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MOBILE HEALTH AND ARTIFICIAL INTELLIGENCE SOLUTIONS FOR MIGRAINE MANAGEMENT- A LITERATURE REVIEW

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ABSTRACT

Migraine is a common neurological condition that impairs patients' function, creates substantial societal costs, causes disability, and diminishes life quality. The wide range of symptoms, triggers, and treatment responses makes migraine diagnosis and management extremely difficult. The current management strategies rely on patient-maintained diaries, which are prone to recall bias and thus not effective for accurate tracking. Digital technologies, including mobile health applications and artificial intelligence systems, now play a significant role in migraine care, and they are revolutionizing treatment approaches. The new generation of applications uses AI to process biometric and behavioral data to enhance diagnostic accuracy and support individualized treatment plans, thereby supporting both patient autonomy and clinical decision-making. This review evaluates scientific evidence on mobile applications and artificial intelligence systems that support migraine diagnosis, tracking, and treatment. Research indicates the need for randomized controlled trials to establish the clinical value and advantages of these innovative solutions.

KEYWORDS

Migraine, Headache Disorders, Mobile Health, Artificial Intelligence (AI), Machine Learning, Telemedicine, Health Technology

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Introduction

Migraine is a common primary headache disorder characterized by recurrent, unilateral, throbbing pain lasting up to 72 hours. Attacks are often accompanied by photophobia, phonophobia, and nausea or vomiting. In some patients, transient focal neurological symptoms, known as aura, precede the headache, distinguishing migraine with aura from migraine without aura. Migraine most frequently affects individuals in their most productive years, typically peaking between the ages of 30 and 40, and is recognized as a leading cause of disability worldwide. [1,2]

The pathophysiology of migraine is complex and multifaceted. It is increasingly conceptualized as a genetically influenced disorder of sensory processing, potentially involving channelopathy mechanisms and characterized by altered vasomotor reactivity within the central nervous system. In an acute migraine attack, the activation of the trigeminovascular system plays a key role. This system comprises the trigeminal nuclei, ganglia, and ophthalmic division, which innervates meningeal vessels and transmits pain signals. The stimulation of this neural pathway leads to the release of neuropeptides such as calcitonin gene-related peptide (CGRP), substance P, and PACAP-38 (pituitary adenylate cyclase-activating polypeptide). The released neuropeptides trigger neurogenic inflammation, arterial vasodilation, and increased cerebral blood flow. [2, 3]

Migraine is diagnosed clinically based on the International Classification of Headache Disorders (ICHD-3), since no biomarkers have been identified. [4] It is based on a patient's history of at least five prior attacks. For an attack to be classified as a migraine, the headache must meet specific criteria [Table 1]. Migraine is classified as episodic or chronic, depending on attack frequency: episodic migraine involves up to 14 headache days per month, whereas chronic migraine is defined by 15 or more headache days per month. [5]

According to data published in 2021 in Cell Reports Medicine, headache disorders were the third leading cause of years lived with disability (YLDs) globally, after low back pain and depressive disorders. In 2021, the prevalence of migraine was estimated at 1.2 billion cases worldwide. The international number of YLDs attributable to migraine is projected to increase from 43.4 million in 2021 to 52.0 million by 2050, highlighting the growing global burden of migraine. [6]

Table 1. Diagnostic criteria for migraine with and without aura according to the ICHD-3. [7]

ICHD-3 diagnostic criteria	
Migraine without aura	**Migraine with aura**
A. At least five attacks1 fulfilling criteria B-D	A. At least two attacks fulfilling criteria B and C
B. Headache attacks lasting 4-72 hr (untreated or unsuccessfully treated)	B. One or more of the following fully reversible aura symptoms:
C. Headache has at least two of the following four characteristics:	- visual
- unilateral location	- sensory
- pulsating quality	- speech and/or language
- moderate or severe pain intensity	- motor
- aggravation by or causing avoidance of routine physical activity (eg, walking or climbing stairs)	- brainstem
D. During headache at least one of the following:	- retinal
- nausea and/or vomiting	C. At least three of the following six characteristics:
- photophobia and phonophobia	- at least one aura symptom spreads gradually over ≥5 minutes
E. Not better accounted for by another ICHD-3 diagnosis.	- two or more aura symptoms occur in succession
	- each individual aura symptom lasts 5-60 minutes
	- at least one aura symptom is unilateral
	- at least one aura symptom is positive
	- the aura is accompanied, or followed within 60 minutes, by headache
	D. Not better accounted for by another ICHD-3 diagnosis.

Methodology of the Literature Review

The literature review was based on a search of electronic databases, including PubMed, Google Scholar, and the Polish Scientific Bibliography, as well as other peer-reviewed scientific journals. Articles in English and Polish published between 2017 and 2025 were included. The search was performed using the following keywords: migraine, headache disorders, mobile health, and artificial intelligence. Priority was given to review articles, meta-analyses, and clinical studies to ensure high relevance of the discussed solutions.

Monitoring patients with migraine using mobile applications

Multiple methods are currently available for migraine monitoring. Traditionally, symptom tracking has relied on paper diaries, but there is a growing interest in mobile applications as an alternative tool. Given the increasing integration of digital health technologies, migraine-related mobile applications have gained attention as accessible self-management tools. They share several common features, with symptom tracking as their primary function. Other frequently offered components include medication tracking, diary keeping, and psychoeducational materials. A promising direction involves integrating multiple data sources, combining patient self-reports with information collected from external devices such as smartwatches. However, only a small number of apps currently utilize physiological or biometric data from these devices. Economic constraints, including subscription models and in-app purchases, limit accessibility for some patient demographics. Furthermore, a 2022 analysis identified concerning deficiencies in data privacy and security. Many applications lacked transparent privacy policies, and none provided crisis management features, such as emergency connectivity with healthcare providers. Most available apps are designed for daily patient use, but only a few allow data export and sharing with clinicians. These limitations underline the need for further refinement and standardization of digital tools before their widespread clinical integration. [8]

Several prospective studies have evaluated the use of such applications among migraine patients. A recent analysis evaluated the efficacy and user experience of the “Migraine Recorder” application, a tool designed to gather in-depth information on headache patterns and users' general health. The study included 358 adults diagnosed with episodic or chronic migraine who were instructed to use the application for six months. Each entry, taking approximately two minutes to complete, recorded the frequency and intensity of migraine attacks, associated symptoms, triggers, impact on daily activities, work absenteeism, productivity loss, and medication intake. The primary function of the application was to record and monitor headache occurrences retrospectively rather than to predict future episodes. The data entered by patients enabled improved understanding of migraine patterns, identification of potential triggers, continuous monitoring of attack frequency and severity, and evaluation of therapeutic efficacy by both patients and healthcare professionals. While users reported improved communication with their physicians, the study was limited by the absence of a control group, making it difficult to rule out the placebo effect associated with using a novel tool. Furthermore, data analysis was restricted to individuals who remained engaged for the full duration. A substantial attrition rate (58% dropout) potentially undermines the reliability and generalizability of the findings. Despite these limitations, the study offers valuable insights into the feasibility of digital migraine tracking. [9]

Since mobile applications rely heavily on active patient engagement, their effectiveness depends on sustained user compliance. Various questionnaires and scales are employed to collect key information efficiently. One study compared patients using the “Migraine Interactive Care Plan” (MICP) application (121 patients) with a control group (62 patients), examining the number of doctor visits, phone calls, and electronic messages. The app gathered data including the number of headache days and their impact on daily functioning via the "Migraine Check-In" weekly survey, medication use frequency, medication concerns through the "Medication Check-In", and treatment satisfaction on a monthly 5-point Likert scale. MIDAS scores were collected at baseline and every 3 months. Integration with electronic medical records enabled clinicians to monitor patient progress and intervene appropriately. Results showed a decrease in average headache days per week from 4.54 to 2.86 after 26 weeks. Patients using the app had significantly fewer doctor visits (10.7%) compared to controls (42%), with no increase in phone or electronic contacts, indicating no added workload for medical staff. Longer app use correlated with higher patient satisfaction. These findings highlight the potential of integrated digital tools to enhance patient engagement while optimizing clinical efficiency. [10]

In addition to symptom-tracking platforms, several mobile applications incorporate therapeutic features such as guided relaxation exercises. One such example is the “RELAXaHEAD” app, which combines daily headache diary entries with 20-minute progressive muscle relaxation (PMR) sessions over a 90-day period. PMR sessions were available in short (5-minute) and extended (15-minute) formats. On average, participants engaged in PMR sessions for 22 days throughout the study period, with a mean session duration of 11 minutes. Participants who interacted with the app at least twice weekly during the first month experienced, on average, four fewer headache days in the second month compared to baseline. However, despite initial enthusiasm, long-term adherence proved challenging. Feedback indicated that the audio recordings became monotonous, and participants struggled to incorporate the 20-minute daily sessions into their routine. Nine participants withdrew, citing time constraints or increased anxiety. A key limitation was the inability to objectively verify protocol adherence (e.g., attentiveness during relaxation). Moreover, medication use was not tracked, which may have influenced the observed changes in headache frequency. Nevertheless, the study suggests that mobile-based relaxation interventions show promise as adjunctive therapies in migraine management. [11]

A subsequent study evaluated the same application in an acute care setting, recruiting patients presenting to the emergency department (ED) with migraine attacks. Participants met ICHD criteria and had a MIDAS score indicating significant disability (>5). The study assessed the feasibility of using the app for post-discharge self-management over 90 days. Results were promising, showing a mean 38-point reduction in MIDAS scores and high user satisfaction - 85% of participants would recommend the app and 91% would recommend PMR. However, engagement levels were suboptimal, with a median of only 34 diary entries and 13 relaxation sessions over the three-month period. These findings illustrate both the therapeutic potential and the ongoing challenge of maintaining patient engagement in post-emergency digital care. [12]

A 2025 survey study by Young et al. involving users of the Migraine Interactive Care Plan (MICP) highlighted key patient preferences for digital tools. The majority of respondents (75%) expressed a desire to customize the frequency of tracking reminders, and nearly 83% were interested in tracking medication treatment and response. Furthermore, participants emphasized the value of recording personal observations via free text, which facilitates the identification of unique triggers often missed by standardized forms. These findings suggest that flexibility and personalization are critical factors for sustaining patient engagement with mobile health platforms. [13]

Forecasting and predicting migraine attacks

Accurate forecasting of migraine attacks is critical for timely intervention, and patient demand for reliable predictive tools remains very high. In a survey including 565 respondents, nearly 90% expressed a desire for a predictive device, preferably wrist-worn. [14]

The key challenge has been identifying triggers that signal an attack, which traditionally relied on subjective patient perception. These factors can be exogenous or endogenous, making them harder to define [Table 2]. Currently, mobile health applications and wearable devices enable more objective monitoring of triggers and symptoms by collecting vital signs and physiological data. [15]

The primary goal for patients is to anticipate the timing and severity of attacks, as acute medications are most efficacious when administered during the prodromal or early headache phase. Research by Stubberud et al. identified premonitory symptoms (e.g., thirst, edema, thermal dysregulation) and predicting features, like sleep duration, baseline pain intensity, and functional impairment. Furthermore, Katsuki et al. demonstrated that meteorological variables, particularly atmospheric pressure and humidity, significantly influence headache incidence, suggesting their utility as parameters in predictive modeling. Modern AI-driven methodologies now facilitate the integration of these subjective inputs (e.g., electronic diaries) with objective biometric data (from wearables) and environmental metrics to enhance prediction accuracy. [15, 16, 17]

Table 2. Overview of exogenous and endogenous migraine triggers.
Source: Adapted from Adnyana et al. [18]

Trigger factors for migraine attacks	
Exogenous	**Endogenous**
Alcohol consumption	Emotional stress / Anxiety
Specific foods (e.g., chocolate, aged cheese)	Skipping meals
Caffeine (withdrawal or excess)	Menstruation
Food additives (e.g., aspartame, monosodium glutamate)	Hormonal fluctuations (e.g., menopause, pregnancy)
Bright or flickering lights	Sleep disturbances (insomnia, oversleeping)
Smoking / Tobacco smoke exposure	Dehydration
Strong odors (e.g., perfumes)	
Weather changes / Thermal stimuli	
Use of hormonal contraceptives	

A prominent example of this integrative approach is the “mBrain” project, which pairs a mobile application with the “Empatica E4” wearable device. The system collects continuous physiological data - including electrodermal activity (skin conductance), interbeat intervals, skin temperature, and accelerometry - and employs machine learning algorithms (specifically CatBoost) to automatically classify sleep quality and stress levels. Users contribute by logging attacks, medications, and lifestyle factors, creating a comprehensive dataset visualized on an interactive timeline. This allows healthcare providers to identify individualized trigger patterns via a clinical dashboard. While mBrain represents a significant step toward personalized management and enhanced clinician-patient collaboration, it has not yet yielded a fully automated, validated predictive model ready for widespread clinical deployment. [19]

A recent study from 2024 further advanced this approach by utilizing the newer Empatica Embrace Plus device to monitor autonomic nervous system (ANS) alterations specifically during pre-migraine nights. By analyzing physiological metrics such as electrodermal activity (EDA), skin temperature, and accelerometer data in 5- to 10-minute frames, the researchers identified significant differences between nights preceding a migraine attack and migraine-free nights. The predictive model developed using the XGBoost algorithm achieved an accuracy of roughly 80% (0.806) in distinguishing pre-ictal states. These findings underscore the potential of nocturnal biosignal monitoring as a non-invasive method for early migraine detection, although the authors noted that further refinement is necessary for broad clinical application. [20]

Machine learning techniques are increasingly being tested for their predictive potential. For instance, the "Cerebri" application aggregated patient-reported data (prodromal symptoms, sleep, physical activity) with physiological measures (heart rate, muscle tension) collected via wireless sensors during biofeedback sessions. Based on these multimodal data, several machine learning models were developed to forecast next-day headache occurrence. The best-performing model achieved an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.62, correctly predicting headache presence or absence in approximately two-thirds of cases. Significant predictive features included physiological metrics, such as average heart rate, alongside prodromal symptoms like food cravings and chills.

While these results are promising, the predictive accuracy remains moderate, underscoring the need for further validation in larger cohorts. Future research must focus on advanced models capable of processing larger datasets over longer observation periods to improve sensitivity. If achieved, effective attack prediction could revolutionize migraine management by reducing anticipatory anxiety and facilitating preemptive treatment. However, the implementation of such tools requires caution to prevent maladaptive behaviors, such as medication overuse in response to false-positive predictions. [15]

A 2025 narrative review by Dumkrieger confirms that while machine learning holds great promise, individualized prediction models consistently outperform generalized ones, highlighting the need for personalized algorithms adapted to each patient's unique physiology and triggers. However, the field still lacks common standards for evaluating these algorithms, which hinders direct comparison between different predictive tools. [21]

Overuse of painkillers by patients with migraine

Medication Overuse Headache (MOH) represents a significant complication in migraine management. The Polish Headache Society defines MOH as a headache occurring on 15 or more days per month in patients who regularly overuse acute medications for over three months (specifically, ≥10 days for triptans, ergotamine, or opioids, and ≥15 days for simple analgesics or NSAIDs). The cornerstone of MOH management is the withdrawal of the offending agent coupled with the initiation of appropriate prophylactic therapy. Clinical guidelines strongly advocate for restricting acute medication intake while prioritizing effective preventive strategies. [22]

Digital health tools are uniquely positioned to address this challenge. Mobile applications can transform passive patient monitoring into active disease management by providing automated alerts for medication thresholds, quantifying acute treatment efficacy, and tracking consumption patterns in real-time. For example, the "Migraine Interactive Care Plan" (MICP) application prompts users to log medication type and response, creating a feedback loop that encourages self-reflection. Such patient-generated health data (PGHD) is essential not only for empowering patients but also for enabling clinicians to detect early warning signs of analgesic dependence before chronic overuse becomes established. [10]

Furthermore, artificial intelligence enhances MOH risk stratification by integrating complex datasets, including clinical history, biochemical markers, and lifestyle factors. A recent study developed a machine learning algorithm specifically designed to predict excessive medication consumption. The model demonstrated high discriminative ability, achieving a c-statistic of 0.83, effectively distinguishing between probable and definite medication overuse. By facilitating the early identification of high-risk individuals, such AI-driven tools allow for timely therapeutic interventions, potentially preventing migraine chronification and mitigating the severe complications associated with medication overuse. [23]

Supporting the diagnosis and differentiation of headaches

Artificial intelligence models have demonstrated significant potential in classifying various primary headache disorders, achieving accuracies of up to 81% in distinguishing between migraine and tension-type headaches. Crucially, these tools can bridge the expertise gap in primary care. Studies indicate that AI assistance can enhance diagnostic accuracy among non-specialist physicians from a baseline of 46% to an impressive 83.2%. [17]

One promising avenue for automated data collection is the use of medical chatbots. For instance, the chatbot "Vik" was shown to effectively and rapidly gather symptom data remotely, with users completing an ICHD-3-based questionnaire in an average of just 3.24 minutes. While Vik shows promise in reducing healthcare workload by automating routine monitoring and increasing patient engagement, its utility is currently limited to common headache types. The inability to identify rare or complex headache forms poses a risk of misinterpretation, underscoring the need for further research into clinical utility and data quality. [24]

Similarly, the "Migraine Recorder" app employs built-in logic based on ICHD-3 criteria to automatically classify patient-reported episodes, offering a preliminary assessment of whether a headache meets migraine criteria. [9]

Beyond simple questionnaires, advanced AI solutions utilizing Machine Learning (ML) and Deep Learning (DL) are achieving diagnostic accuracies exceeding 90%. These systems often integrate multi-dimensional data, analyzing clinical questionnaires alongside neuroimaging (MRI, fMRI) and neurophysiological signals. A notable example is the Computer-based Diagnostic Engine (CDE), which has proven particularly valuable in high-pressure environments like emergency departments. By synthesizing complex symptom data and multimodal imaging, these systems assist clinicians in the critical triage step of differentiating between primary and secondary headaches. [25]

A validation study of the CDE involving 276 participants compared its performance against diagnoses made by headache specialists using semi-structured interviews. Among the 212 patients who completed both assessments, the system demonstrated robust diagnostic concordance, with approximately 90% sensitivity and 96% specificity. Although the automated assessment required more time than a standard interview, the tool facilitates self-assessment and has the potential to accelerate access to appropriate treatment, particularly in regions with limited specialist availability. However, challenges remain in translating subjective, complex symptoms (e.g., photophobia, phonophobia) into standardized digital formats, which can lead to false positives. Future iterations should aim to integrate longitudinal data from headache diaries and biosensors to refine symptom interpretation. [26]

In summary, computer-based diagnostic tools are increasingly capable of replicating specialist-level assessments, thereby improving care accessibility and empowering patients through self-monitoring. Nevertheless, the reliance on self-reported data introduces potential bias. To ensure patient safety and diagnostic precision, further standardization and rigorous clinical validation of these digital solutions are essential before they can fully complement traditional clinical practice. [27]

Digital Phenotyping and Digital Twin concept

Digital phenotyping is defined as the continuous, real-time acquisition and analysis of behavioral, physiological, and environmental data via personal digital devices, including smartphones and wearable biosensors. This methodology allows for the objective, high-resolution characterization of disease manifestations in a real-world setting, transcending the limitations of traditional, subjective self-reports. In migraine management, digital phenotyping synthesizes active data (e.g., patient-reported outcomes via apps) with passive data (e.g., unobtrusive physiological monitoring) to construct a multidimensional profile of the patient's condition. Such granular data facilitates the identification of individual trigger patterns, accurate attack forecasting, and the tailoring of therapeutic interventions, thus embodying the principles of precision medicine. A concrete example of this potential is the "machine prescription" approach demonstrated by Stubberud et al., where causal machine learning models analyzing 1,446 chronic migraine patients successfully predicted individual treatment responses to preventive medications. This data-driven strategy was estimated to reduce the time-to-response by 35% compared to standard expert guidelines, illustrating how computational models can optimize pharmacotherapy. Artificial intelligence is pivotal in this ecosystem, as machine learning algorithms are required to process the high-volume, high-velocity datasets generated. By automating pattern recognition and predictive modeling, AI supports the transition from reactive care to proactive, personalized management. [28, 29]

The ultimate evolution of this data-driven approach is the creation of a “Digital Twin” - a dynamic virtual replica of an individual patient. Constructed from a comprehensive integration of genetic, clinical, behavioral, and environmental data, a digital twin serves as a sophisticated computational sandbox. It allows clinicians to run simulation-based scenarios to predict treatment efficacy, assess potential adverse effects, and model disease progression without exposing the physical patient to risk. For a complex, fluctuating disorder like migraine, the digital twin holds immense potential. It envisions a seamless bridge between physical clinical data and digital computational models, enabling the optimization of individualized treatment plans before clinical implementation. However, realizing this vision demands robust interdisciplinary collaboration among neurologists, data scientists, and bioengineers, alongside rigorous attention to ethical frameworks and data security. Together, digital phenotyping and digital twin technologies represent the next frontier in the pursuit of truly personalized, data-driven migraine care. [30]

Limitations and ethical issues

Telemedicine has emerged as a valuable complement to traditional face-to-face consultations, helping maintain a close doctor-patient relationship even at a distance. This approach is particularly important for underserved populations, including rural communities in low- and middle-income countries, where access to specialized migraine care is limited. [31]

Despite these advantages in remote monitoring and communication, patient trust remains a critical concern. Commonly reported fears include diagnostic errors, breaches of privacy, reduced human interaction, and perceived increases in healthcare costs. Most patients view AI as an assistive tool rather than a replacement for physicians, underscoring the irreplaceable role of empathy and the therapeutic alliance. Physical examination remains essential at initial consultations and cannot be fully digitized. In parallel, privacy and data protection are paramount, given the extensive use of personal health data collected via mobile apps and wearable devices. Strict compliance with data protection frameworks, such as the EU General Data Protection Regulation (GDPR), is necessary to minimize the risk of data misuse and breaches of confidentiality. [25]

Electronic headache diaries and digital monitoring tools have contributed to improved migraine outcomes, yet important limitations persist. Identifying true triggers remains challenging due to the complex interplay of biological, behavioral, and environmental factors, as well as the burden on patients to log symptoms consistently. Moreover, migraine symptoms such as photophobia and nausea can limit patients' ability to use screens during attacks. The proliferation of heterogeneous digital tools, often lacking interoperability, further complicates data integration and interpretation for both patients and clinicians. [32]

While AI-based approaches hold great promise, they are not without limitations. Diagnostic recommendations generated or supported by AI systems must remain under physician supervision, and most existing studies are limited by small sample sizes, selection bias, and lack of external validation. Additional concerns include algorithmic discrimination, limited transparency, and the risk of exacerbating digital inequalities if vulnerable groups have less access to technology. Addressing these gaps through rigorously designed, prospective studies is essential to establishing the safety, effectiveness, and real-world clinical utility of AI-driven tools in migraine care. Furthermore, the advent of advanced concepts like Digital Twins necessitates even more robust ethical frameworks to safeguard highly sensitive integrated data against unauthorized re-identification and misuse. [25]

Conclusions

Migraine is a highly heterogeneous neurological disorder characterized by diverse triggers and varying clinical manifestations among patients. Consequently, individualized treatment strategies must form the cornerstone of effective management. The systematic acquisition of detailed patient data - encompassing specific triggers, alleviating factors, and therapeutic responses - is essential for tailoring interventions to individual needs.

Mobile health applications offer a scalable, accessible mechanism for collecting this critical information through digital headache diaries and standardized health surveys. The integration of these platforms with objective biometric data from wearable devices (e.g., smartwatches) provides a holistic view of the patient's condition, enabling a deeper understanding of migraine dynamics. Empowered by artificial intelligence algorithms, these technologies hold the potential to transform care by facilitating early attack prediction, supporting diagnostic accuracy, and optimizing therapeutic decision-making in real-time.

Nevertheless, the transition from potential to practice requires caution. Further rigorous research is needed to validate the long-term clinical efficacy, safety, and cost-effectiveness of these emerging technologies. Furthermore, ethical considerations - particularly the robust protection of sensitive personal health data - must remain a paramount priority in the future development and deployment of digital migraine solutions.

REFERENCES

1. Torrente, A., Maccora, S., Prinzi, F., Alonge, P., Pilati, L., Lupica, A., Di Stefano, V., Camarda, C., Vitabile, S., & Brighina, F. (2024). The clinical relevance of artificial intelligence in migraine. *Brain Sciences*, 14(1), 85. https://doi.org/10.3390/brainsci14010085
2. Waliszewska-Prosół, M., Straburzyński, M., Kopka, M., & Nowaczewska, M. (2021). Migrena - współczesne metody leczenia, przyszłe terapie. *Polski Przegląd Neurologiczny*, 17(1), 19–35. https://doi.org/10.5603/PPN.2021.0003
3. Digre, K. B. (2019). What's new in the treatment of migraine? *Journal of Neuro-Ophthalmology*, 39(3), 352–359. https://doi.org/10.1097/WNO.0000000000000837
4. Chen, H. H., Heath, K. M., & Patel, P. R. (2025). Migraine. *Physical Medicine and Rehabilitation Clinics of North America*, 36(4), 701–714. https://doi.org/10.1016/j.pmr.2025.08.002
5. Aguilar-Shea, A. L., & Diaz-de-Teran, J. (2021). Migraine review for general practice. *Atencion Primaria*, 54, 102208. https://doi.org/10.1016/j.aprim.2021.102208
6. Wijeratne, T., et al. (2025). Global, regional, and national burden of headache disorders, 1990–2021, with forecasts to 2050: A Global Burden of Disease study 2021. *Cell Reports Medicine*, 6(10), 102348. https://doi.org/10.1016/j.xcrm.2025.102348
7. Headache Classification Committee of the International Headache Society (IHS). (2018). The International Classification of Headache Disorders, 3rd edition. *Cephalalgia*, *38*(1), 1–211. https://doi.org/10.1177/0333102417738202
8. Minen, M. T., George, A., Camacho, E., Yao, L., Sahu, A., Campbell, M., Soviero, M., Hossain, Q., Verma, D., & Torous, J. (2022). Assessment of smartphone apps for common neurologic conditions: Headache, insomnia, and pain - Cross-sectional study. *JMIR mHealth and uHealth*, 10(6), e36761. https://doi.org/10.2196/36761
9. Bensink, M., Shah, S., Shah, N., Desai, P., Khan, F., Rubin, A., Ailani, J., Dougherty, C., McLeod, K., & Quillen, A. (2021). Tracking migraine digitally: The future of migraine management. *The Journal for Nurse Practitioners*, 17(6), 462-470. https://doi.org/10.1016/j.nurpra.2021.01.014
10. Young, N. P., Ridgeway, J. L., Haddad, T. C., Harper, S. B., Philpot, L. M., Christopherson, L. A., McColley, S. M., Phillips, S. A., Brown, J. K., Zimmerman, K. S., & Ebbert, J. O. (2023). Feasibility and usability of a mobile app-based interactive care plan for migraine in a community neurology practice: Development and pilot implementation study. *JMIR Formative Research*, 7, e48372. https://doi.org/10.2196/48372
11. Minen, M. T., Adhikari, S., Seng, E. K., Berk, T., Jinich, S., Powers, S. W., & Lipton, R. B. (2019). Smartphone-based migraine behavioral therapy: A single-arm study with assessment of mental health predictors. *npj Digital Medicine*, 2, 46. https://doi.org/10.1038/s41746-019-0116-y

12. Minen, M. T., Friedman, B. W., Adhikari, S., Corner, S., Powers, S. W., Seng, E. K., Grudzen, C., & Lipton, R. B. (2021). Introduction of a smartphone-based behavioral intervention for migraine in the emergency department. *General Hospital Psychiatry*, 69, 12-19. https://doi.org/10.1016/j.genhosppsych.2020.12.009
13. Young, N. P., Stern, J. I., Steel, S. J., & Ebbert, J. O. (2025). Mobile app-based interactive care plan for migraine: Survey study of usability and improvement opportunities. *JMIR Formative Research*, 9, e66763. https://doi.org/10.2196/66763
14. Huttunen, H.-L., Halonen, R., & Koskimäki, H. (2017). Exploring use of wearable sensors to identify early symptoms of migraine attack. *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 500–505. https://doi.org/10.1145/3123024.3124435
15. Stubberud, A., Ingvaldsen, S. H., Brenner, E., Winnberg, I., Olsen, A., Gravdahl, G. B., Matharu, M. S., Nachev, P., & Tronvik, E. (2023). Forecasting migraine with machine learning based on mobile phone diary and wearable data. *Cephalalgia*, 43(5), 510-519. https://doi.org/10.1177/03331024231169244
16. Katsuki, M., Tatsumoto, M., Kimoto, K., Iiyama, T., Tajima, M., Munakata, T., Miyamoto, T., & Shimazu, T. (2023). Investigating the effects of weather on headache occurrence using a smartphone application and artificial intelligence: A retrospective observational cross-sectional study. *Headache*, *63*(5), 585–600. https://doi.org/10.1111/head.14482
17. Lee, W., & Chu, M. K. (2025). The current role of artificial intelligence in the field of headache disorders, with a focus on migraine: A systematic review. *Headache Pain Research*, 26, 148-165. https://doi.org/10.62087/hpr.2024.0024
18. Adnyana, I. M. O., Suherlim, R., & Widyadharma, I. P. E. (2024). Various trigger factors of migraine: A review of pathophysiology and mechanism. *International Journal of Research and Review, 11*(4), 347-357. https://doi.org/10.52403/ijrr.20240439
19. Van Der Donckt, J., Stojchevska, M., Vandenbussche, N., Ongenae, F., De Brouwer, M., Steenwinckel, B., … Paemeleire, K. (2022). mBrain: Towards the continuous follow-up and headache classification of primary headache disorder patients. *BMC Medical Informatics and Decision Making*, 22(1), 1-34. https://doi.org/10.1186/s12911-022-01810-7
20. Kapustynska, V., Abromavičius, V., Serackis, A., Paulikas, Š., Ryliškienė, K., & Andruškevičius, S. (2024). Machine learning and wearable technology: Monitoring changes in biomedical signal patterns during pre-migraine nights. *Healthcare*, *12*(17), 1701. https://doi.org/10.3390/healthcare12171701
21. Dumkrieger, G. (2025). The promise of machine learning in predicting migraine attacks. *Cephalalgia*, *45*(11), 1–12. https://doi.org/10.1177/03331024251391207
22. Rożniecki, J. J., Stępień, A., & Domitrz, I. (2018). Leczenie migreny przewlekłej - zalecenia opracowane przez Grupę Ekspertów Polskiego Towarzystwa Bólów Głowy... *Polski Przegląd Neurologiczny*, 14(2), 60–66. https://doi.org/10.5603/ppn.59286
23. Ferroni, P., Zanzotto, F. M., Scarpato, N., Spila, A., Fofi, L., Egeo, G., Rullo, A., Palmirotta, R., Barbanti, P., & Guadagni, F. (2020). Machine learning approach to predict medication overuse in migraine patients. *Computational and Structural Biotechnology Journal*, *18*, 1487–1496. https://doi.org/10.1016/j.csbj.2020.06.006
24. Chaix, B., Bibault, J.-E., Romain, R., Guillemass, A., Neeral, M., Delamon, G., Moussalli, J., & Brouard, B. (2022). Assessing the performances of a chatbot to collect real-life data of patients suffering from primary headache disorders. *Digital Health*, 8, 20552076221097783. https://doi.org/10.1177/20552076221097783
25. Espinoza-Vinces, C., Cantillo Martínez, M., Atorrasagasti-Villar, A., Gimeno Rodríguez, M. del M., Ezpeleta, D., & Irimia, P. (2025). Artificial intelligence in headache medicine between automation and the doctor-patient relationship. A systematic review. *The Journal of Headache and Pain*, 26(1), 192. https://doi.org/10.1186/s10194-025-02143-8
26. Cowan, R. P., Rapoport, A. M., Blythe, J., Rothrock, J., Knievel, K., Peretz, A. M., Ekpo, E., Sanjanwala, B. M., & Woldeamanuel, Y. W. (2022). Diagnostic accuracy of an artificial intelligence online engine in migraine: A multi-center study. *Headache*, 62(8), 870–882. https://doi.org/10.1111/head.14324
27. Woldeamanuel, Y. W., & Cowan, R. P. (2022). Computerized migraine diagnostic tools: A systematic review. *Therapeutic Advances in Chronic Disease*, 13, 20406223211065235. https://doi.org/10.1177/20406223211065235
28. Petrušić, I. (2025). Digital phenotyping for migraine: A game-changer for research and management. *Cephalalgia*, 45(7), 113–133. https://doi.org/10.1177/03331024251363568
29. Stubberud, A., Gray, R., Tronvik, E., Matharu, M., & Nachev, P. (2022). Machine prescription for chronic migraine. *Brain Communications*, 4(3), fcac059. https://doi.org/10.1093/braincomms/fcac059
30. Gazerani, P. (2023). Intelligent digital twins for personalized migraine care. *Journal of Personalized Medicine*, 13(8), 1255. https://doi.org/10.3390/jpm13081255
31. Spina, E., Tedeschi, G., Russo, A., Trojsi, F., Iodice, R., Tozza, S., Iovino, A., Iodice, F., Abbadessa, G., di Lorenzo, F., Miele, G., Maida, E., Cerullo, G., Sparaco, M., Silvestro, M., Leocani, L., Bonavita, S., Manganelli, F., & Lavorgna, L. (2022). Telemedicine application to headache: A critical review. *Neurological Sciences*, 43(3), 3795-3801. https://doi.org/10.1007/s10072-022-05910-6
32. Schroeder, J., Chung, C.-F., Epstein, D. A., Karkar, R., Parsons, A., Murinova, N., Fogarty, J., & Munson, S. A. (2018). Examining self-tracking by people with migraine: Goals, needs, and opportunities in a chronic health condition. *Proceedings of the ACM on Human-Computer Interaction*, 2(CSCW), Article 135. https://doi.org/10.1145/3196709.3196738