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An mHealth Application for Collection and Analysis of Gestational Diabetes Data

Miguel Torres-Ruiz, Rolando Quintero, Carlos Guzmán-Sánchez-Mejorada, Kwok Tai Chui, Magdalena Saldaña

***Abstract*—Nowadays, appropriate lifestyle interventions can reduce the development of Type II Diabetes Mellitus in the Mexican population. Early diagnosis and treatment of this disease can contribute to preventing long-term complications, generating new public health initiatives that reduce the risk of this disease. In this work, we propose using information and communication technologies, particularly mobile devices, to collect information from patients with this condition and treatment follow-up for subsequent evaluation. The goal is to design a healthcare-oriented system with tools for preventing, diagnosing, treating, monitoring, analyzing, and characterizing this disease, transforming how interventions are currently applied. As a first stage, the mobile application's design, development, and concept tests have been addressed in a multi-platform environment for various devices and operating systems such as Android and iOS. We assumed as a hypothesis that mobile health applications (m-health) open up new opportunities to face the current challenges regarding the capacity for care, monitoring, and treatment of patients in clinics in person and other factors that derivatives of the SARS-CoV-2 pandemic have emerged. Thus, it is intended to evaluate the efficacy of an intervention of lifestyle changes compared with the standardized treatment in women who had gestational diabetes as a preventive method for Type II Diabetes Mellitus.**

***Index Terms*—Diabetes, mHealth application, gestational diabetes data.**

I. Introduction

Smartphones are renowned for enhancing the exploration of health-related information within mobile health (mHealth). These systems aim to enhance patients' quality of life by enabling improved communication between medical professionals and patients [1].

On the other hand, eHealth belongs to computer-dependent services in the healthcare sector. At the same time, mHealth involves mobile platforms designed with specific attributes aimed at enhancing healthcare provision [2]. Developers and initiatives in mHealth employ mobile devices like personal digital assistants and mobile phones for diverse functions. These functions encompass clinical decision support systems and data-gathering tools for healthcare practitioners, aiding health behavior transformation and assisting patients in managing chronic illnesses within their communities [3].

The perspective of online healthcare services and our perception of them has been transformed by the impact of COVID-19 [4]. Consequently, hospitals and healthcare providers have grappled with the escalating influx of patients and the need to prevent infections [5].

In the aftermath of the COVID-19 pandemic, there has been a substantial surge in the public's interest in the potential of mobile wireless technology for public health, often called mHealth. Numerous prior studies have underscored the value of mHealth as a pivotal tool for individuals, healthcare practitioners, and decision-makers in tackling the multifaceted challenges brought about by the COVID-19 crisis. These challenges encompass alleviating the strain on hospitals, ensuring access to credible information, monitoring symptoms, and addressing mental health concerns [6].

Over the past couple of years, an array of studies has delved into various facets of the intersection between COVID-19 and mHealth, investigating how the latter can contribute to mitigating the health repercussions of the pandemic and fostering the adoption of mHealth solutions. This proliferation of studies has inadvertently introduced a degree of complexity for researchers, as they are frequently confronted with the need to discern and select specific attributes of the mHealth system from the expansive array of research available. Various issues have arisen to continue carrying out the supervision and monitoring of interventions, mainly the COVID-19 pandemic, which has caused health personnel to be primarily directed to assist patients in this health crisis. Similarly, other diseases, such as gestational diabetes, have ceased to be a priority due to the saturation of public medical care.

According to statistics, approximately 20.4 million births, constituting 15.8% of global pregnancies, are estimated to be impacted by diabetes. Among these cases, gestational diabetes mellitus (GDM) accounts for 83%, while the remaining 17% are attributed to type 1 and 2 diabetes (IDF Diabetes Atlas, 2019). It is firmly established that diabetes during pregnancy carries a significant risk of unfavorable pregnancy outcomes [7]. These encompass an elevated likelihood of congenital anomalies, stillbirth, and infant mortality in pregnancies complicated by pre-existing diabetes compared to the general population [8]. Additionally, pregnancies affected by GDM and pre-existing diabetes exhibit a heightened incidence of preterm delivery, birth injuries, neonatal intensive care requirements, maternal pre-eclampsia, and other complications [9].

Pregnancy is a well-established phase during which women exhibit heightened receptiveness to health-related information for making decisions. With the growing adoption of personal digital technology [10], mHealth has the potential to serve as a highly effective and efficient tool for substantially expanding

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the reach and influence of health interventions during this period.

The effective management of diabetes during pregnancy demands precise regulation of blood sugar levels, requiring individuals to make lifestyle modifications, monitor their glucose levels, and potentially use medications within a relatively brief timeframe. Inadequate control of blood sugar levels can lead to adverse consequences for both the mother and the baby, including conditions such as preeclampsia, birth-related complications, severe maternal health issues, admission to the neonatal intensive care unit (NICU), neonatal hypoglycemia, fetal growth irregularities, and even stillbirth [11].

During pregnancy, women with diabetes typically have around 15 in-person appointments with a team of healthcare professionals, including obstetricians, diabetologists, diabetes nurses, dietitians, and others. However, during the early stages of pregnancy, when the fetus is particularly susceptible to congenital abnormalities, less than 15% of women with type 1 diabetes and 40% of those with type 2 diabetes can reach the recommended glycemic targets [12]. Consequently, despite receiving thorough and specialized medical care, the management of blood sugar levels often falls short, increasing the risk of adverse pregnancy outcomes that could have been prevented among women with diabetes [13].

So, the onset of the COVID-19 pandemic has introduced obstacles to the traditional model of regular in-person visits that defined the healthcare management of diabetes during pregnancy. This situation has underscored the necessity for alternative methods of delivering care. Thus, creative strategies in virtual healthcare, such as mobile health technology that enables communication between patients and healthcare providers, present a hopeful solution for promoting the health and well-being of both mothers and their unborn children throughout pregnancy.

In fact, mobile health interventions enable communication between patients and healthcare providers and have the potential to address significant obstacles and enhance both glycemic control and pregnancy outcomes. Consequently, these technologies should adhere to the best practice standards for patient-centered communication.

On the other hand, overweight and obesity have increased worldwide, particularly in Mexico, the first country with this pathology. The country has a high prevalence of obese women of reproductive age. One of the most critical issues is associated with pregnant women. Critical moments of weight gain in early postpartum (6 months) and late postpartum (≥12 months) should be considered. This characteristic is related to the leading risk factor in developing gestational diabetes and subsequent development of Type II Diabetes Mellitus. Given that Gestational Diabetes Mellitus is typically identified during the third trimester of pregnancy, the window for intervention is quite limited. In the country, there is no data on the prevalence of obesity during pregnancy, which makes it challenging to address and prevent gestational diabetes adequately [14-16]. Therefore, to generate new public health policies that make it possible to deal with this type of disease, it is necessary to have digital tools that make tasks such as monitoring, follow-up, analysis, and collection of information on patients with this type of disease more efficient.

Due to this situation, there is an urgent need for technological tools to replace this medical monitoring of patients. It has become one of the biggest challenges in applications oriented towards healthcare. Thus, the application of Information and Communication Technologies [17,18] in interventions to promote public health opens up new opportunities and challenges to face, demonstrates the effectiveness, and shortens the gaps in the care of health services, allowing professional medical assistance at any time and place, health education, self-monitoring and control with greater adherence to the treatments and interventions of patients in real-time.

Today, the use of mobile devices by the population in Mexico and the world has proliferated. In the same way, the emergence of applications that complement the lifestyles of society, such as games, Internet messaging services, alarms, and photo editors, among others, have made mobile devices a necessary artifact of use and essential for daily life. Constant technological innovation has perfected mobile device hardware and software features and specifications. In this sense, the issue of health services has not been widely exploited, so there is a lack of applications for mobile devices that reinforce the medical benefits offered aimed at monitoring physiological variables (heart rate, glucose level, pulse oximetry, among others), to determine the situation when the variable being monitored presents out-of-range conditions and complicate the patient's health status [19].

Recently, digital health has gained recognition and has become a well-established element in maternal healthcare. There is ample evidence endorsing the effectiveness and cost-efficiency of these interventions, encompassing telemedicine and various other technologies rooted in computer science [20,21].

Summing up, this work encompasses the introduction of a mobile application to compile and control gestational diabetes mellitus in a women's population, analyzing the benefits that the mHealth app offers with statistical analysis in comparison with a set of pregnant women who make their control with classical face-to-face interventions. We have focused on developing a mobile application and information analysis services based on statistics to know and generalize the behavior of the disease, taking a considerable sample of interventions.

The paper is organized as follows: Section 1 presents the background concerning gestational diabetes, its effects, and how information and communication technologies induce and assist the disease. Section 2 outlines the state-of-the-art regarding mobile applications' innovation, implementation, and function in mHealth and diabetes interventions. Section 3 shows the methodology employed to design the mobile application and the statistical analysis. Section 4 presents the relevant findings concerning the analysis, and includes the results of the mobile application implementation, and Section 5 describes our conclusions and future work.

II. Related Work

According to [22], in nonpregnant adults with diabetes, mHealth interventions have been associated with statistically and clinically significant improvements in glycemic control. Hence, there is potential for enhanced glycemic management during pregnancy by implementing mHealth interventions.

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However, it is crucial to weigh this potential benefit against the possible downsides of virtual healthcare delivery [23]. Certain vulnerable patient groups, such as individuals facing language barriers or lacking access to technology, may encounter substantial difficulties with mHealth. Additionally, concerns may arise regarding the quality of virtual healthcare delivery and its potential impact on clinical outcomes [24].

Due to limitations imposed by COVID-19, which hinder in-person communication between patients and healthcare providers, it may threaten the specialized and intensive care essential for expectant mothers with diabetes to reach their glycemic goals and enhance pregnancy outcomes. Therefore, as we shift from traditional face-to-face ambulatory care to virtual healthcare, it is crucial to maintain a strong emphasis on patient-centered communication between patients and providers.

In this scenario, [25] proposed the best practices for patient-provider communication during medical interactions encompass six key elements: 1) nurturing the patient-provider relationship, 2) collecting relevant information, 3) conveying essential information, 4) preparing for shared decision-making, 5) addressing emotional aspects, and 6) facilitating disease- and treatment-related behaviors.

In [23], a comprehensive survey of the existing literature on the advantages and drawbacks reported by patients concerning mobile health technologies that support patient-provider communication, with a specific focus on their application in diabetes management during pregnancy was analyzed. Additionally, the study evaluated how well mHealth technologies align with the established best practice standards for patient-centered communication, as validated by [25].

Additionally, [26] put forth a research study to examine the cost-effectiveness of mHealth interventions employed by pregnant women. A secondary objective was to evaluate the methodological rigor of the identified cost-effectiveness studies. Their findings indicate that mHealth interventions could be cost-effective and economically efficient. However, further evidence is required to conclusively determine their cost-effectiveness with positive maternal and child health outcomes and their impact on longer-term healthcare service use.

As mentioned previously, mobile health artifacts could effectively enhance involvement, knowledge, and diabetes-related health outcomes in pregnant individuals. [27] designed 'SweetMama', an interactive mobile application with a patient-centric focus intended to provide support and education to pregnant individuals with diabetes who have limited financial resources. The main goal was to assess the user experience and the degree of acceptability of 'SweetMama'. The app comprises both static and dynamic components. The static elements encompass a personalized homepage and a resource library, while the dynamic aspects involve the delivery of a diabetes-specific curriculum rooted in a theoretical framework. These dynamic features include (a) motivational messages, tips, and goal-setting aligned with treatment and gestational age, (2) reminders for appointments, and (3) the ability to mark content as 'favorite'. In the usability assessment, individuals with low income who were either experiencing gestational or type 2 diabetes used SweetMama for two weeks. Participants provided qualitative feedback through interviews and quantitatively through validated measures assessing usability and satisfaction. Additionally, user analytics were employed to document the duration and nature of interactions users engaged using the mobile application.

[28] presented 'Medicaid', a digital dashboard to register and monitor glycemic control in pregnant women with type 2 diabetes. The results of their study evidenced that digital health technologies possess the potential to revolutionize healthcare for Medicaid-enrolled individuals coping with type 2 diabetes during pregnancy. The objective is to manage their blood glucose levels effectively, a critical factor for achieving a successful pregnancy and childbirth. The process of distilling the needs and preferences of patients and healthcare providers and incorporating them, alongside insights from prior research and theory, into developing applications offers significant promise in addressing complex healthcare challenges.

Thus, [29] developed a study to establish an infrastructure encompassing data processing algorithms, blood glucose (BG) prediction models, and a suitable mobile application for managing electronic patient records. The objective was to facilitate personalized BG prediction-based recommendations for patients with gestational diabetes mellitus. An electronic diary management mobile app was developed alongside software for data exchange and continuous BG signal processing. These two components were integrated to gather essential data required for the personalized BG prediction system. Data related to meals, BG measurements, and various events were collected through the mobile app and continuous glucose monitoring (CGM) system processing software. The dataset was used to fine-tune and evaluate the BG prediction model, which included an algorithm for dynamically adjusting coefficients.

The World Federation of Obesity has alerted that childhood obesity is poised to become the predominant health challenge in the upcoming decade. Research indicates that factors like maternal obesity during pregnancy significantly impact fetal programming and are robust predictors of childhood overweight and obesity. Consequently, fostering healthy eating habits during pregnancy emerges as a crucial strategy for preventing the intergenerational transmission of obesity. In this context, mobile health programs hold promise as potentially more effective alternatives to traditional face-to-face interventions, particularly in situations like the COVID-19 pandemic [30]. They assessed the efficacy of mobile health (mHealth) intervention in mitigating excessive weight gain among pregnant women receiving care at family healthcare facilities. Moreover, [31] conducted a randomized controlled research study to ascertain if a mobile phone-based real-time blood glucose management application for remotely sensing women with gestational diabetes mellitus (GDM) was as effective in regulating blood glucose levels as the conventional method of in-person clinic attendance.

On the other hand, the influence of specific fields of Artificial Intelligence has induced new application domains to prove intelligent approaches. Thus, recommender systems have the

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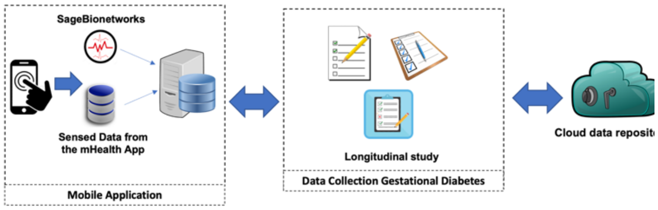

Fig. 1. The general framework of the mobile application for the monitoring and collection of gestational diabetes data

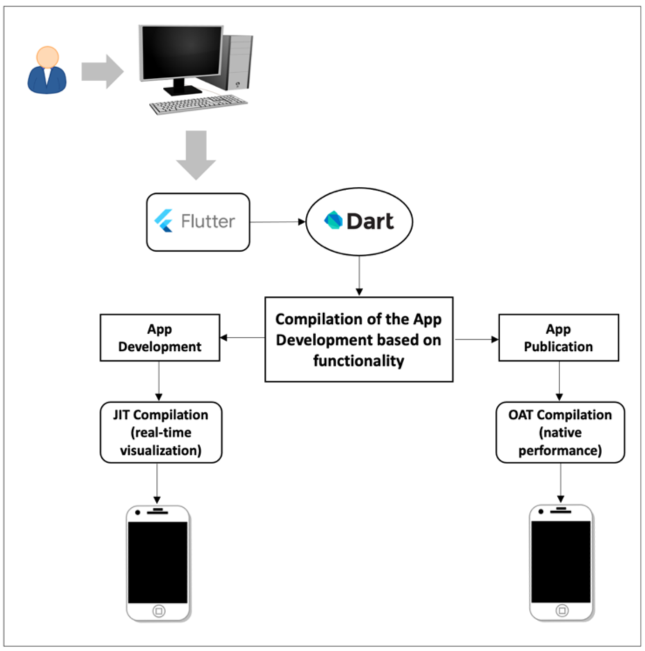

Fig. 2. Compilation in Dart

potential to partially supplement the role of healthcare professionals in educating and monitoring women with gestational diabetes mellitus, thereby alleviating the workload on both the patients and healthcare systems. [32] developed the 'DiaCompanion-I', a mobile-based personalized recommendation system driven by data, offering real-time individualized recommendations primarily focusing on predicting postprandial glycemic responses. This study sought to elucidate the impact of 'DiaCompanion-I' on glycemic levels and pregnancy outcomes in women diagnosed with gestational diabetes mellitus. According to the results obtained from the statistical analysis, the authors think incorporating 'DiaCompanion-I' into the treatment regimen will likely yield greater effectiveness in enhancing glycemic control and improving pregnancy outcomes among GDM patients. Furthermore, utilizing the app will contribute to a reduction in the frequency of clinic visits.

Advancements in digital health and machine learning are reshaping the clinical healthcare environment. Individuals from diverse geographic regions and cultural backgrounds can now take advantage of the portability of wearable devices and smartphones to continuously monitor their health. [33] argued that there is a critical provision to design machine learning techniques that are easily understandable by clinicians to aid in the management, monitoring, and risk assessment of gestational diabetes patients throughout their pregnancies, as well as modifying and developing proven medical devices for patients to use at home, promoting better clinical outcomes through timely interventions in virtual community settings and virtual consultations. Additionally, these innovations should be accessible and economically viable for women of various socioeconomic statuses and access to healthcare resources.

In the context of machine learning methods, accurately predicting postprandial blood glucose levels holds significant importance in the management of diabetes. In [34] a comprehensively a data-driven blood glucose model using a decision tree gradient boosting algorithm is proposed. This model predicted various aspects of postprandial glycemic responses. It employed meal-related data sourced from a mobile app diary, which included information about the glycemic index, the context of food consumption (including details about previous meals), individual patient characteristics, and responses from patient behavioral questionnaires. The authors also established a set of rules to identify incorrect meal records and filter out flawed data. Analyses were conducted on the complete food diary dataset, focusing mainly on the data about the specific meal for which postprandial blood glucose responses were calculated. Multiple gradient boosting models were trained and assessed, and parameter selection was performed through random search cross-validation.

III. Methods and Materials

The continuous monitoring of chronic diseases through assistance services, based on the collaboration of health operators, patients, and community members, has become one of the main challenges for technology. Thus, this section presents the general design of the mobile application and the statistical analysis concerning the case study.

A. *Mobile Application Design*

The Chronic Care Model (CCM) is an evidence-based conceptual framework developed by the United States [35]. The World Health Organization (WHO - World Health Organization) proposed an innovative framework for the Care of Chronic Conditions (ICCC - Innovative Care for Chronic Conditions), extending the CCM model to define an international reference model.

Considering the model, we propose mobile and web computing applications that will allow the collection of patient information, monitoring, and follow-up of treatments related to type II diabetes mellitus.

Fig. 1 shows the general framework for designing and implementing the mobile application and its interaction to collect medical data.

According to Fig. 1, we can appreciate the general framework proposed for developing the mobile application. The general process consists of data acquisition through access to the mobile application to collect information from each female patient who will participate in a future longitudinal study. The data collected from each patient is stored on a temporary server. In contrast, the data streaming is sent to the cloud server developed with Firebase.

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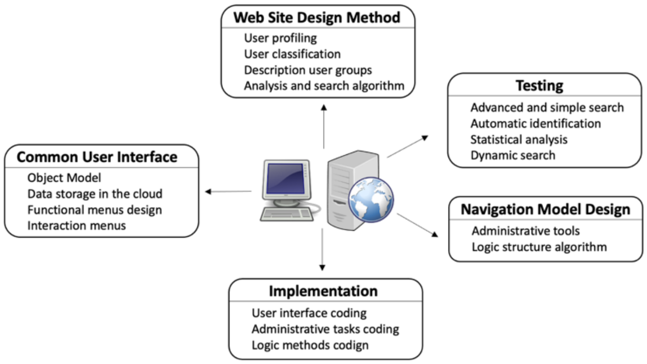

Fig. 3. Architecture based on services for the App design

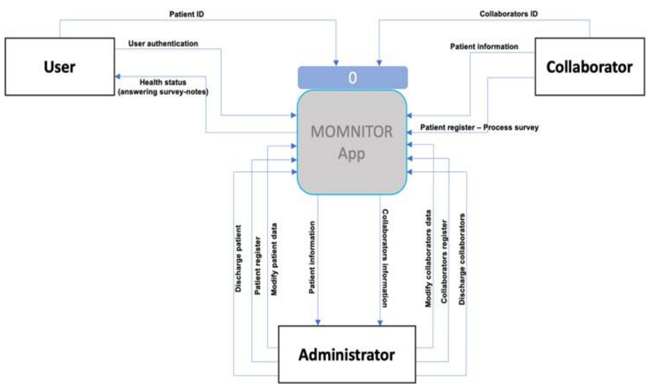

Fig. 4. Mobile app context diagram and actors

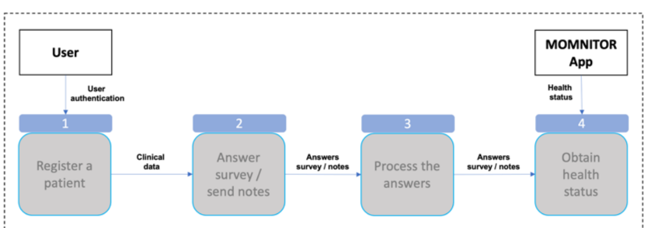

Fig. 5. Mobile App Logical Data Flow Diagram

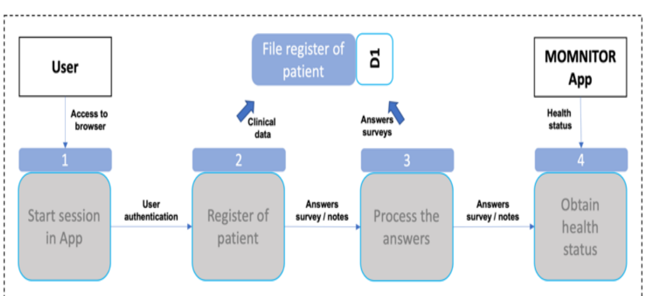

Fig. 6. Mobile App Physical Data Flow Diagram

The mobile application was designed and implemented using the development framework FlutterFlow, which provides tools to create software interfaces.

Google developed it, and its launch took place in 2018. Flutter develops apps that can run on both Android and iOS. Therefore, it focuses on developing hybrid apps with native performance.

The proposed m-Health application was designed considering the following characteristics:

– **Fast development.** It allows us to develop applications faster by providing us with tools to speed up/improve both the development and the performance of the application.

– **JIT compilation vs. OAT with Dart.** Previously, many frameworks have been presented that aim to find excellent performance. However, for one thing or another, the vast majority fail to fulfill what they promise since they are based on web views, among other features, which in one way or another end up penalizing/slowing down the application's performance. On the other hand, FlutterFlow has a native performance thanks to Dart, a programming language created by Google that performs two types of compilation depending on the objective we have at each moment.

Initially, FlutterFlow performs JIT (Just In Time) compilation during the mobile application's development. This type of way of executing the code implies that the compilation of a program is done during its execution and not before its execution. It is what allows us to use tools such as Stateful Hot Reload and to be able to visualize the changes in real-time. In this first compilation type, the code must be interpreted by a virtual machine.

Later, when the development of the application is ready and makes a release, the code is compiled ahead of time (OAT), that is, before its execution, converting the code written into Dart to native code to get better performance on the device, reduce its size to a minimum and remove other things that are only useful during development mode. In this second type of compilation, a virtual machine does not need to interpret the code since the device does it directly (see Fig. 2).

– **Efficient graphics engine.** The mobile application uses Skia to improve interface performance. This process is not left to the platform, as in other frameworks, allowing applications with high FPS (Frames Per Second) to be made using Skia for rendering. Skia is a 2D graphics rendering library (written in C++) that only needs a single canvas (Canvas), which contains everything that is running FlutterFlow and to which we add the elements of our interface—causing our applications to be high-speed and consume very few resources. Canvas is an element introduced in HTML that allows us to generate graphics through our code dynamically.

– **Open Source.** Both FlutterFlow and Dart are OpenSource, both are open source, which means that a large amount of documentation is constantly generated thanks to the contributions of Google combined with those of the rest of the developer community. All this work by the community causes the popularity of this SDK to continue to increase.

Fig. 3 shows the services and operations implemented as part of the design of the mobile application, considering, among them, the data analysis based on operational indicators and characterization of the disease.

As part of the general design, we developed a context diagram concerning the actors of the mobile application, where

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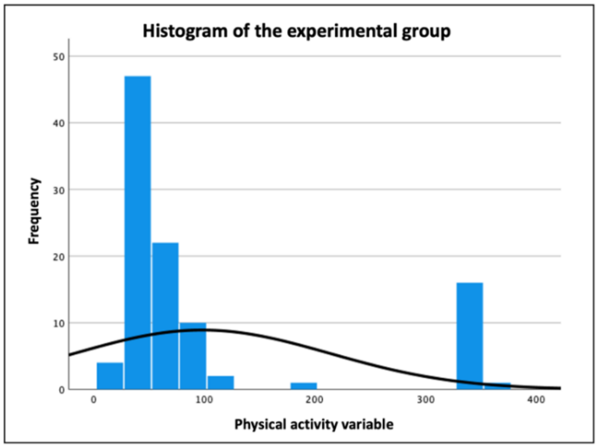

Fig. 7. Frequency distribution concerning physical activity in pregnant women who used the mHealth application

TABLE I
FREQUENCY AND STATISTICS OF 'PHYSICAL ACTIVITY' VARIABLE IN THE EXPERIMENTAL GROUP

PHYSICAL ACTIVITY IN EXPERIMENTAL GROUP

Valid data	**Frequency**	**Percentage (%)**	**Valid Percentage**	**Accumulated Percentage**
15	4	3.9	3.9	3.9
30	45	43.7	43.7	47.6
40	1	1.0	1.0	48.5
50	1	1.0	1.0	49.5
55	6	5.8	5.8	55.3
60	6	5.8	5.8	61.2
65	7	6.8	6.8	68.0
70	1	1.0	1.0	68.9
75	2	1.9	1.9	70.9
80	4	3.9	3.9	74.8
85	1	1.0	1.0	75.7
95	1	1.0	1.0	76.7
100	4	3.9	3.9	80.6
110	1	1.0	1.0	81.6
115	1	1.0	1.0	82.5
180	1	1.0	1.0	83.5
340	1	1.0	1.0	84.5
350	15	14.6	14.6	99.0
360	1	1.0	1.0	100.0
Total	**103**	**100.0**	**100.0**	

three leading roles can be observed: User, Collaborators, and Administrator. Likewise, the functions implemented for each actor and role within the mobile application are considered in this diagram.

In the same way, this diagram shows the data flows and the interconnection between them, guaranteeing an open functionality. Thus, it is possible to establish communication with the database server and the mobile application (see Fig. 4).

Regarding the logical data flow, Fig. 5 presents the logical data flow diagram, which shows the interaction between the user and the mobile application to capture information related to their health status, considering for this, responses to a survey

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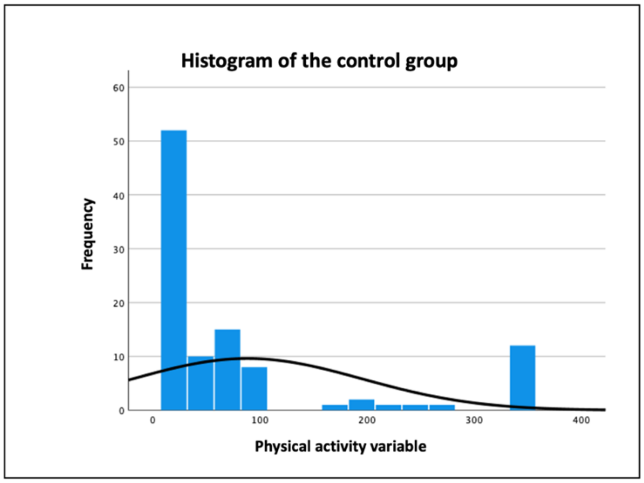

Fig. 8. Frequency distribution concerning physical activity in pregnant women who were at health facilities to continue gestational diabetes monitoring

TABLE II
FREQUENCY AND STATISTICS OF 'PHYSICAL ACTIVITY' VARIABLE IN THE CONTROL GROUP

PHYSICAL ACTIVITY IN THE CONTROL GROUP

VALID DATA	FREQUENCY	PERCENTAGE (%)	VALID PERCENTAGE	ACCUMULATED PERCENTAGE
20	31	30.1	30.1	30.1
30	21	20.4	20.4	50.5
40	6	5.8	5.8	56.3
45	2	1.9	1.9	58.3
50	1	1.0	1.0	59.2
55	1	1.0	1.0	60.2
70	5	4.9	4.9	65.0
80	10	9.7	9.7	74.8
85	1	1.0	1.0	75.7
100	6	5.8	5.8	81.6
105	1	1.0	1.0	82.5
180	1	1.0	1.0	83.5
200	2	1.9	1.9	85.4
210	1	1.0	1.0	86.4
240	1	1.0	1.0	87.4
270	1	1.0	1.0	88.3
350	12	11.7	11.7	100.0
TOTAL	**103**	**100.0**	**100.0**	

that was previously prepared with the support of physicians specializing in gestational diabetes.

The final objective is to have the patient's general state of health based on the calculation made by the mobile application according to the algorithms implemented.

Moreover, Fig. 6 presents the physical data flow diagram, where the mobile application's and user's functions and interactions can be seen.

A. Case Study Definition and Statistical Analysis

The Chronic Care Model (CCM) is an evidence-based conceptual framework developed by the United States [35]. The World Health Organization (WHO - World Health Organization) proposed an innovative framework for the Care of Chronic Conditions (ICCC - Innovative Care for Chronic Conditions), extending the CCM model to define an international reference model.

The mobile application was implemented considering the specifications of the CCM model. Thus, we design a longitudinal study to analyze the health condition of pregnant women with gestational diabetes.

In this case, we correlated information regarding subjects with supervision based on the mobile application and pregnant women with health interventions and control made face-to-face in health facilities.

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TABLE III
CORRELATION OF THE EXPERIMENTAL GROUP WITH 'PHYSICAL ACTIVITY' AND 'MET PER WEEK' VARIABLES

		Physical activity (cluster)	MET per week (cluster)
Physical activity (cluster)	Pearson correlation	1	0.833 **
	Sigma (bilateral)		< 0.001
	N	103	103
MET per week (cluster)	Pearson correlation	0.833 **	1
	Sigma (bilateral)	< 0.001	
	N	103	103
** The correlation is significative in the level 0.01 (bilateral)			

TABLE IV
CORRELATION OF THE CONTROL GROUP WITH 'PHYSICAL ACTIVITY' AND 'MET PER WEEK' VARIABLES

		PHYSICAL ACTIVITY (CLUSTER)	MET PER WEEK (CLUSTER)
PHYSICAL ACTIVITY (CLUSTER)	PEARSON CORRELATION	1	0.589 **
	SIGMA (BILATERAL)		< 0.001
	N	103	103
MET PER WEEK (CLUSTER)	PEARSON CORRELATION	0.589 **	1
	SIGMA (BILATERAL)	< 0.001	
	N	103	103
** THE CORRELATION IS SIGNIFICATIVE IN THE LEVEL 0.01 (BILATERAL)			

After obtaining the necessary permission from the pregnant women, electronic answers were taken from the mobile application to a sample of 206 subjects, divided into an experimental group (control-based app) and a supervised group (control-based in person), representing an equivalent percentage of 50% for each group. The sample of pregnant women was selected randomly by applying the RANDBETWEEN function in MS EXCEL to an anonymous email list of all patients.

We formulated three research questions: The first was to find the crucial aspects of using mobile applications to follow the monitoring and control of gestational diabetes in pregnant women. For this purpose, we use descriptive statistics.

Our second research question explored whether there were differences in the overall evaluation of using mobile applications for medical interventions related to gestational diabetes between experimental and control groups. For this purpose, the independent sample t-test procedure was employed to analyze the dataset.

Our third research question was to test whether there were differences between experimental and control groups in the variables involved in evaluating the monitoring of the disease. Therefore, the stepwise regression method was applied to locate the most important variables related to these groups. The stepwise regression procedure excludes the non-statistically significant independent variables from the final model. Thus, we created two multiple regression models for evaluating the groups' satisfaction: experimental and control. Statistical analysis was developed using IBM SPSS (Statistical Package for Social Science) Statistics V20 software.

IV. RELEVANT FINDINGS

B. *Statistical Analysis*

The results regarding the pregnant women with supervision based on the mobile application demonstrated that mobile health interventions are both viable and well-received by the intended audience, addressing obstacles to obtaining health information and promoting engagement with antenatal care in a patient-centered approach.

Thus, implementing mHealth interventions could positively impact the health outcomes of both mothers and children. The available evidence for mHealth interventions indicates promising initial effectiveness in various aspects of pregnancy-related health, such as promoting healthy gestational weight gain, aiding in smoking cessation, enhancing mental health, improving women's adherence to treatments like diabetes care, and expanding access to antenatal care.

According to the variables considered in the research study, analyzing the frequency of 'physical activity' between the experimental and control groups is crucial. Thus, Table 1 describes the 'physical activity' frequencies in the experimental group. Additionally, Fig. 7 shows the frequency distribution concerning this variable in pregnant women who used the mobile application.

The most significant values regarding the statistics measures of the physical activity in the experimental group are as follows: the mean corresponds to 98.25, with a standard error of the mean equal to 11.373. The median is 55, with a mode of 30, a standard deviation (σ) equal to 115.425, and a variance (σ^2) of 13,322.896.

On the other hand, Table 2 describes the 'physical activity' frequencies in the control group. Additionally, Fig. 8 depicts the frequency distribution concerning this variable in pregnant women face-to-face at health facilities to continue the monitoring related to gestational diabetes.

Concerning the statistics values corresponding to the 'physical activity' variable in the control group, we obtained the following data: the mean corresponds to 88.59, with a standard error of the mean equal to 10.534. The median is 30, with a

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TABLE V

COMPARISON OF WEEKLY PHYSICAL ACTIVITY MINUTES, ENERGY CONSUMPTION, AND SEDENTARY BEHAVIOR BETWEEN THE EXPERIMENTAL AND CONTROL GROUPS

Variable	**Experimental Group**					**Control Group**				
	Pre-eval.	**Pos-eval.**	***p-value (1-factor)***	***p-value (2-actors)***	**Dif.**	**Pre-eval.**	**Pos-eval.**	***p-value (1-actor)***	***p-value (2-actors)***	**Dif.**
Weekly physical activity minutes	98.25	84.67	0.12	0.25	13.58	88.59	85.05	0.338	0.676	3.54
Energy consumption	840.13	591.88	0.12	0.24	248.24	512.77	1489.52	0.005	0.011	-976.75
Sedentary behavior	5.73	4.84	< 0.001	0.002	0.88	5.70	6.04	0.020	0.040	-0.34

TABLE VI

COMPARISON OF D COHEN AND G HEDGES VALUES REGARDING PHYSICAL ACTIVITY, MET, AND SEDENTARY BEHAVIOR VARIABLES OF THE EXPERIMENTAL AND CONTROL GROUPS

Effect sizes of paired samples						
Variables	**Experimental Group**			**Control Group**		
	d Cohen	***g Hedges***	**Stand**	***d Cohen***	***g Hedges***	**Stand**
Physical activity	0.113	0.112	120.53	0.041	0.041	86.12
Energy consumption	0.115	0.115	215.04	0.574	0.692	382.21
Sedentary behavior	0.320	0.317	2.77	0.871	0.825	1.66

TABLE VII

COMPARISON OF CHI-SQUARED AND MCNEWAR-BOWKER TESTS FOR PHYSICAL ACTIVITY AND NUTRITION VARIABLES BETWEEN EXPERIMENTAL AND CONTROL GROUPS

		Experimental Group		**Control Group**	
		Physical activity	**Nutrition**	**Physical activity**	**Nutrition**
Chi-squared	Value	18.322	17.643	14.763	13.543
	gl	11	10	9	8
	Asymptotic significance	**0.081**	**0.061**	**0.091**	**0.089**
McNemar-Bowker	Value	21.111	19.762	18.761	18.989
	gl	13	12	11	12
	Asymptotic significance	**0.079**	**0.082**	**0.096**	**0.098**

mode of 20, a standard deviation (σ) equal to 106.909, and a variance (σ^2) of 11,429.616.

Moreover, we explored a correlation analysis with the hypothesis that physical activity is directly related to the metabolic equivalent of task (MET), defined by the amount of consumed energy while sitting quietly. The MET is calculated concerning the rest. Thus, we show that MET values represent the activity intensity for the experimental and control groups. The correlations between the experimental and control groups with ‘physical activity’ and ‘MET per week’ are presented in Tables 3 and 4, respectively.

Thus, a value of 0.954 means a high correlation between the physical activity and the MET. In addition, the significance level is equal to 0.05, representing 5% of the entire sample. We used the statistical test based on the Bivariate Pearson correlation for this case.

The decision-making consists of if $\rho < 0.05$, the null hypothesis is rejected. It is significant when below 0.05 (5%) and highly significant when below 0.01 (1%). The calculated ρ-value is 0.001, well below 5% and even 1%. Therefore, the null hypothesis is rejected, leaving us with the research hypothesis. In this way, we concluded that through the hypothesis test, there is a correlation.

According to the results obtained from the control group, the result equivalent to 0.589 represents a low correlation between physical activity and the MET. Perhaps it is evidence that the habits related to physical activity were not registered continuously, or the consumption of MET is high among small pregnant women in the control group.

Based on the review of the results derived from the statistical analysis, particularly the correlations between the physical activity and MET data applied to the experimental group and the control group in their pre- and post-stages, we can infer that the use of the mobile application contributed to the reinforcement, supervision, and control of the recommended actions to prevent the development of type 2 Diabetes in women in the gestational stage. Thus, it satisfies the first research question.

On the other hand, Table 5 presents the comparison of weekly physical activity minutes, energy consumption (MET), and sedentary behavior between participating groups. We measured the effect of differences between the two groups to obtain the value of the relative force of the difference among the mean of the experimental and control groups (see Table 6).

For the experimental group, we applied the *d Cohen* test to quantify the difference in size between two populations. Thus,

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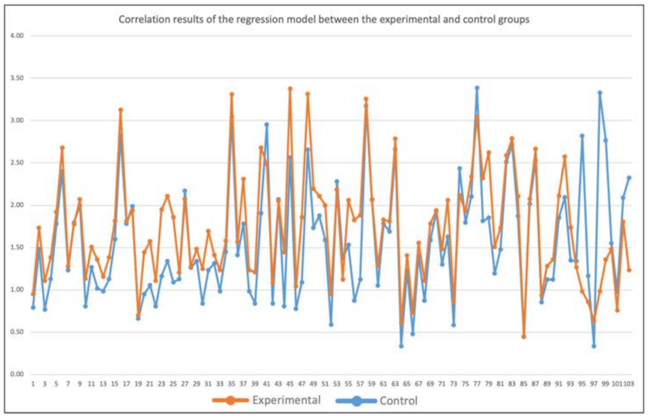

Fig. 9. Association effect between the experimental and control groups with the regression approach

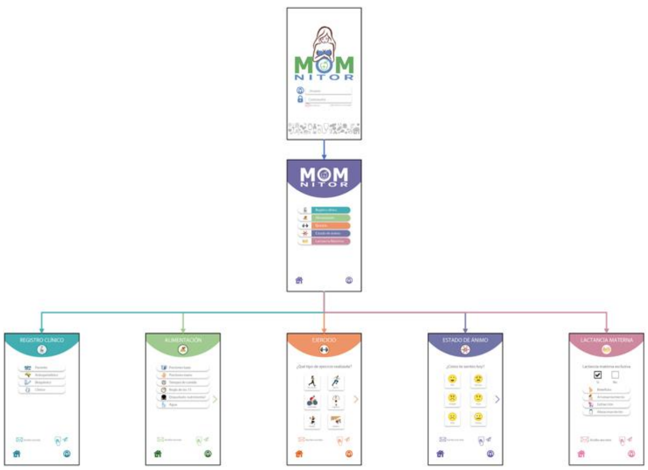

Fig. 10. The structure-tiered and graphical user interfaces of the MOMNITOR mobile application

Fig. 11. The structure-tiered and graphical user interfaces of the "Food" section

the obtained value was 0.113, corresponding to the 'physical activity' variable. It represents a low effect in the differences between groups.

Moreover, the *g Hedges* correction was employed to calculate the hypothetical distribution of the physical activity variable and measure the effect of the mean adjusted difference by the correlation using the standard deviation instead of the variance.

In this case, the obtained value was 0.112, representing a low impact on the difference between the groups. The values obtained to the *d Cohen* and *g Hedges* for the 'MET' variable were the same, 0.115, representing a slight difference between groups. On the contrary, the 'sedentary behavior' variable obtained the following values for the *d Cohen* and *g Hedges*: 0.320 and 0.317, respectively. It means a significant difference exists between the groups considering this variable (see Table 6).

Therefore, the second research question is satisfied, according to the findings. The statistical analysis revealed the differences obtained by employing the mobile application regarding the traditional face-to-face control in an overall evaluation. Tables 3, 4, 5, and 6 support this assumption.

Finally, the relationship between physical activity and consuming fruits and vegetables implies a good health balance in pregnant women. So, an analysis based on *chi-squared* and *McNewar-Bowker* tests was also applied. The first one was employed to assess observed results with expected results. The test evaluates whether a difference between observed and expected data arises from random chance or if it means a significant relationship between the variables under investigation.

The *McNewar-Bowker* test allows us to contrast the number of individuals who initially do not have the characteristic of interest with those who, after the intervention (or a specific time), have made the change and now present the characteristic of interest. The primary function is to compare the change in the distribution of proportions between two measurements of a dichotomous variable and determine that the difference is statistically significant. Table 7 presents the results corresponding to these tests for the physical activity and nutrition variables of both groups of pregnant women.

The results presented in Table 7 for both tests in the experimental group reveal that the significance level is high; in other words, the results infer that they are strong association between physical activity and the nutrition variables to improve the monitoring and supervision tasks with the mobile association. In contrast, the results of the tests in the control group evidence that the association is slightly small regarding the values of the experimental group.

Finally, Fig. 9 depicts the results of the regression model implemented to analyze the difference between both groups. In the chart, we can observe that the values concerning supervision and monitoring were correlated to show the effect of using the mobile application in contrast to the control-based face-to-face. Thus, the orange color reflects more sensibility and better correlation of the experimental group compared to the control group represented by blue.

It is crucial to mention that the results described in Table 7 and the correlation data from the regression model of both groups make valid the third research question, focused on demonstrating better monitoring and supervision of gestational diabetes using the mobile application.

C. *Mobile application results*

Various official standards and documents theoretically validated each of the elements that make up the mobile application.

For example, for the "Clinical Record", the NOM-004 health standard was used as a basis; for the "Food" section, the SME, GPC – DM-Canada, ADA, INSP, PAHO-WHO, and WHO

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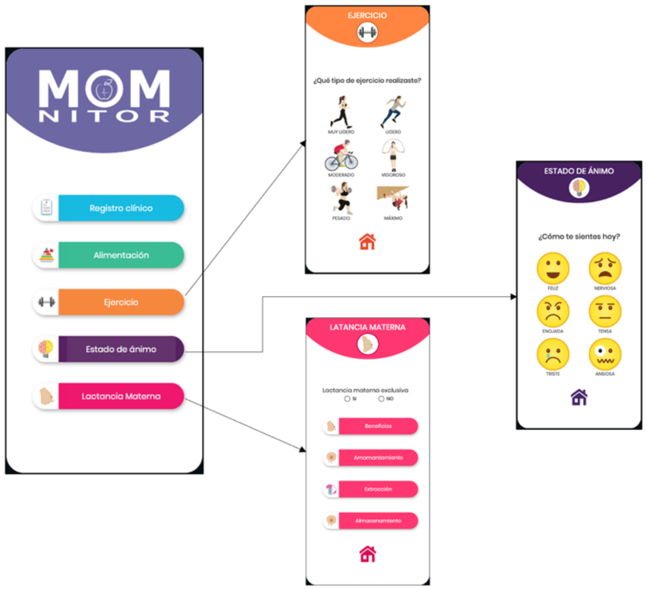

Fig. 12. The structure-tiered and graphical user interfaces of the sections: Exercise, Mood, and Breastfeeding

Standards were used. For “Exercise”, the items were validated with the GPAQ, IEP, and WHO standards. In the same way for “Mood”, the EVEA and EPDS were used, and finally, for “Breastfeeding” we used the standard from UNICEF as a validating instrument.

On the other hand, Fig. 10 shows the complete design of the mobile application with its five navigation levels considered for the follow-up, monitoring, and control of patients at risk of gestational diabetes.

At this time, the graphical user interface of the mobile application was implemented in Spanish because the longitudinal study was applied in regions remote from regional hospitals and health facilities or whose distance is considerable to monitor pregnant women daily.

Below, we present some images of the mobile application developed in the FlutterFlow framework for a multi-platform environment for mobile devices. Fig. 11 shows the integration of the submenus that belong to the “Food” interface, and all registered data are stored in the mobile app. Moreover, Fig. 12 depicts the interfaces that belong to the structure of “Exercise”, “Mood”, and “Breastfeeding”.

V. Conclusion and Future Work

The role of smartphones in healthcare and well-being is increasingly indispensable. Furthermore, this technology allows caregivers to monitor and tend to their loved ones effectively. Particularly for individuals with physical disabilities or limited mobility, mobile health (mHealth) proves highly advantageous as it enables patients to engage with portable devices fully.

A growing body of evidence underscores mHealth's capacity to curtail healthcare expenses, amplify accessibility, and elevate the caliber of patient care—nevertheless, users' acceptance and integration of mHealth stand as pivotal prerequisites to fully exploit its potential. Therefore, comprehending the factors influencing this adoption is imperative for its triumph.

According to our analysis, we concluded that mHealth assumes a highly significant role in the lives of individuals, proving advantageous for citizens, healthcare practitioners, and policymakers alike. It addresses challenges by expanding the dissemination of accurate information to individuals across various geographical locations and to healthcare professionals. It, in turn, mitigates the spread of misinformation and uncertainty. It enables the tracking of symptoms and mental well-being of citizens, facilitates home monitoring and isolation, identifies novel predictors, optimizes the allocation of healthcare resources, and lessens the strain on medical facilities.

The findings revealed that using mobile applications, at least in gestational diabetes monitoring, allows us to improve pregnant women's supervision, control, diagnosis, and treatment. Moreover, the statistical analysis demonstrated that pregnant women with traditional face-to-face supervision failed in some checkpoints to maintain good health, resulting in consequences such as overweight and blood pressure problems.

Therefore, mHealth emerges as a top-tier option for enhancing the patient-physician dynamic through tele-visits, its application in fever management, furnishing real-time data to healthcare providers, monitoring populations, and identifying diseases through data collected across diverse locations. Consequently, within the context of the COVID-19 pandemic, substantial room remains for researchers to pioneer inventive endeavors. Given the limited healthcare resources in developing nations during the outbreak, this investigation delves into the array of prospects available to providers of health services.

Nevertheless, the findings are constrained by their susceptibility to bias, often stemming from factors such as unclear blinding, significant attrition rates, inadequate randomization, small sample sizes, and reliance on self-reported outcome measures.

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