Implementation of Intelligent process automation (IPA) based Clinical Decision Support System For Early Detection and Screening of Diabetes

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Abstract

Diabetes mellitus has become a leading cause of disease-related deaths in the world. Once an individual is diagnosed with diabetes, a series of processes will be required to keep the blood sugar regular and help avoid hyperglycemia and hypoglycemia. Self-Management of diabetes is complex and involves constant glucose monitoring, diet management, care, support, exercise, and insulin management. These processes are expensive because they require detailed record-keeping of medications, activities, and a timely report to doctors to assist them in making an informed decision that will subsequently help the patient heal. Other challenges include the high cost of treatment, lifestyle changes, education, lack of medication adherence, and treatment plans.

Our approach is to adopt the Early screening technique and detect the risk of diabetes unobtrusively. Early screening is a technique that can help detect Type 1, 2 diabetes and achieve preventive care according to the guidelines set by WHO and recommended by the American Diabetes Association (ADA). Unobtrusive systems allow a doctor to screen for diabetes while he is unaware.

We followed the Design Science Research model (DSRM) and started by using systematic literature review (SLR) guidelines to search the most popular journals limiting the results tied to studies that discussed the screening and detection of the risk of diabetes.

We reviewed the architecture, features, and limitations of the various tools and technologies using the following classification: Continuous Glucose Monitoring Systems (CGMS), Flash Glucose Monitoring Systems (FGMS), and the Unobtrusive Systems. In addition, under the unobtrusive system, we studied the Child Health Improvement through Computer Automation (CHICA) system. While there is evidence that supports its benefits and usefulness, we found some required enhancements from the literature in the areas of decision support systems, data entry automation, and flexible integration with other systems.

The artefact built during the development phase is an Intelligent process automation (IPA) system that can be implemented within the health sector for early screening and detection of diabetes unobtrusively. Developing this artefact will allow us to understand the possible issues and challenges of implementing an automation process in a medical institution. We evaluated the artefact using a mix of quantitative and qualitative methods. This method allowed us to answer the research questions and understand the value of automation to medical practitioners. The value includes speed, reduce cost, and error while safeguarding the lives of the medical professional on active duty.

The results show that the system can enhance patient-doctor interaction, reduce patient wait time, and optimize the glucose monitoring process. However, there were challenges such as cost of implementation, training of staff, and the increased workload within the system. In addition, potential challenges identified include fear of job loss and aversion to change during implementation within the hospital.

This study has also allowed us to understand the integration of robotic process automation with machine learning within the healthcare sector. We hope that this study will contextually position IPA within the technological stack of health care institutions and add to the body of knowledge on this subject.

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Table of Contents

1.1 List of Figures

1.2 List of Tables

2 Introduction

2.1 Background

In a bid to gain insights into the future of a hospital, the Deloitte Center (Gordon *et al.*, 2017) adopted a crowd simulation technique involving different researchers worldwide. The study revealed the following features of a future hospital.

- Centralized decision-making systems, continuous and real-time clinical monitoring of patients.
- Improved Hospital experience of patients using Artificial Intelligence and Machine Learning techniques.
- Enhanced development and learning among caregivers allowing them to do the essential core of their task- using a combination of Robotic Process Automation (RPA) and AI.
- Increased efficiencies and productivity through automation of most back-office processes.

Using the research data, they could paint a scenario that starts when a patient enters a hospital. A staff directs him to an intelligent room equipped with a digital console's ergonomic, styled, noise-free capabilities.

This setup allows the patient to access his medical records, information, and statistics from a monitor connected to a cloud-based centralized app. At the same time, patients possess personalized body items that help to continuously monitor their vitals and notify the professionals of any abnormalities. The digital console replaces nurses in the setup, and sessions with medical professionals are recorded and stored automatically in the patient's online Electronic Health Records (EHR).

According to Gordon *et al.* (2017), there was a drop in government expenditures in 2015 to 26% from 38% in 2001. The research also indicated an increase in outpatient service and long-term care to 46% from 31% in that same period. As a result of the numerous benefits derived from this intelligent setup, the Cleveland clinic began its journey into the future in 2014, followed by the New Children Hospital in 2017.

In both implementations, the model created a command centre connected to wearable devices and sensors that aids decision-making by providing real-time data and tools to make quicker, clinical, and operational decisions. These tools can include wearing devices or sensors placed near or on patients. They called wearable devices to extract and transfer real-time data from the patient to the command centre. Helpful information or vital stats can be extracted from the sensors, processed, and stored in a centralized electronic record system. Thus, the system contains a vast amount of information about a patient that is always available and real-time.

The underlying need for the high adoption of technology in the future health care systems are speed, efficiency, performance, accuracy, reduced costs, and increased revenue. In addition, there is a need to efficiently manage medical centre resources such as beds, staff, and assets (Emanuele and Koetter, 2007) while ensuring that care quality is not compromised.

Hospitals and Medical Centers consistently manage various functions that cut across different clinics and departments such as patient management, bed management, and treatment management to keep the hospital functioning and running. Development of a supportive care plan that includes dietary, monitoring test results, and tracking vital signs at any point in time in the hospital.

Emanuele and Koetter (2007) note that poor management of resources can lead to overcrowding, less doctor-patient time, delay in discharging a patient, and decreased patient satisfaction. The decrease in patient satisfaction is further evident in reduced doctor-patient visitation time and reduced quality of care, leading to unnecessary tests, increased medical errors, and complications.

For instance, in Australia, the major challenges of healthcare systems are shortages of medical practitioners in both urban and rural areas. Another noticeable issue is the increase of medical errors (Armstrong *et al.*, 2007). Medical

errors cost Australia 2 billion dollars annually, and according to (Wilson *et al.*, 1995), these errors are avoidable. Healthcare challenges are fundamental and cut across every aspect of the health care system in developed countries. It is the same thing, and it is universal. In summary, they primarily include the rising cost of health care, the increased expectation of quality patient care, the rise in the number of older people, low and equitable access to quality healthcare (Norris, 2002).

According to Emmanuel *et al.* (2007), workflow and automation systems can reduce or eliminate some of the challenges associated with the medical industry, such as reducing cost, medical errors, and saving human lives. In addition, Gartner (2003) predicted that, in the future, the workflow would be a significant part of health information systems. There lies the opportunity for tools such as BPM, SharePoint workflow, and RPA to automate these activities and address concerns such as staff shortages, optimized and efficient utilization of hospital resources, timely and real-time delivery of patient care, support, and treatment.

Intelligent automation can help the workflow adapt to changing needs and respond to trends in a clinical process. The occurrence of diseases can be predicted using AI and ML techniques. For instance, the rise of diseases such as diabetes, cardiac arrest, heart failure, a virus, and the detection of bacteria. Intelligent automation can help identify and treat infected patients and protect doctors who are at risk of contracting these diseases.

As specified by Emanuele and Koetter (2007), an automation\workflow engine can connect to systems and retrieve real-time and historical data from patients in other to identify problems quickly. Automation can enable early identification, which subsequently leads to early monitoring and support of care

It is possible to use automation to determine the likelihood of a patient having a disease, although there is a level of percentage likelihood. Intelligent automation can extract data from various sources, integrate them, and feed a dashboard system right on a doctor's desktop. Intelligent automation can identify hidden patterns in the data, present it to a doctor, and make future patient health recommendations. These can speed up visitation time spent on diagnosing by quick problem identification, increase the quality of care and improve patient and doctor relationship

Despite the numerous benefits be gained by automation, they also come with challenges which include access to data. Health care institutions are usually reluctant to adopt Business Process Modelling (BPM) procedures and workflow (Emanuele and Koetter, 2007). A perfect system will be centralized cloud-based electronic records. Still, the reality is that most of this data might not be available or exist in incompatible formats such as paper form, closed systems. Another primary concern aside from accessibility is the low tolerance for failure. Small failures or errors in the system can potentially lead to the death of a patient.

There is a perceived value from implementing and automating health care systems such as improved decision making, convenience, availability of a variety of information. In the future, automation is an important driver necessary to achieve essential health care outcomes (Norris, 2002). These drivers can enhance interactions between patients and clinicians but can also come at a cost. For example, increased level of complex challenges with integrations between systems. In 2005, the productivity commission presented a paper that showed that technology adoption and implementation in health care processes have bought considerable benefits to the Australian community which outweighs the cost.

To show the feasibility, importance, and usability of intelligent automation in combating diseases, In this study, we attempt to use Intelligent automation to establish the likelihood of Diabetes Mellitus in a patient.

2.2 Problem Definition and Motivation

The World Health Organization (2016) statistics are staggering, showing a reported rise of diabetes globally. The number of people living with diabetes soared to 422 million in 2014 from 108 million in 1980, representing an 8.5% increase. In 2012, 3.7 million people reportedly died before they reached the age of 70 years, while 1.6 million people died in 2016 because of diabetes (WHO, 2016). According to El-Gayar *et al.* (2013), diabetes is a chronic illness that requires constant continuous care, management, and support to prevent further complications. Dovc and Battelino (2020) describe diabetes as a condition caused by autoimmune destruction of the cells responsible for secreting insulin

into the body, causing an unbalanced glucose level with reliance and dependence on an insulin infusion. This disease occurs if the pancreas does not produce adequate insulin for regulating blood sugar or glucose (WHO, 2016).

After screening, detecting, and diagnosing diabetes, the affected individual will undergo a strict regime or series of tasks that include constant glucose monitoring, care, support, management, and exercise. Strict control is necessary to avoid hypoglycemia (low blood sugar) and hyperglycemia (high blood sugar level) in the blood. Ultimately, allowing the individual to have normality in their everyday life. Unfortunately, these tasks must be self-managed by the individual and supervised by a healthcare professional. El-Gayar *et al.* (2013) defined Self-management as a set of functions that an individual must do to live well and deal with the associated chronic conditions or complications of an illness, noting also that these tasks can have an associated mental and emotional, and physical effect on an individual.

The diabetes self-management process often comes with the following challenges. First, high cost of devices, proper treatment plans, changes in lifestyle, absence of resources for education, and lack of adherence to treatment plans (Brown and Bussell, 2011, Buysman *et al.*, 2017) set a high barrier to constant monitoring and control of sugar level. Second, according to Bailey *et al.* (2016), there are various factors to consider and more than one way to measure and achieve reasonable glycaemic control. Finally, the self-management process requires a great deal of data acquisition, storage, and analysis, according to El-Gayar *et al.* (2013), which can be expensive and demand a high learning curve despite the advances in care and support monitoring tools and technology that helps with these processes.

Early screening aid preventive care according to the guidelines set by WHO. The US Preventive Task Force (1996) acknowledged that preventive care in line with set standard guidelines is critical in preventing diseases and avoiding future complications among children. Preventive care also aligns with the American Diabetes Association (ADA) recommendation for detecting Type 1, 2 Diabetes (T2D) through screening. However, attaining preventive care through screening by medical institutions has a lot of barriers such as physician time constraints, lack of knowledge about screening, basic management for diabetes capacity, lack of education, and poor communication with patients and families (Lee *et al.*, 2014).

2.3   Solution Objectives

This study endeavours to investigate the development of an intelligent automation process-based unobtrusive system to screen, identify, and detect the risk of diabetes in a patient at an early stage.

To fully understand the gaps and the value of intelligent automation, we will begin our study by first reviewing the existing tools, techniques, and technologies that can help screen, identify, and detect the risk of diabetes at an early stage.

We aim to investigate the inherent challenges involved in developing and deploying an unobtrusive system using intelligent automation bots. The research and its outcome potentially can encourage developers, data scientists, and automation developers to build Artificial Intelligence (AI) and Machine Learning (ML) models and integrate with an unobtrusive automation process.

The primary goal of this study is to develop an unobtrusive system using an automation prototype of intelligent software bots that can assist the doctors in the extraction of information from different devices and make a smart and helpful diagnosis and prediction of the likelihood of diabetes in a patient. Furthermore, these bots can safely be deployed as a forerunner to help doctors know the expectation before and during a patient interaction.

Intelligent automation can connect with other systems and applications in use in a typical New Zealand Medical institution and use Machine learning models to predict and accurately diagnose the possible illness before and during contact with a medical professional.

The automation software bots can

- Serve as a front-line defence for doctors to get an understanding of a patient's illness. As a result, it can potentially protect a doctor from highly infectious diseases
- The bots can help reduce the patient-doctor visitation time, thereby providing more access to vital medical resources
- Reduces the risks of error in diagnosis. The intelligent bots will assist the doctor by making recommendations that otherwise might have been overlooked.

The solution, when fully implemented, can save lives, provide access to medical facilities, and reduce errors of diagnosis,

In summary, the objective of the study will be to

- Review the tools, techniques, and technology that can help screen, identify, and detect the risk of diabetes at an early stage.
- Evaluate the use of intelligent automation within the health system in detecting the risk of diabetes.
- Study and evaluate the integration of Machine learning models with automation such as robotic process automation.
- Build an unobtrusive system using an intelligent automation robot connecting to hospital systems, applications, sensors, and devices.
- To understand possible issues and challenges of implementing an intelligent automation process in an NZ medical institution.
- To give an understanding of the motivation of implementing an RPA process in a hospital.
- For the implementation of a generic IPA prototype that can adopt and use ML models for predicting diseases.
- Build an initial framework and conceptual model RPA implementation.
- Add knowledge to the existing body of research.

Given the above, we hope to answer the following questions

- What tools, techniques, and technologies are currently available to help screen, identify, and detect the risk of diabetes at an early stage? Refer to section 3.1 for the answer to this question.
- What are the gaps in the current techniques and technologies available in screening for the risk of diabetes?
- Is it possible for automation to integrate with ML models and accurately diagnose diseases?
- What are the benefits of implementing an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the challenges and barriers to developing and implementing an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the required features and enhancement of an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the limitations of an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- How usable is Intelligent process automation-based unobtrusive system for determining the risk of diabetes?

2.4 Scope of study

This study intends to investigate the value that IPA robots provide to a medical doctor. The scope of the study will not cover Artificial intelligence and Machine learning techniques but rather focus on the integration between RPA and

Machine Learning. Furthermore, it will attempt to use existing ML models to assist the medical doctor in caring for his patient.

2.5 Research Contributions

This study aims to understand the interaction between Artificial Intelligence, Machine learning, and automation and their value to the health sector. In addition, we shall study the feasibility of implementing an unobtrusive system using intelligent process automation bots to guide medical practitioners in diagnosing diseases.

In doing this, we hope to contribute to the growing global research on RPA. In addition, the research outcome serves as a basis for predicting types of diseases.

Contributions of the thesis are as follows:

- Provide insights and information on how intelligent automation can be utilized within medical institutions.
- Identify the best way to implement intelligent automation to assist doctors.
- Identify the knowledge and tools that can be used to assist patients.
- This will show the feasibility of implementing intelligent automation in a medical facility.
- The research will create a software robot that can predict two or more diagnoses based on the data that have been fed into the system or extracted from sensors and devices.

3 Literature Review

This section reviews the literature that is related to this research and is in two parts. In the first part, we searched and selected relevant literature for studying the various existing tools and technologies for screening and detecting the risk of diabetes. The second part attempts to provide a deep understanding of RPA, justification, issues, benefits, perceived value, and limitations. Finally, we concluded with a discussion on intelligent process automation and its potential in filling the gaps found in the current study and state of RPA.

In the conclusion of the literature review, we discuss the state of the research, overall gaps and establish the conceptual framework.

3.1 Review of Tools for Early Detection and Screening of Diabetes

The following paragraphs present the steps adopted in our strategy to search and select relevant literature to review various tools and technologies.

First, we used the SLR methods provided by Chomutare *et al.* (2011), who observed that the research-based literature provides adequate history, justification, and applications while market-based tools offer the maturity and overall features of the applications. Additionally, the literature-based applications compare the functionality with the recommendations in clinical guidelines.

Next, we searched for studies on diabetes detection and screening tools, filtering out research papers not written in English. We used the following search keywords. The "+" in the list below refers to "and"

- "Automation" + "diabetes"

- management of diabetes "experience with automation"

- automation + diabetes +technology + computerization

- diabetes (or insulin or blood glucose) + self-management application (+ Mobile + PDA or Smartphone)

- Diabetes technology, Glucose sensors, Connected care, Computer decision support, Insulin pumps, Insulin therapy

In line with our objective early detection of the risk of diabetes, we begin by summarizing the list of requirements that must be satisfied by the tools and technologies under review. The requirements include self-monitoring (by capturing weight, insulin levels, blood pressure), alerts and reminders, integration with a Personal Health Record system (PHR), communication, and a decision support system for screening for diabetes. As suggested by Huang, Soljak, Boehm, and Car (2018), numerous diabetes applications and tools technology are available both commercially and understudy that meet these requirements.

Next, we proceed to classify and discuss the various tools and technologies. Ghosh *et al.* (2020) classified blood glucose estimation and measurement as direct and indirect based on the patient's level of involvement and participation. They defined the direct method as technologies that enable the determination of diabetes by taking blood samples with the awareness of the patient and indirect as a non-invasive method of screening for diabetes when the patient is unaware. This non-invasive nature was also implicitly referred to as unobtrusive in Anand *et al.* (2004)'s study. However, for ease of review, we have classified the technologies that can help detect and screen for the risk of diabetes as follows: Continuous Glucose Monitoring Systems (CGMS), Flash Glucose Monitoring System (FGM), and Unobtrusive Systems. The CGMS and FGMS are classified as direct methods, while the Unobtrusive is indirect.

3.1.1 Direct Method Systems

3.1.1.1 Continuous Glucose Monitoring Systems (CGMS)

A popular method for screening and early detection of diabetes is glucose monitoring. Glucose monitoring helps individuals to assess their glycaemic status and know their insulin requirements. Historically, glucose concentration was decided and evaluated by placing a piece of copper in the urine (Dovc and Battelino, 2020). These evolved into the Self-Monitoring of Blood Glucose (SMBG). SMBG works by detecting the glucose level from the blood through finger pricking. However, SMBG is considered inconvenient and unacceptable by diabetic patients (Lucisano *et al.*, 2016), evolving to a more portable handheld meter called the Continuous Glucose Monitoring (CGM) device, which can measure glucose levels directly from the blood. CGM systems have been available for 15 years (International Standard Organisation, 2003).

The CGM systems consist of disposable sensors used to measure the level of glucose in interstitial fluid (Dovc and Battelino, 2020, Fokkert *et al.*, 2017) at intervals and have numerous characteristics. First, they can transfer semi-continuous glucose Fokkert *et al.* (2017) data to a dedicated receiver or smartphone or cloud systems for further processing, analysis, and decision. Second, the shared data provides information on glucose levels fluctuations and variability. In addition, the CGM can exist in an implantable state where health care professionals embed the form sensor beneath patients' skin to read and transmit data to a body device (Dovc & Battelino, 2020).

Various studies highlight the usefulness of CGMS and improved glycaemic control because of its use (Langendam *et al.*, 2012, Poolsup *et al.*, 2013). Research has also shown the efficacy of CGM in reducing HBA1c and avoiding hypoglycaemia (Juvenile Research Group, 2008). In addition, Dovc and Battelino (2020) note that the CGMS has been successfully used in pregnancy complicated by Type 1 Diabetes (T1D), leading to savings worth millions of US dollars. As endorsed by the American Diabetes Association (2019), health care professionals have used it as a standard of care for people with T1D.

Besides the high prediction accuracy (Bailey *et al.*, 2018) of the CGM devices, there are other important features of the CGM such as the ease of use, miniaturization, data management, and a secure connection with different applications and data. First, connecting to other devices is an important feature that allows the device to provide add-on features such as decision support, notification, and reminders to individuals and healthcare professionals. Dovc and Battelino (2020) compared a few CGM products such as G6, Guardian Sensor 3, Eversense, and Freestyle libre/libre, two manufactured by Dexcom and Medtronics Senseonics, and Abbott, respectively. Out of the four devices, only Eversense is embedded beneath the skin by healthcare professionals.

In addition, the G6, Guardian Sensor 6, and Eversense have claims, trends, or alerts with some data sharing capabilities (Bailey *et al.*, 2018; Dovc & Battelino, 2020). The data-sharing features allow vendors to develop apps that can extend the features of the CGM devices. For example, Bailey *et al.* (2018) list mobile phone apps and software integrating CGM to provide and display glucose data. Also, Dexcom has a G5mobile phone, Medtronic has a Guardian connect app, Abbot has a libre link and libre linkup software. Bailey *et al.* (2018) further note that these mobile apps allow for the data sharing, connectivity and provide other experience that allows the increase in the safety of Seniors who are either incapable of self-management or support.

However, the device comes with its limitations. CGMS requires frequent calibration of the system, about twice daily to allow for a reliable "correlation" (Fokkert *et al.*, 2017) between interstitial and capillary glucose results. Secher *et al.* (2013) and Murphy *et al.* (2008) argued that there are limited benefits and mixed outcomes for pregnant women with diabetes. They provided a list of barriers that include skin limitations, frequent alarm notifications, and cost, and inconsistencies between sensor values. In his study, Feig et al. (2017) documents about 80% expressing frustrations, with 48% experiencing skin irritations. Most of these devices have been less intuitive and not particularly user-friendly and will require the help of professionals to set up and use. Deriving the maximum benefits of the CGM and CGM Extensions is dependent mainly on appropriate usage. Integrating an Electronic Medical Record (EMR) or Personal Health System (PHR) system or sharing data with a qualified healthcare professional is vital. Some of the CGM devices reviewed by Bailey *et al.* did not show any visible integration with these systems. The chance of preventing diabetes is significantly reduced if the data is not thoroughly analysed by a healthcare professional.

The frequent calibration of the CGM, among other limitations, was the reason for introducing the Flash Glucose Monitoring (FGM) System. Abbott introduced the Freestyle Libre, a Flash Glucose Monitoring system, into the market in 2014 (Heinemann and Freckmann, 2015). At the time of this study, they were the only manufacturer of the system. According to Fokkert *et al.* (2017), FGM systems are compact and lightweight and do not require frequent calibration by CGMs, only a factory calibration. Heinemann and Freckmann (2015) further confirm that calibration frequency is a significant difference between the FGM and CGM is calibration. FGM systems also measure interstitial glucose using disposable electronics and subcutaneous sensors attached to the skin using a button look-alike to hold it firmly in position. They can measure glucose every minute for 14 days. Afterward, the sensor scans and displays its output on a screen to show trends.

The FGM systems are a vital substitute for individuals who do not want the painful finger pricking associated with Self-Monitoring Glucose System (SMBG) or who do not want to be bothered with the frequent alarm notification and calibrations from CGMs. Scott *et al.* (2018) report the device's high accuracy and that it was not affected by parameters such as type of diabetes, pregnancy sage, age, or BMI, and the system is easy to use and can provide up to 14 days of glucose data. Furthermore, according to Heinemann and Freckmann (2015), the FGM devices surpass the Conventional blood group self-monitoring in the following ways.

- "Intermittent capillary sampling only provides a snapshot of glucose concentrations" (Heinemann & Freckmann, 2015).
- According to international standards (Fokkert et al., 2017), Accuracy is +/- 15% for glucose levels greater than or equal to 100mg/dl and +/- 15 mg/dl for glucose levels less than 100mg/dl.
- Scott *et al.* (2018) described the accuracy of the Freestyle Libre System as depending on data such as age, BMI, insulin usage, pregnancy stage, and type of diabetes.
- BG self-monitoring might take a few minutes while the FGM can scan and read results within seconds. But, according to their study, this information is enough to recommend its usage in pregnant women to support and optimize their glycemic control.
- Conventional BG monitoring is more expensive than FGM at an average of 5-8 tests per day.

Despite its benefits and applications for detecting the glucose status of individuals, the FGMS has some limitations. In a study carried out by Scott *et al.* (2018), they found out that 7% of the participants reported associated symptoms such as bleeding, bruising, erythema, itching, and pain, while Fokkert *et al.* (2017) note limitations such as physiological lag time, sensitivity to local fluctuations. Comprehensive education is also essential and plays a massive role in the adoption (Al Hayek *et al.*, 2017, Bruttomesso *et al.*, 2019). Adolfsson *et al.* (2018) see the less frequent factory calibration as a limitation as patients cannot recalibrate when glucose values do not match confirmed blood glucose test results. They also argued that the 8-hour monitoring trend might make the system easy to use but offers a potentially dangerous limitation to patients at risk of hypoglycaemia.

3.1.2 Unobtrusive Systems

There are not a few justifications for the need for unobtrusive systems. Firstly, limitations such as frequent calibration, alarm notifications, costs, sensor value inconsistencies, skin irritation, intensive education associated with invasive methods, and direct systems like Glucose monitoring have made them very popular. Secondly, an increasing need for further analysis by a healthcare professional and integration with an EMR system. Lastly, the rising importance and popularity of preventive health care where healthcare providers prioritize understanding the risk profile of patients to eliminate future interventions. An ideal glucose monitoring system would be unobtrusive, "not attached to the skin, retain stable long-term calibration, and require minimal maintenance, if any, by the user" (Lucisano *et al.*, 2016).

According to the US Preventive Services Task Force, early analysis and screening for diabetes prevent unnecessary interventions based on established guidelines and technological tools that patients can use and comply with set guidelines (Carroll *et al.*, 2011).

Carroll *et al.* (2011) discussed just-in-time information delivery and defined it as screening and receiving notifications during the patient-physician visits while the physician is taking notes. Although Preventive systems are increasingly

becoming popular and ubiquitous, we shall limit the scope of discussions to the Child Health Improvement through Computer Automation (CHICA) system.

3.1.2.1 Overview of CHICA System

Anand *et al.* (2004) described the CHICA system as a client-server architecture system, while Hannon *et al.* (2017) explains that the system is tightly integrated with an electronic medical record and uses a pre-screener form for eliciting information from patients. The pre-screener form can be accessed on basic mobile devices (Hannon *et al.*, 2017) and captures the family history, race, ethnicity, and an assessment form for physicians. Subsequently, Optical Character (OCR) component scans and extracts information from the forms.

It contains a module that applies pre-defined logic using Ardern MLM Rule-based parsing processor to analyse captured data and decision support while ensuring compliance with the general standard practice in a paediatric clinic (Carroll *et al.*, 2013; Carroll *et al.*, 2011). A tightly coupled integration with an Electronic Medical Record (EMR) provides the setups and configuration of diagnostic codes, orders, prescriptions, and laboratory data from an integrated and centralized portal (Biondich and Grannis, 2004). Integration with other systems provides the CHICA system with a feature extension that allows the sending of information to the laboratory for testing, sends out a notification for follow-up appointments, and generates reminder phone calls for an appointment. It also makes the referral and follow-up calls based on glucose levels.

The CHICA system has many applications and benefits. For example, Hannon *et al.* (2017) study showed that the application of CHICA automation increased the screening rates of diabetes four times among youths with a BMI above 85th percentile and two or more risk factors according to the recommended ADA guidelines. In addition, the increase in follow-up attendance is a result of the automaiton.

However, the tight integration of the system with the Indiana University Health primary health care portal and application is a significant limitation for the CHICA system. Although as quickly noted by Hannon *et al.* (2017), there is ongoing work to redevelop CHICA as a web service to provide more availability and widespread usage.

3.2 Robotic Process Automation (RPA) Overview

3.2.1 Introduction

Our literature review in this section will start with definitions and descriptions of RPA. Ratia *et al.* (2018) described RPA as an automation tool that relied on algorithms transformed into software and used to automate tasks usually performed by humans (Lu *et al.*, 2018, Willcocks *et al.*, 2015a, Willcocks *et al.*, 2015b, Lacity *et al.*, 2015). RPA can also be defined as the combined use of method system, software, hardware for automating traditional processes in an organisation (Bataller *et al.*, 2017, Fernandez and Aman, 2018). IEEE Corporate Advisory Group (2017, p11) defines RPA as the use of a "preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management" while Cooper *et al.* (2019) define RPA as the automation of tasks that are repetitive using software programs. Lastly, Agostinelli *et al.* (2020) described RPA as a new automation technology that creates robots capable of mimicking human actions that are highly repetitive simply by using the application interface. Bellman and Göransson (2019) defined RPA as using computer programs to automate business process rules and, in the process, create robots. One should note that the robots are just software running on the computer and not physical robot-like assembly-line robots.

Ratia *et al.* (2018) further explain that RPA as an automation tool that relies on defined as the adoption of software to replace and carry out human-related tasks in an organization (Lu *et al.*, 2018, Willcocks *et al.*, 2015a, Willcocks *et al.*, 2015b, Lacity *et al.*, 2015). Ratia *et al.* (2018) showed a rising influence of the use of RPA among different top executives in their organization in Finland. The top executives are interested in this technology because of its usefulness in automating heavy, manual, costly, and labour-intensive tasks. Organizations in top nations in the world have also shown a rising interest in RPA. In Europe, 54% of firms plan to implement 10 RPA processes by 2020 as revealed by the Information Research Group

RPA is a tool used to create software robots capable of automating tasks that have been assigned to humans. These software robots can perform simple tasks such as navigate to an application such as excel, copy, or scrape data, process the information, and paste it into another application. The software robots are also known as digital workers. The software robot is just another human employee that is performing routine tasks. Aguirre and Rodriguez (2017) surmise users build these robots by connecting activities to form a sequence that conforms and satisfies a set of business rules. It can automatically create this set of activities by recording the actions of humans or tracing the execution of humans while performing a task (Moffitt *et al.*, 2018). Most RPA software provides a simple recorder that can record the subject matter expert carrying out their regular tasks. There has been a rising debate on whether machines are beginning to take over jobs meant for humans. However, from these descriptions, robots are not meant to replace humans.

Recent trends such as the rising cost of professionals, a considerable volume of repetitive tasks, and data availability have shown the need for automation (Ratia *et al.*, 2018). In addition, a robot can minimize the risk to medical personnel in the discharge of their duties. Therefore, most organizations will avoid such dangers by employing robotics, especially in the health care sector.

In a research conducted by Ratia *et al.*(2018) to investigate the potential value of RPA in the private health care sector and the capability of an organization to adopt the use of RPA, they found out the eventual justification is to be able to create value for organizations, stakeholders and companies. Turnaround times, cost-effectiveness, and operational excellence (Hofmann et al., 2020) are part of organizations' motivations to use software robots.

3.2.2 Characteristics of RPA

One should note that it is necessary to view automation characteristics from both the technical and process perspectives. These two major perspectives usually complement each other (Ratia *et al.*, 2018). Ratia *et al.* argue that the ease of integration and scalability are significant features of an RPA process. First is upgradability which is the capability of the flow chart updated to the current state of system execution. Second is resiliency which is the capability of robots to learn and deal with new behaviour, thirdly is scalability which is the capability of the software bots to auto-scale based on volumes and lastly, auditability (Agostinelli *et al.*, 2020). These are some of the essential features an RPA process should have.

RPA allows medical personnel such as clinicians, doctors, and nurses to focus on value-based tasks and patient dealings and outsourcing the traditional manual work to the RPA software bots. Ratia *et al.* (2018) further found that RPA relies on a well-defined process with few errors. Errors in the traditional method can be cascaded efficiently out as output—garbage in and Garbage out. In addition, the robot can efficiently spill out errors that do already exist in the manual process (Romao *et al.*, 2019).

Around the world, RPA processes are deployed by professionals in highly repetitive situations (Romao *et al.*, 2019), human-intensive labour, and high cost (Lu *et al.*, 2018), thereby creating software robots that act like humans and performs tasks and activities by imitating humans (Lacity *et al.*, 2015). These robots can help perform inherently repetitive tasks, and some of the general cases include periodic reporting, data entry, generation of mass emails, archiving, and conversion of data (Hofmann *et al.*, 2020).

3.2.3 RPA Tools

The rising influence of the RPA has seen a rise in the number of firms and technologies providing process automation. Many RPA vendors have started to emerge (van der Aalst *et al.*, 2018) in the past few years following the rise in the demand for digital workers (Bellman and Göransson, 2019). Hofmann *et al.* (2020) used freely available tools for their study. He noted the presence of several tools in the market classified based on functionalities, regions, and players in the commercial markets. Popular tools for producing software robots include UiPath, workfusion, blue prisms, automation anywhere, and kryonsystems. Cooper *et al.* (2019) found that organizations involved in his research purchased licenses from Automation Anywhere, Uipath, Win automation Blue Prism for automation. There are also free license tools that are available for use. Agostinelli *et al.* (2020) identified the following vendors that offer their tools without the need for paying any license automation anywhere, assist edge, Giant, Kryon, Rapise, Tagui, Uipath, Visual cron, Winautomation, and work fusion. Organizations deploy RPA into their environment by buying licenses

from consultants and building the bots internally. External consultants are engaged to help deploy service automation or consume a cloud service.

While analysing the RPA tools, Hofmann *et al.* (2020) identified and classified the tools into three major areas: data-related, system integration, and process enhancement. These major areas consist of 8 functional characteristics. The eight functional areas include data related: transfer and analysis of data, file processing, system integration, application, service, and input device, and while process enhancement tools comprise of the tools that orchestrate flow such as loops, branches, and triggers. These features cut across the tools. Agostinelli *et al.* (2020) were able to show, using his classification framework, that UiPath and Automation Anywhere are some of the top RPA tools. UiPath is a client-server architecture with low GUI-based coding, a powerful recorder, and a 2-star rating in log quality. Automation anywhere was found to have a 3 star in their log quality. Without the need to write code like in traditional software systems such as pythons and c#, the RPA tools provide a graphical user interface that consists of series of drag and drop to create software robots. Although some of the tools require you to write code snippets, those bots can be built without writing a single line of code.

There have been other automation tools before RPA. For instance, RPA is direct evolution from the Straight-through processing (STP) (van der Aalst *et al.*, 2018) in the nineties. According to Bellman and Göransson (2019), the major difference is that STP required a change to the underlying systems, unlike RPA. One of the distinguishing features of the RPA tools have from the previous tools is the considerable cost of changing software packages such as Enterprise resource planning software (ERP) like SAP. That is all-encompassing and has its internal control systems (Bellman and Göransson, 2019). This feature is one of the commercial selling points of UiPath, an RPA vendor, who offer components to help interact with SAP, one of the largest ERP software in the world.

Many RPA vendors have started to emerge (van der Aalst *et al.*, 2018) in the past few years following the rise in the demand for digital workers (Bellman and Göransson, 2019). Without the need to write code like in traditional software systems such as pythons and C#, the RPA tools provide a graphical user interface that consists of series of drag and drop to create software robots. Although some of the tools require you to write code snippets, automation specialists often build the bots without writing a single line of code.

3.2.4 Categorization and classification of robots

There are different ways to distinguish and categorize between the robots. Hofmann *et al.* (2020) and (Lacity and Willcocks, 2017) categorize software robots based on their inputs, structured and unstructured software. Others classify based on if the bot is rule-based, knowledge-based, and learning-based. It is important to note the difference between rule-based, knowledge-based, and learning-based. Rule-based seek to apply predefined rules (Aguirre and Rodriguez, 2017) while knowledge-based recursively search systems and presents information to its users. Learning-based robots use machine learning for learning from data. Most RPA projects have focused on rule-based software robots (Aguirre and Rodriguez, 2017, Asatiani and Penttinen, 2016, Lacity and Willcocks, 2017). Software robots are classified by the extent of automation and human involvement to be attended or unattended (Hofmann *et al.*, 2020).

Hofmann *et al.* (2020) further distinguish between RPA and Robotic Desktop Automation (RDP). While RDP is concerned with automating unattended processes, RDA is involved with working in the front office and human activities in an attended way (Seasongood, 2016, Llewellyn Evans, 2017). One should note that Hofmann's classification is now called unattended and attended bot. Unattended bots are robots that run in the background or on a virtual desktop and can be controlled or monitored on an orchestrating platform while an attended bot runs side by side with the user. The operations of an attended bot are visible to the user. Agostinelli *et al.* (2020) propose a classification framework that comprises the software architecture: standalone or client based, Coding factors: the level of coding, types of recording available, the ability of tools to auto adapt and understand user routines, types of automation which can be unattended, attended and hybrid and the quality of logs produced by the software robots. The log qualities are measured using (Van der Aalst et. Al 2012).

3.2.5   How RPA works?

Early RPA started with simple conditional statements. It has since evolved to have a drag and drop interface where IT professionals use simple drag and drop to build complex automation. The software robots created by the RPA processes interact with applications with different layouts and interfaces via the front end, often mimicking how a human will interact with the same app (Bygstad and Iden, 2017, van der Aalst *et al.*, 2018).

Although RPA robots can work with different interfaces like databases and APIs (Hofmann et al., 2020), they exist mainly in the presentation layer. It does not impact the underlying structure of the application (Lacity and Willcocks, 2015, Lacity and Willcocks, 2017). RPA identifies elements on the application interface using selectors. However, the underlying infrastructure or components must be robust, stable enough to allow for the identification of these selectors (Mendling *et al.*, 2018, Penttinen *et al.*, 2018).

RPA is lightweight, secured, and does not affect the infrastructure or data structure of the hosting app. RPA development environment comprises a high, intuitive, and easy-to-use interface for building robots. The development process involves connecting different activities\elements and tools in an orchestrator (Hofmann *et al.*, 2020) while ensuring compliance with business rules (Aguirre and Rodriguez, 2017, Lacity and Willcocks, 2017). In contrast to the standard software development environment, it uses and can make new changes or create processes by just moving activities around in an orchestrator manner.

Using a computer application interface (Cooper et al., 2019), RPA can perform complex computer programming tasks by accepting and providing an output. It does this without the need for modification of application structure or architecture or infrastructure. Furthermore, the imperfection of computer systems leads to the need for RPA. Other justifications for RPA include the difficulty, high cost associated with making system changes. Cooper *et al.* (2019) found out in their research that applications of RPA in cash orders, HR, Supply Chain, Finance, and basic general accounting. According to the firms involved in the study, this results in cost savings ranging from 10% to 70%.

IT professionals commonly use automation for extracting from and save databases, email extraction, and copy documents (Lacity *et al.*, 2015, Willcocks *et al.*, 2015b). Over the years, there has been another form of technology such as chatbots that accepts voice and keyboard (Hill et al., 2015), the early form of RPA used in the financial industry to track transactions by automating repetitive tasks. Traditional screen scraping technology has the feature for extracting information directly from interfaces. Most organizations have started to implement chatbots (Romao *et al.*, 2019) on their websites. RPA combines these technologies to carry out human actions. It uses an approach that works without redesigning interfaces (Agostinelli *et al.*, 2020). (Agostinelli *et al.*) also noted with the integration of artificial intelligence, RPA can evolve to deal with non-standard and standard tasks.

Romao *et al.* (2019) defined RPA as a tool to automate manual, rule-based, and highly repetitive tasks. It replaces humans and RPA tasks ranging from data entry, processing standard requests, or customer service queries. A chatbot is also a tool in the RPA space that can be deployed on a website and typically act like a human in processing standard queries from customer (Romao *et al.*, 2019). RPA complements other business applications and rarely replaces them. For example, they can scrape information from the screens, integrate data from different sources and store it in other locations or fill forms on screens. Lastly, RPA, together with Artificial intelligence and Machine Learning, can also be used to automate tasks requiring human cognition (Romao *et al.*, 2019, Willcocks *et al.*, 2015a).

3.2.6   Applications of RPA

The past few years have seen RPA applied to different sectors, including procurement and warehousing, data mapping, quantity management, contract management, and supplier relationship management (Hofmann *et al.*, 2020). Although, in all these areas, the strategic approach for most organisations is to ensure the ongoing management of software robots successfully and sustainably (Hofmann *et al.*, 2020). One should note that the list provided by Hofmann *et al.* (2020) does not include a doctor-patient relationship interaction in the healthcare system.

Significant time savings, complexity, return on investment (ROI), several available time-consuming tasks are necessary factors making RPA a potential for its application in taxation services. Hofmann *et al.*'s research the application of RPA to several functions ranging from collecting tax information from clients, aggregating and reviewing information from the trial balance, preparing their tax returns, and in Advisory services. Other uses of RPA

include helping clients automate those manual tasks, thereby allowing clients to focus on their core business functions. Lastly, RPA has found applications in auditing, assurance, and compliance.

The financial industry has been one of the earliest and most aggressive adopters primarily due to the cost and presence of many legacy applications combined with regulatory challenges (Bellman and Göransson, 2019). As a result, there are applications of RPA in capital markets, processing requests, reporting transactions, correcting data, increased accuracy, aggregating data for analytics and debit balance processing, and much more in the financial industry.

3.2.7 Candidate Process For RPA

Justification and suitability of a process ripe for RPA are dependent on if the traditional process follows a rule-based structure and integrates more than one system (Aguirre and Rodriguez, 2017, Asatiani and Penttinen, 2016, Penttinen *et al.*, 2018). There are two major scenarios or conditions that a process must fulfil to be a candidate for robotic process automation. First, the business process must be structured, have digital inputs, and secondly, be rules-based (Cooper *et al.*, 2019). Leopold *et al.* (2018) acknowledge that the essential requirement for RPA is for a business process that requires little or no mental engagement. According to Fung (2014), tasks that do not involve too much thinking or are subject to human judgments are highly repetitive with huge volume and need to integrate with diverse systems are said to be ready for RPA. Finally, standardized tasks with limited errors provide potential opportunities for automation.

3.2.8 Limitations of RPA

Although there are several benefits and values associated with deploying RPA to an organization, one should note that an inefficient and error-prone pre-defined process can easily lead to automation that ends up with inadequate process steps and cause an increase in overall cost (Hofmann *et al.*, 2020). Using the six sigma methodology, Linderman *et al.* (2003) determined an acceptable maximum error rate for a bot to be effective. However, Agostinelli *et al.* (2020) identified four challenges associated with the available tools, including improper logging leading to a series of mixed log sequences belonging to several other routines. Secondly, most RPA tools do not allow for automation of the detection of routines that are a good candidate for automation. Thirdly, there is no automated way of identifying processes for automation as candidate routines are usually determined from interviews, studying process traditional routines, and observation of workers. Lastly, there is a lack of a testing environment for most RPA based solutions. Testing is usually done through a series of trial-and-error adjustments are made to fix the errors.

Although the previous implementation of RPA has heavily relied on structured inputs (Romao *et al.*, 2019), there is an increasing capability of RPA to handle and process unstructured inputs such as huge documents, text, and voice. In addition, there is a rising demand for traditional RPA to be more intelligent and think like humans. Due to the lack of auto-discovery of routines, RPA relies heavily on the Subject Matter Expert, which increases the cost of development.

Despite the huge number of potential values derived from RPA, it impacts the workforce and can lead to a low employment rate. First, it can change the roles of employees (Bellman and Göransson, 2019). For example, machines can replace 47 % of total jobs in the U.S in a few years (Frey and Osborne, 2013). Furthermore, according to Arntz, Gregory, and Zierahn (2016), there is a possibility that machines will replace 9 % of OECD jobs. These statistics show that the massive potential of RPA can result in significant job loss for the economy.

Bellman and Göransson (2019) quickly remind us that even though RPA tools can help reduce costs, they are usually not free and can lead to a potential net loss. In addition, RPA implementation can often lead to underfunding, resistance to change, and compliance risk.

3.2.9 Intelligent Process Automation

There has been a rising global demand for RPA bots to do repetitive tasks and auto evolve and learn new behaviour like humans. Organizations want the bots to begin to think like humans when it comes to performing tasks or computing. The field of artificial intelligence and machine learning has seen a lot of advancement in recent years. This study does not attempt to do a deep dive on artificial intelligence and machine learning but rather focus on the integration between RPA and Machine learning resulting in Intelligent Process Automation (IPA), a concept or technology currently spreading globally. However, we will provide a preliminary review of Artificial Intelligence (AI).

Lacity *et al.* (2018) defined AI as a concept that makes computers have the same cognition as human beings. A significant part of human being cognition is the ability to learn from experience and have memory. Many researchers over the years have been studying these fields for a long time leading to a breakthrough that is due to the increased computational power and availability of data and data storage, cloud processing, and complex mathematical computation and algorithm (Bellman and Göransson, 2019).

There have been different technological applications and advances, such as cognitive analytics, virtual assistants, and artificial intelligence (AI). For instance, these technologies create personalized stories, identify future risks and display them to patients using Cognitive analysis. Virtual assistants also help answer questions and queries about patients' diagnoses, recovery times, and daily medication.

There are numerous benefits associated with the application of Artificial Intelligence. For example, AI can help simplify and streamline the admission process. From the admission to room allocation, diagnosis, and discharge of a patient, AI can help physicians and medical staff by providing customized guidelines and information to patients either directly or through virtual assistants, thereby eliminating repetitive processes and steps and allowing the patients time to read the instructions.

A more recent innovation in health informatics is the Clinical Decision System (CDS). According to Emanuele and Koetter (2007), these systems helps and assist medical practitioners in providing access to data, information and allows the doctors to make informed decisions. Although CDS has been deployed and adopted in hospitals, they have mostly been rule-based.

CDS works by the system connecting to an application such as the EHR and extract the patient Records. A rules-based engine connects to the EHR, performs some logic based on rules, and sends alerts and notifications to the relevant personnel. It is important to note that the rules are developed and captured from studying and understanding a subject matter expert.

A more recent technology is the use of intelligent automation. Intelligent automation allows the development of an automation system that thinks and learns like human beings, while a rule-based system cannot adjust or change by itself. Mohanty and Vyas (2018) noted that the greatest weakness of the RPA robots before now is the strict adherence to its program. As a result, the RPA robots require an IT professional to document and layout every possible instruction and code. However, there is a problem for the bots if it encounters new and unfamiliar information. This weakness is a significant justification for machines that can think.

Bellman *et al.* (2019) defined intelligence automation as the combination of AI and RPA to develop robots with the same cognitive experience as human beings. This field is a relatively new area as most RPA vendors are just beginning to integrate Machine learning into their RPA tools. Tools like UiPath have developed components that make it easy to consume ML models, extract data from different sources, and make predictions or learn from themselves. The combination of AI and RPA (Mohanty and Vyas, 2018) is Intelligent Process Automation (IPA). IPA has broadened the scope of available tasks for automation. While RPA is beneficial for the structured input and data, RPA can help sort the unstructured data that are not clean (Bellman and Göransson, 2019). It can also provide a level of decision-making capability to the bots. Although RPA is a starting point for an organization, the hallmark of success for an RPA automation is the evolution to IPA. Vendors have started introducing AI and ML in their tools.

One of the largest RPA software providers, Uipath, has seamlessly integrated with Artificial Intelligence third-party AI developers such as Google, IBM, and Microsoft to create components that allow you to build intelligent bots quickly.

3.3 Summary of Literature Review

In the first section of this review, we classified the different ways of detecting and screening glucose into a continuous glucose monitoring system, flash glucose monitoring system, and unobtrusive system. For each of the categories, we discussed the architectural differences, strengths, and limitations. Both FGM and CGM have limitations such as skin irritations, frequent alarm notifications, cost and inconsistencies between sensor values, and difficulty in learning to

use the devices. These limitations with FGMs and CGMs devices have made the Unobtrusive systems very popular. Our study was limited to the CHICA system for the unobtrusive system. The main benefits of the Unobtrusive system are the capability to assist in detecting and early prevention of diabetes, thereby potentially avoiding the hassles of self-management\care of diabetes and making required lifestyle changes.

The CHICA system also comes with limitations, such as tight integration with the institution's EMR and the manual method of completion of forms by patients and physicians. Moreover, our studies show that there could be improvements in areas such as data entry automation, decision support system, and flexibility to integrate and work with the various hospital systems. Apart from this, we believe that recent technological advances such as the highly fast-paced and scalable robotics process automation, artificial intelligence, and machine learning in the combined areas of automation and decision support can significantly improve the outcomes of the unobtrusive system.

There has been a lot of study on RPA, but there has not been a lot of far-reaching effort on intelligent automation. Also, there is not a lot of research focused on healthcare using RPA. One should note, Ratia *et al.* (2018) carried out their research on the impact of RPA in the health sector in Finland. In that instance, the methodology also involved using interest groups that were external to the medical institutions. As mentioned in their review, the qualitative approach adopted does not guarantee reliability and validity. However, there are some positives from the study, such as using Walter *et al.* (2001)'s functional-oriented value analysis to understand the value of RPA to an organization. Walter *et al.*, and Bellman *et al.*'s approach adopted the inductive and semi-structured approach in their respective study. Cooper *et al.* (2019) also adopted the semi-structured approach. Bellman and Göransson (2019) began with a case study deployed and used by participants in a bank. Cooper *et al.* (2019) also used participants from the top 4 accounting firms in their research.

In the second section of our literature review, we studied the different RPA tools currently commercially available and provided by a few vendors. There has been significant research using those tools. Agostinelli *et al.* (2020)'s research did a comparative study on the numerous tools available. The case study automated a purchase-to-pay process that runs on a sap application. The study successfully automated around 40,000 purchase orders using various tools. He further outlined the challenges and the limitations of RPA over the Business Process Model (BPM) instead of on the workers in an organization.

Cooper *et al.* (2019)'s approach provides a lot of insights on AI but unfortunately dwelled too much on the advantage of BPM over RPA. Instead, it sought ways to improve BPM using AI instead of showcasing the numerous benefits of RPA or otherwise considering the Intelligent Process Automation (IPA).

Hofmann *et al.* (2020) also noted that RPA is yet to develop to its full potential and that RPA is still in its early stages. Although predicted by some consultancies, RPA is just one step away from intelligent and cognitive automation. Finally, RPA has now evolved to have intelligent and cognitive automation capability. The future prediction of the RPA trend is that there will be the integration of cognitive automation into software robots. Based on these, software robots can evolve to complete new tasks. In addition, the learning from the robots will lead to a deeper understanding of the functional areas where they operate and provide an increase in value to stakeholders.

4 Research Methodology

4.1 Introduction

The purpose of this chapter is to discuss the methodology and tools that we adopted for this study. In addition, the methodology chapter will show how we addressed and answered our research questions.

The literature review discussed in the previous chapter systematic review research (SLR) guidelines and searched most of the popular journals limiting the results tied to studies that addressed the screening and detection of the risk of diabetes. We reviewed the various architecture, features, and limitations of the existing tools and technologies from our search results.

Using the literature review, we answered the question on the tools, techniques, and technologies currently available to help screen, identify and detect the risk of diabetes at an early stage. The review also allowed us to understand the gaps of the current techniques and technologies.

The objective of the second method was to determine the usability of an Unobtrusive system to detect the risk of diabetes in a patient. In addition, we hope that we can answer questions around the limitations, benefits, barriers, and challenges of implementing an unobtrusive system within a medical institution.

To study the importance, usability, challenges of the development of Intelligent Process automation integrated with a Machine Learning Model to predict the likelihood of diabetes in a patient and address the above research questions, we adopted the Design Science Research Methodology (DSRM).

4.2 Overview of the Design Science Research Model (DSRM)

We refer to Kuechler and Vaishnavi (2008) for a detailed Design Science Research Methodology history.

Design Science Research Methodology (DSRM) involves building socio-technical artefacts like software, processes, algorithms, or systems to solve a problem (Myers and Venable, 2014, Jayaraman *et al.*, 2020). DSRM involves using rigorous process steps to solve problems by design, develop, demonstrate, evaluate artifacts, eventually communicating the results and contributing to the research knowledge base (Peffers *et al.*, 2007). Peffers et al. (2006) noted that the artifacts might include constructs, models, and instantiations. Owen (1997)'s summarized the design research as follow

"*Knowledge is generated and accumulated through action. Doing something and judging the results is the general model ... the process is shown as a cycle in which knowledge is used [creatively] to construct (create) works, and works are evaluated to build knowledge.*" (p.38).
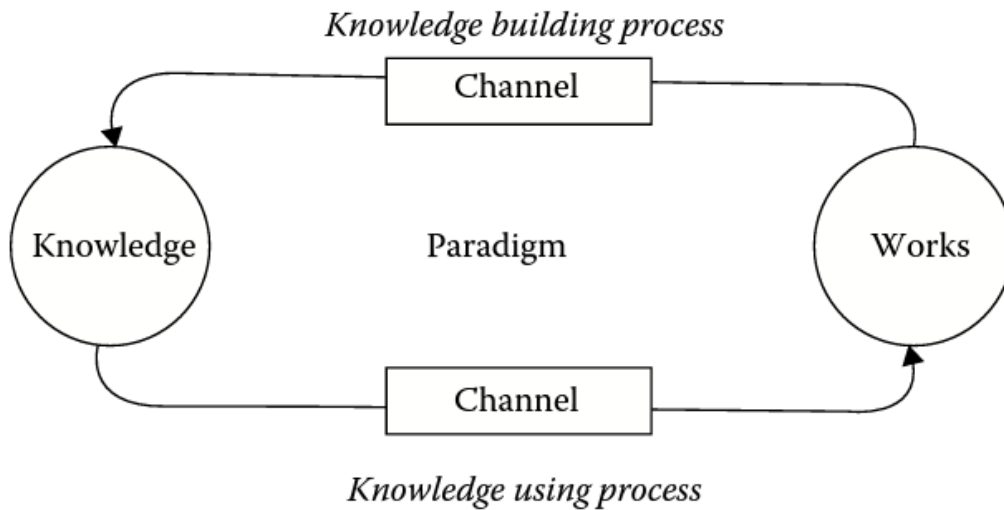
Figure 1 Diagram from Owen, C. (1997. showing an iterative process for generating and reusing knowledge

The diagram above is an iterative model proposed by Owen *et al.*, and shows how knowledge can be built and generated from works or actions through a process.

Researchers have often asked questions about the difference between design science research and routine design in computer science. Kuechler and Vaishnavi (2008) argue that the contribution of original knowledge and a low intellectual design risk distinguish between design science and routine design. The low intellectual risk is the presence of a degree of certainty on the feasibility of the design. In summary, routine design is simply the application of existing knowledge as a solution to a problem (Hevner *et al.*, 2004).

Although Hevner and Wickramasinghe (2018) noted that DSRM is helpful and prudent in situations where there is a need for innovative solutions, high user adoption, and satisfaction, there are still some drawbacks with the model.

Peffers *et al.* (2007) argued that the lack of a consistent and commonly accepted framework for DSRM is a significant contributor to the slow adoption of DS Research.

Ahmed and Sundaram (2011) suggests lack of a conceptual process and mental model for research presentation as reasons for the low adoption of design science in information systems

4.3   Previous Design Science Research (DSR) Methodology

Since Design Science was first introduced in Engineering by Hoffman *et al.* (2004), numerous design science research models have been used.

Peffers *et al.* (2007) introduced problem identification and motivation, the definition of solution objectives, design and development, demonstration, and communication in their model. Their objective was to contribute to the Information system research by providing an acceptable framework for DSR and a mental model for research presentation, evaluation, and communication.

Kuechler and Vaishnavi (2008) presented a model that included problem awareness, suggestion, development, evaluation, and conclusion.
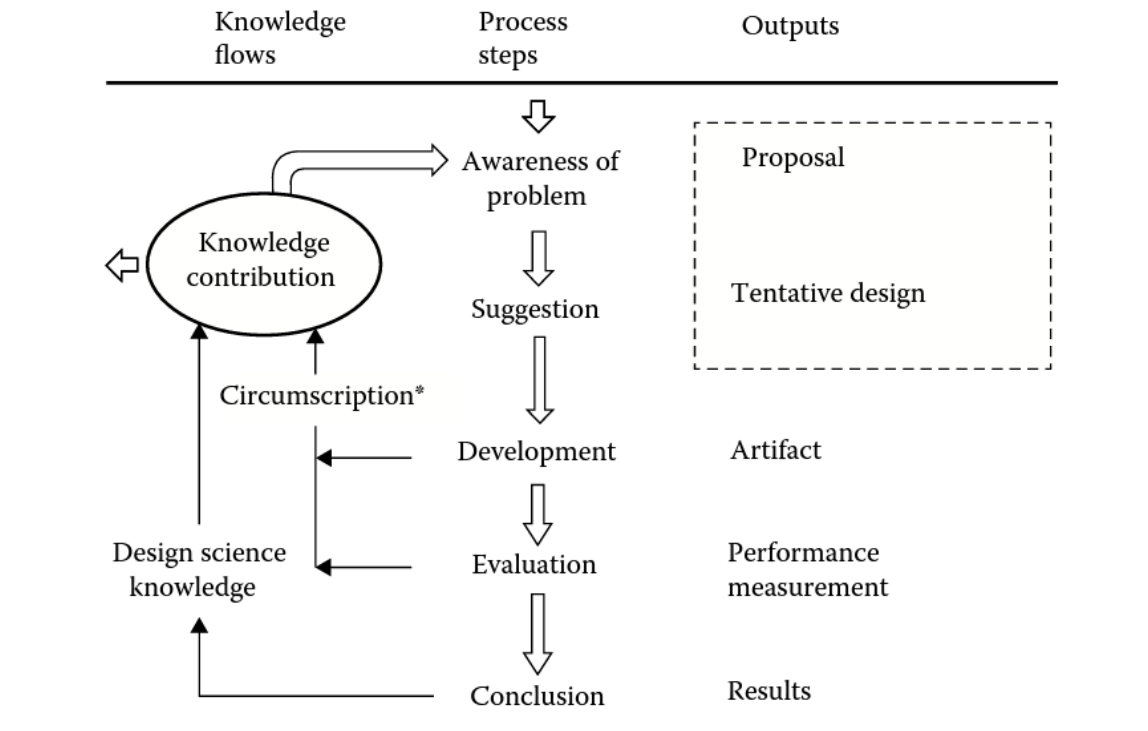
Figure 2 Kuechler and Vaishnavi (2008) model

Hevner *et al.* (2004) proposed a research framework that includes environment, Information science (IS) research, and knowledge base. The environment phase consists of activities centred around people, organizations, and technology and whose objective is to define the business needs and relevance of the study. The IS research consists of Information science activities for building and evaluating artifacts, while the knowledge base stores knowledge gained from the IS Research activities.

According to the proposed framework, they further categorize the problem identification, motivation, and solution objectives into an environmental group that provides the business needs or relevance of the research. At the same time, design and development, including evaluation activities, belong to the information science group.

Iterative loops are included between the environment and the knowledge base and allow for continuous updates of business needs with information derived from the knowledge base. There is also an iterative loop between the development and evaluation to refine the developed artefacts.

Peffers *et al.* (2007) suggested four ways to begin research under the DSRM: problem-centred initiation, objective-centred initiation, and design and development initiation. Purao (2002)'s model categorizes the output of design science according to their level of abstraction and type of knowledge created, which can be constructs, instantiations, models, theories.

Crow (2015) used the Vaishnavi's model because of its alignment to a Masters Level Research (Vaishnavi and Kuechler, 2015). However, while recognizing the similarities of the Vaishnavas and Peffers model, they rejected Peffer's model because of its difficulty operationalizing.

Kao *et al.* (2016) used a design research model that satisfies three objectives: consistency with prior literature established DS Research and DS Research presentation model, and evaluation.

4.4   Adopted Design Science Research Model

We applied the design science research methodology derived from the model adopted by Kao *et al.* (2016). The primary consideration for this selection was its consistency with existing literature, DS Research nominal process, and mental model outlined for DS research presentation and evaluation.

The process consists of six activities: problem identification, motivation, the definition of solution objectives, design, and development, demonstration, evaluation, and communication. Figure 3 depicts the phases adopted for our study.

We introduced an iterative approach between the development phase and the demonstration phase. This approach is consistent with agile principles that allow for the improvement of artefacts from design and development based on feedback collected from the Demonstration phase.

The following guidelines proposed by Gregor and Hevner (2013) were complied with

- Produce a visible artefact.
- Develop a technology-based method that is relevant to business problems- Problem reliance.
- Rigorously demonstrate the utility, quality, and efficiency of the design artefact through well-grounded evaluation methods.
- Provide transparent and verifiable contributions in the areas of design artefact, methodology.
- Rely on the rigorous method to the construction and evaluation of the artefact.
- Utilize available means to reach the desired end.

The problem identification, motivation, and solution objectives phases as related to this project have been discussed extensively in the previous chapters of this study. We will address the design, development, evaluation, and communication stages in the following sections of this chapter.
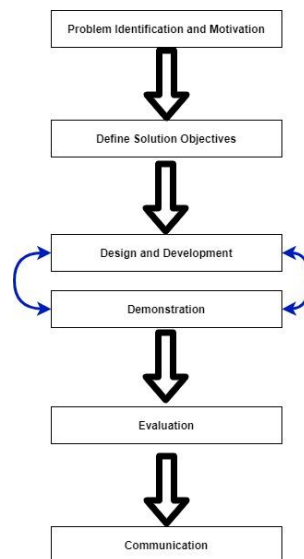

Figure 3 Modified DSRM model

4.5   Problem Centred Approach

A distinguishing feature of our model is the capability to start the research from any of the above phases. For example, a study can begin from one of the following: problem-centred initiation, objective-centred solution, design, development-centred initiation, client/context initiation.

Our research is a problem-centred initiation. We wanted to develop a better method to understand the feature requirements for automation that can assist medical practitioners within the medical industry. The literature review on the existing technologies for detecting the risk of diabetes and self-management of diabetes provided us with insights into the problems associated with the current tools and technologies and self-management of diabetes.

4.6 Problem Identification\Motivation

This phase defines the specific research problem and justifies the value of the solution. According to Ahmed and Sundaram (2011), the idea behind this phase is to provide an opportunity for future researchers to scrutinize the answer and accept the result. It also helps the researcher understand the reason associated with the research and the problem trying to solve. The identification or awareness of the problem may come from multiple sources, including industry trends and the output of a previous design science research study. As explained by Hevner *et al.* (2004) and supported by Kuechler and Vaishnavi (2008), the outcome of this phase may vary from a formal or informal proposal for new research consisting of the business needs an outline of the underlying problems. We have, in previous sections, discussed the problem and motivation behind this study.

4.7 Definition of Solution objectives

The objectives of the solution infer from the problem identification and definition. The objectives can be qualitative and quantitative and should support the solutions identified in the problem identification and motivation phase. As discussed previously in the "Aims and Solution Objectives" chapter, the objectives of the study are

- Review the tools, techniques, and technology that can help screen, identify, and detect the risk of diabetes at an early stage.
- Evaluate the use of intelligent automation within the health system in detecting the risk of diabetes.
- Study and evaluate the integration of Machine learning models with automation such as robotic process automation.
- Build an unobtrusive system using an intelligent automation robot connecting to hospital systems, applications, sensors, and devices.
- To understand possible issues and challenges of implementing an intelligent automation process in an NZ medical institution.
- To give an understanding of the motivation of implementing an RPA process in a hospital.
- For the implementation of a generic IPA prototype that can adopt and use ML models for predicting diseases.
- Build an initial framework and conceptual model RPA implementation.
- Add knowledge to the existing body of research.

4.8 Design and Development

Researchers create the artifact, constructs, models, methods, and instantiations in this phase. An artifact is a carefully designed outcome that can produce information contributing to the body of knowledge when studied. Consistent with Peffers *et al.* (2007)'s study, we extensively discussed the artifact's functionality, architecture, and description in the next section, Design and Development.

To be able to evaluate the automation, we designed and developed a prototype. The prototype, as seen below, consists of the following modules:
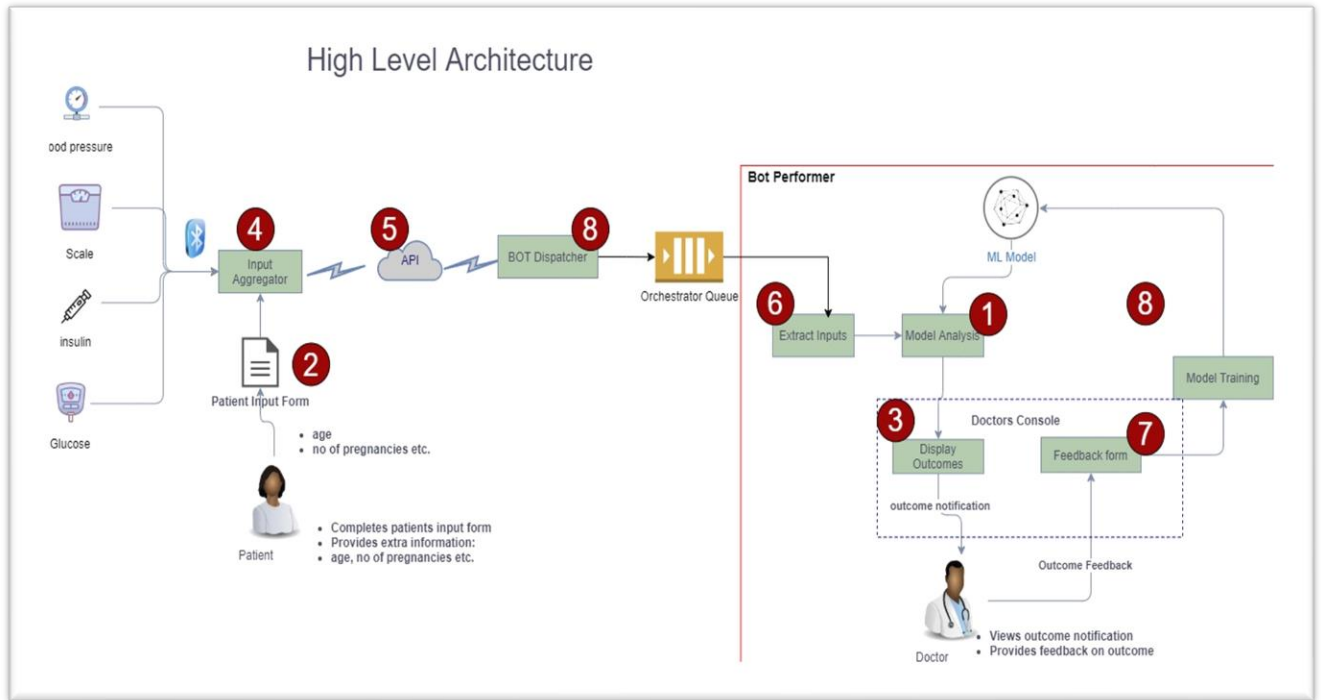
Figure 4 High-level architecture diagram of artefact

4.8.1 Connected Devices

The connected devices measure and extract the following values: Blood pressure, skin thickness, insulin, glucose, and body composition. In addition, it uses the following devices for measuring body vitals.

4.8.1.1 Blood Pressure Device

The unit of measurement of blood pressure used in the study is the mmHg, and for the project, the measurement device is Withings BPM connect. The "Withings BPM connect" is a Wi-Fi smart blood pressure monitor. This device consists of the available Advanced Programming Interface (API), Wi-Fi, and Bluetooth features that integrate the device with the Input aggregator. Furthermore, it provides data synchronization via Wi-Fi and Bluetooth.

In our study, the BPM connect was used to measure the diastolic blood pressure, and the unit of measurement is the mm Hg. The diastolic pressure is also referred to as the bottom number is the heart muscle in between beats. Diastolic pressure measures the force of blood against the artery walls as the heart releases, and the ventricles refill the heart with the blood. This force occurs when the heart is getting filled with blood.

4.8.1.2 Withings body scale

Body composition scales estimate the fat level in percentages, water, and muscle in the body using Bioelectrical Impedance Analysis (BIA) (Collier *et al.*, 2020). These scales use BIA to estimate percentages in the body by sending an electrical impulse through the body. Next, the resistance or impedance from these tissues is measured using a formula that incorporates a person's age, weight, height, and gender. Finally, the total body fat, muscle water, and bone density are estimated using these parameters.

A Study by Franco-Villoria *et al.* (2016) describes the scale as a set of electrodes placed in a mat or footpad. This pad sends an electrical signal conducted by ionized fluid in tissue. The tissue acts as a conductor for the electrical signal (Kyle *et al.*, 2004). The impedance value, which indicates the body resistance, can be interpreted using statistical manipulation to determine the body fat. Franco-Villoria *et al.* (2016) further highlight the accuracy of this device compared to using a standard formula to determine compositions. Still, a 2016 consumer report expresses that the home-use body scales estimation can vary by over 21%.

We adopted the Withings body scale to monitor weight, body fat, water, including muscle and bone mass in this research. The Withings smart body composition scale is a Wi-Fi-enabled digital device that costs 110.57 USD and uses bioelectrical impedance analysis, an electrical signal to measure body composition, including fat, muscle mass, and water percentage bone mass. It accomplishes this by measuring how long a signal moves through the body and back. One should note that the signal moves slower through fat and faster through harder material.

The device measures 12.8 x 12.8 x 0.9 inches and can synchronize to a mobile health app with access to an Advanced Programming Interface. It can be used by up to about eight people simultaneously. The device measured the % body fat, weight, and BMI and provided them to the input aggregator through the available API. In addition, the device has other valuable functionalities, such as a daily weather forecast.

4.8.2 The Withings Body Composition Scale and Blood Pressure Devices Integration
There are two available services from the developer platform for integrating the Withings Device into applications.

   a. **Data API-** This is an Open API for retrieving user health and wellness data. It uses the OAuth authentication protocol to authenticate requests between users and applications successfully.
   b. **Device and Logistics API**- allows partners to
      1. Deliver pre-activated and pre-configured devices\services to program members and patients, removing the function of device setup and activation.
      2. Use of the drop shipment API to deliver devices directly from Withings to program members or patients.

For our integration, we used the Data API service. The steps required to use the service are as follows

   a. Register for the Withings API.
   b. Implement the OAuth security protocol.
   c. Discover and start using the API resources like the "GetMeas" method that returns a list of measures based on the timestamp.

An authorization code called access token is required to access data API services as an input parameter that allows the Withings Server to know that a partner can access the user's data. The access token is given together with a refresh token as soon as the user provides authorization. The refresh token retrieves another access token upon expiration. The access token is valid for 3 hours, and the API allows 120 requests per minute.

4.8.3 Input Aggregator
The input aggregator function is to extract and retrieve measurements and values from the various connected devices. It also provides a web interface that serves as the Patient Input form. We developed the patient form using a low-code development platform called Outsystem.

Input Aggregator uses the patient input form to receive information directly from the patient, such as age and number of pregnancies. It can also make API calls to the device interface via Bluetooth and API to extract measurements from BPM, Withings body composition, and blood glucose measurement devices. The aggregator has a simple backend database structure that stores information. See below for the database schema.
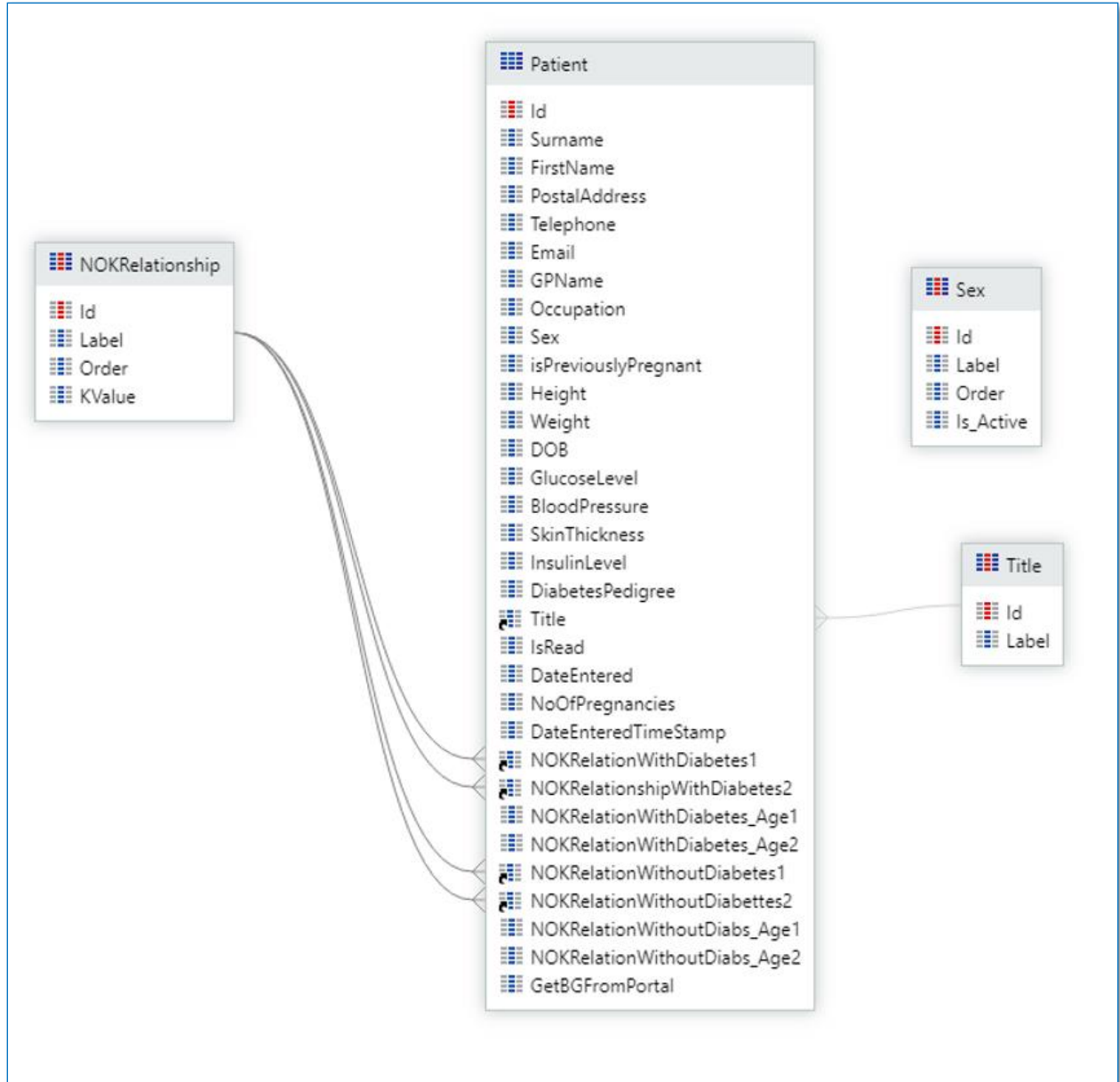
Figure 5 Database entity diagram of artefact

4.8.4   Database Structure

The schema uses three main tables for storing information. The tables and some of the essential attributes are below

Attribute	Data type	Information stored
ID	GUID	This is a unique identifier that is generated for every
Surname, First name	Text	Patient name
Sex	Text	Patient sex and choices include Male\Female
IsPreviouslyPregnant	Boolean	The selection that allows a patient to indicate previous pregnancies
Height	Decimal	Measured patient height in cm
Weight	Decimal	Measured patient weight in kg

DOB	Datetime	Date of birth used in computing patient age
Glucose Level	Decimal	Level of glucose measured in mg/dl
Blood Pressure	Integer	Blood Pressure measured in mm HG
Insulin Level	Decimal	Insulin Level measured in U/ml
Diabetes Pedigree Function	Decimal	The computed value that represents the degree to a patient is likely to have diabetes based on family history
No of Pregnancies	Integer	No of past pregnancies
NOKRelationWithDiabetes (1&2)	GUID-Secondary value	This is related to the NOKRelationship table to capture the relationship with families living with diabetes
NOKRelationWithoutDiabetes(1&2)	GUID-Secondary value	This is related to the NOKRelationship table to capture the relationship with families living without diabetes
NOKRelationWithDiabetesAge (1&2)	Integer	Age when the family was first diagnosed with diabetes
NOKRelationWithoutDiabetesAge (1&2)	Integer	Age during the last non-diabetic examination. If not available, the current age of the family member can be captured

Table 1 Patient Table

4.8.4.2   NOKRelationship Table

This table stores values for the different relationships and their estimated constants, representing a percentage of genes that a relative shares.

The K value represents the estimated constants. The K value is 0.5 when a relative is a parent of a full sibling, 0.25 when the relative is half-sibling, grandparent, aunt, or uncle, and 0.125 when the relative is a half aunt, half-uncle, or first cousin.

4.8.5   BOT Performer

The bot performer processes and analyzes data and applies the machine learning model. The bot performer is built using the UiPath platform and designed to work as unattended automation that can be started and monitored by the logged user.

The user can start the BOT performer either by using shortcut keys or manually from the robot tray. Then, the performer begins processing by getting its input from the orchestrator queue to perform this function. The bot performer accomplishes these functions mainly through the following sub-components.

4.8.6   Input Extractor

The Input Extractor extracts data from different interfaces such as the Advanced Programming Interface provided by the Input aggregator through the orc. Its function also includes extracting, transforming, and loading the inputs from the orchestrator queue on a First-in-first-out (FIFO) basis. It also does all the necessary conversions and validations of the input.

4.8.7   Model Engine

The performer also consists of a model engine based on a Machine Learning model that can classify input data into positive or negative diabetes cases. The model engine classifies the data provided through the input aggregator and displays the results to the doctor through the Doctors Console.

4.8.8   Doctors Console:

Doctors and medical workers interact with the bot through the Doctor's Console. The bot provides the output or results of the analysis through this console to the doctor. The doctor can subsequently provide status feedback on the outcome to the bot through this console, which eventually passes to the model training module. In cases where the result is considered wrong, the doctor can provide the correct input to the bot. The classification of these records is, however, set by the doctor based on his observation.

4.8.9 Model Training

Model Training module handles the bot's various training by accepting the doctor's feedback and passes them to the ML training algorithms. We construct the feedback from the inputs loaded from the queue alongside the output of the ML algorithm. This feedback aims to improve the accuracy of the bot in determining the risk of diabetes.

4.8.10 BOT dispatcher

The job of the bot dispatcher is to retrieve patients' data through the API exposed by the Input Aggregator. Subsequently, the dispatcher makes the data available to the performer via the queue. The bot performer can then read the data of the queue. The UiPath queue stores and processes the input data using a first in- first-out (FIFO) model. This design allows multiple performer bots to run on different doctor machines and reading data off the queue. We developed the bot performer using the UiPath automation.

4.8.11 UIPATH Automation Platform

The UiPath platform consists of the following components

1. UiPath studio is where all the orchestration takes place and is a drag and drop flowchart modeling tool. The studio provides tools that allow the development of robots that can interact with a diverse range of software and solutions such as SAP, consuming and calling advanced programming interfaces, performing complex tasks, and employing and using Artificial Intelligence and Machine Learning. The studio is the building environment for the robots.

2. UiPath Orchestrator is used for orchestrating, managing, scheduling, and monitoring the robots. It connects robots to machines, schedules them, and manages functions like stopping and starting the bots. It is a web-based tool that provides a dashboard that allows a user to monitor the activities of the robots

3. UiPath robots are the automation unit used to run the processes\packages developed in UiPath studio. The robot can be set up and managed through the UiPath Orchestrator. It is a unit made up of the user account context and the machine or computer to run the bot. This robot can subsequently be assigned to a process to run under the robot context, combining the machine and user account. A robot can either be attended to or unattended.

A robot can perform its tasks using the following components

    a) **Service-** The robot service communicates using the inter-process communication channel with the studios, robot agent for receiving and processing information. It is also responsible for communicating the heartbeat of the robot to the orchestrator. It holds the robots' credentials and can work either as a Service mode or user mode.

    b) **Executor -** The robot executor's task is to execute (Start\Stop) a robot based on the signal received from the orchestrator or robot agent.

    c) **Robot Tray-** The robot tray serves as the user interface of the Robot. It's a WPF application that provides an interface for viewing and managing bots. The tray is accessible from the system tray in the taskbar.

Robots run under two different kinds of automation

    1. Attended automation: These types of robots usually run under the guidance and supervision of a human. The bot is usually started and managed directly by a human, which does through the robot tray. The tray itself provides a list of the already configured robot.
    The attended robot runs under the same credentials as the human, triggering the automation.

    2. Unattended automation-: According to information from the UiPath site, this automation performs more complex and highly repetitive tasks. As a result of the complexity of the automation tasks, the bot typically requires a higher level or elevated level of privilege and is managed, monitored from the orchestrator platform. They also run without human supervision and are physically unseen.

4.8.12 The Prima Indian Database

The dataset behind the Machine learning model is the Prima Indian database. The database represents the Pima Indian female (Islam and Jahan, 2017) population near Phoenix, Arizona. The National Institute of Diabetes and Digestive and Kidney has studied the residents for more than 56 years due to the widespread cases of diabetes (Knowler *et al.*, 1981, Knowler *et al.*, 1978).

Researchers asked each community resident over five years to undergo a standardized examination every two years, including an oral glucose tolerance test. Diabetes was diagnosed during examination using WHO standards and, according to Smith *et al.* (1988), consisting of 2 hours post-load plasma glucose. Thus, the dataset is well-validated data that help predict the date of onset of diabetes longitudinally. This Prima Indian dataset is available through the University of California at Irvine (UCI) data repository. Researchers in machine learning experiments have widely used the data repository.

Bache and Lichman (2013) note that the Pima Indian data has been used, previously by researchers, to investigate indicators of diabetes within patients according to WHO standards. UCI repository contains 768 instances of observations and nine attributes consisting of eight high-risk feature variables. Table 2 provides a summary of the eight feature variables and their units of measurement.

The class variable takes on the binary value of 0 or 1, with 0 indicating a healthy person and signifying a diabetic patient. All the patients in these datasets are females at least 21 years old living near Phoenix, Arizona. In subsequent sections, we discuss skin thickness and diabetes pedigree in more detail and how we could extract this information from the device.

Variable	Units of Measurement
Skin Thickness	mm
Insulin	U/ML
Body Mass Index (BMI)	Kg/M2
No of pregnancy	-
Diabetes Pedigree Function (DPF)	-
Blood Pressure	mm HG (*1 mmol/L equals 18 mg/dl*)
Age	-
Glucose level	MG/dl

Table 2 Feature variable

4.8.13 Skin Thickness

Measurements of skinfold thickness using callipers is a technique that is useful in assessing and monitoring the nutritional status of patients who are unable to use scales. Traditionally, the Skin calliper is a tool used for measuring skin thickness but can be prone to errors or variation due to the challenges of grabbing skin at the different measurement sites (Marshall *et al.*, 2014). The skin grab, the compression of the fold, and the exact timing challenges to using the Skin Calipers. Marshall *et al.* (2014) noted that the following are potential measurement sites: triceps, biceps, subscapular, and supraillac. Deurenberg and Deurenberg-Yap (2009) observe that it is advisable to measure the thickness of more than one skinfold thickness site to get insight into the subcutaneous fat instead of just one site. The total body fats can subsequently be predicted from the skin thickness (Durnin and Womersley, 1974), although with some considerable error over 5%. Deurenberg and Deurenberg-Yap (2009) highlight that measuring skinfold thickness requires many skills and can be challenging to measure in elderly patients. In some cases, especially for research purposes, standardized equations are used to calculate body fats.

We considered the Jackson and Pollock Formula (Jackson and Pollock, 1978, Jackson *et al.*, 1980, Nevill *et al.*, 2008) to compute the % body fat from the measured skin thickness. The Jackson and Pollock equations are multiple regression equations that can estimate the body density from a sum of skinfold thickness and age.

In our study, we measured the body fat percentage using the Withings body composition scales. We substituted the Jackson and Pollock Formula value to reverse calculate the body density from a 2-body component model. The body density determines the sum of skin thickness. Since the sum of skin thickness represents a 4-site taken at the abdominal, thigh, triceps, and supraillac, we took an average of the skin thickness to get a value for the skin thickness, which was provided to the Input aggregator for determination of the diabetes risk by the bot.

4.8.13.1   Jackson-Pollock 4 Body Fat Formula for Males

1. Measure the following skinfolds (in millimetres) with body fat callipers: Abdominal, Tricep, Thigh and Suprailiac

2. Calculate body density

Body Density = (0.29288 x sum of skinfolds) – (0.0005 x square of the sum of skinfolds) + (0.15845 x age) – 5.76377

3. Calculate the Body Fat Percentage

Body Fat Percentage (%) = (495 / Body Density) – 450

4.8.13.2   Jackson-Pollock 4 Body Fat Formula for Females

If you want to calculate body fat using the Jackson-Pollock 4-spot method, and your test subject is a female, use the formula below.

1. Measure the following skinfolds (in millimetres) with body fat callipers: Abdominal, Tricep, Thigh and Suprailiac

2. Calculate body density

Body Density = (0.29669 x sum of skinfolds) – (0.00043 x square of the sum of skinfolds) + (0.02963 x age) + 1.4072

3. Calculate the Body Fat Percentage

Body Fat Percentage (%) = (495 / Body Density) – 450

4.8.14   Diabetes Pedigree Function

Smith *et al.* (1988) developed the Diabetes Pedigree Function (DPF) to synthesize the diabetes mellitus history in relatives and the genetic relationship of those relatives to the subject. It measures the risk a patient is likely to be diagnosed with diabetes based on influences from relatives living with or without diabetes.

The diabetes pedigree function as adapted from the Smith's is below

$$DPF = \frac{\sum_i k_i (88 - ADMi) + 20}{\sum_j k_j (ALC_j - 14) + 50}$$

where:

 i ranges over all relatives, who had developed diabetes by the subject's examination date;

 j ranges over all relatives, who had NOT developed diabetes by the subject's examination date;

Our study limited the number of relatives to 2 each for relatives with and without diabetes.

K is the percent of genes shared by the relative. and. equals 0.500 when the relative. is a parent or full sibling, * equals 0.250 when the relative? is a half-sibling, grandparent, aunt, or uncle, and * equals 0.125 when the relative, is a half aunt, half-uncle, or first cousin

ADMi is the age in years of a relative when diabetes was diagnosed.

ACL is the age in years of relative during the last diabetic examination. If there was no examination, the recent age is adopted

According to Smith *et al.* (1988), The constants 88 and 14 represents the maximum and minimum ages at which relatives of the subjects that participated in this study were diagnosed with diabetes.

Smith *et al.* (1988) added constants 20 and 50 to the final results for both family members diagnosed with diabetes and without diabetes as seen in table 3 because of the following:

1. A subject with no relatives would have a DPF value slightly lower than average

2. The DPF value would decrease relatively slowly as young relatives free of DM joined the database

3. The DPF value would increase relatively quickly as known relatives developed DM.

Using the above formula, we computed the diabetes pedigree function for a fictitious patient with two family members diagnosed with diabetes and a random selection of 2 family members without diabetes, as shown in Table 3 below.

Family members diagnosed with diabetes					
i	relationship	k	ADM	88-ADM	K(88-ADM)	K(88-ADM)+20
1	father	0.5	45	43	21.5	41.5
2	Brother	0.5	40	48	24	44
					Sum	**85.5**
Family members without diabetes					
i	relationship	k	ACL	ACL-14	K(ACL-14)	K(ACL-14) +50
1	mother	0.5	50	36	18	68
2	Aunt	0.25	40	26	6.5	56.5
					Sum	**124.5**
		DPF	**0.686747**			

Table 3 Diabetes pedigree function

4.9 Demonstration

This research phase demonstrates the use of the artifacts to solve the problem outlined in the problem identification and motivation phase using activities such as proof of concept, case studies, and trials.

This section presents some selected snapshots to illustrate and demonstrate the Unobtrusive system capability, features, and functionalities to solve the problem as outlined in the problem identification and motivation section. The functionalities are

- Patients queue system
- Patients online form
- Doctor's console
- Robots control centre
- Integration with the blood pressure, glucose, and body composition scale
- Diabetes pedigree composition module

Figure 6 shows the Patient Online form. The online form captures personal details such as patients' names, date of birth, sex, and next of kin information. The responsive online form can be deployed and used across various devices, including laptops, tablets, or mobile phones.
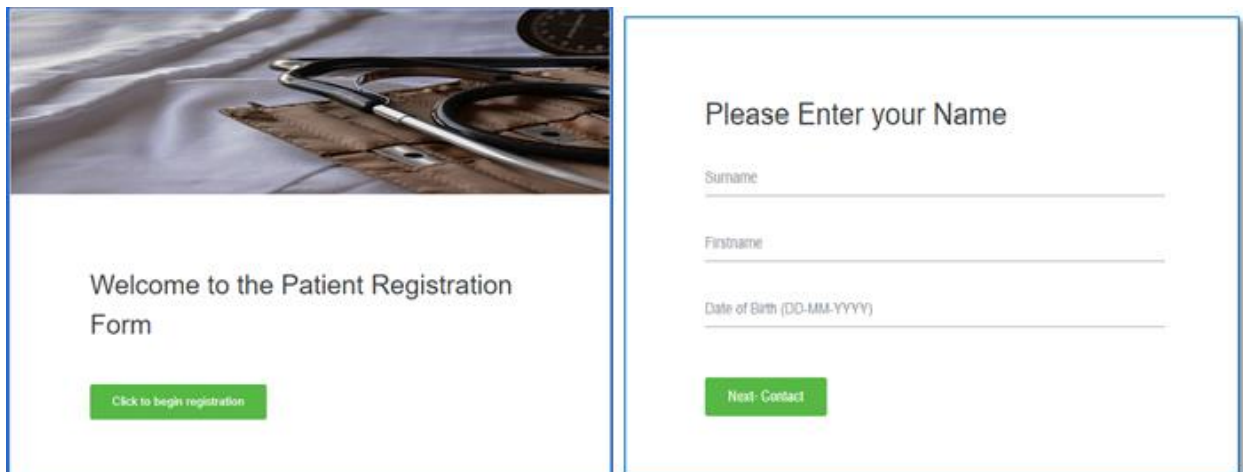
Figure 7 shows the prompt for tests in the online form. At this stage, patients proceed to take their tests. The online form displays measurements from the devices. The form also allows the patient to provide the results as input to the form manually.

Figure 8 shows the prompt for the next of kin information in the online form. The bot uses the information provided on this screen to calculate the diabetes pedigree function. Smith *et al.* (1988) developed The Diabetes Pedigree Function (DPF) to synthesize diabetes mellitus history in relatives and the genetic relationship of those relatives to the subject. The Design and Development chapter will give more details on the computation of the DPF.

Figure 9 shows the patient queue. The queue contains details of the patients that are available for processing. The bot selects patients from this queue on a First-In-First-Out (FIFO) basis.

Figure 10 shows the bot launch pad. The two bots: Inputs aggregator and Diabetes Predictor, can be started from the pad. However, the Inputs aggregator runs in the background and starts the Diabetes Predictor using shortcut keys on the keyboard.

Figure 11 presents the Doctors Console. Patients' information supplied from the various tests and inputs alongside the output of the machine learning processing is available to the doctor for review through the console. The console also allows the doctor to accept and reject the result.

Figure 6 Patient Online Form
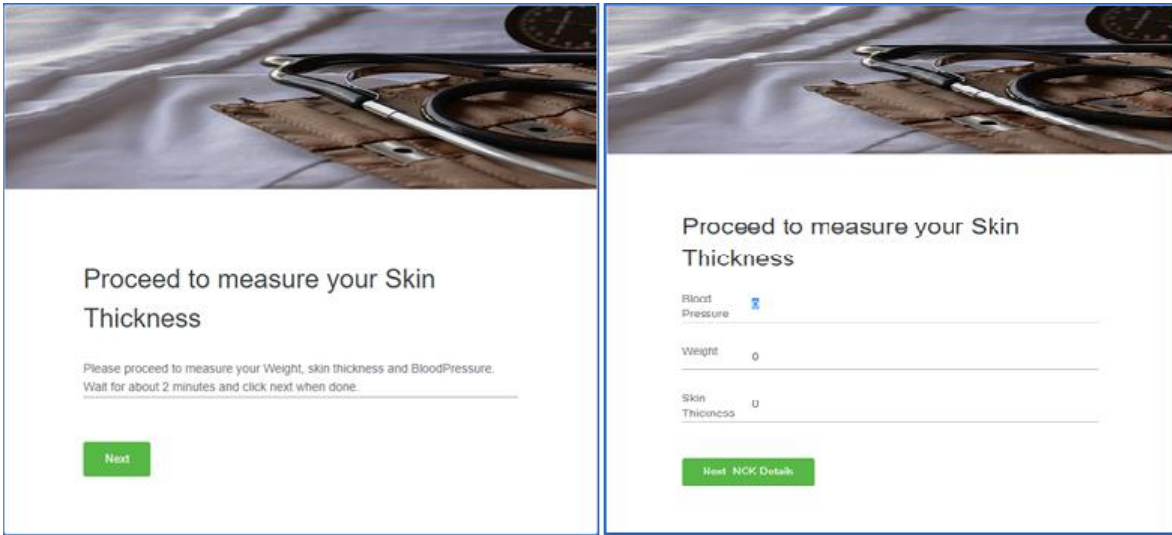
Figure 7 Patient Online Form- device measurement prompt
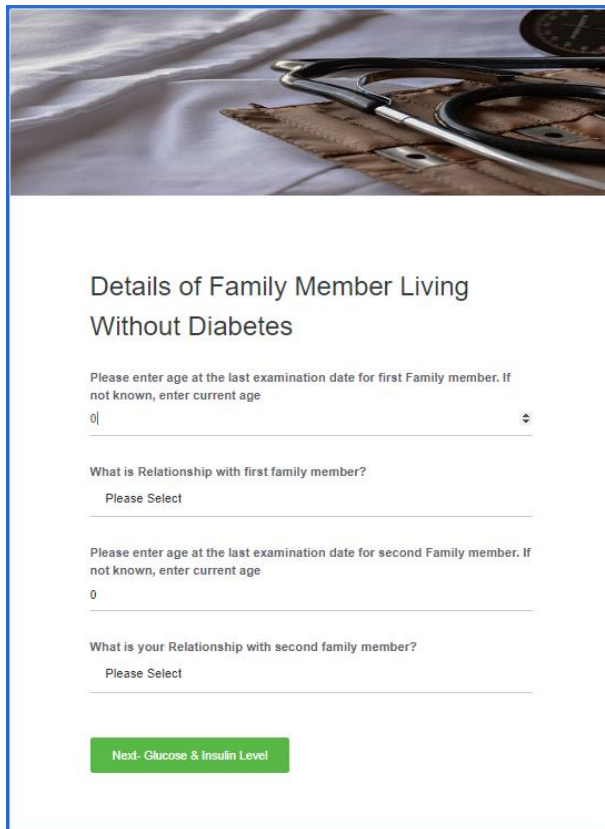
Figure 8 Patient Online Form- Next of Kin Prompt

Figure 9 Patient Queue

Figure 10 Bot Launchpad

Figure 11 Doctors Console

4.10 Evaluation

This phase involves evaluating, testing, and seeing if the developed artifacts solve the problem through observation and measurement.

4.10.1 Overview of evaluation

In our study consistent with the DSR principle, the evaluation phase's objective is crucial to show rigour (Hevner *et al.*, 2004). and align the research as a design science research study. However, there is a different definition of Evaluation in the context of DSR. For example, Scriven (1998) defined evaluation as a process of determining and establishing the worth and significance of an artefact. On the other hand, Weiss and Weiss (1998) describe evaluation as the systematic assessment of process outcomes by comparing them with a set of already established standards.

4.10.2 Evaluation strategy

Evaluation of an artefact can be either external or internal or based on the research method, whether quantitative or qualitative (Herselman and Botha, 2015). Verschuren and Hartog (2005) classified evaluation as either Ex-ante or Ex-post. Verschuren and Hartog (2005) further defined Ex ante evaluation as evaluating an artefact before its development and implementation, while Ex post evaluation is evaluating an artefact after design, development, and construction.

In this study, we evaluated the artefact using the Ex post method to receive feedback from experienced health care workers and professionals such as doctors and nurses on the performances of the bot and its usability in the health sector. The evaluation is also essential to get feedback on the bot and decide whether to deploy the bot in a live environment.

The evaluation was conducted at the Eval 3 stage as shown in the General DSR Evaluation Pattern diagram described by Donnellan and Helfer (2012), as indicated in Figure 12. According to Donnellan and Helfer (2012), the Eval 3 stage allows us to understand the performance of the artefact, which is a prototype to determine the effectiveness, efficiency feasibility, robustness, suitability, and usability of the automation in the health sector.

Donnellan and Helfer (2012) further outlined the following available methods for evaluation at Eval 3 stage.

- Artifact Demonstration
- Experiment with artefact

- Surveys
- Expert interview
- Focus group

In this study, we adopted the artefact demonstration and used a mixture of a qualitative and quantitative questionnaire to evaluate the artefact.
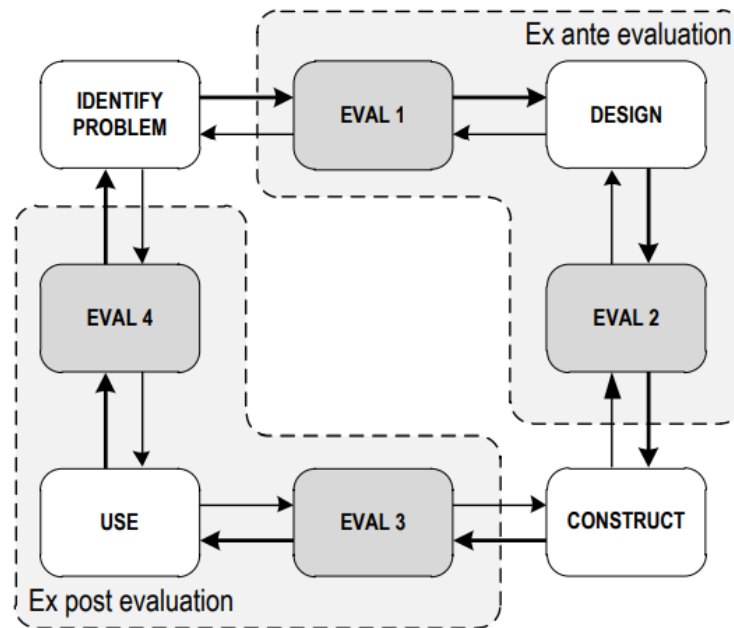
Figure 12 Donnellan and Helfer (2012): Evaluation activities within a DSR process

4.10.3 Evaluation Criteria

To prove the usefulness and usability of an artefact, Gregor and Hevner (2013) proposed the evidence should satisfy criteria such as validity, utility, quality, and efficacy. A rigorous design evaluation would use various analytics to simulations to determine and measure these criteria (Gregor and Hevner, 2013).

This criterion represents the evidence on the worth of the artifact and will be determined using the artefact demonstration and questionnaire surveys. To systematically show the achievements of the artefacts, evaluations should be guided by evaluation criteria as proposed by March and Storey (2008) in Figure 13 below.

	Construct	Model	Method	Instantiation
Completeness	X	X		
Ease of use	X		X	
Effectiveness				X
Efficiency			X	X
Elegance	X			
Fidelity with real world phenomena		X		
Generality			X	
Impact on the environment and on the artefact's users				X
Internal consistency		X		
Level of detail		X		
Operationality			X	
Robustness		X		
Simplicity	X			
Understandability	X			

Figure 13 March and Storey (2008): Evaluation criteria for DSR artefacts

4.10.4 Questionnaire Design

To evaluate the artefact, we designed our questionnaire to collect both quantitative and qualitative data online.

The quantitative section is where users select from a list of options in the form of closed-ended questions. The closed-ended questions consist of a set of responses and choices for selection by the participants to choose.

The questions allow us to describe and evaluate the profile of the participant, their environments, and activities. The closed questions are a mixture of evaluative continua, agreement continua, and comparative scales. According to Glasow (2005), the Evaluative continua are numerical and adjectival scales, while the agreement continua are agreed or disagreed types of questions.

The qualitative section of the research consists of the collection of data from open-ended texts. These research methods are beneficial in understanding and analysing opinions in a subject domain and extracting the participants' experience using the artefact.

This approach is required to get a deeper understanding of the human experience. According to Qualitative research, approaches are a systematic process for understanding humans' interactions and environment (Ormston *et al.*, 2014). Typically, this approach involves a small sample size, unique and focused.

The open-ended survey questions allow us to collect the thoughts and opinions of the participants in their own words. The aim is to explore ideas that might not have been captured in the options for a closed-ended question, thereby collecting additional insights. The open-ended questions were helpful because of the medical field, where we have less familiarity and choice limitations.

The questionnaire's objective is to explore and describe physicians' experiences and their perception of the artefact. The intention is not to produce a theory but to gather ideas and opinions. Therefore, we do not aim to make inferences or produce a theory.

We distributed the questionnaire through Qualtrics, which is an online survey tool. In the online questionnaire, participants were required to watch a 10-minute video demonstration of the artefact, read the participant information sheet for more information, and provide their consent to participate in the survey.

4.10.4.1 Sampling Strategy

To select a sampling technique, we considered the nature of the participants.

The participants selected are health professionals and are very busy, not easily accessible, and available due to the demand of their profession. Therefore, we chose a non-probability sampling method called convenience sampling to

select participants that are accessible and available. Finally, we considered the available time to completion, costs, and study convenience to determine the research strategy.

5 Results

The section presents and reviews results collected from the data collection phase. The questionnaire section contains both qualitative and quantitative questions. The questions are categorized as follows: Profile, Practice, Standards, Technology, Research sections. Refer to Appendix A for the questionnaire.

We applied descriptive analysis to the quantitative sections and thematic analysis to the qualitative sections of the questionnaire. We followed Braun & Clarke's (2006) 6-step framework for the thematic analysis. Researchers commonly use the thematic framework because it offers a straightforward, step-by-step approach to study. We applied a top-down or theoretical thematic analysis to answer research questions summarized below:

- What are the benefits of implementing an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the challenges and barriers to developing and implementing an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the required features and enhancement of an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- What are the limitations of an unobtrusive system using Intelligent process automation for determining the risk of diabetes?
- How usable is an Intelligent process automation-based unobtrusive system for determining the risk of diabetes?

We adopted Braun & Clarke's six-phase thematic analysis framework, including the following steps:

Step 1: Become familiar with the data,

Step 2: Generate initial codes,

Step 3: Search for themes, Step 4: Review themes,

Step 5: Define themes,

Step 6: Write-up.

We present our findings under the following categories:

- Participant Profile analysis
- Participant Practice Analysis
- Clinical Standards Analysis
- Technology and Research analysis
- Thematic analysis

5.1 Participant Profile Analysis

There was a total of 15 participants in the research. All the participants are randomly selected spread in four different countries, including Nigeria, New Zealand, Canada, and the United Kingdom. From the diagram in fig 14, New Zealand holds the highest number with 6 participants.
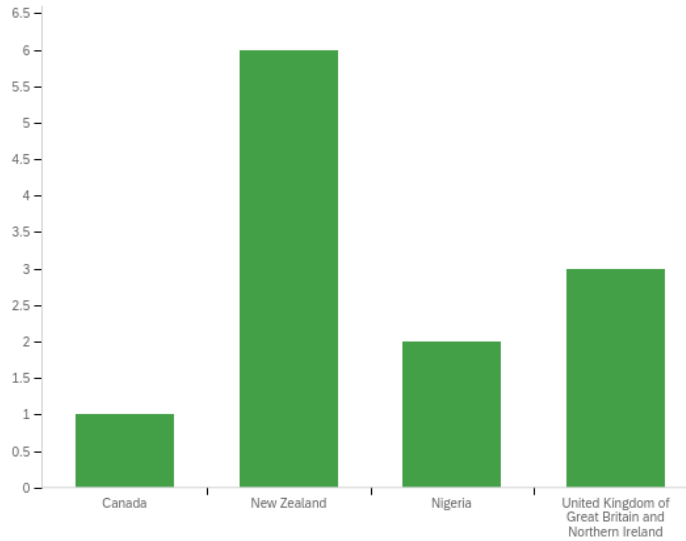
Figure 14 Please select a list of countries

80 % of the participants were female, with 20% male, as seen in figure 15. Figure 16 displays the age group of participants. Only 2 out of the participants were above 55, while the rest were between 25 to 55 years old.

There was a participant without an institution at the time of the research. However, most of the participants worked at either a GP clinic or a hospital. Thus, there are many participants, at 65%, who work in hospitals, as indicated in figure 17.

Figure 18 shows that the participants worked in a range of roles within their respective institutions. For example, there are five specialists, three registrars, two house officers, and senior house officers with a medical officer. Others are GPS and senior registrars.
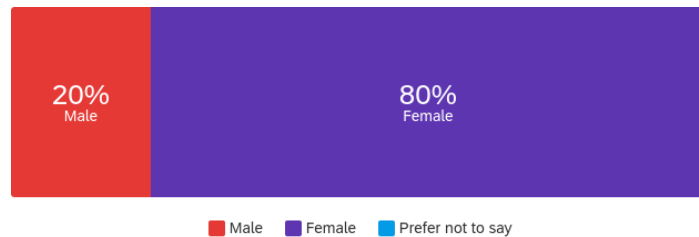
Figure 15 Please select gender
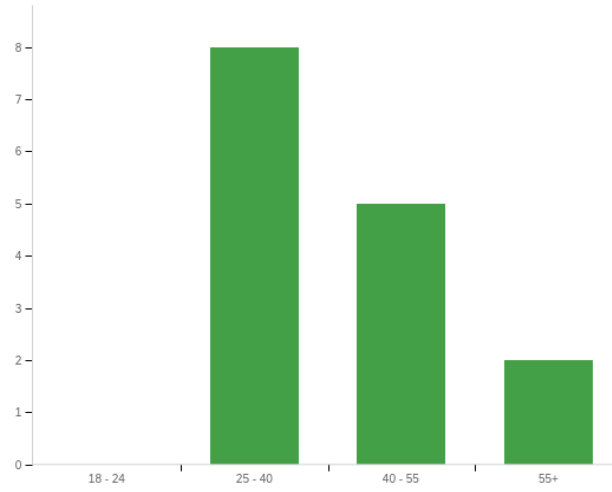
Figure 16 Please select age groups
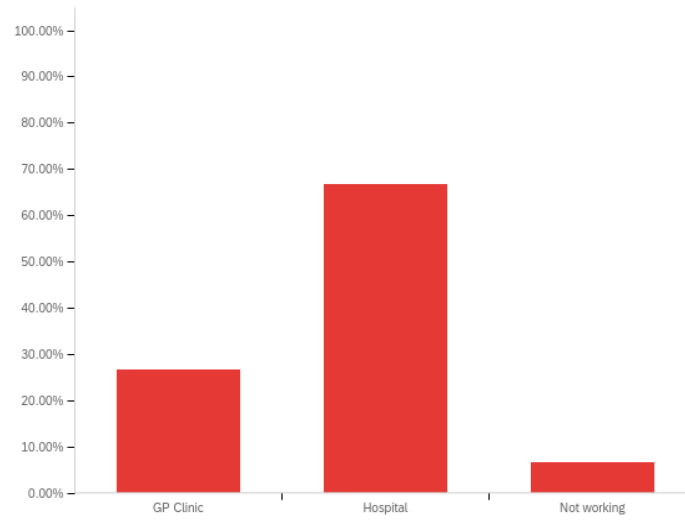
Figure 17 Select the option below that best suits your role in your institution
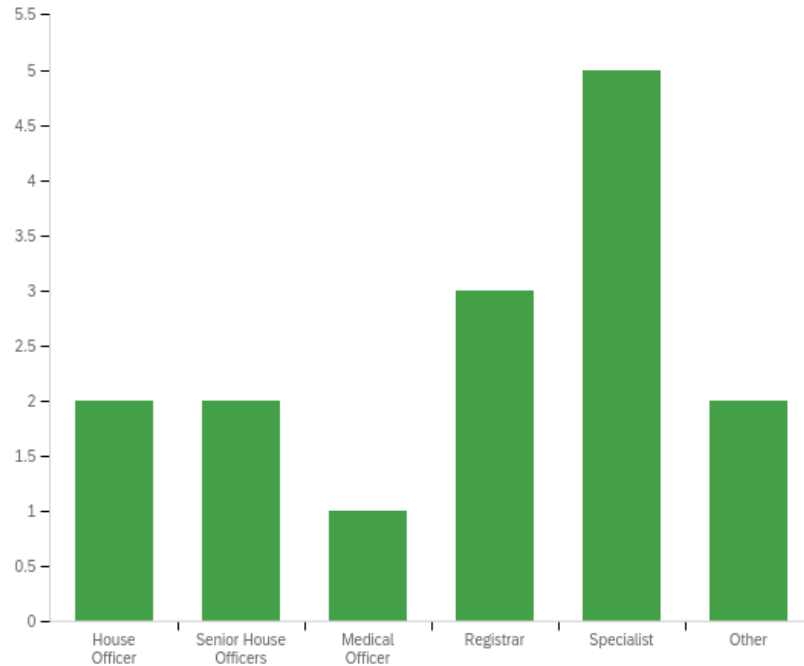
Figure 18 Select the option below that best suits your role in your institution

5.2 Practice Analysis

As indicated in figure 19 – 22, the results show that most participants in a typical day attend to more than an average number of patients. Above 65% of participants actively treat between 11 to 30 diabetic patients in a typical day, with 1 participant treating between 31 to 50 patients daily. In addition, 71% of the participants spend between 5 to 10 mins to diagnose the risk of diabetes in a patient, with 2 participants consuming more than 15 mins. Half of the participants sometimes treat diabetic patients, with another half always treating a diabetic patient.
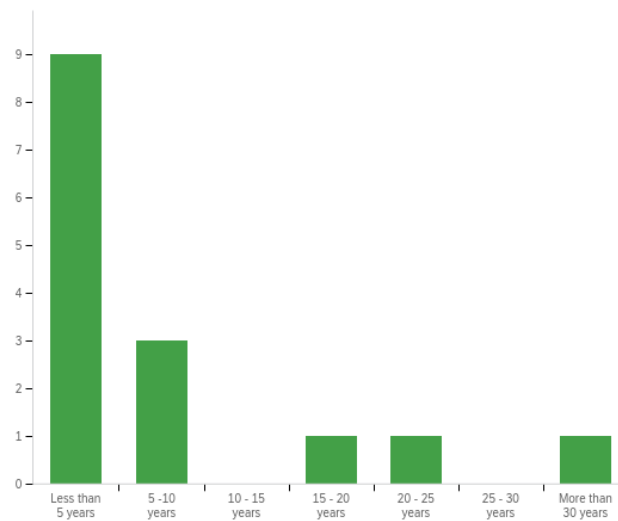
Figure 19 How many years have you spent working in this role?
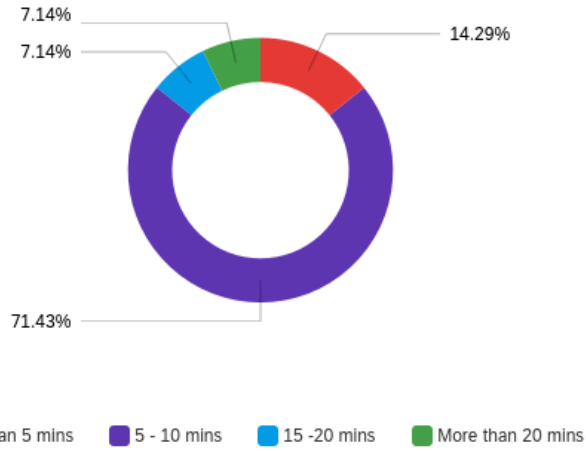
Figure 20 What is the estimated average patient-doctor time do you take to predict the risk of diabetes?
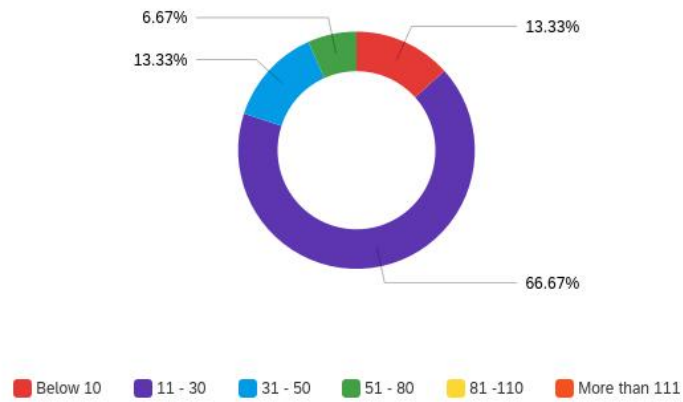
Figure 21 How many patients do you typically see in a day?
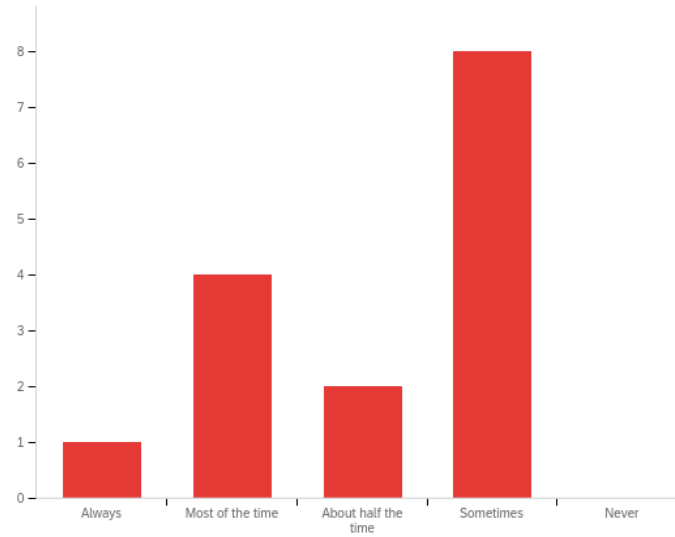
Figure 22 How often do you normally detect diabetes in your patients?

#	Answer	%	Count
1	Always	6.67%	1
2	Most of the time	26.67%	4
3	About half the time	13.33%	2
4	Sometimes	53.33%	8
5	Never	0.00%	0
	Total	100%	15

Table 4 How often do you normally detect diabetes in your patients?

5.3 Standards Analysis

87% of participants agree that the processes adopted by the bot do not align with known standards of the determination of the risk of diabetes as seen in Figure 23. Figure 24 shows the standards selected by participants. They include the American Diabetes Federation, European Association for the Study of Diabetes, International Diabetes Federation, World Health Organization, Diabetes UK. Other participants do not think that the bot aligns with standard practice. They observed that the artefact did not capture some relevant information such as ethnicity and lifestyle. In contrast, others maintained that determining the risk of diabetes should be part of an overall cardiovascular risk assessment.
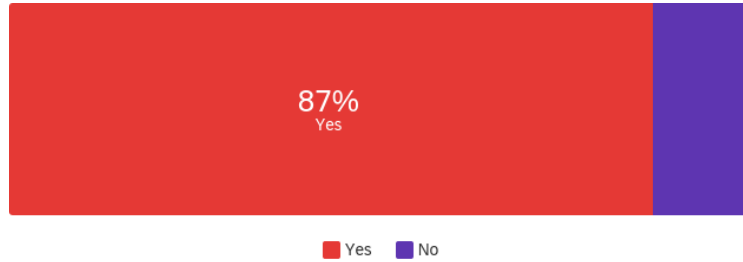
Figure 23 Do you think the processes adopted by the bot align with the standard practice of determining the risk of diabetes?
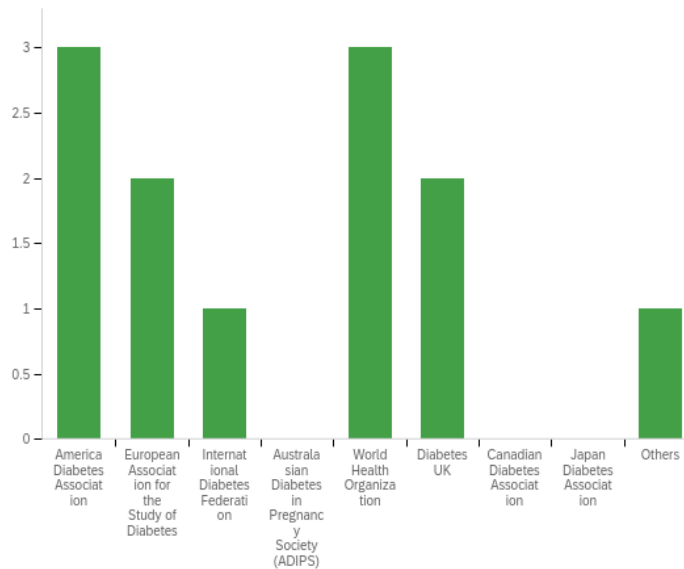
Figure 24 Please select from the list below the standards of practice you think the bot aligns with for determining the risk of diabetes in a patient.

5.4 Technology and Research Analysis.

In this section, we review the results associated with the usability of the bot within health institutions to determine the risk of diabetes. We measured usability in time savings, enhanced patient-doctor interactions, staff workload, and visitation frequency.

Figures 25 – 28 show patient-doctor interaction, time savings, the potential to reduce staff workload, and frequency of visits to the hospital. However, 71% of participants think that the bot will significantly improve doctor-patient interaction, and 29% believe that the process is too cumbersome and unusable. In addition, 43% do not agree that the artefact can reduce hospital visitation, while 36% are uncertain.

The thematic analysis in the next section will further provide a deeper understanding of the issues and reasons why some of the participants think the bot is unusable.
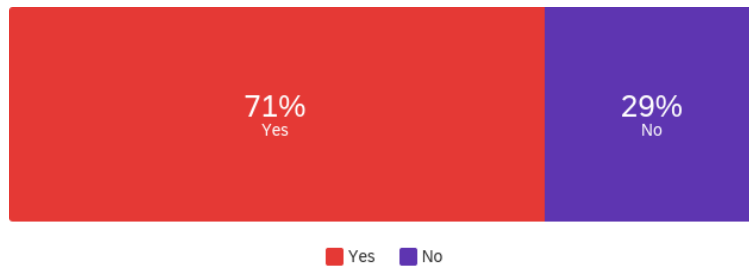
Figure 25 Will the technology concept shown in the video potentially improve the quality of patient-doctor interaction?
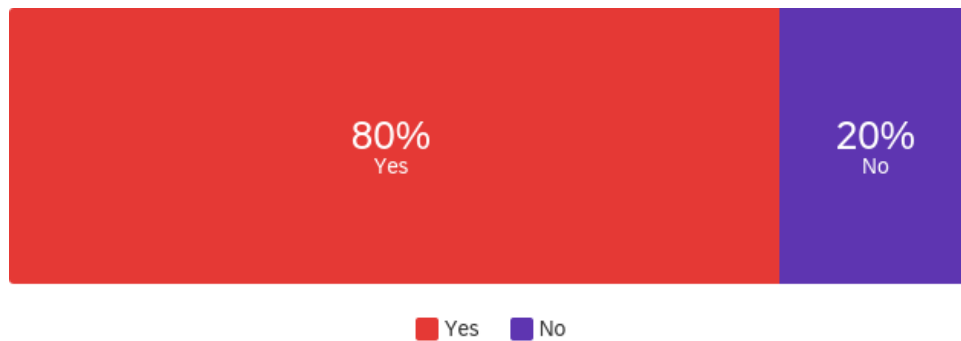
Figure 26 Do you think the technology concept will result in time savings during consultations?
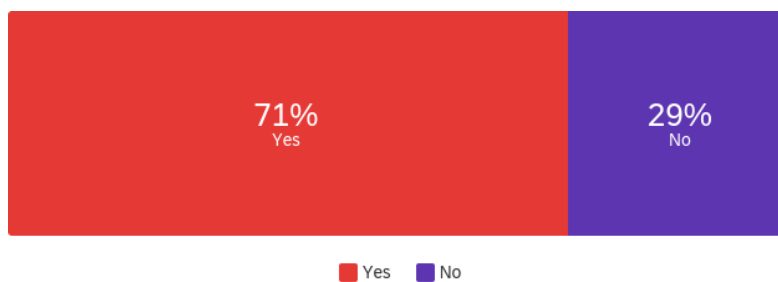
Figure 27 Do you think the technology concept shown in the video has the potential to reduce the staff workload?
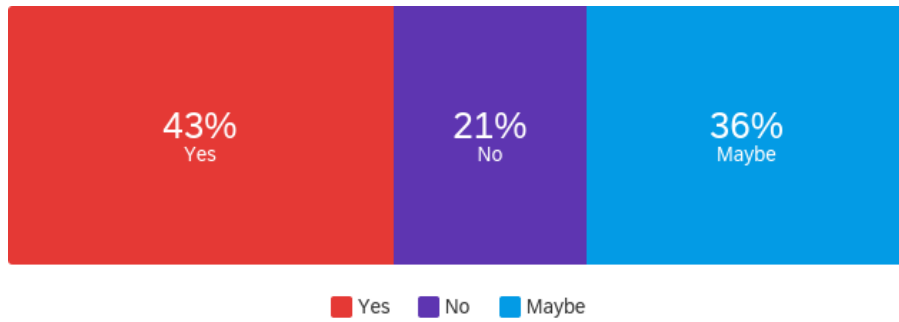
Figure 28 Will the technology shown in the video reduce the frequency of visit of the patient to the hospital?
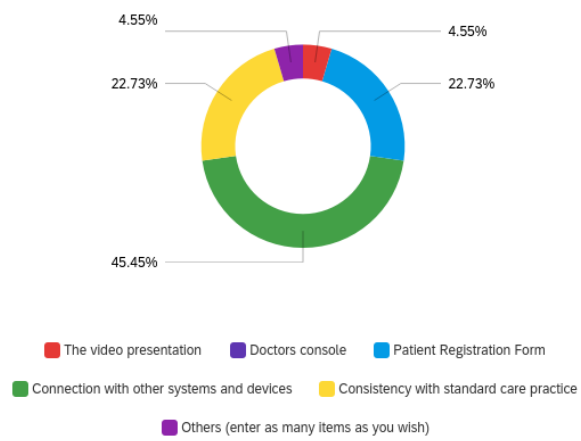
Figure 29 What is it that you like most about the research and the bot?
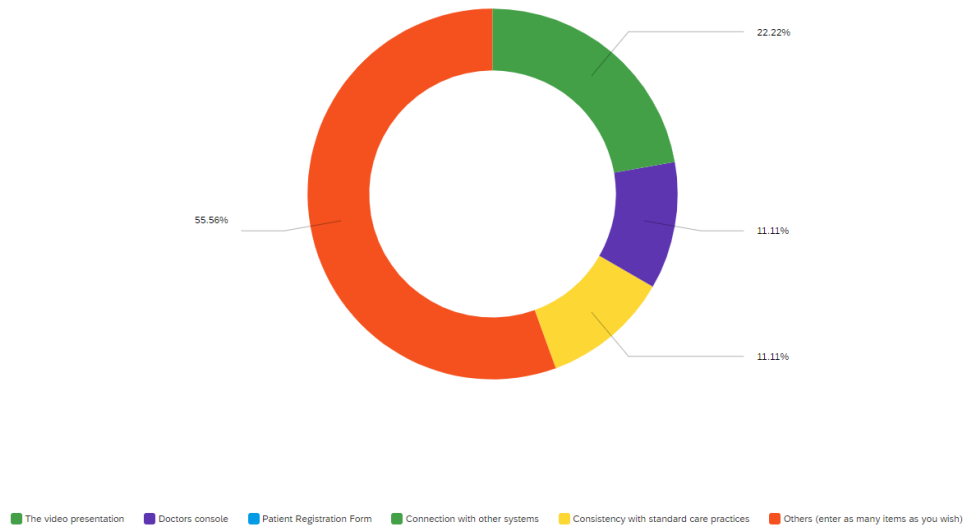
Figure 30 What is it that you like least about the research and the bot?

5.5 Thematic Analysis

Five themes were identified in this study from 21 focused codes, as seen in table 5, and represent five major areas of the study: Limitation, challenges, benefits, usability, and enhancement.

5.5.1 Technology Benefits

These are the perceived benefits to the day-to-day work of the physicians. In this area, participants identified the following themes: enhanced patient-doctor interaction improves patient wait time, helps to detect and screen for diabetes, and optimal glucose monitoring.

Enhanced patient-doctor interaction: Participant perceived that the technology has the potential to integrate information from different systems and devices and helps to backup follow up discussions and counselling with a rich source of information and data

Patients wait time: Participants express that the technology can run through the system and extract and analyze information while attending to other patients. Thus, the artefact helps to reduce wait time. In addition, it can help to screen and detect early high-risk diabetic patients while helping to monitor and maintain a healthy and optimal glucose level.

5.5.2 Technology Challenges

The cost and training of staff were critical challenges identified by participants. First, participants noted that the implementation in most health institutions could be expensive as most personal devices or health care devices might not be affordable by both the health care providers and the patients. Second, healthcare institutions should consider extensive staff training and accessibility issues for older patients before implementing the system.

Finally, Participants also believed that the staff's aversion to change and fear of job losses could resist implementing the technology.

5.5.3 Technology Enhancement

Enhancements suggested by the participants include outcome classification. For instance, participants recommended the racial classification of patients and believed that the inputs should capture racial information. Capturing the racial information is required to improve the accuracy of the algorithm. In addition, participants believe that a patient who

belongs to a specific group has a high risk of diabetes. Besides Race, participants suggested that additional information such as macrosomic baby's history and POC lipid profile check are necessary to improve the algorithm's accuracy.

5.5.4   Technology Limitation

Participants suggested that there is much missing information that the technology has not captured that can impact the outcome. For example, the researchers did not consider information such as ethnicity and lifestyle. They believe that although the process complies with known standards, It is an isolated method of determining the risk of diabetes. Healthcare professionals typically consider the screening of diabetes as part of an overall Cardiovascular testing approach. The system and its process are complex and would require an intense staff engagement.

5.5.5   Technology Usability

The themes in this section consist of application and communication. In this section, the expectation is to understand how the participants will use the technology. Most participants mentioned that the device would be used as an information source to properly advise their patients and help them detect the risk of diabetes while helping\encouraging them to make some lifestyle changes.

In terms of applications, the participants perceive that the technology has high applicability in non-clinical settings and should use the technology at home.

Focused Codes	Sample Narratives
Enhanced Patient-Doctor Interaction	*The fact that one has access to the blood glucose levels immediately, there is synchrony between all the vitals which may enable the doctor to have most of the information immediately*
Patient wait time	*It also reduces waiting time for the patient, because once they come in, they are made to immediately fill in their data while the doctor maybe rounding up some other consultation. Once done, the details are immediately open to the doctor and they get an idea of what to do. This saves the time they could have verbally asked or rule out the Risk factors*
Detect and screen diabetes in patients	*It will help in health promotion as patients who are high risk can be advised on cutting down on some modifiable risk factors that can prevent them from developing diabetes.*
Optimal glucose level Monitoring	*optimal blood sugar control* *better monitoring of blood glucose level in high risk patients.*
Training and Accessibility Issues	*The patients can input their data without help from the receptionist as they check in for their appointments, but it would be difficult to have a dedicated nurse assigned to checking all their BP as they present in the GP surgery.*
Affordability of resources\technology	*Computer literacy of patients, literacy of patients, availability of adequate number of computers, hitch free network*
Resistance to change	*Cost of infrastructure* *Aversion for change* *Fear of job losses*
cost and affordability	*ore financial implications in terms of installation and buying of more devices to enable patients finish with their consultation on time.*
Outcome classification	*A focus needs to be on sound clinican-patient interaction, full assessment, lab. workup, and then appropriate follow up. Those who clearly have a higher risk as in impaired glucose tolerance, strong FH, high BMI (esp. >30), belong to certain racial groups (Maori, polynesian and to a lesser degree asian) and who do not exercise would be followed up more closely also (on our recall system.*

Counselling and Discussions	*Primary care providers use overall CVD risk assessment tools a lot to determine management steps.*
Onscreen Manuals and User guides	*better explanation in video form, that can be used to educate about the device.*
Streamlined and simplified Process	*A much simpler assessment is simply to get the BMI, a quick family history , whether (in a woman) there were any pregnancies with gestational diabetes.* *The technique is cumberome. As specified before, a simple clinical assessment would be more appropriate.*
Additional Information Capture	*You need to incorporate past history of big babies, GDM and previous diagnosis of PCOS in women.*
Extended for usage in home setting	*Technology Enhancements: should be done outside clinic or hospital* *with more explanations in the process- potentially if patients could do this at home prior to attending clinic*
Incomplete Process	*Diabetes risk would be incorporated in the overall assessment of cardiovascular risk rather than as a lone entity.* *I don't want the patient to go to the hospital!. I want to know that their overall risk profile has been assessed (not just diabetes). My job is to keep them away from the hospital!*
Isolated diagnostic method	*As described, diabetes is part of a spectrum of risk factors for CVD. As such a more 'global' approach is indicated and follow up laboratory request for HbA1c result among other results (renal markers, liver profile for evidence of fatty liver or alcohol excess, Urinary albumin/creatinine ratio, lipids...)would be requested.*
Complex Assessment process	*The technique is cumbersome. As specified before, a simple clinical assessment would be more appropriate.*
Vital information not captured	*Though it has captured a reasonable amount of risk factors it has not considered some others like ethnicity, lifestyle*
Increased staff engagement	*I can see situations when the staff have to help patients to interact with the terminal. Rather frequent occurrence of patients needing help with IT device interaction.*
Communication	*I will reassure the patient if probability is low. If high, will encourage lifestyle changes and regular checks for early detection and management.*
Application	*Not sure. Unless it can be accessed in the non-healthcare environment ie pre-clinic or prehospital.*

Table 5 Sample codes from analysis

6 Discussions

In this study, we built and evaluated an artefact using the design science research model. Our evaluation involved a video demonstration presenting the features of the artefacts to health physicians in roles that include specialists, registrars, house officers, and medical officers from 4 major countries. Subsequently, we presented the results of the evaluation in chapter 3.

The purpose of this chapter is to discuss and analyze the results of the evaluation of the impact of the Intelligent Process Automation (IPA) based unobtrusive system for screening and detecting the risk of diabetes in a patient. Second, we will discuss the results alongside our literature review that has explored various technologies for detecting the risk of diabetes, use of IPA, and value of IPA to healthcare institutions in screening and predicting the risk of diseases. Finally, this chapter will cover the following topics: early screening and preventive care standards, the usability of IPA to healthcare physicians, barriers and limitations to implementing an unobtrusive system, the value of RPA to the unobtrusive system, the effectiveness of the system to predict and detect the risk of diabetes and suggestions for future research.

Previous literature has already established numerous benefits gained through the early detection and treatment of diabetes. They had argued that early detection of diabetes is crucial to preventing the expensive management and treatment of the disease. According to Herman *et al.* (2015), early detection and treatment allowed practitioners to discover and treat cardiovascular risk factors quickly, supporting the World Health Organization (2013)'s assertion on the importance of screening for reducing the complications of diabetes. Our research supports this argument by showing that 46% of the participants agree that the frequency of visits to the hospital will reduce. A reduction in the frequency of visits will generally indicate either the prevention of diabetes or drop to a more manageable level.

Participants also identified that the system could quickly help identify or reduce the likelihood of missing out on high-risk patients. This situation has consequences. According to Ratheau *et al.* (2011), the effects of not diagnosing diabetes can lead to blindness, amputations, kidney diseases, heart strokes, and in the worst case, death. Participants agree that the system can alert doctors to the risk of diabetes, although it does not offer any solutions.

Compliance with weight reduction is a benefit of early screening for most patients. In a study carried out by Rhodes *et al.* (2006), they found out that about 61% of the respondents agree that compliance to early screening will help weight reduction, while 52% of physicians believe that the follow-up screening is beneficial to overweight patients.

Our study was able to achieve the Just-in-time information delivery model. The "Just in time" information delivery is a situation where the physicians receive information on the screen during a patient visitation time at the same time while conversing with the patient. Although, Computer alert and reminder systems are an effective way to improve rates of preventive services (Dexter *et al.*, 2001, McDonald, 1976). According to Anand *et al.* (2004), a reminder at the time of note entry is often too late as this event takes place after the patient has left, thereby requiring, in some cases, further visit the clinic. This timeliness is even more critical in paediatric practice, where preventive services often include developmental assessment, risk assessment, counselling, and anticipatory guidance.

We were able to discover from our study that the ubiquitous system can help eliminate confirmation bias. Confirmation bias is a reasoning strategy among patients trying to evaluate a hypothesis based on some set of evidence despite the inconsistencies (Mamykina *et al.*, 2006). According to participants, the information available from the bots can serve as a basis for further active discussion, reasoning, and analysis, thereby eliminating confirmation bias.

Due to these immense benefits, unobtrusive systems are gaining widespread use worldwide, and there are increasing studies around this field. We have established in this study that unobtrusive systems can help screen out high-risk patients with diabetes and allow them to make lifestyle changes and manage their blood glucose better.

According to World Health Organization (2016), a downside to early screening is the likelihood of more diagnosed cases that will add to the healthcare system workload, which can be a challenge.

In our study, participants observed that there is a likelihood that the current setup and configuration of the system will increase the workload and the number of staff required to help patients such as the elderly complete the patient input form and go through the process. In addition, they mention that it will be costly to have dedicated professionals to assist patients in some countries. This position is consistent with Rhodes *et al.* (2006), who argued that professionals should first hire the support and healthcare staff to cope with workloads before establishing a screening and detection system. This step is necessary because the care, treatment of diabetes require a range of healthcare professionals ranging from physicians to surgeons (Hannon *et al.*, 2017). Therefore, failure to cope with the workload can often lead to poor patient care. Furthermore, simply adding new cases to a healthcare system without additional investment will result in inferior average care in the absence of compensating efficiencies (World Health Organization, 2003).

The reason for this workload consideration, according to our findings, is that patients diagnosed with diabetes require ongoing and organized care provided by skilled healthcare providers. In addition, in our study, the participants all agreed that an integrated plan consisting of continuous education, counseling, and consistent follow-up could help enhance the outcome of the bot. Finally, there are available systems and solutions in telemedicine that can help with this diabetes care management.

Compliance with established screening guidelines is an essential step in the diabetes management lifecycle. 87% agreed that the automation process complies with known and established procedures. Top of the list of guidelines agreed by participants to comply with is the American Diabetes Organization (ADA) and the World Health Organization (WHO).

Our literature review already established that preventive care, in line with set standard guidelines (US Preventive Task Force, 1996), can help prevent diseases and avoid future complications among patients. Automation of early screening process can help achieve a achieve that standard, consistent and management approach. In response to the need for a standard set of criteria, international bodies, in 2000, released screening procedures for identifying children with diabetes. For instance, the American Diabetes Association (ADA) and the American Academy of Pediatrics (AAP) released screening guidelines screening children with Type 2 diabetes. Their guidelines recommended that children with body mass index in the 85th percentile and any two additional risk factors should be screened with a fasting plasma glucose (FPG) or a 2-hour glucose tolerance test (OGTT) every two years starting at age ten years or at the onset of puberty. In 2010, the ADA modified its guidelines to include HBA1c tests for diagnosing diabetes at 6.5% for diabetic patients and 5.7 to 6.4% for prediabetes for adults and children (American Diabetes Association, 2010). In Lee *et al.* (2014)'s study, they found that 84% of physicians ordered HbA1c test based on the recently revised ADA guidelines on diagnosing diabetes,

Another potential improvement identified in our study is the inclusion of HbA1c as inputs into the adopted ML algorithm. Glycated hemoglobin (HbA1c) is a standard method for monitoring glycemic control in diabetes (World Health Organization, 2016). There are several benefits to be derived from using HbA1cA patient is not required to be in a state of fasting before testing. Ideally, it should be measured twice a year in people with type 2 diabetes and more frequently in type 1 diabetes patients. Although there are several controversies, with some expressing concerns over the non-glycemic test factors impacting deepHbA1c, they argued that patients are not required to fast before testing. In addition, the cost of the HbA1c testing approach is also controversial. Some have argued that the process is cheap while, Kao *et al.* (2016) 14 suggested that HbA1c is comparably more affordable and effective than most screening methods. This study uses inputs such as the number of times pregnant, plasma glucose concentration at 2 hours in glucose tolerance test, diastolic blood pressure, body mass index, diabetes pedigree to predict the likelihood of diabetes. However, participants agreed on the use of Hb1Ac to improve the accuracy of the systems algorithm.

Participants also suggest that the diabetes care treatment and management should be comprehensive cardiovascular (CVD) risk assessment, ethnicity and lifestyle consideration, and lipid profile check. This position is consistent with the guidelines set by WHO (World Health Organization, 2016), stating that diabetes care management should cover a holistic approach and should be able to support healthy lifestyles, diabetes, monitoring of blood glucose, prevention of the risk of cardiovascular diseases. They should also establish the criteria for referral across the different health institutions. These, according to Lee *et al.* (2014), represent the most critical standards for diagnosing diabetes.

Nowadays, the trend is a movement away from provision health services in a silo's way to more integrated care to advance universal health coverage by increasing the efficiency and effectiveness of service delivery and care for a patient in a holistic manner.

According to a global report from World Health Organization (2016), an integrated cardiovascular disease (CVD) risk approach covers the management of hypertension, strokes, diabetes, and other CVD risk factors. The Integrated health services can also include continuous health promotion, disease prevention, diagnosis, and treatment through different levels of care during a patient's lifetime. Mohan *et al.* (2008) specified in their study that besides reducing morbidity and mortality, an integrated approach is necessary to manage the short-term complications of diabetes and the long term. An integrated can also include blood pressure control, reduce strokes and deterioration of vision, hypertension.

There are many examples of solutions and studies that implemented the integrated approach. For example, in mobile computing for diabetes, HealthPia (Carroll *et al.*, 2007) developed a system called GlucoPhone that attempts to incorporate health care into everyday life by integrating a cell phone and a glucometer. The measuring blood glucose and sending a text message to an online database for further review by professional health professions. This architecture is similar to the one adopted by the DiaBetNet project in Preuveneers and Berbers (2008)'s study. It is essentially a diabetes estimation game played by children to teach them how to self-control and manage the disease.

Holopainen *et al.* (2007) also developed a mobile diabetes management system for home-care treatment coupled with real-time patient-doctor communications using an information systems architecture similar to our study. Mohan *et al.* (2008). Becker *et al.* (2004) developed a mobile phone-based diabetes support system that requires users to input information regarding their daily condition rather than using sensors. There are various other systems available for diagnosing diabetes by capturing information supplied such as their age, blood pressure level, body mass index, and the diabetes pedigree function (Jaafar and Ali, 2005). However, the study carried out by (Jaafar and Ali, 2005) does not perform diagnosis but showcases patient management and monitoring capabilities.

Another concept in the field of telemedicine is personalization. For instance, the system developed in Jaafar and Ali (2005) seeks to incorporate personalization as a critical dimension in the management of patients by improving the quality of patient-centred health-care by providing ongoing relevant feedback to the patient, thereby encouraging and eventually improving overall the patient's self-care management of diabetes and cardiovascular disease.

In their work, Carroll *et al.* (2013) implemented the T2D at pediatric primary care practices by using a computer decision support system called the Child Health Improvement Through Computer Automation (CHICA). They argue that such systems could help overcome the barriers of prediabetes and T2D described by pediatricians.

Our literature review extensively discussed the importance of preventive care and its compliance with recognized standards (Anand et al., 2004). However, studies have shown that preventive care goals in health establishments are challenging to achieve, and the infrastructure to support them is often inadequate (US Preventive Task Force, 1996, Kottke *et al.*, 1993). Rhodes *et al.* (2006) listed Inadequate patient education materials, selection of appropriate screening methods, follow-up counselling, attitudes of patients and family to initial screening which can lead to non-compliance as some of the common barriers to screening. Our study revealed additional barriers such as the high cost of devices, digital literacy in some countries, usability by elderly patients, fear for job losses and aversion for change. Addressing such barriers to screening should be an integral part of the ongoing refinement of screening guidelines.

Our findings show the importance of patient education, counselling, and follow-up as essential components of diabetes management. However, it is not enough to alert patients to the risk of diabetes. Patients also need to understand the principles and importance of a healthy diet, adequate physical activity, avoidance of tobacco and harmful use of alcohol, adherence to medication, foot hygiene, and appropriate footwear, and the need for periodic assessment of metabolic control and the presence or progression of complications (World Health Organization, 2013). For instance, type 1 diabetes and gestational diabetes patients require strict blood glucose control to avoid complications (World Health Organization, 2016).

The deficit in education can likely lead to admittance or hospitalization among persons living with diabetes. WHO World Health Organization (2016) suggests an increasing number of findings that indicate that inpatient diabetes education enhanced communication can reduce the risk for early readmissions into hospital (Magee *et al.*, 2014, Donnellan and Helfer, 2012). Part of the follow-up and discussions should include a diabetes discharge plan for diabetes continuity as the management of diabetes can be fraught with challenges.

6.1   Value Perception of RPA to an Unobtrusive System

Value to stakeholders of a business or institution is often considered the primary justification for automation. Our research has provided an opportunity to understand the value derived from the implementation of IPA in a healthcare institution. Stakeholders see value as a balance between benefits and the cost (Lapierre, 2000, Ojala and Helander, 2014).

The balance is the difference and can include a range of things that include high outcomes and efficient utilization of resources. Most researchers in their study have attempted to determine the value of technology to stakeholders, customers, and staff. For example, Walter *et al.* (2001) used function-oriented analysis to determine the value. According to Ratia *et al.* (2018), Walter *et al.*'s model contains functions that can help to measure value both directly and indirectly. Direct values are often measurables and consist of profit, gains, and volumes of tasks to be accomplished, while the indirect function relies on perception and cannot be quantified. The indirect value to an organization consists of innovating and creating new products and services, better and efficient ways of working.

There are many direct and indirect values or benefits derived from the implementation of RPA by organizations. Of course, the financial industry has seen an enormous share of these benefits. However, other sectors with a lot of information flowing around and rich data have also derived from these benefits.

To determine the value of IPA within and healthcare institutions, we adopted both a quantitative and qualitative approach similar to Ratia *et al.* (2018). As a result, we studied the use of IPA to examine the benefits of an unobtrusive system to determine and predict the risk of diabetes.

In our study, 71% of the physicians agreed and confirmed that the IPA system could improve patient-doctor interaction. Reasons given include the richness of information available to the doctor at the time of diagnosis that allows the doctor to provide insight and reliable information to his patient and avoid confirmation bias. In addition, most physicians agree that the outcome of the bot processing can be used as a basis for discussion, improves documentation, and increases understanding of trends.

As earlier established, this is consistent with Carroll *et al.* (2011)'s Just-In-Time information delivery, where doctors receive the results, alerts, or notifications during patient consultation even though the doctor is attempting to treat a

different disease. The capability of IPA to integrate with other interfaces or systems comparable to traditional software allows it to bring information at the fingertip of the physicians. Furthermore, IPA can extract this information from these systems without changing (Bellman and Göransson, 2019) to the underly systems and software packages, thereby saving the cost of making these changes. Thus, the artefact developed in this study can be integrated into a cost-effective way into most hospital systems without significant change to hospital systems and applications.

One of the most outstanding values of RPA is the need not to change the underlying application. This value represents a significant difference between RPA and other automation systems (van der Aalst *et al.*, 2018). It is simply just replacing humans (Asatiani and Penttinen, 2016).

Out of the participants, only about 14% spend less than 5 mins to predict the risk of diabetes. 70% see a minimum of between 11 to 30 diabetic patients in a day, and 27% see a diabetic patient most of the time. It is evident from this study that determining the risk of diabetes constitutes a primary day-to-day task for physicians. Out of these physicians, a huge 80% of the doctors agree that the concept will result in time savings during consultations. A summary of the benefits of RPA in accounting according to Cooper *et al.*'s research includes Quantity, Speed (Romao *et al.*, 2019).

There is an indirect value such as decreased processing time and improved accuracy, and associated costs. Also, these costs could include increased unemployment, income inequality (Romao *et al.*, 2019), and fundamental social problems such as fear of job losses and aversion to change.

Finally, one should note that the perception of value for other participants in the different countries might be different. Ratia *et al.* (2018) acknowledge that the value function of RPA is not different from any other automation process but finds its uniqueness in the indirect value. This research showed two significant outcomes: understanding the potential of RPA in the healthcare sector and the capability gained to use IPA to enhance and improve their processes. First, RPA bots can carry out other higher functions such as process and decision automation and data capturing (Romao *et al.*, 2019). Second, RPA can quicken the time to achieve value, which is possible due to the speed involved in developing new bots. Most development usually adopts the agile framework for developing bots in a 2- 3 weeks sprint timeframe methodology. Romao *et al.* (2019) argue that there is also substantial potential value in integrating intelligence and automation in business process management. The software bots usually created by humans can work silently in the background while allowing humans to focus on high-value and prioritized tasks (Romao *et al.*, 2019). Thus, RPA can significantly help automate routine administrative business processes in private health care, allow staff to focus more on patients, and create better products and services.

7 Conclusions and Recommendations

This chapter presents the limitation of our current study, future opportunities, and improvements of the research.

This research has shown the usability of intelligent automation process-based unobtrusive systems in medical institutions to screen, identify, and detect the risk of diabetes in a patient at an early stage. Our objective was to investigate the inherent challenges involved in developing and deploying an unobtrusive system using intelligent automation bots.

However, due to time limitations, our study did not include the implementation of unobtrusive systems in medical institutions. However, it will be helpful to study the usability of such systems on real-life people and scenarios and connect to existing technologies available in hospitals.

Future work will seek to investigate the practicability and usability of the system within medical institutions in New Zealand in detecting and predicting the likelihood of patients developing diabetes. We hope that this study will encourage developers, data scientists, and automation developers to build Artificial Intelligence (AI) and Machine Learning (ML) models and integrate with an unobtrusive automation process in detecting and screening for diseases beyond diabetes.

Although this study primarily used self-measuring devices such as blood glucose, blood pressure, and percentage fat level within the system, we recommend that future studies connect automation systems to hospital-grade devices, applications, and systems. Localization of the study within countries and institutions will also ensure the robustness of the system.

Future works should seek to address the limitations on the scope of this study. The American Diabetes Association (2020) classified diabetes into the following general categories:

1. Type 1

2. Type 2

3. Gestational diabetes mellitus

4. Specific types of diabetes due to other causes

Similarly, Al Jarullah (2011) limited the classification to only Type-1 and Type-2 diabetes. However, our study did not distinguish between Type-1 and Type-2 diabetes in determining the risk of diabetes in a patient. Different studies have shown the importance of classification in the treatment of diabetes. For instance, Zhou et al. (2020) revealed that the different types have their respective clinical presentations. The American Diabetes Association (2020) also recognizes the importance of the diabetes classification for determining the kind of therapy and treatment an individual will receive. Therefore, to aid clinicians in determining the appropriate treatment procedure to recommend, future works should improve the current study by classifying diabetes into the relevant category.

Type 1 diabetes is "caused by the destruction of the pancreatic beta cells" (Zhou *et al.*, 2020), resulting in insulin deficiency. Thus, type 1 diabetes is insulin-dependent. On the other hand, resistance to the "transportation of insulin to the cells" (Zhou *et al.*, 2020) causes type 2 diabetes. Both types can lead to life-threatening medical complications, such as strokes, heart attacks, and are heterogeneous with varying presentations.

In our study, diabetes was screened and detected using a model that relied on the glucose level, high blood pressure, body mass index, age of an individual, and the number of pregnancies. In the future, we recommend further studies in diabetes screening parameters to improve accuracy further.

A recent update from American Diabetes Association (2020) on diagnosing diabetes includes using either the fasting plasma glucose (FPG) value or the 2-h plasma glucose (2-h PG) value during a 75-g oral glucose tolerance test (OGTT). In addition, they further confirmed the suitability of FPG, 2-h PG during 75-g OGTT, and HbA1C for diagnostic screening.

Despite the high cost, HbA1c can increase the effectiveness of screening and diagnosis. For example, a study by Lee *et al.* (2014) involved a series of tests carried out by pediatricians and family physicians in the US. A response rate of 50% found that (58%) medical providers ordered HbA1c as an initial test. They also found that an increasing number of pediatricians included HbA1c at 63% as part of their initial screening compared with Family doctors at 49%. Their test confirms that most practitioners are willing to adopt HBA1c acknowledge the critical role it has come to play in screening practices alongside regular and typical tests.

Therefore, future research must seek to include HBA1 as part of their measurement and subsequently improve the model's accuracy.

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Appendix A- Questionnaire

Risk of diabetes

Hello,
 I am a master's degree researcher at the School of Natural and Computation Sciences, Massey University.

I am conducting a study on using Intelligent Process Automation technology to predict and detect the risk of diabetes in a patient.

I would like to know your thoughts on this study. Please note that your responses are anonymous, and you can skip any questions you are not comfortable with.

 To participate in this survey, you will need to

Click here to watch a 10 minute demonstration on the technology.

Read the Participant information sheet for more information on the survey.

Provide your consent if you would like to continue the survey in the next page

Thank you for your participation.

End of Block: intro

Start of Block: consent

Consent

I have read, or have had read to me in my first language, and I understand the Information Sheet provided in the previous page.   I have had the details of the study explained to me, any questions I had have been answered to my satisfaction, and I understand that I may ask further questions at any time.   I have been given sufficient time to consider whether to participate in this study and I understand participation is voluntary and that I may withdraw from the study at any time. I agree to participate in this study under the conditions set out in the Information Sheet.

○ I consent (1)

○ I do not consent (2)

End of Block: consent

Start of Block: Profile Question

Q1 In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

Q2 Please select your Gender:

○ Male (1)

○ Female (2)

○ Prefer not to say (3)

Q3 Select your age group:

○ 18 - 24 (1)

○ 25 - 40 (2)

○ 40 - 55 (3)

○ 55+ (4)

Q4 Select your current clinical settings where you currently work

○ GP Clinic (1)

○ Hospital (2)

○ Not working (3)

Q5 Select the option below that best suits your role in your institution

○ House Officer (1)

○ Senior House Officers (2)

○ Medical Officer (3)

○ Registrar (4)

○ Specialist (5)

○ Other (6) _____

Q6 How many years have you spent working in this role?

○ Less than 5 years (1)

○ 5 -10 years (2)

○ 10 - 15 years (3)

○ 15 - 20 years (4)

○ 20 - 25 years (5)

○ 25 - 30 years (6)

○ More than 30 years (7)

End of Block: Profile Question

Start of Block: Practice

Q7 What is the estimated average patient - doctor time do you take to predict the risk of diabetes?

○ Less than 5 mins (1)

○ 5 - 10 mins (2)

○ 15 -20 mins (3)

○ More than 20 mins (4)

Q8 How many patients do you typically see in a day?

○ Below 10 (1)

○ 11 - 30 (2)

○ 31 - 50 (3)

○ 51 - 80 (4)

○ 81 -110 (5)

○ More than 111 (6)

Q9 How often do you normally detect diabetes in your patients?

○ Always (1)

○ Most of the time (2)

○ About half the time (3)

○ Sometimes (4)

○ Never (5)

Q10 Do you think the processes adopted by the bot align with standard practice of determining the risk of diabetes?

○ Yes (13)

○ No (14)

Skip To: Q12 If Do you think the processes adopted by the bot align with standard practice of determining the ris... = No

----

Display This Question:

If Do you think the processes adopted by the bot align with standard practice of determining the ris... = Yes

Q11 Please select from the list below the standards of practice you think the bot aligns with for determining the risk of diabetes in a patient.

☐ America Diabetes Association (1)

☐ European Association for the Study of Diabetes (2)

☐ International Diabetes Federation (3)

☐ Australasian Diabetes in Pregnancy Society (ADIPS) (4)

☐ World Health Organization (5)

☐ Diabetes UK (6)

☐ Canadian Diabetes Association (7)

☐ Japan Diabetes Association (8)

☐ Others (9) _____

Q12 Why do you think that the bot does not align with any standard of practice?

_____

_____

_____

_____

_____

End of Block: Standards

Q13 Will the technology concept shown in the video potentially improve the quality of patient - doctor interaction?

○ Yes (1)

○ No (2)

Q14 Please state the reasons why the concept cannot potentially improve the quality of patient - doctor interaction in your own words.

_____

_____

_____

_____

_____

Q15 Do you think the technology concept will result in time savings during consultations?

○ Yes (13)

○ No (14)

Q75 Please state the reasons why the technology concept shown in the video cannot result in time savings during consultations

_____

_____

_____

_____

_____

Q16 Do you think the technology concept shown in the video has the potential to reduce the staff workload?

○ Yes (13)

○ No (14)

Q76 Please state the reasons why the technology concept shown in the video cannot reduce staff workload

_____

_____

_____

_____

_____

Q17 Will the technology shown in the video reduce the frequency of visit of the patient to   the hospital?

○ Yes (1)

○ No (2)

○ Maybe (3)

Q77 Please state the reasons why the technology concept shown in the video cannot reduce the frequency of patients' visit to the hospital

_____

_____

_____

_____

_____

Q19 What other benefits do you think can be derived by practitioners or specialist using this technology within the clinical settings?

_____

_____

_____

_____

_____

Page Break

Q20 How best will you relay the outcome of the bot to the patient?

_____

_____

_____

_____

_____

Q22 What challenges do you think is likely to be encountered during implementation of this technology in your institution?

_____

_____

_____

_____

_____

Q23 How do you think that the technological concept shown in the video can be improved?

_____

_____

_____

_____

_____

Q25 What kind of clinical devices do you think will help improve the accuracy of the bot prediction?

_____

_____

_____

_____

_____

Q28 What is it that you like most about the research and the bot?

☐ Doctors console (5)

☐ Patient Registration Form (6)

☐ Connection with other systems and devices (7)

☐ Consistency with standard care practice (8)

☐ The video presentation (4)

☐ Others (enter as many items as you wish) (10)
_____

Q73 What is it that you like least about the research and the bot?

☐   Doctors console (5)

☐   Patient Registration Form (6)

☐   Connection with other systems (7)

☐   Consistency with standard care practices (8)

☐   The video presentation (4)

☐   Others (enter as many items as you wish) (10)
_____

Q78 What enhancements would you suggest that can improve the item(s) that you like the least in the previous question?

_____

_____

_____

_____

_____

Q31 How did you find the video in terms of communicating its ideas?

○ Clear (1)

○ Confusing (2)

○ Informative (3)

Q32 Do you have any other suggestions that can improve or enhance the outcome of the research?

_____

_____

_____

_____

_____

End of Block: Research Questions

Appendix B: Participant Information Sheet

Participant Information Sheet

Study title: **Implementation of an IPA based Clinical Decision Support System for Early Detection and Screening of Diabetes**

Locality: **Massey University Albany Campus, Auckland**
Ethics Application ID ref.: 4000023448

Researcher **Seun Famurewa** Contact email: **sfamurewa@yahoo.com**

Researcher Introduction

My name is Seun Famurewa, and I am a master's degree student at Massey University, School of Natural and Computational Sciences. My supervisor is Dr Atiq Arzoo.

Invitation to Participate in this Research Study

We invite you to take part in our questionnaire to study the use of Intelligent Process Automation to detect or determine the risk of diabetes in a patient in a clinic or hospital.

Completion of the questionnaire will also provide information required for further improvement of both the study and the automation.

Whether or not you take part is your choice. If you don't want to take part, you don't have to give a reason. If you do want to take part now, but change your mind later, you can pull out of the study at any time.

This Participant Information Sheet will help you decide if you'd like to take part. It sets out why we are doing the study, what your participation would involve, what the benefits and risks to you might be, and what would happen after the study ends.

If you agree to take part in this study, you will be asked to sign the Consent Form. You will be given a copy of both the Participant Information Sheet and the Consent Form to keep.

Please make sure you have read and understood all the pages.

WHAT IS THE PURPOSE OF THE STUDY?

The statistics from the World Health Organization (2016) are staggering showing a reported rise of diabetes globally. The number of people living with diabetes soar to 422 million in 2014 from 108 million in 1980 representing an 8.5%

increase. In 2012, 3.7 million people reportedly died before they reached the age of 70 years while 1.6 million people died in 2016 because of diabetes (WHO, 2016).

According to WHO and supported by the US Preventive Task Force, early screening aid preventive care, aligned with set standard guidelines, is an important factor to prevent diseases and avoiding future complications among patients. This Preventive care approach also aligns with the American Diabetes Association (ADA) recommendation for detecting Type 1, 2 Diabetes (T2D) through screening.

Attaining preventive care through screening by medical institutions have a lot of barriers such as physician time constraints, lack of knowledge about screening, basic management for diabetes capacity, lack of education and poor communication with patients and. Various studies have shown that an unobtrusive automated system such as Intelligent process automation could help eliminate the barriers of screening for prediabetes and diabetes in patients

The study is not funded and is strictly for the purpose of obtaining a master's degree in information science from Massey University

WHAT WILL MY PARTICIPATION IN THE STUDY INVOLVE?

You have been chosen to participate in the study because you have studied and graduated as Medical Doctor.

The study will involve you watching a 10-minute video and completing a questionnaire. Both the video and questionnaire are available in the cloud and access links shall be provided to you.

The questionnaire has been designed to gather information of the relevance of this technology in the day to day clinical and hospital processes and procedures

To help ensure the data set is diverse and provides stable information, we'd like to see at least 30 responses for this questionnaire. More responses help to increase diversity in this regard and allow the research to achieve its best outcomes.

Participants are invited to complete the associated survey. A short period of time is required to complete the survey.

WHAT ARE THE POSSIBLE BENEFITS AND RISKS OF THIS STUDY?

By participating in this research, you will be helping the team to

1. Gather insights and information on how intelligent automation can be utilize within medical institutions
2. Identify the best way to implement intelligent automation to assist doctors
3. Identify the knowledge and tools that can be used to assist patients
4. Understand the feasibility of implementing an intelligent automation in a medical facility.
5. To contribute to the existing body of knowledge

The research will create a software bot that can predict and detect the presence of a disease based on the data that have been fed into the system or extracted from sensors and devices.

This study has been evaluated by peer review and judged to be low risk.

WHO PAYS FOR THE STUDY?

There is no cost to you, the participant, for taking part in this study.

WHAT ARE MY RIGHTS?

Participating in this study is completely voluntary and you are free to decline to participate, decline to answer any question, or to withdraw from the research at any practicable time, without experiencing any disadvantage.

You, the participant has a right to access information about you, collected as part of this study. You will be told of any new information about adverse or beneficial effects related to this study which may impact upon your health.

The questionnaire is designed to ensure that no personal identifiable information (PII) is collected at any point in the questionnaire. Feel free to withdraw your consent or inform us if find any PIIs in the questionnaire

WHAT HAPPENS AFTER THE STUDY OR IF I CHANGE MY MIND?

Electronic data and records will be the responsibility of the Principal researcher

WHO DO I CONTACT FOR MORE INFORMATION OR IF I HAVE CONCERNS?

If you have any questions, concerns, or complaints about the study at any stage, you can contact the following researchers involved in the study:

Dr Arzoo Atiq: Senior Tutor, School of Natural and Computational Sciences, Massey University, Albany Auckland.

Phone: +64 (27) 8281979

Email a.atiq@massey.ac.nz

This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named in this document are responsible for the ethical conduct of this research. If you have any concerns about the conduct of this research that you want to rais

e with someone other than the researcher(s), please contact Professor Craig Johnson, Director - Ethics, telephone 0 6 3569099 ext 85271, email humanethics@massey.ac.nz."