Review Article

Role of Digital Health in FGIDs, A Mini Review

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Abstract

Treating functional GI disorders (FGIDs) caused by abnormal gut-brain interactions requires an understanding of individual GI pathophysiology as well as the patient's behaviors. Many physicians frequently struggle to manage these patients due to a lack of knowledge regarding the patient's pathophysiology and behaviors. Many digital tools for collecting and recording patients' health information, which also include patient communication, are available to assist the physician in better understanding the patient. The purpose of this review is to assess how digital health can help FGIDs treatment and the interpretation of GI physiology testing.

Keywords: Functional GI disorders, FGIDs, digital health

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Introduction

Functional GI disorders (FGIDs), diseases of gut-brain interaction, require understanding the patient's GI pathophysiology and their adaptive behavior, for individual management. However, GI physiology tests require an expert to interpret the results case by case, there is more evidence that customized counseling leads to improve FGIDs treatment[1] and because there is no clear biomarker for tracking disease activity, treatment options are often based on the patient's history. Physicians suggest FGIDs patients to manually track their symptoms with dietary, behavioral, and other triggers in order to see whether there is a relationship, but compliance is poor, especially with paper trackers.[2]

The term "digital health" refers to the use of digital information, data, and communication technologies to collect, exchange, and analyze health data in order to improve patient health and health-care delivery.[3] The dominant concept is mobile health (mhealth), which is related to other concepts such as telemedicine, eHealth, and artificial intelligence (AI) in healthcare, according to a review of the definition in 2020.[4] Nowadays, digital health is becoming widely adopted in medical systems. In this article, we will review role of digital health in FGIDs divided by technology.

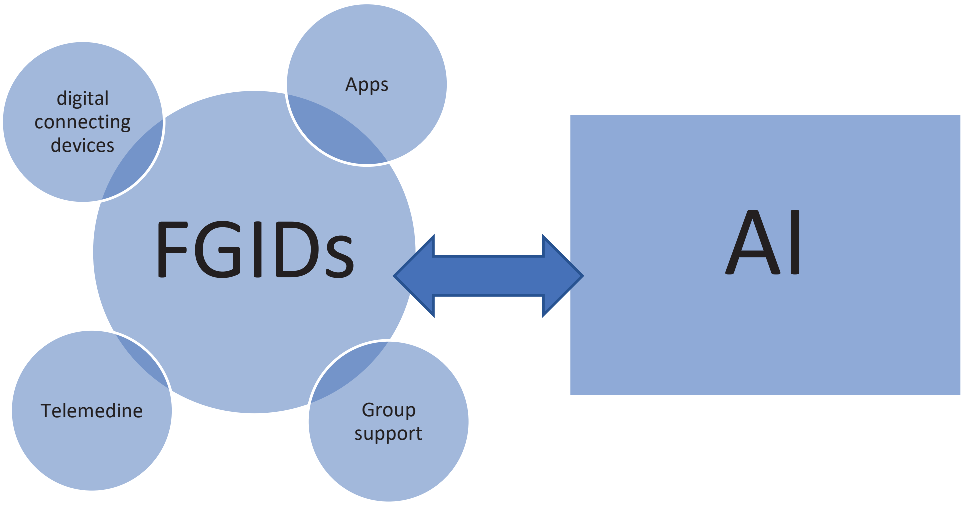

Figure 1 Types of digital health divided by technology.

1. AI and FGIDs

AI is becoming a popular field of study. According to PubMed, more than 3,800 papers totaling artificial intelligence research were published in a single year in 2022. In FGIDs, AI is mostly used to interpret GI physiology tests, find new parameters and analyze questionnaires and images in FGIDs patients. We focus on using AI for interpretation.

1.1 AI and GI physiology tests

In a study by Sandos R et al. from Sweden in 2006, it was shown that the interpretation of esophageal manometry (EM) with a water perfused system by AI showed an accuracy of 60-100%.[5] Nowadays, esophageal manometry has been developed into a high-resolution era. The results of AI interpreted esophageal manometry differ depending on algorithms and machine learning models. While AI interpretation of EM generally exhibits high sensitivity and specificity (over 80%), one study reported a 3% rate of misclassified swallows.[6-8]

Table 1 AI studies interpreting esophageal manometry according to Chicago classification (CC)

Author/year	Type of machine learning	Number of samples	Accuracy	Limitations
Wang (7)/2021	Supervised deep learning EMD- DL model	226 cases	Overall, 91.32% with 90.5% sensitivity and 95.9% specificity	Train AI by divided data into minor/normal/major motility disorders, whereas CC4.0 is no longer divided into minor and major motility disorders
Kou (8)/2022	Supervised with rule-based model, Xgboost, and artificial neural network (ANN) based on CNNs**	1741 cases	88% for 6-swallow-types model 93% for 3-category swallow-pressurization IRP value with mean absolute error of 4.5 (mmHg)	Overlap of EGJOO* with other swallow types causes confusion and misinterpretation may be due to an unbalance in training set categories and ambiguous diagnosis of EGJOO according to CC 4.0
Kou (6)/2021	Supervised with Long short-term memory (LSTM) of deep-learning model	1741 cases	88% accuracy but the number of misclassified swallows is high	This model is based on single swallow data Model is developed before CC 4.0

*EGJOO = Esophagogastric junction outflow obstruction **CNN = convolutional neural network

Unsupervised machine learning was demonstrated in one study using simple linear discriminative analysis (LDA), but this model is only the first step toward automatic diagnosis.[9] Moreover, a long-term high-resolution esophageal manometry (HREM) recording for 24 hours, demonstrated in a study from Germany, using AI interpretation can reduce the time to interpret from 3 working days to 10-20 minutes.[10]

Other GI physiology tests, such as simultaneous videofluoroscopy and pharyngeal HRM, and high resolution electrogastrogram, using AI to classify between normal and abnormal patterns were showing an accuracy between 70-90%.[11,12] AI was used to find a new parameter for GERD diagnosis in ambulatory pH monitors, but the accuracy was not higher than the older methods.[13] In term of using AI in measuring pH impedance parameters, 80-90% accuracy of AI was shown in some parameters, including number of reflux episodes and PSPW index (post-reflux swallow-induced peristaltic wave). PSPW index is the novel pH impedance parameter which cannot be calculated by a software program and is a time-consuming manual measurement.[14]

Functional luminal imaging probe (FLIP) is a new technology combining with endoscopy, providing three-dimensional diameter, volume and pressure changes, which has recent studies using AI for distinguishing between subtypes of achalasia and fecal incontinence (FI) diagnosis. The results showed a high specificity and moderate sensitivity for FI[15] and a high accuracy for distinguishing between spastic (type 3) and non-spastic achalasia (type 1 and 2).[16]

1.2 AI for questionnaire analysis in FGIDs

GERD questionnaires were reported using AI to distinguish between GERD and non-GERD, including erosive esophagitis (EE) and non-EE, but the accuracy varied from 62-100%.[17] Furthermore, AI was shown to have an accuracy of about 55% in identifying symptomatic models between irritable bowel syndrome (IBS) with constipation and functional constipation when analyzing questionnaires in constipation patients.[18]

1.3 AI for image analysis in FGIDs

In image analysis, AI was used to analyze intestinal motility from video capsule endoscopy and showed 70% sensitivity.[19] In Thailand, the study by Rattanachaisit P et al. from Chulalongkorn University showed AI diagnosed dyssynergic defecation with 60% accuracy from abdominal radiography.[20]

1.4 AI for other analysis methods in FGIDs

AI was used for diagnosing IBS with bowel sound analysis in one study. By utilizing an AI model, that uses a logistic regression based on IBS Acoustic Index models derived from 26 bowel sound features, the accuracy of diagnosing IBS was approximately 90%.[21] However, in a systematic review of computerized analysis of bowel sounds for the diagnosis of gastrointestinal conditions in 2018, it was not recommended to use bowel sounds without additional studies in clinical practice.[22]

1.5 AI for FGIDs treatment

An AI system (ENBIOSIS) was developed for a personalized nutritional strategy based on a patient's individual microbiota. A study of IBS patients using this system compared standard IBS-diet versus AI based diet and showed an improvement in IBS-SSS score in the AI based diet and a statistically significant increase in the Faecalibacterium genus in the personalized nutrition group.[23]

AI for interpretation of FGIDs tests, questionnaire analysis and images showed moderate accuracy especially in the GI physiology tests. To improve accuracy, it is important to develop more advanced machine learning models and have more training sets.

2. Applications (apps) and FGIDs

According to a systematic review and meta-analysis in 2021, personalized mobile interventions such as mobile apps can improve lifestyle behaviors in patients with chronic diseases.[24] Moreover, IBS patients showed a high compliance rate for symptom diaries recorded on a smartphone application.[25]

Dietary advice and lifestyle notifications are featured in more than half of the health apps available in smartphone stores. Only 15% of GERD-mobile applications are based on evidence-based studies, and the systematic review revealed a wide range of app quality heterogeneity.[26] According to the current published data, apps for IBS were found with the highest number of FGIDs, which included symptom tracking,[25,27] meals and GI symptoms,[28,29] and daily life stress and GI symptoms.[30] In addition, two randomized-controlled trials (RCT) of mobile apps and IBS were reported to improve quality of life and the efficacy of IBS-treatment.[29-31] One is the "Heali AI", a mobile nutrition app, using AI to scan barcodes for nutrition information and adapted to avoid FODMAPS diets for IBS patients.[29] Another is the "Zemedy" mobile app, which was developed to treat IBS patients through cognitive behavioral therapy (CBT).[31] Similarly, a web-based application of low FODMAPs showed good efficacy in managing IBS symptoms.[32] In functional gastroduodenal disorders, mobile app-based symptom reporting has been developed in pictograms and showed a good correlation with the symptom-based scoring systems.[33]

Table 2 Examples of mobile apps in FGIDs

Application	Disease	Description	Available
Zemedy	IBS	app to track stress, emotions, symptoms, and a tailored CBT 6- week training program	IOS, android https://www.zemedy.com/
Dieta	IBS	app can analyze and predict triggers, classify stool forms using AI captures, and offer personalized GI doctor and dietitian consultations.	IOS, android https://dietahealth.com/
augGI	Constipation	using AI to classify stool characterizations by patient-capture images and correlate them with a logged diet	https://www.auggi.ai/
bowelle	IBS	app for tracking food, symptoms, emotions, stress, bowel movements, and water intake and displaying them in graphs and connecting to Apple Health.	IOS https://bowelle.com/

Mobile applications show benefit in helping FGIDs patients, especially IBS patients and doctors for symptom management and psychological treatment. However, using the mobile application for symptom analysis should be cautioned due to the lack of studying mobile application accuracy. Moreover, the elderly and the mobile-unfriendly patients seem to have no benefit from applying.

3. Digital connected devices and FGIDs

Wearable devices have been developed for tracking physiologic changes with correlated health information such as step counts, vital signs, and sleep duration. A study with the data from Fitbit showed that a low number of activity metrics, in steps and sleep, related to the severity of constipation[34] and this was similar to a study of the "Lifecoder" pedometer from Japan which revealed a correlation between the high number of step counts and the improvement of symptoms in IBS patients.[35] The other innovative wearable devices are "AbStats", which is a biosensor placed on the abdominal wall for recording, classifying, and evaluating bowel function; and "G-Tech Patch", which is a wireless patch recording electrical signals from the GI tract.

4. Telemedicine

A systematic review of telemedicine and digestive diseases shows that telemedicine may be effective in managing disease activity and improving quality of life in digestive diseases.[36] However, home-based CBT and Skype hypnosis were reported to be less effective than standard CBT and face-to-face hypnosis in studies of IBS patients.[37,38] In Thailand, telemedicine is available, including web-based and mobile applications that charge per visit and per minute-consultation.

5. Group support

Patients with FGIDs frequently feel worried about their illness due to the absence of demonstrable pathology on standard testing. For example, IBS patients seem to feel frustrated, isolated, and dissatisfied with information received, available treatment, and the health system in general, so group education and group support allowing the patients to share experiences are recommended.[39] According to the most recent online search (Nov 2023), there are approximately ten FGIDs groups supported by Thai social media: the largest group in the Thai language is the GERD supported group, with 4600 members and the largest group in English is IBS support (official), with 103,000 members.

Conclusions

Many reports reveal that digital health can improve the efficacy of FGIDs treatment. Understanding the patient's pathophysiology and behaviors could help physicians select the appropriate treatment. Digital health may become an important modality in the new era of FGIDs treatment.

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