# Fynex: Work in Progress on a Web-based Approach That Implements a Hybrid Recommendation System for Preventing and Treating Diseases based on Eating Disorders

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Abstract: Diseases based on eating disorders have been considered a health issue worldwide. It is worrying due to the increased complexity of treatments for diseases such as Diabetes, Hypertension, Obesity, and Anorexia. We present Fynex as a web-based expert system that implements a hybrid recommendation system that supports Healthcare Professionals and Patients with recommendations on nutritional plans and physical activity. It provides functionalities to have detailed follow-up and control regarding the evolution of a particular treatment regarding these diseases. This solution poses a decision-making system for Healthcare Professionals and Patients, fostering the medical processes (i.e., treatments, progress, and decisions) in an integrated and systemic way. We evaluated this tool following a pilot study based on pre-post experimentation, and reported the findings and results considering participants' performance and perceptions, basing our analysis on (0-5) Likert scales, open-ended and YN responses, regarding their experience interacting with Fynex— analyzing the users' perceptions on satisfaction and usability on the web-based application. Our preliminary findings suggest that Fynex is effectively a friendly user-centered approach that successfully increases medical processes, healthcare control, and treatment satisfaction.



## 1 INTRODUCTION

The worldwide population (i.e., the youth population) usually does not have correct eating habits, which increases the chances of being diagnosed with a disease based on eating disorders (Candela, 2016). These diseases based on eating disorders such as Diabetes, Hypertension, Obesity, and Anorexia are considered a global problem, as this could result in possible cardiac complications, glucose intolerance, and insulin resistance, among others (Thomas et al., 2019). Moreover, medical controls are not generally customized, monitoring of these diseases is limited, and the lack of communication with healthcare professionals (HcP) could become critical beyond the South American context.

There are numerous solutions with scaffolds for health applications in this context. For example, MyDiabetes.diet (Garcia et al., 2001) or DialBetics (Waki et al., 2014), have a similar approach to treating this type of diseases. Furthermore, the research work "Internet of Things based on electronic and mobile health systems for blood glucose continuous monitoring and management" (Barata et al., 2019), applies Internet of Things (IoT) on glucose monitoring to be measured in real-time to provide patients control over their signs. However, these solutions restrict the monitoring of the treatment through single applications, focusing either on the patient or HcP.

Hybrid Recommender Systems combine different techniques (i.e., recommendation systems) to produce outputs to complete or complement their best features and make better conjoint recommendations (Seth and Sharaff, 2022). Due to the hybrid technique's usefulness, many recommendation systems have technically integrated it (e.g., implementation of solutions in e-commerce). However, unfortunately, there is a lack of hybrid recommendation systems focused on medicine, with only 5% adopting this approach (Danilova and Ponomarev, 2017). Recommendation systems focused on medicine use different methods, such as K-Means and association rules. For example, supervised models define which drugs have helped certain patients with specific symptoms— the supervised model is one of the most common methods

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applied to recommendation systems. However, they usually point to multiple diseases without delving into them (Stark et al., 2019).

We present Fynex as a friendly and user-centered web-based application, that supports HcP and patients with treatments regarding diseases based on eating disorders. It has a hybrid recommendation system, a messaging chat, and a visual system to visualize the evolution of a patient, among others. Furthermore, it integrates Artificial Intelligence (AI), pretending to support medical on-time decision-making processes. Also, it focuses on customized treatment follow-up, which both HcP and patients could use.

This healthcare-based solution seeks to increase the satisfaction of both HcP and patients regarding medical treatments and decision-making processes. Hence, this paper presents Fynex and the result of our first pilot study using the web-based tool. We evaluated the participants' perception of satisfaction before and after using the application through questionnaires to analyze the behavior and impact of the solution preliminary— we followed a pre-post experimentation approach (Miller et al., 2020). We also describe the pros and cons of this pilot. We report the preliminary findings and results of this pilot study, pretending to answer and analyze how the satisfaction of Patients and HcP is impacted regarding the treatment of diseases based on eating disorders, when supported by an intelligent system based on a hybrid recommendation system.

Our work contributes to Healthcare Applications and User-Centered Interaction literature. We evaluate Fynex as an information and communication technology (ICT) for healthcare and medicine, customizing HcP and Patient's experience to support decision-making processes (i.e., home care monitoring, or diagnostic support) regarding treatments, and on-time medical control. This approach uses the benefits of autonomous, e-health-based, and customized medical processes addressing diseases based on eating disorders.

## 2 FYNEX: DESCRIPTION

We introduce a web-based application called Fynex that provides a friendly, user-centered, and interactive Graphical User Interface (GUI) to support HcP and patients in medical processes regarding eating disorders. Fynex is presented to end-users who are particularly involved in the treatment of one of the following preliminary diseases: (1) Diabetes, (2) Hypertension, (3) Obesity, and (4) Anorexia Nervosa. Therefore, the platform provides features and functionalities to improve the satisfaction perceived by these actors (i.e., HcP and patients), by providing a visually attractive GUI that eases the user's interaction on the application, getting the most out of it. It implements a hybrid recommender system (Çano and Morisio, 2017) to present possible nutrition and exercise plans for the patient to follow and apply them in their life (See Figure 1). Besides, the web-based tool presents a monitoring system to keep track of the patient's evolution throughout time. This resulting information is helpful to the patient as to its HcP. Shneiderman's mantra (Munzner, 2014) presents how a tool is intended to manage the information visually through: (1) overview first, (2) zoom and filter, and (3) details on-demand, as required by a user (i.e., HcP and patients). Hence, Fynex provides a dashboard with health-based variables related to the patient's treatment, a system to upload and download test results, a messaging system between the HcP and its patients, and a visual representation of the similarities between the patients, among others (See Figure 2).

Fynex is a monolithic application using Django as its web framework, integrating a Model-View-Template architecture (MVT) (Rull et al., 2009), and Angular JS (Green and Seshadri, 2013) as a frontend framework to improve the dynamism and quality of the web application. Additionally, the application integrates third-party tools such as Scikit-learn (Kramer, 2016), Redis (Carlson, 2013), and IBM Cloud's Object Storage service (Sampé et al., 2018), to support the preprocessing of the information and the development of the web-based tool's management, as of its hybrid recommender system (Çano and Morisio, 2017). The data processing for the information system (i.e., Fynex) supports the recommendation models' implementation to enhance its results and reinforce further decision-making processes of a user. Fynex implements an ETL (Vassiliadis and Simitsis, 2009) to process the information from the Fynex database and be able to use the already trained Machine Learning (ML) models. Once the data is transformed, and loaded, we used a hybridization method to obtain a final recommendation, which we present to the user through the application— memory-based recommendation model, content-based recommendation model, and the ML model-based recommendation model (see Figure 3).

## 3 DATA ACQUISITION

The participants who gathered the experimentation voluntarily had roles of HcP and Patients. In this pilot study, we had a total of 14 participants (N=14)— 50%

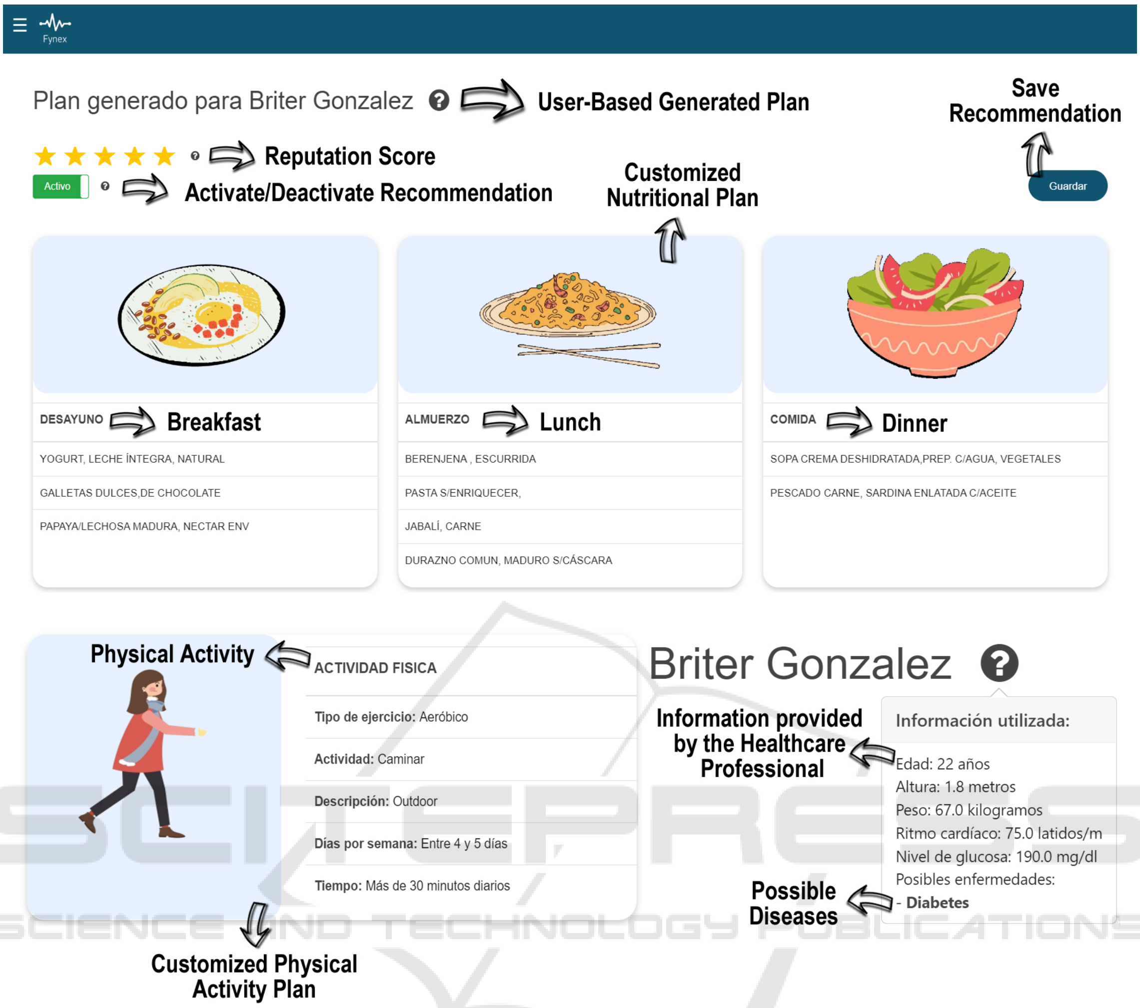


Figure 1: Features/Functionalities of Fynex - Part 1.



(n=7) HcP, and 50% (n=7) patients. We had 64.29% (n=9) male participants (i.e., 85.7% (n=6) HcP, and 42.9% (n=3) Patients), and 35.1% (n=5) female participants (i.e., 14.3% (n=1) Hcp, and 57.1% (n=4) Patients).

Each participant performed specific tasks in the application. At the end of the tasks, the participants in the experimentation phase had to fill out a questionnaire that contained questions regarding the application and how much they recommended Fynex.

We evaluated the tool's effectiveness, usability, and acceptance, considering the participant's perceptions when using Fynex. We followed pre-post experimentation (Miller et al., 2020) based on two questionnaires [quantitative— 0-5 Likert scales (Joshi et al., 2015), and qualitative— Y/N and Open-Ended Questions], which were responded before and after interacting with the web-based tool (See Table 1). To the evaluation of usability, we applied an additional questionnaire based on SUS— System Usability Scale [quantitative— 1-5 scales] (Grier et al., 2013). Moreover, we asked the participants to answer the NPS— Net Promoter Score [quantitative— Percentage from 0-100%] (Mandal, 2014) (See Table 2).

## 4 EXPERIMENTAL APPROACH

We sought to understand the behavior change of the satisfaction perceived by HcP and Patients, before and after the implementation of Fynex. To understand the context involved, we conducted our research on eating disorders and the diseases they might cause (i.e., Diabetes, Hypertension, Obesity, and Anorexia).

We considered in our approach the Biopsychosocial and Cultural Model (BPSCM) (Cruz and Buitrago, 2017) to understand the context based on

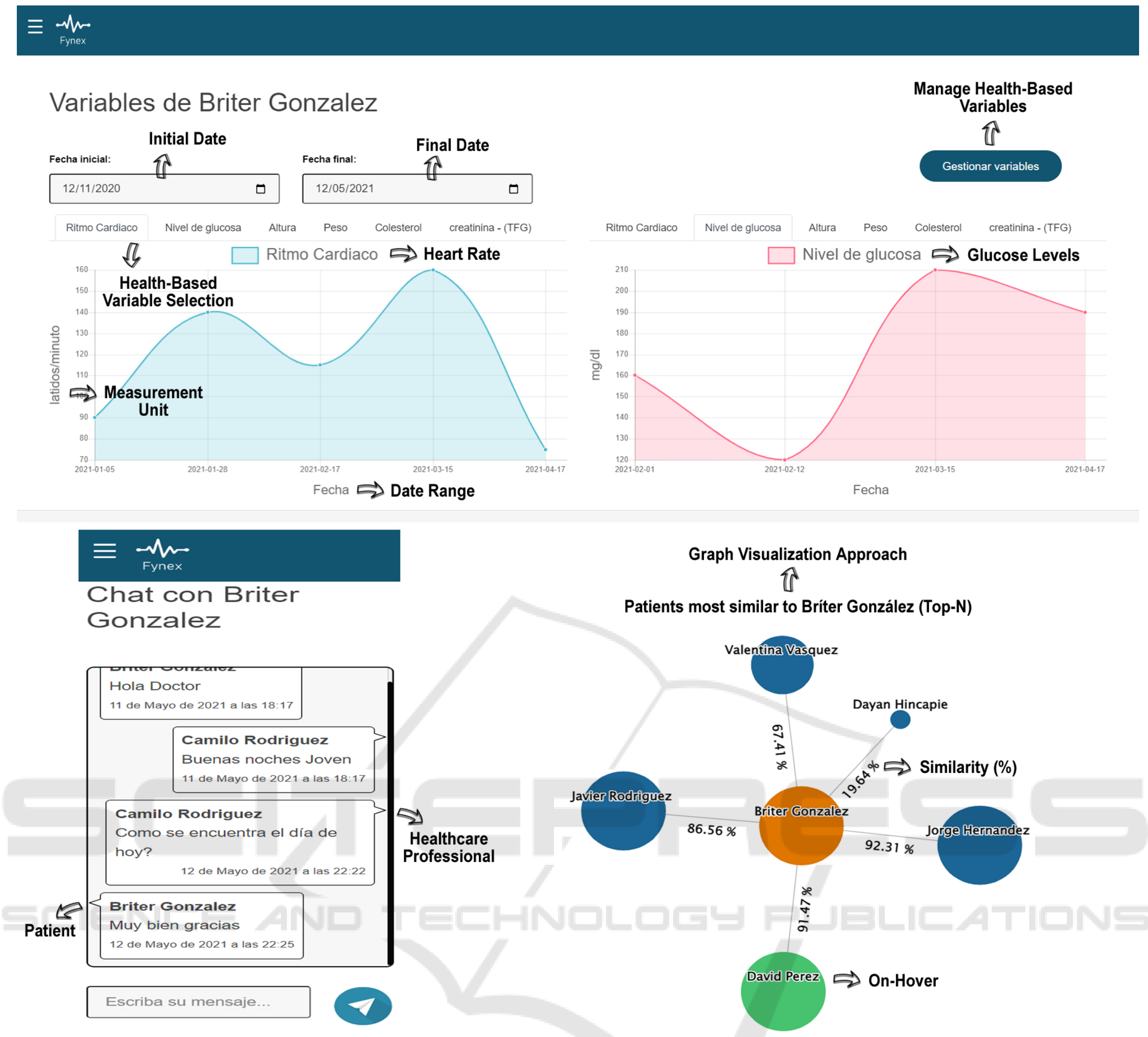


Figure 2: Features/Functionalities of Fynex - Part 2.

the identification of (1) artifacts, (2) means, (3) habits, and (4) beliefs involved, from each participant's perspective (i.e., HcP and Patients), helping in the understanding and enhancement of complex needs— context based on medical processes. Then, we defined how these elements might change if the actors used Fynex, so we can verify if those changes contribute to fulfilling the project's purpose.

Once the hybrid recommendation system of Fynex was developed, we defined three phases for testing and evaluating the model. The first phase was focused on evaluating the recommendation model, using metrics like the ROC curve (de Ullibarri Galparsoro and Fernández, 1998), F1-Score (Lipton et al., 2014), and results of simulations, among others. In the second phase, each participant (i.e., HcP and Patients) was asked to answer how the experience and satisfaction changed (e.g., treatment, support) when using the tool. We calculated the percentage of the increment or decrement of perceived satisfaction when interacting with the tool based on the ACSI (Fornell et al., 1996) (i.e., American Customer Satisfaction Index), as well as the Probit and Logit (Chen and Tsurumi, 2010)— regression model based on independent variables such as age and time with treatment. Moreover, in the third phase, we used Loop11 (Bustamante, 2010) to establish the tasks to perform and to obtain certain metrics (i.e., percentage of completed tasks, usability calculated by the SUS (Grier et al., 2013)— System Usability Scale, and the acceptance calculated by the NPS (Mandal, 2014)— Net Promoter Score).

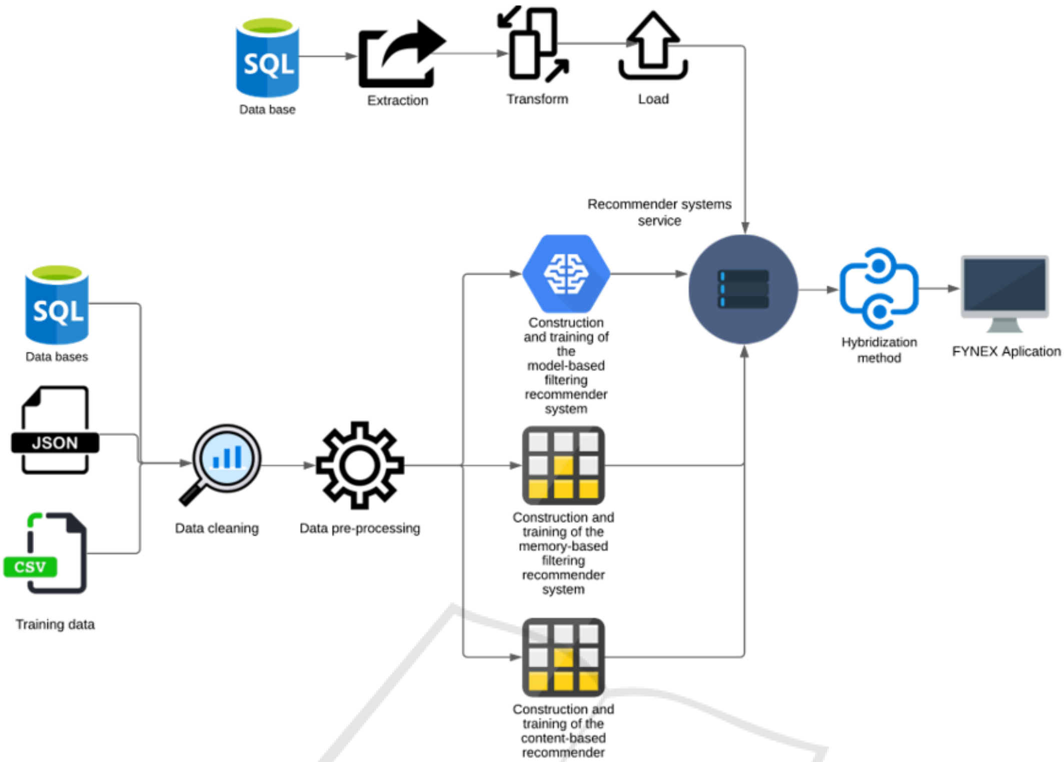


Figure 3: Concept design of Fynex.



## 5 FINDINGS AND RESULTS

We present our findings and results based on the participants' experience on Fynex reported, following the experimental methodology— the methodological process and instruments used, were described in sections 3 and 4.

In the first place, we evaluated the predictive AI models of Fynex, calculating their precision, accuracy, sensitivity, and the F1-Score indicators. In addition, we complemented each model's confusion matrix with the calculation of the ROC curve, which allowed knowing the AUC (i.e., Area Under the Curve) (Fawcett, 2006) to know the probability of a model detecting the disease in a patient in the context— diseases regarding eating disorders.

The diabetes predictive model offered an 85.7% probability of detecting the disease in patients. The predictive model of Arterial Hypertension offered a probability of 83.2% of detecting the disease in patients.

Furthermore, over 25 different recommendations provided by the hybrid recommender system of Fynex for this pilot study, we confronted the results against the ideal nutritional plans for each disease. We considered ideal nutritional plans considering the literature and the particular context— diseases regarding eating disorders. Patients treating Diabetes typically consume 15% to 20% protein, 45% to 50% carbohydrate, and 20% to 35% fat (Gray and Threlkeld, 2015). To treat Arterial Hypertension, there is a standard diet known as DASH (Dietary Approaches to Stop Hypertension), based on consuming between 15% and 20% protein, between 52% and 58% carbohydrates, and between 25% and 30% fat (Campbell, 2017). On the other hand, the diet to treat Obesity is based on low-calorie, low-fat, and low-carbohydrate (Fock and Khoo, 2013). Finally, people treating Anorexia Nervosa usually consume between 15% and 20% protein, between 60% and 65% carbohydrates, and between 20% and 25% fat (Baskaran et al., 2017).

Obtaining an F1-Score between 70% and 85% (i.e., we obtained 77%), we can claim that there is no case of Overfitting or Underfitting, as there is no overtraining of the data when having an evaluation far from perfect. However, there is a sufficiently successful evaluation to deduce that there is also no poor data training (Ying, 2019). In addition, from the analysis of the ROC curves, the probability of correctly detecting Diabetes and Hypertension in patients was 85.7% and 83.2%, respectively, which lets us infer it is a high

Table 1: Questionnaire regarding HcP's and Patient's pre/post-experience using Fynex.

| Question | Type of Question: MC$^{(1)}$, OE$^{(2)}$, LS$^{(3)}$ or YN$^{(4)}$ | Role: HcP$^{(5)}$ or P$^{(6)}$ | Moment of Application: B$^{(7)}$ or A$^{(8)}$ |
|---|---|---|---|
| **Q1**: Provide your gender. | MC | HcP & P | B & A |
| **Q2**: Provide your age. | OE | HcP & P | B & A |
| **Q3**: For how many years have you been a HcP? | OE | HcP | B & A |
| **Q4**: How secure do you feel about the medical recommendations you give to your patients? | LS | HcP | B & A |
| **Q5**: Justify your provided answer in Q4. | LS | HcP | B & A |
| **Q6**: How easy do you consider is it to monitor your patient's health condition? | LS | HcP | B & A |
| **Q7**: How easy is it to communicate with your patient/HcP? | LS | HcP & P | B & A |
| **Q8**: How useful are the nutritional and exercise plans recommended by Fynex, for the treatment of diseases based on eating disorders? | LS | HcP | A |
| **Q9**: Is the website comfortable and attractive, allowing easy use of the application? | YN | HcP | A |
| **Q10**: Is the information offered by the application clear and sufficient? | YN | HcP | A |
| **Q11**: The nutrition and exercise plans recommendations are generated fast? | YN | HcP | A |
| **Q12**: For how many years have you been a medical treatment? | OE | P | B & A |
| **Q13**: Do you think you eat well? | YN | P | B & A |
| **Q14**: Are you in treatment with a nutrition professional? | YN | P | B & A |
| **Q15**: How satisfied are you with your treatment? | LS | P | B & A |
| **Q16**: How much do you trust your HcP's recommendations? | LS | P | B & A |
| **Q17**: Justify the provided answer in Q17. | OE | P | B & A |
| **Q18**: How easy is it to monitor your own health? | LS | P | B & A |
| **Q19**: Is Fynex comfortable and attractive, allowing easy use of the application? | YN | P | A |
| **Q20**: Is the information provided by Fynex clear and sufficient? | YN | P | A |
| **Q21**: How easy is it to use Fynex? | LS | HcP & P | A |
| **Q22**: Would you recommend Fynex to others? | YN | HcP & P | A |
| **Q23**: Provide additional comments | OE | HcP & P | B & A |

*Notes: $^{(1)}$MC: Multiple Choice, $^{(2)}$OE: Open-Ended Question, $^{(3)}$LS: [0-5] Likert Scale,$^{(4)}$: YN:Y/N Questions, $^{(5)}$HcP: Healtcare Professional, $^{(6)}$P: Patient $^{(7)}$B: Before using Fynex, $^{(8)}$A: After using Fynex*

probability of preventing and treating these diseases.

We calculated the usability and acceptance tests through the SUS (i.e., System Usability Scale) and the NPS ( i.e., Net Promoter Score). As a result, HcP obtained an average SUS of 76.69, and the patients obtained a SUS of 90.36. Additionally, the NPS obtained by HcP was 14.29%. Even if the resulting value was not that significant, we considered it a positive possibly recommendation (Mendieta Giron et al., 2017). Likewise, patients resulted with an NPS of

Table 2: Questionnaire to calculate System Usability Scale (SUS) and Net Promoter Score (NPS) of Fynex.

| Question | Scale Option |
|---|---|
| I think that I would like to use this system frequently. | [1-5] SUS |
| I found the system unnecessarily complex. | [1-5] SUS |
| I thought the system was easy to use. | [1-5] SUS |
| I think that I would need the support of a technical person to be able to use this system. | [1-5] SUS |
| I found the features and functionalities in this system were well integrated. | [1-5] SUS |
| I thought there was too much inconsistency in this system. | [1-5] SUS |
| I would imagine that most people would learn to use this system very quickly. | [1-5] SUS |
| I found the system very cumbersome to use. | [1-5] SUS |
| I felt very confident using the system. | [1-5] SUS |
| I needed to learn a lot of things before I could get going with this system. | [1-5] SUS |
| How likely are you to recommend Fynex? | [1-10] NPS |

85.71%, which is a significant value due to the relationship between promoters and detractors.

# 6 DISCUSSION

From the preliminary results and comments received by the participants of this pilot study, Fynex effectively provides friendly and user-centered support to medical processes and healthcare control, regarding diseases based on eating disorders. It integrates AI models and content-based, ML model-based, and memory-based recommendation systems supporting nutrition and physical activity (i.e., medical treatment control or process). Regardless of the results' volatility, satisfaction increased in both roles (i.e., HcP and Patients). From the preliminary results, both feel more satisfied with the treatment process when using Fynex as a support tool. Although both roles consider that the application does offer support, it was more significant in patients than HcP. Hence, we could claim that patients are more open to new technologies and trying different solutions to address their problems more directly. Moreover, the Harris Poll, in association with Stanford University, analyzes these circumstances, particularly HcP satisfaction with health-focused technologies (Wuerdeman et al., 2005). They claim that 55% of HcP are willing to experiment and use new technologies only if other HcP have used them before and have recommended their use.

The results (i.e., before and after interacting with Fynex) show that the HcP's satisfaction increased by 32.95% in the experiment. However, when applying the Probit and Logit technique, the satisfaction increased by 57.6%. On the other hand, the patients' satisfaction increased by 56.96% in the experiment. Also, the increase obtained when comparing the predictions of the patients' models used in the Probit and Logit was 55.47%.

We find that a web-based tool such as Fynex supports and complements medical processes (i.e., healthcare control, diagnoses, and treatments) for HcP and Patients. Based on the participants' comments regarding Fynex, in addition to the different similar tools that exist, the participants found satisfactory the possibility that both HcP and patients could interact in the medical treatment processes synchronously on a single platform. Fynex allows both end-users (i.e., HcP and patients) to have on-time information regarding the available treatment process independently. HcP can monitor their patients and make decisions to support medical treatments. Likewise, patients can access and monitor their health status (i.e., healthcare control), hand in hand with the HcP medical control and decisions. In further research, a deepened analysis will be addressed to complement the preliminary claims presented in this paper.

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