Architecture
Image Studies

Vol.6, Issue 4, pp.1141-1149, 2025
DOI: https://doi.org/10.62754/ais.v6i4.729

https://journals.ap2.pt/index.php/ais/index

Uncovering Behavioral Themes in Mobile Health Counseling: A Topic Modeling Study of Public Health Center Data

Hyo Taek Lee[1]

Abstract

This study examines linguistic and behavioral patterns embedded in mobile healthcare counseling messages by applying text-mining techniques to a large set of public health communication data. A total of 524 counseling sessions collected from the Korean Public Health Center Mobile Healthcare Program between 2021 and 2023 were analyzed. After comprehensive preprocessing and topic modeling using Latent Dirichlet Allocation (LDA), five salient behavioral themes were identified: exercise and motivation, dietary management, stress and sleep, adherence and monitoring, and clinical risk awareness. These topics collectively highlight that lifestyle modification—rather than disease-specific instruction—is the central focus of digital counseling within public healthcare settings. The findings reveal that exercise and dietary guidance dominated the counseling narratives, while emotional expressions such as encouragement, reassurance, and motivational feedback were strongly associated with higher user engagement. These patterns underscore the crucial role of affective communication in sustaining participation and supporting behavior change in mobile health environments. The analysis further demonstrates that consistent monitoring cues and feedback loops function as important mechanisms that reinforce adherence. Methodologically, this study shows how text-mining approaches can effectively quantify behavioral tendencies and latent themes within unstructured counseling data, offering an analytical framework that complements traditional clinical and physiological metrics. Practically, the extracted behavioral insights provide valuable implications for designing AI-assisted digital coaching systems capable of delivering tailored, empathetic, and context-aware guidance. Overall, this study contributes to the growing body of research on digital health communication by presenting a scalable approach to understanding public health counseling language. The findings support future interdisciplinary efforts to integrate linguistic analytics into preventive healthcare, automated coaching platforms, and personalized intervention strategies.

Keywords: *Mobile Healthcare, Text Mining, Behavioral Counseling, Topic Modeling, Public Health Centers.*

Introduction

Background and Research Need

The rapid advancement of artificial intelligence (AI), big data analytics, and the Internet of Things (IoT) has transformed global healthcare systems. Among these innovations, mobile healthcare (mHealth) represents a major shift from hospital-centered, episodic treatment toward personalized, preventive, and continuous care. According to the World Health Organization (WHO), mHealth technologies are now essential components of modern public health infrastructure, enabling accessible, patient-centered, and behaviorally informed service delivery.

In Korea, the Ministry of Health and Welfare launched the Public Health Center Mobile Healthcare Program in 2016 to support lifestyle modification through smartphone applications, wearable devices, and professional coaching. Numerous studies have reported clinical improvements—including weight control, glucose regulation, and increased physical activity—following participation in mHealth interventions. However, despite their demonstrated clinical benefits, an important research gap

[1] Professor, Department of Artificial Intelligence and Big Data, Sehan University, Republic of Korea, Email take1682@sehan.ac.kr, (Corresponding Author)

remains: the mechanisms and behavioral processes underlying successful lifestyle change are not yet fully understood.

Most evaluations of mHealth programs rely heavily on physiological or quantitative indicators such as blood pressure, step counts, or body mass index. Although useful, these indicators cannot capture the cognitive, emotional, and motivational dynamics that shape individual readiness for behavior change. In contrast, counseling text data, the actual communication exchanged between participants and health coaches—contain rich contextual information about user motivation, perceived barriers, adherence patterns, and emotional states. These linguistic signals may directly influence engagement and sustained health behaviors.

Despite their potential value, counseling text datasets from public health centers remain largely underutilized. Over the past decade, Korean public health centers have accumulated a substantial repository of counseling messages through mHealth programs targeting obesity, diabetes, smoking cessation, and lifestyle risk factors. Yet these data have rarely been analyzed systematically, in part due to privacy concerns and in part due to the lack of standardized analytical frameworks for unstructured text. As a result, the behavioral insights embedded in these messages remain unexplored, limiting the ability of public health programs to provide tailored, efficient, and evidence-based digital coaching.

To address this unmet need, text mining and natural language processing (NLP) offer powerful tools for uncovering latent patterns in counseling communication. Analyzing the vocabulary, expressions, and thematic structures used by participants and coaches can help researchers better understand behavioral readiness, psychological barriers, and the types of feedback that may enhance adherence in digital health interventions.

Text Mining and Digital Health Applications

Text mining enables systematic exploration of unstructured linguistic data and has become increasingly important in healthcare research. Core techniques, including word frequency analysis, sentiment analysis, and topic modeling (especially Latent Dirichlet Allocation, LDA)—allow researchers to identify recurring themes, semantic clusters, and behavioral tendencies within large text corpora.

Prior studies have demonstrated that text-mining models can extract clinically relevant information from electronic health records, clinical notes, and patient-generated content. For example, Meng et al. used embedding-based models to capture depressive symptom patterns from clinical documentation, while Zou et al. showed that graph-informed topic models can improve interpretability in medical text analysis. In digital and behavioral health contexts, AI-driven text analytics have been applied to detect user engagement patterns, personalize intervention intensity, and support remote coaching frameworks.

Within Korea, research on mHealth counseling remains limited but growing. Park et al. proposed a classification framework for non-face-to-face counseling data, demonstrating that machine learning techniques can meaningfully categorize counseling messages. These studies collectively highlight that linguistic data offer actionable insights into user motivation, perceived challenges, and behavioral trajectories, complementing physiological datasets.

Applying text mining to counseling data within the Korean Public Health Center Mobile Healthcare Program is particularly timely. Counseling messages often contain emotional expressions (“I feel exhausted,” “I want to try again”), self-reflective statements (“I skipped breakfast today”), and goal-oriented commitments (“I will increase my walking time”), all of which reveal the behavioral context behind health outcomes. Analyzing these texts can illuminate which themes dominate public health conversations, diet, physical activity, stress, sleep—and how these themes reflect user motivation or resistance.

These insights also provide foundational knowledge for the development of AI-assisted digital coaching systems, which require an understanding of linguistic patterns to generate context-aware and empathetic feedback. Text-mining research has shown that linguistic markers can help identify adherence tendencies or behavioral challenges. As mHealth adoption accelerates—particularly after the COVID-19 pandemic—advanced digital coaching systems that learn from counseling language will play a crucial role in scalable, human-centered healthcare.

Purpose and Expected Contributions

This study addresses the research gap by applying text-mining techniques to analyze counseling text data collected from the Korean Public Health Center Mobile Healthcare Program. Specifically, it aims to:

1. identify the most frequently discussed themes in mHealth counseling messages using lexical frequency and topic modeling.
2. categorize behavioral counseling topics—such as diet, exercise, stress, and sleep—into meaningful thematic structures and analyze their prevalence.
3. derive practical implications for designing AI-based digital coaching systems and improving public health counseling strategies.

The expected contributions of this study are threefold:

Methodological Contribution

This study demonstrates the integration of text mining into public health evaluation frameworks by analyzing unstructured counseling data. While traditional health behavior studies rely on surveys or quantitative metrics, this research introduces linguistic analytics as an additional layer of evidence-based assessment.

Empirical Contribution

The study provides one of the first large-scale analyses of counseling language in Korea's public health mHealth system. By revealing recurring themes and communication patterns, it enriches understanding of how behavioral guidance is delivered and received in digital health settings.

Practical Contribution

Findings from this research can inform the development of AI-assisted digital coaching platforms that automate and personalize counseling support. These insights may improve the efficiency and scalability of preventive care services in public health centers. Ultimately, the study aims to bridge the gap between human communication and algorithmic understanding by contributing to the development of context-aware, adaptive, and empathetic digital health systems.

Theoretical Background and Related Research

Conceptual Framework

Mobile healthcare (mHealth) integrates digital communication technologies, wearable devices, and behavioral science to support preventive health management. It represents a transition from episodic, hospital-centered care to continuous, personalized, and user-driven services. In Korea, the Public Health Center Mobile Healthcare Program was implemented to promote lifestyle modification through smartphone-based applications, biometric monitoring, and professional coaching.

From a theoretical perspective, mHealth interventions are grounded in Behavior Change Theory (BCT) and Information Behavior Theory (IBT).

BCT highlights mechanisms such as self-efficacy, reinforcement, and feedback loops, which are central to sustaining behavior change (Bandura, 1986).

IBT emphasizes how individuals seek, interpret, and respond to health information, suggesting that communication patterns reflect cognitive readiness, emotional state, and motivational processes (Wilson, 1999)..

Within mHealth communication, counseling messages exchanged between participants and healthcare professionals contain both instructional content and affective cues. Such messages can reveal motivational readiness, adherence tendencies, perceived barriers, and emotional responses. Applying text mining to these data enables systematic identification of linguistic patterns, semantic clusters, and behavioral indicators that may influence intervention engagement and health outcomes.

This analytical approach underscores the relevance of communication quality, feedback responsiveness, and emotional tone in determining the effectiveness of digital counseling interactions.

Prior Studies

A substantial body of research has examined the impact of mHealth interventions on lifestyle-related health outcomes. In Korea, Kim et al. [11] reported improvements in glucose control and body mass index among users of public health center–based mobile services. Ju et al. [12] found that hybrid interventions combining human coaching with app-based feedback produced higher adherence than automated systems alone. Internationally, Marcolino et al. [4] and Free et al. [5] conducted comprehensive reviews demonstrating that personalized, continuous feedback significantly enhances behavioral adherence. Despite these contributions, the linguistic and communicative dimension of mHealth counseling has been insufficiently explored. Several studies illustrate the potential value of this approach: Park et al. [3] applied machine learning techniques to classify non-face-to-face counseling messages, confirming the feasibility of automated content categorization. Hendrickx et al. [13] used text mining to detect communication patterns and potential empathy markers in medical dialogues. Dwyer et al. [14] examined emotional tone in digital conversations and identified its association with user engagement. In clinical text research, Meng et al. [7] and Zou et al. [6] employed topic modeling and graph-based methods to uncover latent psychological and symptom-related clusters within electronic health records. These studies collectively highlight the promise of text mining for identifying semantic structures and behavioral indicators in health-related communication. However, no prior research has systematically analyzed counseling text generated through Korea's public health mHealth programs, despite the large volume of accumulated messages and their potential relevance for improving digital coaching strategies. Table 1 provides an overview of major studies involving mHealth data and text-mining methodologies, summarizing their data sources, analytical approaches, and principal findings.

Table 1. Summary of Previous Studies on mHealth and Text Mining

No.	Author (Year)	Data Type	Method	Main Findings
1	Kim et al. (2019)	Public health mobile data	Quantitative trial	Improved metabolic control via app–coach feedback
2	Ju et al. (2022)	App + coaching	Mixed methods	Higher adherence through hybrid intervention
3	Park et al. (2024)	Counseling text	Text classification	Identified main behavioral topics in counseling
4	Hendrickx et al. (2021)	Clinical reports	Text mining	Found patient-safety risk terms
5	Meng et al. (2021)	EHR narratives	Topic modeling	Extracted depression-related clusters
6	Zou et al. (2022)	EHR data	Graph topic modeling	Improved interpretability and accuracy
7	Dwyer et al. (2021)	Therapy chats	Sentiment analysis	Emotional tone linked to engagement
8	Cucciniello et al. (2021)	mHealth apps	Systematic review	Feedback frequency is the most influential factor

Research Methodology

Data Collection

This study utilized counseling text data generated through the Public Health Center Mobile Healthcare Program operated by the Korean Ministry of Health and Welfare. The data were collected between 2021 and 2023 from 15 participating local public health centers. A total of 524 counseling records were obtained after removing incomplete, corrupted, or duplicated entries. Each record consisted of time-stamped mobile messages exchanged between healthcare professionals (nurses, dietitians, or exercise specialists) and program participants. Counseling messages primarily address diet, physical activity, smoking cessation, alcohol reduction, sleep patterns, and stress management. All data were fully anonymized prior to researcher access. Personal identifiers—such as names, phone numbers, and health ID information—were removed according to national ethical guidelines for secondary data use. The study was therefore classified as non–human-subject research, and institutional review approval was waived. A transparent and replicable text-mining workflow was established to ensure methodological rigor and analytical reliability.

Data Preprocessing

A multi-step preprocessing pipeline was implemented to ensure uniformity and analytical accuracy. The following procedures were applied:

1. Data Cleaning: Removal of emojis, special symbols, repeated messages, and system-generated elements.

2. Tokenization and Sentence Segmentation: Text segmentation and part-of-speech tagging were conducted using the Open Korean Text (Okt) morphological analyzer.
3. Stopword Filtering: Removal of non-informative or conversational fillers (e.g., "음," "아 네," "저기요") to improve semantic clarity.
4. Normalization: Conversion of colloquial and abbreviated expressions into standard forms to reduce lexical variability.
5. Noun and Compound Term Extraction: Selection of nouns and multi-word expression units as primary analytical components, reflecting the semantic focus of counseling messages.

After preprocessing, approximately 18,000 valid tokens were retained and used for keyword analysis and topic modeling.

Analysis Procedure

The analysis followed a structured five-stage workflow, summarized in Table 2. This approach enabled the integration of quantitative modeling with qualitative interpretation of behavioral language patterns.

Table 2. Stages of Text-Mining Analysis

Step	Procedure	Description
1	Data Collection	Collection of 524 counseling messages from 15 public health centers
2	Preprocessing	Tokenization, cleaning, stopword removal, normalization
3	Frequency Analysis	Identification of high-frequency keywords and co-occurrence patterns
4	Topic Modeling	Extraction of latent behavioral themes using LDA
5	Interpretation	Classification of themes into diet, exercise, stress, adherence, and risk-awareness domains

This multi-step process allowed the identification of core linguistic signals and semantic clusters present in counseling communication.

To determine the optimal number of topics, K values ranging from 3 to 10 were evaluated using the C_v coherence metric. The model achieved the highest coherence score at $K = 5$ ($C\_v = 0.48$), which was selected as the final configuration. The LDA model was trained using the following parameters: $\alpha = 0.1$, η (β) = 0.01, 500 iterations, and random_state = 42 to ensure reproducibility. These parameter choices align with established practices in behavioral text analysis and provide a stable balance between interpretability and semantic granularity.

Analytical Tools and Environment

All analyses were conducted in Python 3.10 under a controlled computational environment. The main analytical tools and their functions are summarized in Table 3.

Table 3. Analytical Tools and Computational Environment

Category	Library	Function	Version
Data Handling	pandas, numpy	Data structuring and processing	Python 3.10
Morphological Analysis	KoNLPy (Okt)	Tokenization and POS tagging for Korean text	0.6.0
Topic Modeling	gensim	LDA-based topic extraction	4.3
Visualization	matplotlib, wordcloud	Keyword clouds and topic distribution visualization	Latest
Development Environment	Jupyter Notebook	Interactive analysis and documentation	Latest

The combined use of LDA topic modeling and keyword co-occurrence visualization allowed for the identification of semantic clusters related to major behavioral topics—such as exercise motivation, dietary control, stress management, and adherence to self-monitoring routines.

This methodological framework ensured interpretability, reproducibility, and analytical validity within the context of public health counseling research.

Results

Keyword Frequency Analysis

After preprocessing, a total of approximately 18,000 tokens were analyzed. High-frequency keywords were primarily associated with diet, exercise, stress, sleep, and behavioral adherence, representing the core themes of counseling interactions in the mobile healthcare program. The Top 20 keywords are presented in Table 4. These frequently occurring terms demonstrate that mHealth counseling at public health centers focuses largely on everyday lifestyle management rather than disease-specific treatment. Words such as exercise, walking, diet, breakfast, and water indicate continual guidance related to physical activity and nutrition, while terms such as stress, fatigue, and sleep reveal the presence of emotional and psychological concerns. Collectively, these patterns suggest that both health coaches and participants emphasize routine behavior modification and emotional regulation as central components of the counseling process.

Table 4. Top 20 Frequently Used Words in Counseling Texts

Rank	Keyword	Frequency	Category
1	exercise	812	Physical activity
2	diet	724	Nutrition
3	sleep	519	Lifestyle
4	stress	502	Mental health
5	walking	487	Exercise
6	breakfast	465	Nutrition
7	fatigue	441	Health condition
8	weight	429	Body management
9	water	412	Hydration
10	snack	401	Nutrition
11	schedule	382	Lifestyle
12	tension	365	Stress response
13	goal	352	Motivation
14	blood pressure	334	Clinical monitoring
15	consistency	322	Behavior adherence
16	sugar	308	Nutrition
17	pain	304	Symptom report
18	step count	299	Activity tracking
19	lunch	288	Nutrition
20	weekend	275	Lifestyle pattern

Topic Modeling Results

Using an LDA model optimized at K = 5, five major latent themes were identified across the counseling text corpus. Each topic was labeled based on its most salient keywords and contextual interpretations. The results summarized in Table 5 reveal that the extracted themes correspond to well-established domains of lifestyle and behavioral counseling. Topics 1 and 2—Exercise and Motivation and Dietary Management—represent the primary lifestyle modification strategies commonly addressed in public health programs. Topics 3 through 5 highlight more psychological and preventive components, including emotional well-being, adherence reinforcement, and risk awareness. As shown in Figure 1, “Exercise and Motivation” accounted for the largest proportion of topic distribution (25.3%), indicating that physical activity encouragement and step-tracking feedback were the most frequent elements of digital coaching. “Dietary Management” represented 21.7% of content, emphasizing the importance of portion control, hydration, and meal regularity. The remaining categories—“Stress and Sleep” (18.9%), “Adherence and Monitoring” (17.8%), and “Clinical Risk Awareness” (16.3%)—illustrate how mHealth communication integrates supportive emotional guidance with preventive health education. Taken together, these results indicate that public health mobile counseling places balanced emphasis on behavioral motivation, daily routine management, and preventive awareness, reflecting the holistic nature of lifestyle coaching programs.

Table 5. Topic Modeling Results

Topic	Label	Top 10 Keywords	Interpretation
1	Exercise and Motivation	walking, stretching, goal, consistency, record, step, plan, coach, continue, feedback	Discussion of exercise goals, encouragement, and activity tracking
2	Dietary Management	diet, meal, breakfast, water, snack, control, sugar, portion, eat, reduce	Counselling eating habits, portion control, and hydration
3	Stress and sleep	stress, sleep, fatigue, rest, tension, relax, schedule, mood, pain, night	Emotional and physical recovery guidance
4	Adherence and Monitoring	consistency, feedback, check, progress, routine, tracking, report, maintain, week, success	Continuous monitoring and motivation for behavioral adherence
5	Clinical Risk Awareness	blood pressure, glucose, weight, record, risk, measurement, hospital, control, prevention, improvement	Preventive counseling on chronic disease indicators

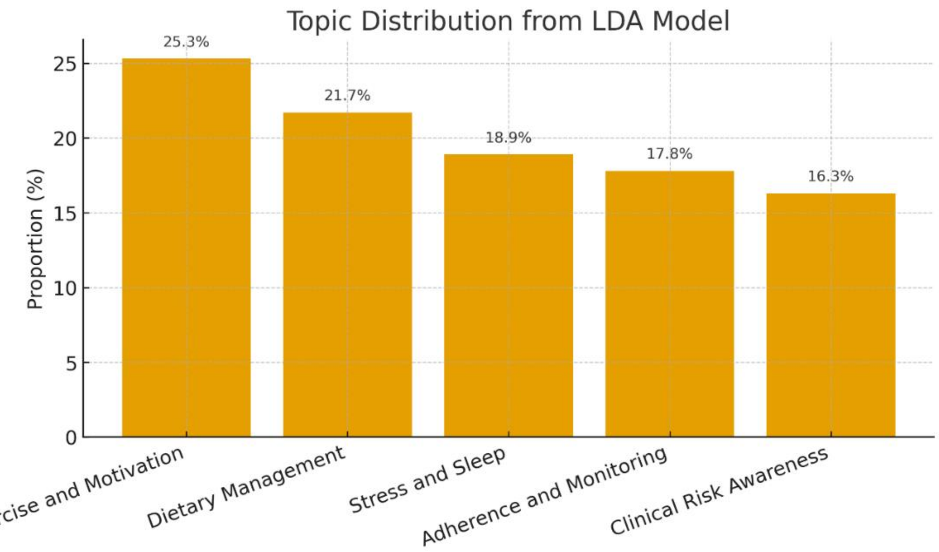

Fig. 1Topic Distribution from LDA Model

Conclusion

This study applied text-mining techniques to counseling messages from Korea's nationwide Public Health Center Mobile Healthcare Program to identify linguistic patterns and behavioral themes in digital health communication. Analysis of 524 anonymized counseling records revealed five major topics—exercise and motivation, dietary management, stress and sleep, adherence and monitoring, and clinical risk awareness. Among these, exercise and dietary guidance appeared most frequently, indicating that lifestyle coaching is the central function of mobile health interventions.

Three key insights emerged.

First, affective communication was essential for participant engagement. Messages containing empathy, encouragement, and supportive tone elicited more active responses, highlighting the importance of emotional interaction in digital counseling.

Second, behavioral adherence was reinforced through consistent feedback and progress monitoring, suggesting that structured digital follow-up strengthens accountability and sustained behavior change.

Third, preventive awareness regarding indicators such as blood pressure and glucose showed that mobile health programs can supplement routine public health services by promoting early risk identification.

Methodologically, this study demonstrates that text mining and topic modeling can effectively uncover behavioral and emotional dimensions that are less visible in survey-based evaluations. Such insights may contribute to the development of AI-assisted health communication systems that personalize counseling strategies based on linguistic patterns.

Several limitations should be noted. The dataset represented counseling messages from only 15 health centers and lacked demographic and longitudinal health-outcome information. Future research should integrate multimodal data—such as biometric indicators and behavioral logs—to improve interpretability and predictive validity.

In conclusion, mobile healthcare counseling is not merely an exchange of instructions but a dynamic form of behavioral and emotional interaction. The findings support the growing role of artificial intelligence in advancing personalized, data-driven, and emotionally responsive digital healthcare models, aligning with broader public health goals of accessibility, prevention, and user-centered care.

Funding:

This research was supported by the 2025 Research Fund of Sehan University.

References

[1] H. Park, M. S. Park, Capturing the trend of mHealth research using text mining, mHealth, (2019), Vol.5, No.1, pp.1–8.

[2] https://doi.org/10.21037/mhealth.2019.09.06

[3]

[4] B. Ozaydin, F. Zengul, N. Oner, D. Delen, Text-mining analysis of mHealth research, mHealth, (2017), Vol.3, No.1, pp.1–8. https://doi.org/10.21037/mhealth.2017.12.02

[5] W. Park, S. Oh, S. Park, Text-Mining-Based Non-Face-to-Face Counseling Data Classification and Management System, Applied Sciences, (2024), Vol.14, No.22, pp.10747–10760. https://doi.org/10.3390/app142210747

[6] M. S. Marcolino, J. A. Oliveira, M. D'Agostino, et al., The Impact of mHealth Interventions: Systematic Review of Systematic Reviews, JMIR mHealth and uHealth, (2018), Vol.6, No.1, e23. https://doi.org/10.2196/mhealth.8873

[7] C. D. Free, G. Phillips, L. Watson, et al., The effectiveness of mobile-health technologies to improve health care service delivery processes: a systematic review and meta-analysis, PLOS Medicine, (2013), Vol.10, No.1, e1001363. https://doi.org/10.1371/journal.pmed.1001363

[8] Y. Zou, A. Pesaranghader, Z. Song, et al., Modeling electronic health record data using an end-to-end knowledge-graph-informed topic model, Scientific Reports, (2022), Vol.12, No.1, 17868. https://doi.org/10.1038/s41598-022-22956-w

[9] Y. Meng, W. Speier, M. K. Ong, et al., HCET: Hierarchical Clinical Embedding With Topic Modeling on EHRs for Predicting Future Depression, IEEE Journal of Biomedical and Health Informatics, (2021), Vol.25, No.4, pp.1265–1272. https://doi.org/10.1109/JBHI.2020.3004072

[10] T. Rachad, A. El Hami, A. El Hilali, Comprehensive framework for developing mHealth-based behavior change interventions, Digital Health, (2024), Vol.10, pp.1–10. https://doi.org/10.1177/20552076241289979

[11] M. Cucciniello, F. Petracca, O. Ciani, et al., Development features and study characteristics of mobile health apps in chronic conditions: a systematic review of RCTs, npj Digital Medicine, (2021), Vol.4, No.1, 144. https://doi.org/10.1038/s41746-021-00517-1

[12] F. Alkhuzaimi, R. Ratna, M. Hancer, The impact of mHealth interventions on service users' outcomes: overview of reviews, Systematic Reviews, (2024), Vol.13, No.1, 192. https://doi.org/10.1186/s13643-024-02624-y

[13] T. Y. Kim, D. J. Kim, J. H. Park, et al., Effects of a Mobile Healthcare Service Provided by Public Health Centers in Korea, Nutrition Research and Practice, (2019), Vol.13, No.6, pp.509–517. https://doi.org/10.4162/nrp.2019.13.6.509

[14] H. R. Ju, E. K. Kang, Y. I. Kim, et al., The Effectiveness of a Mobile Health Care App and Human Coaching Program for Patients With Metabolic Syndrome, JMIR mHealth and uHealth, (2022), Vol.10, No.5, e34531. https://doi.org/10.2196/34531

[15] I. Hendrickx, T. Voets, P. van Dyk, R. B. Kool, Using Text Mining Techniques to Identify Health Care Providers With Patient Safety Problems, Journal of Medical Internet Research, (2021), Vol.23, No.7, e19064. https://doi.org/10.2196/19064

[16] A. Dwyer, A. de Almeida Neto, D. Estival, et al., Suitability of Text-Based Communications for the Delivery of Psychological Therapeutic Services: An Analysis of Therapist and Patient Attitudes, JMIR Mental Health, (2021), Vol.8, No.2, e19478. https://doi.org/10.2196/19478

[17] O. Byambasuren, S. Sanders, E. Beller, P. Glasziou, Prescribable mHealth apps identified from an overview of reviews, npj Digital Medicine, (2018), Vol.1, No.1, 12. https://doi.org/10.1038/s41746-018-0021-9

[18] Y. Ahuja, Y. Zou, A. Verma, D. L. Buckeridge, Y. Li, MixEHR-Guided: A guided multi-modal topic modeling approach for large-scale automatic phenotyping using EHR data, Journal of Biomedical Informatics, (2022), Vol.134, 104190. https://doi.org/10.1016/j.jbi.2022.104190

[19] A. Triantafyllidis, H. Kondylakis, K. Votis, et al., Features, outcomes, and challenges in mHealth for chronic disease management: a review, International Journal of Medical Informatics, (2019), Vol.132, 103984. https://doi.org/10.1016/j.ijmedinf.2019.103984

[20] H. S. Kim, H. A. Park, S. Lee, Factors associated with download and use of mobile personal health records in Korean hospitals, Health Informatics Journal, (2023), Vol.29, No.3, pp.1–12. cc10.1177/14604582231196955

[21] Bandura, A. (1986). Social Foundations of Thought and Action: A Social Cognitive Theory. Englewood Cliffs, NJ: Prentice-Hall.

[22] Wilson, T. D. (1999). Models in information behavior research. Journal of Documentation, 55(3), 249–270.

[23] https://doi.org/10.1108/EUM0000000007145.