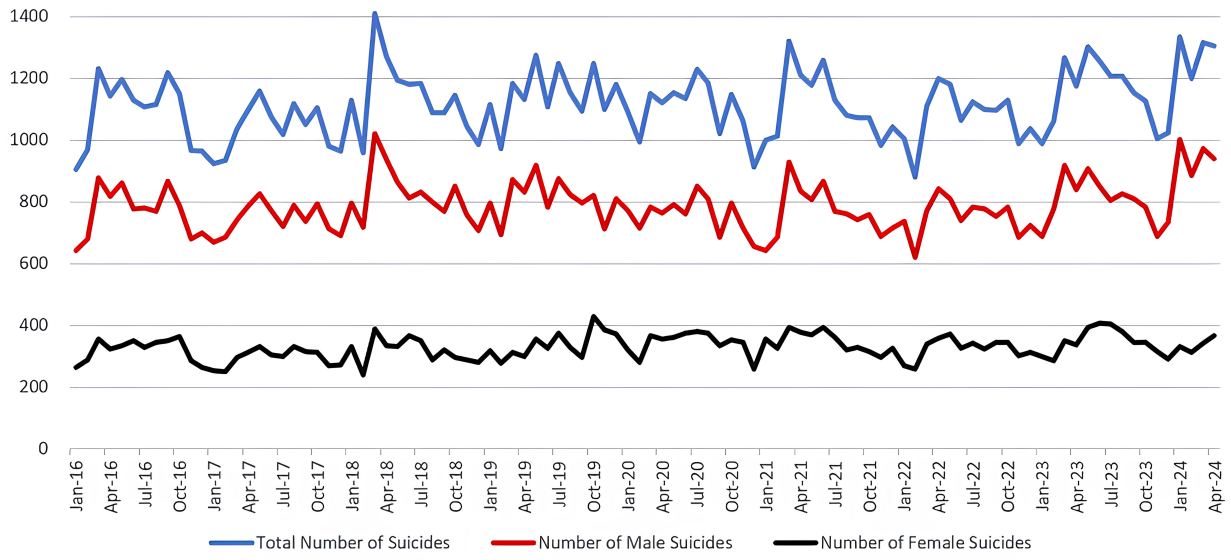

FIGURE 3. Number of suicides.

TABLE 2. Correlations among key variables.

	Total Suicide Search Volume	Total Suicide Cases		Male Suicide Search Volume	Male Suicide Cases		Female Suicide Search Volume	Female Suicide Cases
Total Suicide Search Volume	1		Male Suicide Search Volume	1		Female Suicide Search Volume	1	
Total Suicide Cases	0.202*	1	Male Suicide Cases	0.128	1	Female Suicide Cases	0.456***	1

*$*p < 0.05$; ***$p < 0.001$.*

TABLE 3. Impact of search volume for suicide on suicide rates.

Model	Independent Variables	Dependent Variable	B (SE)	*F*
1	Total Suicide Search Volume	Total Suicide Cases	0.202* (0.938)	4.17*
2	Male Suicide Search Volume	Male Suicide Cases	0.128 (0.702)	1.63
3	Female Suicide Search Volume	Female Suicide Cases	0.456*** (0.327)	25.70***

*Note: B: Unstandardized coefficient; SE: Standard Error; *$p < 0.05$; ***$p < 0.001$.*

4. Discussion

This study utilized data from the Naver Data Lab search engine in South Korea to examine the impact of search volume for suicide on the number of suicides. The key findings are as follows:

First, the analysis of gender differences in search volume for suicide revealed that the average search volume among males was higher than that of females, demonstrating a statistically significant difference. Additionally, the average number of male suicides was found to exceed that of female suicides, which also showed a statistically significant difference. These results indicate that males have higher search volumes and suicide counts than females, aligning with statistics showing that the suicide rate among Korean males is approximately 2.3 times higher than that of females [29], thereby highlighting the seriousness of male suicides.

Second, the fluctuation in monthly suicide counts was observed to be greater among males than females, with males consistently exhibiting higher monthly suicide counts. This highlights the strong seasonality of suicide [12], a phenomenon that has been consistently observed across various countries, including Italy [30], Australia [31], Finland [32] and Lithuania [33]. Climatic factors such as rising temperatures [34], increased sunlight exposure [35], and sudden changes in humidity during spring and summer have been reported to affect depressive moods and impulsive behaviors, including suicide. For males, the peak of suicides occurred around May, while for females, it reached its highest point between March and June before declining. Previous longitudinal regression analyses of suicide count also support the finding that male suicide numbers exhibited steep increases and decreases [36]. These findings underscore the need for targeted suicide prevention interventions during these periods of heightened seasonal vulnerability.

Third, as the overall search volume for suicide increases, the total number of suicides also rises. This result holds true for females as well; as the female search volume for suicide increases, so does the number of female suicides. In contrast, the male search volume for suicide did not significantly affect the number of male suicides. This indicates that there are gender differences in the expression of emotional pain related to suicide. For females, the act of searching for suicide-related information may serve as a risk factor for predicting suicidal behavior. According to attitude theory, there is a significant correlation between attitudes towards specific subjects or issues and the individual's behavior [37]. This suggests that the behavior of searching for suicide is rooted in thoughts or negative emotions about suicide, ultimately leading to a complex process that may result in suicidal attempts. In this context, previous studies using search data to explore suicide [27, 28] have also reported correlations between suicide rates and search volume. However, most of these studies relied on simple correlation coefficients or visualized time-series trends, lacking analyses that reflect demographic factors such as gender. For instance, Song *et al.* [27] identified similar trends between suicide-related search volume and suicide rates but did not present quantitative results such as regression coefficients. Likewise, Kristoufek *et al.* [28] used Google Trends data to examine overall population trends, yet failed to conduct subgroup-specific analyses. In contrast to these earlier studies, the present study applied separate regression models

by gender and statistically verified the structural relationship between search volume and suicide rates. This allowed for a clearer understanding of the extent to which search behavior influences suicide rates.

The pronounced effect of search volume for suicide on the number of female suicides warrants further investigation into the underlying motives for media use. Males tend to use media to fulfill personal interests, whereas females utilize it for information seeking, health management, communication and lifestyle purposes [25]. The differences in media usage purposes based on gender may relate to suicide searches. Specifically, females might engage in suicide searches as a means of expressing emotional pain, communicating or seeking help while having suicidal thoughts or intentions. However, it is crucial to consider the connection to suicide, as it cannot be divorced from female depression. Most suicides stem from depression, and the prevalence of depression among females is approximately twice that of males [38]. Depression exacerbates rigid thinking, helplessness, stress and emotional pain. Consequently, while diverse suicide prevention information and services are disseminated through media, they may not be effective in mitigating immediate suicide risks.

Men's searches for suicide-related information may be interpreted as curiosity or information-seeking rather than as behaviors indicating suicidal intent. However, considering that men exhibit higher search volumes for suicide and a higher average number of suicides compared to women, it cannot be ruled out that these searches may reflect underlying suicidal thoughts related to unrecognized emotional pain. Men tend to have lower awareness of their negative emotions or stress [39, 40] and may cope in less mature ways [41]. Therefore, understanding the differences in attitudes and behaviors based on gender, and developing tailored intervention strategies that consider these differences, is essential.

Based on the findings of this study, several recommendations are proposed. First, it is imperative to develop suicide prevention strategies that take into account both seasonal and gender-specific characteristics. In terms of seasonal considerations, targeted interventions should be implemented during the period from March to June, when a notable spike in suicide rates occurs. These interventions may include awareness campaigns, mobile counseling services and suicide risk screening assessments. Furthermore, intervention strategies tailored to gender-specific traits are essential. Particularly, it is crucial to employ differentiated approaches for suicide prevention based on gender. For women, immediate in-person intervention is necessary to mitigate suicidal crises, especially for individuals diagnosed with depression or exhibiting interest in, or intent to commit, suicide. Conversely, for men, expressing negative emotions and seeking help is paramount. Thus, non-face-to-face interventions, such as telephone or online methods, should be employed to assess suicidal crises, with intensive interventions adapted according to the level of crisis severity.

Second, there is a pressing need for the establishment of a comprehensive database on suicides, underpinned by big data analytics, coupled with ongoing monitoring efforts. Currently, research addressing the influence of media portrayal or online searches related to suicides primarily references the Suicide Media Guidelines. These guidelines were established based on evidence indicating that sensationalist reporting of celebrity suicides or related incidents can trigger copycat behaviors, consequently elevating suicide rates. Although adherence to these guidelines varies across countries, ongoing efforts aimed at enhancing compliance through regular monitoring and interdepartmental consultations are critical to mitigating instances of copycat suicides.

However, existing studies primarily emphasize improving journalist practices within media and communication fields, whereas research examining this phenomenon from a social welfare perspective remains notably scarce. Therefore, it is essential to explore the impact of compliance with the Suicide Media Guidelines on suicide rates from a social welfare standpoint and to systematically collect and analyze data on suicide-related factors using big data, such as search volume metrics. Such efforts will provide foundational data to evaluate the effectiveness of online suicide prevention initiatives and programs. Adopting a data-driven approach will not only furnish critical insights for policy-making but also significantly contribute to the development of effective suicide prevention strategies.

Third, there is a need to establish a multifaceted social safety net for suicide prevention. Given the widespread use of smartphones and advancements in Artificial Intelligence (AI) technology, a system should be developed to detect and respond to suicide risk signals online at an early stage. AI-based clinical decision systems using deep learning have been able to predict COVID-19 infection, symptoms, recovery and even mortality risk through data modeling [42]. In a similar vein, AI-based suicide prevention programs have been developed in the United States and Australia to provide online suicide prevention services. Trained AI chatbots respond to anonymous users, offering empathy and identifying high-risk language patterns from the collected data to relay to healthcare professionals. In Australia, AI-trained chatbots identify crisis language used by anonymous users and respond with empathetic language, relieving suicide crises and connecting users to professional counselors via phone for emergency intervention if high-risk language is detected.

Such AI-based suicide prevention programs not only analyze collected data and identify suicide crises to provide relevant information based on the level of crisis but also facilitate anonymous interactions. This reduces the stigma associated with counseling and improves accessibility. Moreover, these programs can immediately transition from non-face-to-face to face-to-face interventions depending on the severity of the crisis, and the entire intervention process is recorded as data, allowing for the provision of enhanced services. Thus, expanding early interventions for suicide through development of AI-based online suicide prevention programs is essential, necessitating diverse approaches in cooperation with local communities. These suggestions contribute to the construction of a more effective social safety net through an integrated and systematic approach to suicide prevention.

The limitations of this study are as follows. This study analyzed the impact of suicide-related search volume on the increase in suicide deaths, and by operationalizing search volume as a variable and utilizing big data analytics, attempted a methodologically scientific approach. This approach is mean-

ingful in that it identified gender differences in the influence of suicide search volume as one of the predictive factors of suicide. However, it provides insights into the importance of online or media-based suicide prevention initiatives. Future research will need to conduct a comprehensive analysis considering various factors. First, the consideration of control variables is necessary. Given that suicide is influenced by a variety of physical, psychological and socio-environmental factors, this limits the depth of interpretation of the results of this study. Second, social issues, such as celebrity suicides, may have impacted the increase in search volumes for suicide. Third, as there are differences in the number of suicides by age, it is important to analyze this relationship by age group; however, the limitations of secondary data prevented this analysis in the current study. Fourth, the statistical correlations derived from this study have limitations in directly predicting or explaining real-world suicidal behaviors. The relationship between search volume and suicide rates may be influenced by specific time periods or external factors (*e.g.*, media coverage, social events), reflecting the inherently probabilistic nature of statistical regularities. Therefore, while the results of this study may offer preliminary insights for identifying high-risk groups, they should not be interpreted as causal evidence for policy application or clinical decision-making without further empirical validation.

Despite these limitations, this study provides essential foundational data for the development of suicide prevention policies aimed at reducing suicide rates and promoting prevention initiatives in South Korea. To build on these findings, future research should empirically examine the extent to which the statistical patterns identified in this study correspond to actual suicidal behaviors or attempts. Such studies should incorporate external variables beyond search volume and suicide rates, including psychological factors, media coverage and mental health indicators. Additionally, multilayered analyses that account for demographic factors such as age, occupation and region are required. Longitudinal tracking of high-risk populations is also essential to assess the practical applicability of digital behavior-based suicide prediction models. These follow-up studies could facilitate the development of early intervention systems that are more responsive to suicide risk, while also providing an evidence-based foundation for implementing effective and sustainable suicide prevention strategies grounded in digital data.

5. Conclusions

This study contributes to the growing field of digital epidemiology by empirically examining the association between internet search behavior and suicide rates in South Korea, with a particular focus on gender differences. By utilizing longitudinal data from 2016 to 2024 and applying gender-stratified regression models, the research demonstrates that increases in suicide-related search volumes—particularly among women—are significantly associated with rises in suicide rates. These findings suggest that online search behavior may serve as an early indicator of suicidal ideation, offering a valuable tool for timely intervention and targeted suicide prevention policies.

From a practical standpoint, this study underscores the potential of integrating digital data, such as search trends, into national suicide surveillance systems. Moreover, the results inform gender-sensitive mental health policies by highlighting distinct patterns in male and female search behaviors and their implications for suicide risk.

Despite its contributions, several limitations must be acknowledged. First, the reliance on secondary data restricts the ability to explore psychological, environmental and socioeconomic confounders. Second, some references, especially foundational studies, may not fully capture recent technological advances and evolving search behavior trends. Future research should prioritize updating the evidence base with post-pandemic data and more recent sources. Third, the correlational design limits causal inference; thus, longitudinal studies incorporating real-time behavioral data and psychological assessments are needed. Finally, age- and region-specific analyses were not conducted due to data constraints, but they are essential for designing more localized and demographically sensitive interventions.

To strengthen digital suicide prevention strategies, future studies should integrate diverse variables such as mental health service usage, media influence and AI-based risk detection systems. Ultimately, this research serves as a springboard for developing predictive public health models and reinforces the importance of early detection tools rooted in digital behavior, particularly in hyper-connected societies like South Korea.

AVAILABILITY OF DATA AND MATERIALS

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

AUTHOR CONTRIBUTIONS

SK—led the initial development of the manuscript and conducted the literature review. KHJ—provided overall supervision and guided the refinement of the research framework. DS—contributed to data analysis and interpretation. HJC—coordinated the writing process and ensured consistency across sections. YK—supported the final synthesis and critical revision of the manuscript. All authors participated in reviewing and approving the final version. All authors jointly conceptualized and designed the study.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Institutional Review Board (IRB) of Jeonbuk National University (JBNU IRB 2025-01-008), and the study procedures were conducted in accordance with the Declaration of Helsinki. As this research used only aggregated, de-identified secondary data that are publicly available, informed consent from individuals was not required.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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