INVESTIGATING THE ADOPTION OF AI BASED INTERVENTIONS USED TO DIAGNOSE DIABETES BY DOCTORS IN MAHARASHTRA & KARNATAKA: CRITICAL ASSESSMENT AND PROPOSED FRAMEWORK

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DECLARATION

I, hereby declare that the presented work in the thesis entitled "Investigating the Adoption of AI based Interventions Used to Diagnose Diabetes by Doctors in Maharashtra & Karnataka: Critical Assessment and Proposed Framework" in fulfilment of the degree of **Doctor of Philosophy (Ph. D.)** is the outcome of research work carried out by me under the supervision of Dr Maninder Singh, working as Associate Professor, in the Mittal School of Business of Lovely Professional University, Punjab, India. In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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<u>**CERTIFICATE**</u>

This is to certify that the work reported in the Ph. D. thesis entitled "Investigating the Adoption of AI based Interventions Used to Diagnose Diabetes by Doctors in Maharashtra & Karnataka: Critical Assessment and Proposed Framework" submitted in fulfilment of the requirement for the reward of the degree of **Doctor of Philosophy (PhD)** in the Mittal School of Business, is a research work carried out by Mrinmoy Roy, 41900059, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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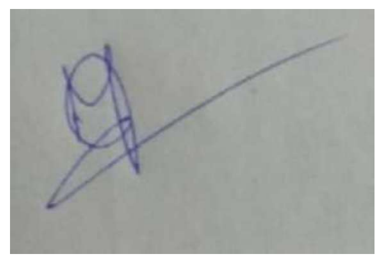

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ABSTRACT

The incorporation of AI into the healthcare sector, particularly in the realm of disease diagnosis such as diabetes, presents medical practitioners with auspicious prospects as well as formidable obstacles. Determining the extent to which physicians in Maharashtra and Karnataka, two Indian states renowned for their heterogeneous healthcare environments, have embraced AI-driven interventions for diabetes diagnosis is the objective of this thesis. The escalating global prevalence of diabetes and the potential for AI to revolutionize diagnostic accuracy and efficiency are the driving forces behind this research. However, to fully harness the potential of AI in clinical practice, it is imperative to conduct a thorough analysis of the various factors that impact healthcare professionals' acceptance and utilization of this technology.

The principal aim of this study is to assess the preparedness and inclination of medical practitioners in the states of Maharashtra and Karnataka to adopt AI-driven interventions in the context of diabetes diagnosis. From a methodological standpoint, quantitative data are gathered using a structured questionnaire that includes the following constructs: Behavioural Intention (BI), Subjective Norms (SN), Perceived Risk (PR), Personal Innovativeness (PI), Affordability (AF), Perceived Usefulness (PU), & Perceived Ease of Use (PEOU); Result Demonstrability (RD); and Personal Innovativeness (PI). The responses to this questionnaire have been carefully crafted to elicit physicians' perspectives, memories, and beliefs regarding AI-powered diabetes diagnostic devices.

The survey findings offer significant insights into various critical facets. To commence, the research investigates the extent to which physicians have faith in the effectiveness and comprehensibility of outcomes produced by AI-driven diabetes diagnostic instruments, with a focus on the perceived demonstrability of results. Furthermore, it investigates the degree to which medical professionals perceive AI-driven interventions as harmonious with their current diagnostic methodologies and individual inclinations, considering aspects such as technological applicability, compatibility, and congruence with their approach to providing care. In addition, the study investigates the personal innovativeness of physicians, their apprehensions regarding cost-effectiveness, their assessments of the utility and usability of AI-based diabetes diagnostic services, their behavioural intentions, subjective norms, perceived risks, and previous encounters with such services.

Through a thorough analysis of these factors, the research makes a valuable contribution to the advancement of knowledge regarding the adoption landscape of AI-based interventions in

diabetes diagnosis among medical practitioners in the states of Maharashtra and Karnataka. On the basis of the discovered results, a framework is suggested that can serve as a guide for the successful incorporation of AI technologies into clinical practice. This framework is customized to suit the varied viewpoints and requirements of healthcare practitioners in the area. The primary objective of this framework is to promote well-informed decision-making and facilitate the effective execution of AI-driven interventions that improve the delivery of diabetes care and patient outcomes.

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CHAPTER-1

1.1 INTRODUCTION

Diabetes, often referred to as "Chronic Metabolic Disease," is a significant issue in worldwide healthcare systems. Diabetes affects 537 million individuals aged 20–79, according to IDF projections, and 374 million individuals have impaired glucose tolerance (IDF, 2021). According to available data, 693 million people worldwide are predicted to be affected by diabetes by 2045, with a rise in prevalence predicted from 8.8% in 2017 to 10% in that year (Cho, 2018; Fitzmaurice, 2017). According to recent data, 46% of diabetics receive no treatment at all or no diagnosis at all. Diabetes risk factors include being older, being of a certain ethnicity, smoking, being obese, and not exercising enough (Deshpande, 2008). Snags are the primary origin of increased indisposition & impermanence in individuals with diabetes, and they significantly raise the financial strain on healthcare systems around the globe. Cardiovascular illness, renal disease, neuropathy, retinopathy, and lower limb amputation are examples of complications. AI and associated know-how have the potential to significantly advance diabetes care. AI in diabetes management is transforming healthcare by improving accuracy, efficiency, usability, and satisfaction for all stakeholders: providers, patients, beneficiaries, and carers. A thorough examination of recent medical literature from PubMed and similar databases reveals 4 important dissimilar, & intricate groups of emerging policies & use cases where artificial intelligence is transforming diabetes management. These comprise clinical decision assistance, automated retinal screening, predictive risk stratification of groups, and patient self-management systems. Numerous cutting-edge artificial intelligence-powered decision-support solutions are now on the market and will soon be released. These consist of insulin pumps, glucose monitors, retinal imaging devices, smartphone apps, predictive modelling software, and more. The application of AI to diabetes diagnosis is going to take off shortly. Finding the variables affecting physicians' usage of AI for diabetes diagnosis is the main objective of this study.

Diabetes has a substantial impact on mortality and morbidity rates (Papatheodorou, 2016). Preventive and early detection interventions for diabetes are equally important. Although 10% of global health spending ($760 billion) is attributed to diabetes, one in two people with the disease are unaware that they have it, making control of the condition difficult.

- **The Global Healthcare System and Non-Communicable Diseases (NCDs)**

The global healthcare system is made up of a wide range of concerns and components, which reflects the complex and interdependent nature of healthcare globally. The provision of medical services, competent healthcare workers, adequate funding, dependable health information systems, effective leadership and governance, and the availability of medical supplies and equipment are all essential components of healthcare systems (Hoffman, 2018). The World Health Organisation (WHO) prioritises building health systems. To deliver efficient and fair treatment, it is imperative to make certain that the infrastructure is kept up to date, the health staff is highly motivated, and trustworthy information is easily available. The COVID-19 epidemic has dyed the significance of having affordable, effective, & equitable access to high-quality treatment. A well-run healthcare system is essential. The effects of poverty on people's physical and mental well-being, mental health issues, non-communicable diseases, and climate change are just a few of the numerous urgent issues confronting healthcare systems worldwide today (Efthymiou-Egleton, 2016). Healthcare is impacted by political, economic, and environmental issues, which in turn affect patients' admittance to caution & general health. In summary, the worldwide healthcare system is dynamic and complicated, requiring strong leadership, adequate resources, and a coordinated effort to address the vast range of health needs of individuals.

The high cost of diabetes care is a result of the condition's global prevalence. The IDF, 2019 estimates that diabetes affects 463 million individuals globally, with an additional 374 million experiencing weakened glucose tolerance. Through 2045, diabetes is predicted to distress 693 million individuals globally. It is anticipated that the prevalence of diabetes will rise from 8.8% in 2017 to 10% in 2045 (Fitzmaurice, 2017).

The majority of illnesses and medical conditions known as non-communicable diseases (NCDs) are not caused primarily by infectious agents or infections. Hereditary, behavioural, physiological, and environmental factors interact in a complicated way to generate various chronic illnesses.

- **The Indian Healthcare System & burden of NCDs**

The four principal NCDs are cardiovascular disease, malignancy, diabetes, and COPD. In 2016, low and middle-income countries accounted for more than 75% of non-communicable disease-related fatalities, with over 46% of those fatalities affecting individuals under the age of 70 (Bulto, 2017). The prevalence of chronic illness is on the rise, even in India, where noncommunicable diseases constituted 61.8% of all fatalities in 2016 (Global Health Estimates, 2015), up from 53.6% in 1990. Noncommunicable diseases are the primary cause of mortality among individuals aged 40–69, accounting for 73.2% of insurance claims (ISL, 2017). Non-communicable diseases account for the majority of deaths in India; these include cardiovascular and pulmonary diseases, cancer, diabetes, and numerous endocrine disorders. Disability-Adjusted Life Years (DALYs) in India increased from 30.9% to 55.4% between 1990 and 2016, according to noncommunicable disease morbidity data. Disability-adjusted life years (DALYs) in India have risen primarily due to noncommunicable diseases, including endocrine disorders, cardiovascular disease, chronic obstructive pulmonary disease, and diabetes (Feigin, 2016). Those who are overweight, have hypertension, diabetes, elevated fasting plasma glucose, elevated total cholesterol, engage in regular alcohol consumption, or smoke are more susceptible to the development of non-communicable diseases (ICMR, 2017).

In 2017, non-communicable diseases initiated an estimated 4.7 million fatalities in India, constituting 49% of the total causes of mortality in the country. The leading cause of mortality was cardiovascular disease (23%), followed by pulmonary disease (9%), cancer (6%), and diabetes (2.4%). NCDs accounted for nearly half of all DALYs, and among those under the age of 70, 65% of all preventable fatalities occurred (Menon et al., 2019).

NCDs, such as diabetes, cancer, heart disease, and chronic obstructive pulmonary disease, account for 74% of all deaths. Modifiable behavioural risk factors, such as smoking, eating poorly, not getting enough exercise, and problematic alcohol usage, are shared by many NCDs and can lead to obesity, high blood pressure, cholesterol, and other health issues. "More than three-quarters of NCD deaths occur in low- and middle-income countries; thus, they remain a significant public health burden in all countries" (WHO, 2020). A diverse array of social influences impact the development of specific habits. Noncommunicable diseases (NCDs) are becoming more prevalent in India, according to research, and if preventative measures aren't taken quickly, the nation may lose a lot of money and miss its development goals. If we can cut these illnesses by 2%, our GDP can increase by 1% (Bloom, 2014).

In India, diseases and cancers cause 66% of all deaths (6,047,000), including 22% of deaths that occur before their time (WHO, 2020). According to data from Globocan (Bray, 2018), 2,720,251 cases were reported prevalently, 1,324,413 new-fangled gears were described, & 8,51,678 deaths were registered in India in 2020. "The health system can potentially reduce deaths from non-communicable diseases by effectively and fairly addressing preventive risk factors." (WHO, 2013). The WHO's global stroke strategy to avoid & succeed in non-communicable illnesses 2013–2020 (extended to 2030) suggests the following general criteria for national programs:

- Life-course approach
- Empowerment of people and communities
- Evidence-based strategies
- Universal health coverage
- Management of real, perceived or potential conflicts of interest
- Human rights approach
- Equity-based approach
- National action and international cooperation and solidarity
- Multisectoral action

There are nine health targets in the SDGs, three of which are related to NCDs. The World Health Organisation (WHO) released an action plan to address noncommunicable diseases (NCDs) during the World Health Assembly. Lingering illnesses, including cancer, COPD, MG, & chronic disease virus (CDV), account for more than 80% of early deaths from NCDs (World Health Organisation, 2021). The first of its kind, the National NCD Monitoring Framework was created by India in response to World Health Assembly Resolution 66.10. It contains KPIs unique to the nation, along with a list of ten goals and twenty-one benchmarks that the nation intends to meet by 2025. Future increases in the incidence of non-communicable diseases (NCDs) have been linked to several risk factors, including longer life expectancy, altered lifestyles, and growing industrialization and urbanization (Gupta, 2018). Sarveswaran (2020) states several biological and behavioural antecedents cause non-communicable diseases (NCDs). These risk factors include excessive fat and sodium intake, inactivity, smoking, high blood pressure, diabetes, and cholesterol. Geetha (2020) states that those with prior conditions are more likely to contract COVID-19. These illnesses include CVD, lung disease (COPD/bronchial asthma), hypertension, and diabetes mellitus. The Indian government launched "Population-based screening of major NCDs" in primary healthcare settings and throughout communities to fight diabetes, hypertension, & the 3 most frequent cancers: oral, breast, and cervical (WHO, 2021).

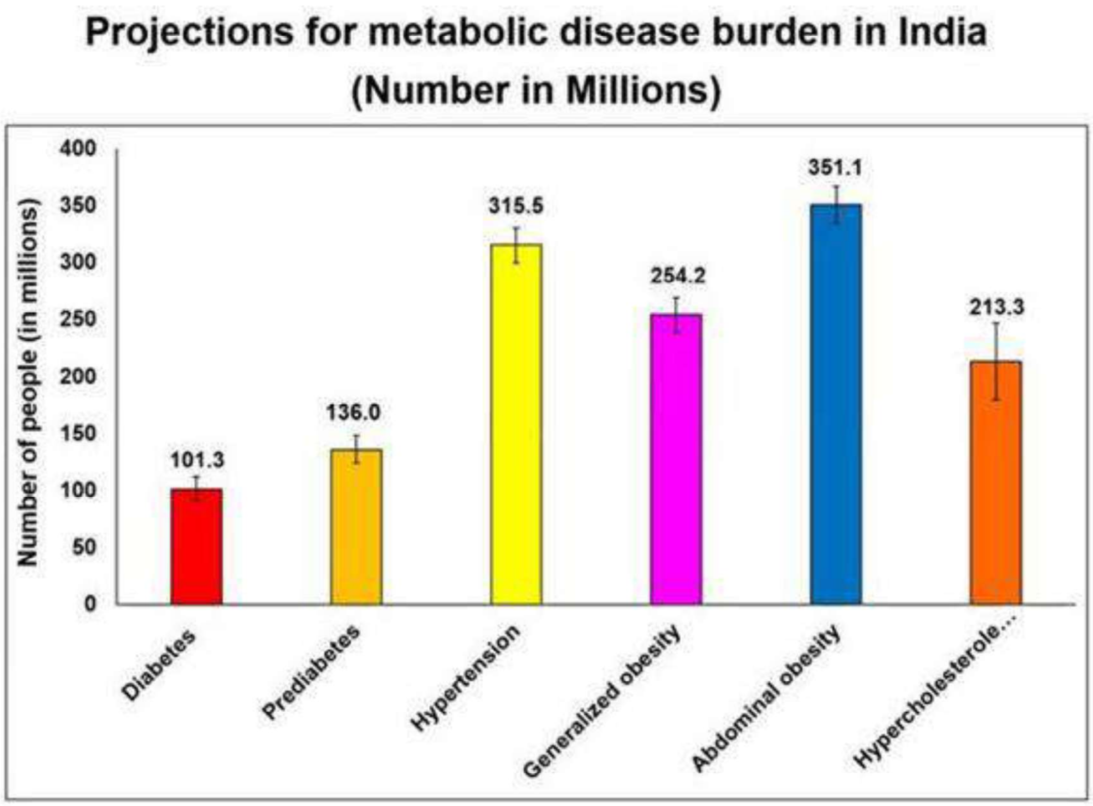


Fig. 1.1: Projection of NCD burden in the India

1.1.1 Diabetes as a Lifestyle Disease

Lifestyle diseases do not transmit from person to person like infectious diseases do. Many ailments have their major cause in our daily habits. We all know about smoking, binge drinking, eating poorly, and choosing a sedentary lifestyle over physical activity. Conversely, long-term adoption of these behaviours may lead to significant health complications such as diabetes or hypertension.

The primary cause of lifestyle disorders is the daily actions of individuals. Such conduct gives rise to diseases that are potentially lethal as well as incurable. Individuals with substantially disturbed cardiovascular rhythms are those who have unhealthy lifestyles and are in jeopardy of mounting long-lasting non-communicable illnesses. Lifestyle diseases are mostly caused by poor nutrition, inactivity, poor posture, and an irregular biological clock. Lifestyle diseases are caused by bad habits. Furthermore, diabetes is a result of living an unhealthy lifestyle. Diabetes is mostly caused by a poor diet, inactivity, heredity, alcohol consumption, and smoking. Diabetes, then, is a chronic illness that is also brought on by a person's lifestyle decisions.

Diabetes is a lifelong metabolic disease that arises from either insufficient or improper usage of the insulin produced by the body. Blood sugar regulation is the function of insulin. One common consequence of uncontrolled diabetes is elevated blood glucose, or hyperglycaemia, which can damage many body systems and organs, including the blood vessels and brain system if left untreated.

In people over the age of 18, the prevalence of diabetes was 8.5% in 2014. Diabetes-related diseases claimed the lives of 1.5 million people worldwide in 2019, with people under the age of 70 accounting for 48% of these deaths. Diabetes was linked to approximately 4,60,000 fatalities from kidney disease and an extra 20% from cardiovascular disease as a result of elevated blood sugar (The Global Impact of Disease Study, 2019).

Diabetes has been associated with a 3% upsurge in age-standardized impermanence rates between 2000 and 2019, an increase of two decades. The mortality rate associated with diabetes has risen by 13% in lower-middle-income countries, posing a threat to global health (WHO, 2022).

- **Type 1 Diabetes**

Type 1 diabetes, which is also referred to as adolescent, childhood-onset, insulin-dependent, or insulin-deficient diabetes, is characterized by the daily need for insulin injections as a result of inadequate insulin secretion. Type 1 diabetes affected 9 million individuals globally in 2017; the majority of these individuals resided in nations characterized by comparatively high per capita incomes. Type 1 diabetes is distinguished by the abrupt onset of visual impairment, extreme fatigue, polyuria, polydipsia, chronic hunger, and rapid weight loss (WHO, 2022). The exact aetiology of type 1 diabetes remains unknown; however, both genetic and environmental factors probably contribute to its development. Specific genetic markers have been associated with a heightened prevalence of type 1 diabetes. It is crucial to bear in mind that the initiation of an autoimmune reaction can only be triggered by an external stimulus, such as a virus (Xie, 2018). In type 1 diabetes, the immune system erroneously targets pancreatic beta cells for destruction because it misidentifies them as foreign invaders. Autoantibodies selectively target the beta cell surface proteins during this immune response. The progressive decline in insulin production due to beta cell depletion results in insufficient regulation of blood glucose levels (Iqbal, 2018).

- **Type 2 Diabetes**

Type 2 diabetes arises due to a compromised sensitivity of the body to insulin. Non-insulin-dependent diabetes or adult-onset diabetes are alternative names for this condition. Diabetes is classified as ICD-9 class 2 in 95% of diabetic patients. Absence of physical activity and obesity are two primary risk factors for type 2 diabetes. While generally less severe, the symptoms of type 2 diabetes and type 1 diabetes are alarmingly similar. Due to this, it could be years before the illness is officially diagnosed, commencing from the moment symptoms manifest. Only adults were previously diagnosed with this form of diabetes; nevertheless, there has been an increasing prevalence of the condition among children (WHO, 2022). While the majority of cases involve adults, there has been a notable increase in recent diagnoses of younger individuals who are affected, which may be attributed to the juvenile obesity pandemic.

- **Gestational Diabetes**

An estimated 3-9% of expectant women are afflicted with gestational diabetes. Gestational diabetes is distinguished by heightened echelons of glucose in the plasma and is precipitated by insulin resistance induced by placental hormones. While there is an increased jeopardy of emerging type 2 diabetes in folks with a previous history of gestational diabetes later in life, the condition frequently resolves itself following childbirth (Yang, 2022). Hormones produced by the placenta are crucial for the development and maturation of the foetus during pregnancy. However, these hormones may impede the consistent functioning of insulin in the maternal body. Progesterone and human placental lactogen are two substances that possess the capacity to stimulate insulin resistance in maternal cells, leading to a subsequent reduction in the intestinal absorption of glucose (Ellahham, 2020). To ensure that the developing fetus receives sufficient nutrition, blood glucose levels are increased. As a preventative measure against insulin resistance, the maternal pancreas commonly produces an excessive quantity of insulin. Nevertheless, a subset of women are unable to activate this protective mechanism, resulting in the onset of gestational diabetes. Pregnant women who consistently and significantly exceed the diagnostic threshold for diabetes but still experience elevated blood sugar levels may potentially be diagnosed with gestational diabetes. Pregnant and postpartum, women who have gestational diabetes are consistently and substantially heightened to encounter complications. The prospective susceptibility of these mothers and their offspring to type 2 diabetes is elevated. In disparity to the citations of symptoms, prenatal screening is regarded as the standard procedure for the diagnosis of gestational diabetes (WHO, 2022).

- **Impaired glucose tolerance and impaired fasting glycemia**

IFG and IGT denote transitional phases that exist between prediabetes, diabetes, and normalcy. While not invariably predisposing, those who have received a diagnosis of IGT or IFG have a significant vulnerability to developing type 2 diabetes. There is an increased prevalence of type 2 diabetes among individuals with intermediate dysglycemia. Ascertained through an oral glucose tolerance test, individuals diagnosed with IGT demonstrate elevated blood glucose levels that do not yet progress into the diabetic range. On the other hand, IFG is distinguished by elevated fasting blood glucose levels, which function as an indicator of impaired glucose regulation when an oral glucose challenge is absent.

Both conditions are indicative of the pancreas producing inadequate insulin or insulin resistance. The susceptibility of individuals with IGT or IFG to develop diabetes is heightened, underscoring the criticality of early identification and lifestyle modifications to avert or postpone the initiation of this chronic metabolic disorder. Consistent monitoring and focused interventions, including adjustments to one's diet and heightened physical activity, are essential for the effective management and potential reversal of these glycemic abnormalities.

- **Health impact**

Prolonged diabetes complications may arise in the cardiovascular and vascular systems, as well as the eyes, kidneys, nerves, and nervous system. Diabetes increases the risk of heart attack and stroke in adults by a factor of two to three (Sarwar et al., 2010). One potential consequence of the complications listed below is the need for amputation of the affected limb: foot ulcers, neuropathy (an injury to the nervous system that elevates the susceptibility to infections), or impaired blood circulation. A primary cause of blindness, diabetic retinopathy is brought about by years of gradual damage to the retina's microscopic blood vessels. According to a 2022 Lancet Global Health report, the global prevalence of diabetes-related blindness is estimated to affect around one million people. Diabetes is identified by the National Institute of Diabetes and Digestive and Kidney Diseases (2014) as the principal cause of kidney failure. Individuals diagnosed with diabetes are at an increased risk of experiencing adverse or critical outcomes that are linked to a range of contagious illnesses, including COVID-19.

- **Diagnosis & Treatment**

Early diagnosis is made possible by blood glucose testing, which is comparatively inexpensive. Diabetes treatment entails modifying one's diet and exercise routine in addition to reducing blood glucose levels and other blood vessel damage risk factors. A lack of randomised trials to demonstrate the effectiveness of screening for diabetes or pre-diabetes notwithstanding, early intervention can potentially lower the incidence of complications in the future. Because the tolerance in the vignette has jeopardy dynamics (obesity, hypertension, & family history of diabetes), screening is necessary. Many with type 2 diabetes are thought to have had the complaint for more than five years before diagnosis, with about 25% of cases already having microvascular issues.

1.1.2 Management of Diabetes

Diabetes is a lifestyle-related ailment that impacts countries with lower and moderate incomes (LMICs) at a disproportionate rate, in contrast to countries with higher incomes. This is influenced, in part, by ageing populations and rising obesity rates, both of which are intensified by unhealthy dietary habits and lack of physical activity (Globe Health Action, 2020; Chatterjee et al., 2017). Uncontrolled chronic elevated blood glucose levels, or hyperglycemia, have the potential to result in various microvascular complications, including diabetic nephropathy, neuropathy, retinopathy, and cardiomyopathy (Shaw et al., 2010). Diabetic nephropathy, more commonly referred to as diabetic kidney disease (DKD), impacts between twenty and forty per cent of those who have the condition. Diabetes onset is typically observed to transpire within a decade, according to Gheith et al. (2016) (Xie et al., 2018). To prevent microvascular complications in diabetics, it is critical to closely monitor and regulate blood pressure and other risk factors, including blood sugar levels (BMJ, 1998, 2000). In patients with diabetes, cardiovascular complications are the leading foundation of mortality & morbidity. The risk of mortality increases by a factor of two or four in individuals with diabetes. As per the findings of Benjamin et al. (2003), the development of chronic heart failure (CHF) is the principal aetiology of the unfavourable prognosis among individuals with diabetes. Epidemiological evidence suggests, via IGT and/or IFGD, that early complications may accompany elevated blood glucose levels in individuals transitioning from a normal glycemic state to diabetes (Eddyania et al., 2005).

Early detection of individuals with diabetes or prediabetes is crucial for reducing the severity and complications of the disease during intervention (Deedwania et al., 2005; Diabetes Care, 2005). The early detection of diabetes offers numerous advantages. Preventing the deterioration of beta cell capacity is among the numerous benefits of early intervention in diabetes management, which also entails controlling glycemia and associated abnormalities such as hypertension and dyslipidemia (BMJ, 1998). Individual health can be improved while the financial, psychological, and other burdens imposed on communities and individuals are reduced.

Toumpanakis et al. (2018) state that the principal objectives of diabetes management are the preservation of blood sugar levels in the vicinity of normalcy and the aversion to perilously low levels. Dietary changes, physical activity, weight loss, and the administration of appropriate medications are frequently utilized in this context. Individuals with diabetes who are well-informed about their condition and actively participate in their treatment have a significantly reduced likelihood of experiencing serious complications (Nathan et al., 2005; Ann. of Int. Med., 1995).

A symptom of diabetes is elevated blood glucose, which is caused by the inability or insufficiency of the body to synthesize insulin, thereby impeding its utilization. The potential severity of the side effects associated with this illness may have detrimental effects on multiple organ systems, consequently reducing the overall quality of life. The necessity for personalized treatment is becoming increasingly apparent in the healthcare industry due to the complexity and prevalence of diabetes. Enhanced patient outcomes could potentially result from the significant transformation in diabetes treatment that this innovative approach enables. An alarming increase in the prevalence of diabetes is a substantial concern in the realm of global health (Yun, 2021). As of 2019, the IDF estimates that the worldwide prevalence of diabetes has accumulated to 463 million individuals. It is projected that the figure will experience a significant surge by 2045, given that delayed response affects an estimated 700 million individuals. An improper diet, excessive sitting, an ageing population, and obesity are all factors that contribute to the global increase in diabetes cases.

The ability of personalized medicine to identify the genetic factors that impact an individual's susceptibility to diabetes is an essential element in the treatment of the disease. Genetic screening can identify individuals who are at risk of developing diabetes, allowing for the prompt implementation of targeted preventative therapies and lifestyle modifications (Petrie, 2018). In addition, genetic information provides medical professionals with invaluable guidance concerning the most effective medication regimen for specific patients. Implementing this approach reduces the probability of adverse drug reactions and ineffectual treatment (Cryer, 2016). By being incorporated into personalized treatment regimens, ubiquitous technology and continuous glucose monitors serve as cutting-edge devices that enable diabetics to actively manage their condition. Patients can govern their dietary, exercise, and medication regimens more efficiently when they have access to real-time data and individualized feedback (Ashrafzadeh, 2019). According to Rescalli (2022), this approach empowers individuals to take charge of their health.

1.1.3 How Diabetes is Diagnosed

Diabetes is analysed with an investigation for glucose content in the plasma & through the following demonstration (WHO, 1999).

• Plasma glucose near at least 7.0 mmol/L (126 mg/dL) during fasting. To perform this examination, blood is drawn after a fasting period, specifically in the morning before breakfast, following an adequate period of fasting for the patient throughout the night.
• Plasma glucose level exceeding 11.1 mmol/L (200 mg/dL) 2 hours following a 75gm OGTT
• Manifestations of "hyperglycemia" accompanied by plasma glucose levels exceeding 11.1 mmol/L (200 mg/dL) during periods of refusing to eat or non-fasting
• Glycated haemoglobin (HbA1C) exceeding 48 mmol/mol (>=6.5 DCCT%) Care for Diabetes (2010).

To validate a positive outcome in the absence of any ambiguous hyperglycemia, attempt to replicate any of the aforementioned procedures on an unrelated day. Formal glucose tolerance testing, which may require as much as two hours and provides no prognostic advantage over the fasting test, is considerably more difficult to administer and requires significantly more time to measure than fasting glucose levels (Saydah et al., 2001). As of now, the diagnostic criteria for diabetes consist of 2 fasting glucose interpretations that exceed 7.0 mmol/L (126 mg/dL).

The World Health Organization (2006) defines impaired fasting glucose as a blood glucose level ranging from 6.1 to 6.9 mmol/L (110-125 MG/dL). Patients are considered to have impaired glucose tolerance when their plasma glucose levels remain within the range of 7.8 mmol/L (140 mg/dL) to 11.1 mmol/L (200 mg/dL) two hours after consuming 75 g of glucose. Santaguida (2005) identifies the concurrent development of type 2 diabetes and cardiovascular disease as a significant risk factor associated with the second pre-diabetic stage. A widely held belief holds that glycated haemoglobin offers a more precise prognostic indicator of future cardiovascular disease and mortality risk compared to fasting glucose.

- **Concept of Artificial Intelligence (AI) and its propagation in Healthcare Systems of the World & India**

AI is transforming the provision of health services in several affluent environments, particularly in specialized domains like pathology and radiology (Hosny, 2018; Chang, 2019; Jha, 2016). The advancement mentioned above has been enabled by the widespread availability of massive datasets and cutting-edge analytical techniques that utilize them. The acceptance of artificial intelligence (AI) as a potential solution for health problems has increased in low-income and middle-income nations due to the development of mobile computing capabilities and IT infrastructure (Wahl, 2018). Global progress towards the health-related SDGs is inadequate as a result of these obstacles, which include a severe shortage of medical personnel and inadequate public health surveillance systems (Lozano, 2017; Bartolomeos, 2018). Although not limited to these countries, the correlation between these issues and higher rates of mortality and morbidity justifies their particular attention (Alkire, 2018; Kruk, 2018).

AI-driven health technologies have the potential to offer remedies for these and additional systemic issues. For example, in certain contexts, AI-driven interventions have reduced the burden of medical personnel and improved clinical decision-making, according to Guo (2018). In addition, progress in the field of artificial intelligence has enabled the proactive detection of disease epidemics, which has accelerated the formulation of policies and the implementation of initiatives (Lake, 2019). Before widespread implementation or expansion of these therapies in low-income and moderate-income settings can occur, a multitude of obstacles must be surmounted. These challenges encompass practical, ethical, and legal implications.

A growing number of prominent donor organizations and members of the international health community are coming to the understanding that these concerns must be addressed promptly to ensure that low-income and middle-income communities can benefit from developments in artificial intelligence and digital health (USAID, 2019). Since 2015, numerous international conferences have been convened, such as the Digital Investment Principles (2018), ITU (2017), and Digital Principles (2017). The World Health Assembly, for example, adopted a resolution in May 2018 regarding digital technology for universal health coverage (WHO, 2018). The High-Level Panel on Digital Cooperation of the United Nations Secretary-General issued a critical 2019 recommendation that by 2030, all adults must have affordable access to digital networks, health and financial services, and digitally-enabled financial systems. Implementing this would have a substantial impact on the achievement of the Sustainable Development Goals (UN, 2018). The Lancet and Financial Times formed a collaborative commission in October 2019 to investigate the possible consequences associated with universal health care, digital health, and artificial intelligence (Kickbusch, 2019). The publication of the report by this commission is anticipated to occur in 2021.

1.1.4 Use of AI in the Management of Diabetes

The integration of artificial intelligence technology into medical devices intended for the management of diabetes. Body Guardian, the first medical device to incorporate artificial intelligence (AI), received approval from the US FDA in 2012 in conjunction with a patch-like electrocardiogram (ECG) that incorporated an algorithm for detecting arrhythmias. Following that era, a multitude of nations, including Europe, Japan, the United States, and China, have made strides in their legislative endeavours about programmed medical devices, which incorporate artificial intelligence. In recent years, the United States and Europe have approved an exponential growth in the number of medical devices powered by artificial intelligence. This trend can be attributed to the progress made in clinical applications and the exponential development of deep learning technology (Muehlematter, 2021).

A multitude of medical devices that brand custom of AI & machine learning have received approval from the FDA thus far. Despite cardiology, oncology, and radiology accounting for the majority of these approvals, diabetes care is linked to three AI-based medicinal diplomacies (Benjamens, 2020). As of 2020, twelve distinct varieties of AI-based medical devices have been authorized in Japan. It is essential to observe, nevertheless, that none of these medical devices have received approval to treat diabetes. On the contrary, their exclusive function is the analysis of images about radiology and diagnostic imaging.

The primary areas of focus for endeavours to integrate artificial intelligence (AI) into clinical environments to diagnose and treat diabetes are as follows: automated retinal screening, risk stratification, animal self-management tools, and clinical diagnosis support (Ellahham, 2020). Automatic retinal screening, the first category of AI technology, utilizes fundus images to independently determine the existence or non-existence of diabetic retinopathy, a significant complication associated with the condition. The FDA approved the IDx-DR device, which was developed by Arithmetical Diagnostics Inc., in 2018. This approval was based on the device's outstanding diagnostic performance, which had been verified through clinical trials (Abràmof, 2018). In the absence of the specialized expertise possessed by an ophthalmologist, this artificial intelligence technology may inadvertently diagnose diabetic retinopathy in certain patients. Subsequently, primary care physicians are faced with the choice between reevaluating the IDx-DR device one year later or obtaining an ophthalmologist to examine the fundus photographs of their patients. This device enhances the ability to identify and diagnose diabetic retinopathy, particularly in areas with limited access to ophthalmic care, such as geographically isolated regions.

The provision of diagnostic assistance is categorized under the second heading. Current research focuses on developing artificial intelligence (AI) solutions that replicate "hidden tips of treatments by a specialist," such as adjusting insulin dosage, as opposed to merely assisting with diabetes diagnosis. Advisor Pro, manufactured by DreaMed Diabetes, Ltd., is an instance of a 2018 FDA-approved product. This system employs artificial intelligence (AI) to facilitate remote evaluation and recommendation of the need for insulin dose adjustments. This is accomplished through the transmission of data from devices that monitor blood glucose (SMBG) and continuous glucose monitoring (CGM) to a cloud server. Subsequently, physicians can assess the suggestions and furnish patients with the most suitable information. This article presents the results of a clinical intervention conducted in 2020 (Nimri, 2020) to evaluate the efficacy of this artificial intelligence technology. In this excellent study, 108 patients diagnosed with type 1 diabetes were randomized into two distinct groups: those who were managed manually (received insulin treatments from a diabetes specialist) and those who were managed by AI (received insulin treatments from an AI system). The results of the study indicated that the rates of hypoglycemia and adherence to the desired blood glucose concentration were similar between the group managed manually by experts and the group guided by artificial intelligence. In forthcoming times, medical devices propelled by artificial intelligence will gradually supplant diabetes specialists in scenarios involving comparable insulin administration adjustments.

The instrument for patient self-management is classified under the third category. A portion of those who have been diagnosed with diabetes have pre-existing knowledge of self-management tools due to their engagement in self-assessment of diverse biometric data, which includes actively monitoring blood glucose levels via SMBG. The AI-generated notifications of the patient self-management tools resemble those generated by a diabetologist and assist the user in more consistently regulating their blood sugar. This particular capability is integrated into the artificial intelligence system known as the Medtronic Guardian Connect System. The FDA granted certification in 2018 to this CGM-based device that was accompanied by a smartphone application. This is evidenced by the AI's application of continuous glucose monitoring (CGM) data to forecast and notify the patient of an impending hypoglycemia episode one hour in advance. Based on the information provided by the product, the alert demonstrates an accuracy rate of 98.5% and transpires precisely thirty minutes before the onset of hypoglycemia. The utilization of this technology in conjunction with patients' biometric information to notify them of hypoglycemia may present some interpretive challenges. Following this, the patient may proceed with the administration of medication, including glucose tablets, to reduce the likelihood of hypoglycemia and the potential complications that may result.

1.1.5 AI based Diabetes Diagnosis and its Origin

Diabetic retinopathy is the most prevalent severe complication of the form of diabetes. Furthermore, it is significant to mention that within the first two decades of the disease's progression, diabetic retinopathy affects almost all patients diagnosed with type 1 diabetes and 60% of those diagnosed with type 2 diabetes (Fong, 2004). Significant achievements have resulted from the implementation of artificial intelligence in the fields of disease detection and ocular data collection (Rahim, 2016, 2019; Saha, 2016). Research has suggested that the utilization of ophthalmic data may have the potential to diagnose diabetes (B. K. Ma, 2019). Throughout history, diabetes has been effectively controlled or alleviated in China by incorporating traditional Chinese medicine (TCM) principles and techniques. Furthermore, an abundance of research has demonstrated that Traditional Chinese Medicine (TCM) can be utilized to effectively treat or eradicate diabetes (Mou, 2016; Wang, 2019; Xiao, 2018; Oduro, 2020). Consequently, the tongue and pulse—two somatic and physiological characteristics of the patient—are utilized to establish the diagnosis in this study, by TCM methodology. Fundus photography is utilized in conjunction with the palpable tongue and pulse pattern to enhance the accuracy of diabetes diagnosis.

In light of the efficacy of Traditional Chinese Medicine (TCM) in the management of diabetes and the implementation of fundus photography, the researchers have employed a random forest algorithm for machine learning to analyze and diagnose physiological and physical feature data acquired from monitoring devices.

Globally, diabetic retinopathy remains the primary aetiology of persistent blindness in the adult population of working age (Barth, 2021). By utilizing its rapid point-of-care detection, artificial intelligence (AI) can aid in the prevention of diabetic retinal disease (DR) blindness in a variety of healthcare settings, including primary care, endocrinology, and diabetes clinics, pharmacies, hospitals, and community centres (Campbell, 2021). Significant strides have been achieved in the domain of deep learning methodologies, including advancements in computational capacity and the implementation of convolutional neural networks, since the inception of AI for DR over two decades ago. Kaggle is an online data scientist-centric community through which tens of thousands of distinct algorithms were developed during the 2015 Kaggle data science competition (DRD, 2022). These algorithms exhibited superior performance to the human evaluation of one hundred thousand retinal images acquired from primary care examinations. A multitude of research teams across the globe persistently employs this publicly available dataset in their endeavours to devise revolutionary algorithms (Kaggle, 2022).

1.1.6 Definitions of AI based Diabetes Diagnostic System

The utilization of laboratory environments has been employed to analyze artificial intelligence (AI) algorithms designed to detect DR from retinal images (Figueiredo, 2015). Recent years have witnessed an increase in the diagnostic precision of these algorithms due to the incorporation of machine-learning techniques (Abràmoff, 2016; Gulshan, 2016). However, autonomous and secure implementation in primary care necessitates real-time clinical decision-making at the point of care, diagnostic accuracy that is not influenced by age, race, or ethnicity, and autonomy (i.e., a use case that eliminates the need for human expert review) to ensure a dependable disease level output for the overwhelming majority of patients (Hansen, 2015). Before this, the FDA had not approved any artificial intelligence system, and there had been no comparative studies involving it and an independent gold standard consisting of the greatest quality imaging techniques, fundus imaging and OCT.

Diabetes diagnostic systems analyze data, generate predictions, and diagnose complications associated with diabetes using artificial intelligence (AI) methodologies. Huang (2023) asserts that these systems are capable of generating models that can provide medical diagnoses and prognostications about diabetes and complications. Data obtained from various sources, including devices, mobile applications, healthcare encounters, and diagnostic investigations, is utilized to ascertain these predictions. The primary areas of focus for the integration of artificial intelligence (AI) in diabetes management are as follows: decision support systems, risk assessment and prediction, autonomous insulin delivery, and diagnostics (Nomura, 2021). Diabetes can potentially be detected by not so experienced clinicians or in uncovered regions from medical services using AI-based diagnostic tools (Liu, 2020). Moreover, these systems possess the capacity to forecast complications, diminish healthcare costs, improve screening and diagnosis rates, decrease mortality and morbidity, and enhance overall quality of life. They are also capable of administering medications that are more specific and have a shortened duration of action. Moreover, artificial intelligence possesses the capacity to identify behavioural patterns in diabetic patients that result in hypoglycemia or hyperglycemia.

1.1.7 Types of AI based Diabetes Diagnostic Systems

An impending paradigm shift is anticipated in the domain of clinical medicine, wherein the incorporation of artificial intelligence will be prominent, with deep learning emerging as its distinctive attribute. By training on health data that has undergone evaluation and assessment by human experts, the AI system primarily seeks to acquire hands-on experience. By implementing this training procedure, the AI system's capability to evaluate recently acquired data of the same character and gain knowledge has been enhanced. This interpretation possesses the capability to diagnose or predict a medical condition. A wide range of responsibilities can be accommodated through the integration of artificial intelligence. The responsibilities mentioned above include the development of computer vision applications that are specifically engineered to decipher radiological images, and the utilization of time series analysis to extract relevant information from health records or DNA sequences (Zhou, 2020). Health data obtained from the electrocardiogram is also incorporated into these analyses. A considerable number of genomics investigations have made extensive use of machine learning (ML) and deep learning (DL), two fundamental AI components. In recent times, there has been considerable interest in DL, which is an expansion of ML, as a potentially effective solution to the difficulties linked to genome categorization and prediction. When contemplating the detection of intricate patterns in datasets replete with features and the management of extensive amounts of data, the DNN framework is regarded as a more adaptable and expandable structure. Multiple strata of non-linear transformations comprise it (El Attar, 2020). Reportedly, the DNN architectures that are most widely employed include CNN, RANN, RBM, and LSTM (Shrestha, 2019).

In recent decades, the application of DNA sequencing to disease prediction has acquired prominence. Concurrent evaluation of the expression of nearly every gene in the genome is feasible. At present, the obstacle is the comprehensive data analysis required to attain a profound understanding of biological mechanisms and the processes that underlie human diseases. The DNA genes encode the protein molecules, which are considered the "workhorses" of the cell because they perform all essential functions (Nguyen, 2016). The process of expressing a gene is fundamentally equivalent to the production of the associated protein. Insulin is one of the proteins that can be synthesized by the human body. Diabetes mellitus (DM) may develop as a consequence of a disruption in insulin secretion, which may be attributed to a genetic mutation occurring in the sequence of the insulin gene. Diabetes, an exceedingly prevalent chronic ailment worldwide, has the potential to result in substantial enduring ramifications if not timely identified and managed. In recent times, numerous challenges have been addressed through the implementation of ML techniques. These challenges include determining the prognosis of cancer (Huang, 2023), heart disease, encephalitis, and diabetes (Uddin, 2023; Hossain, 2021). Recent studies have demonstrated that ML is capable of producing and predicting patient profiles that likelihood of developing type 2 diabetes (Aguilera-Venegas, 2023; Zhao, 2023; Xia, 2022; Ejiyi, 2023; Hennebelle, 2023). A study was conducted in Bangladesh to examine eighteen characteristics of T2DM (Haque, 2022). The principal contribution of this study was the utilization of the LR model by the authors to integrate demographic and clinical data; this approach yielded the most optimal outcomes (83.8% accuracy and 70% F1-score). Nevertheless, there is room for improvement in the performance through the integration of supplementary functionalities about individuals' dietary habits, lifestyle selections, and medical diagnoses. An 81% accurate system for detecting diabetes was developed by combining the ADASYN oversampling technique with the XGBoost model. To generate feature weights related to diabetes, an explainable artificial intelligence (AI) methodology was applied, making use of the LIME and Shapley additive explanations (SHAP) frameworks. Additionally, a website and an Android mobile application have been created with the purpose of detecting diabetes in women. The authors' detection technique was subject to scrutiny regarding its dependability, owing to its restricted emphasis on eight features. Scholars have employed various artificial intelligence (AI) methodologies, including deep learning and machine learning models, to identify critical ailments including Alzheimer's disease, liver, heart, and epidermis, among others. As a result, the accuracy of disease diagnosis methods employing the Boltzmann machine, kNN, SVM, fuzzy logic, logistic regression, decision trees, and artificial neural networks is investigated in the relevant literature.

Table 1.1: Common AI Approaches Used in Diabetes Care

Sl No	**Method**	**How it works**	**Applications**
1.	Convolutional neural network (CNN)	Consisting of numerous neuron layers, convolution layer neurons selectively process limited subsets of the input image, akin to a filter. Despite transforming the entire input image, the parameters of these neurons remain constant. Comprehend the	"Retinal Screening"

		principle of "backpropagation." CNN layers detect the presence of unique features across the entire space, progressively identifying a greater quantity of high-level features.	
2.	Random forest	A collection of trees of judgment is assembled. Every tree takes into account a randomized set of characteristics to assess root nodes and divides.	“Retinal screening, self-management aids for patients, decision support, and prediction models”
3.	Multilayer perceptron	By interconnecting neurons in each layer with those in the subsequent layer—which includes neurons in the input layer, output layer, and multiple concealed layers—each layer is fully connected to the one that follows. Master	“Prediction models, patient self-management tools”

		the concept of "backpropagation."	
4.	Support vector machine (SVM)	A classification method that yields binary outcomes is seldom applied to multiclass problems; however, there are methods available for multiclass SVM. The algorithm operates by augmenting a high-dimensional space with new information and locating a hyperplane that divides the optimal two groups (by maximizing the margin, or distance between the plane and adjacent data points).	"Retinal Screening, decision support, prediction models, patient self-management tools"
5.	Logistic regression	Method for classifying binary outcomes. Predicts the likelihood of a given outcome (between 0 and 1) by its attributes. Gain	"Prediction models"

		knowledge of the model coefficients through maximum probability calculation. Searches a line or hyperplane that most accurately represents the data points.	
6.	Fuzzy logic/ fuzzy system	Indicate membership in a particular class with a probability value between 0 and 1, as opposed to a deterministic decision (0 or 1).	"Artificial pancreas, sensors, decision support, and retinal screening"
7.	K-nearest neighbours algorithm	The algorithm divides input data into numerous categories according to its k nearest neighbours.	"Retinal Screening, decision support, prediction models, patient self-management tool"
8.	Natural language processing	Methods and instruments for enhancing the efficiency of computational processes involving human language interpretation,	"Prediction models"

		inference, and processing	

1.1.8 Significance of AI based Diabetes Diagnostic Systems

Owing to the analysis of patient statistics by artificial intelligence, the correctness of diabetes prognosis has increased, foremost due to enhanced medical outcomes & more individualized treatment options. Furthermore, artificial intelligence has accelerated the discovery of medications to treat diabetes, thereby expanding therapeutic options. The implementation of self-management technologies and decision-making systems powered by artificial intelligence has enabled patient-centred care and empowered patients to take a more proactive approach to managing their diabetes. However, comprehending and data security concerns must be resolved before the ethical use of AI in medical facilities can commence. In its entirety, artificial intelligence possesses the capacity to revolutionize the management of diabetes and improve worldwide health.

- **AI Predicting Diabetic Retinopathy:**

Retinopathy is the greatest predominant adverse magnitude of diabetes. Conventional diabetes and retinopathy caused by diabetes mellitus are treated in a fragmented, disorganized, and segmented manner; curing them may require some of the most substantial and costly resources. To address these deficiencies in medical care, novel approaches that leverage digital technology are required (Gunasekeran et al., 2020). The acuity of AI systems in the detection of diabetic retinopathy is exceptional. Artificial intelligence algorithms are capable of discerning the initial signs of acute retinopathy with an equivalent degree of precision as endocrinologists through the analysis of patient datasets. Automated deep learning-based DR screening techniques with a significant degree of specificity and sensitivity (> 90%) have been introduced. Nevertheless, the presentation of these bottomless learning processes in clinical scenarios is subpar due to the constraints imposed by open-access datasets (Tao Li et al., 2019).

- **AI in Early Diagnosis of Type 2 Diabetes:**

Type 2 diabetes mellitus which is resistant to insulin is the most prevalent form of the disease, accounting for an estimated 90–95% of all documented cases of diabetes. Globally, it is projected that 439 million people will be affected by the year 2030 (Yanling et al., 2014). In high-risk patients, artificial intelligence models have demonstrated potential in forecasting the onset of type II diabetes. The capacity to forecast the occurrence of diabetes on a larger magnitude through the use of binary classification algorithms constructed from zero and intricate correlations among discrete individual indicators. An ensemble of binary classification algorithms optimized with the Adam method for fundamental structures obtained a respectable 86% accuracy rate. The utilization of this artificial network-based approach is critical for decision-making tools as it produces accurate data that enables personalized treatment.

1.1.9 AI based Diabetes Diagnostic System Adoption by Doctors

(Han, 2015) Patients with diabetes who are most prone to avoidable complications—including avoidable emergency room visits, hospital stays, and readmissions—are presently identified through predictive modelling propelled by artificial intelligence. Prominent physician groups, health systems, and health plans utilize artificial intelligence (AI) to "mine" through vast quantities of unstructured digital patient data with the following objectives in mind: proactively ascertain and characterize diabetes populations, identify patients at risk for diabetic co-morbidities, determine patients eligible for specialized diabetes disease management programs, and uncover relevant proteins and genes that promote diabetes. At this time, AI provides decision-support tools to physicians and other healthcare professionals who deal with individuals who have disabilities. Physicians may employ machine learning methodologies to tailor diabetic treatments to enhance adherence and overall health outcomes. Medical personnel benefit from the utilization of AI-powered tools for non-invasive diabetes diagnosis (Shu, 2017), as well as for more accurate assessment and monitoring of diabetic wound severity (Wang, 2017) and diabetic neuropathy (Katigari, 2017). By leveraging innovative sensors, pumps, smartphone applications, and other artificial intelligence (AI) developments, the optimization and enhancement of diabetes care are yielding advantages for clinicians and individuals with disabilities (PWDs). The principal objectives are to improve the regulation of blood glucose, mitigate occurrences of hypoglycemia, and enhance patient satisfaction and reported outcomes. There is a growing trend in the market for RT-CMG devices powered by artificial intelligence (AI). These devices aim to aid clinicians and individuals with disabilities (PWDs) in monitoring and enhancing A1c levels, reducing hypoglycemic episodes (particularly at night), and facilitating glycemic control improvement.

A 2017 meta-analysis examined published clinical trials that investigated the most recent computerized artificial intelligence algorithm-based automated, personal, or real-time continuous glucose monitoring devices (RT-GCM).

Through the utilization of symbolic reasoning and machine learning methodologies applied to the electronic devices of individuals who have received a diabetes diagnosis, it is possible to discern and quantify significant lifestyle behaviours. This enables individuals to make more informed decisions regarding their activities. Regular wound care participation is now feasible for individuals with diabetes and their caregivers through the implementation of an AI smartphone camera system. Possible advantages of this innovation consist of expedited wound recovery, reduced travel expenditures, and diminished healthcare expenditures. There has been significant patient support for the exploration of AI-augmented telemedicine as a prospective remedy for delivering medical aid to pregnant women with gestational diabetes within the comfort of their residences. Data from activity sensors, blood pressure monitors, glucose sensors, and computer-interpretable clinical practice guidelines were incorporated into the study (Rigla, 2018).

1.1.9.1 Development and Evolution of AI based Diabetes Diagnostic Adoption

An investigation into rigorous therapy is justified on account of its established effectiveness in preventing the advancement of complications related to diabetes, such as retinopathy, nephropathy, and neuropathy. This has been determined following decades of meticulously planned trials. In contrast, a recent study comprising 300,000 patients who had been diagnosed with type 2 diabetes and initiated medical treatment revealed that 31% of patients discontinued all medication use within three months, increasing to 44% within six months, and reaching 58% discontinuation within a year. Letters (2018) found that a mere 40% of the participants ultimately resumed the use of their diabetes medication. A dearth of up-to-date, vital health information often hinders the delivery of optimal care for individuals diagnosed with diabetes, thereby hindering their capacity to make well-informed choices concerning intensive therapy and rigorous diabetes management. Even though technological advancements afford individuals across diverse sectors unprecedented and cost-effective access to critical information, their impact on the management of diabetic patients seems to be comparatively limited. The issues about current information regarding treatments for diabetes are further complicated by the swift progression of medical knowledge. The index of biomedical literature had amassed more than 28 million articles as of June 2018, with an approximate annual influx of 850,000 citations (NCBI, 2018). Throughout their lives, every individual will produce health-related data over one million gigabytes, which is equivalent to 300 million volumes. It is estimated that health data lacks structure in 80% of instances. Examples of sources of information include clinical notes, discharge summaries, imaging and laboratory results, hospital records, clinical trials, and nonclinical data sources including genomic data, information on social determinants of health, and device and sensor data (also referred to as Internet of Things data) (Lewis, 2018). 90% of an individual's health outcomes are correlated with exogenous factors and genetics; therefore, clinicians and individuals with disabilities must collect and utilize this information to make informed health decisions (Aggarwal, 2016).

At this time, enormous volumes of vital data are being utilized by artificial intelligence (AI) to satisfy the needs of customers in every industry, including healthcare. According to a 2017 survey of mobile health app publishers and developers, diabetes will continue to be the most significant medical condition with the greatest market potential for digital health solutions shortly. Furthermore, it is expected that artificial intelligence (AI) will have the greatest transformative impact on the digital health industry, as predicted by 61% of the respondents. Clinically effective AI applications for diabetes are still in short supply, despite the existence of literature documenting advancements in AI for healthcare (Yeung, 2018) and the approval of novel AI-powered devices for diabetes treatment (Young, 2018). This segment elucidates notable progressions in artificial intelligence that may persist in their applicability to caregivers, families, primary care physicians, endocrinologists, and individuals with disabilities.

1.1.9.2 Efficiency and Effectiveness of AI based Diabetes Diagnostic Systems

This meta-analysis represents the first attempt to evaluate the diagnostic efficacy of deep learning (DR) through the integration of all prospective studies and the utilization of multiple algorithms; it goes beyond a narrow focus on deep learning or machine learning alone. To enhance the rigour of the inquiry, relevant literature was initially obtained from medical databases using the specified retrieval method. Following that, the obtained studies were evaluated using the established criteria for diagnostic assessments (McGrath, 2017). As of March 21st, the final meta-analysis comprised 129,759 irises derived from 21 distinct studies. Through the utilization of real-world settings for all research, the risk of bias commonly associated with retrospective studies was effectively mitigated. By employing meta-regression analysis to examine the source of heterogeneity, it became apparent that such variation might be justified by flaws in artificial intelligence algorithms. To gain a more comprehensive understanding of the variables that influence the AI diagnosis of DR, researchers performed a subgroup study. Furthermore, it was observed that inquiries conducted in non-Asian regions exhibited superior diagnostic efficacy in comparison to studies conducted in Asian nations. The inconsistency that was noted was attributed to several factors, including extensive algorithmic training, increased algorithm utilization frequency, possession of large data sets, incorporation of a greater number of cases, and relatively high-quality data. Research studies that recruited participants from medical research centres, hospitals, or clinics observed greater diagnostic efficacy compared to those that utilized patients from alternative sources. The increased percentage of patients affiliated with medical research institutions or centres, as well as the decreased rate of errors in retinopathy diagnoses by clinicians, may contribute to this observation. Additionally, it has been observed that the diagnostic effectiveness rises as the sample size of the study increases.

These efficacy metrics generate diagnostic-accuracy metrics, such as sensitivity and specificity, when incorporated into AI-based diagnostic systems. These metrics are assessed relative to a predetermined reference standard. Using these parameters, several AI systems have been demonstrated to be effective and safe, leading to De Novo approval and subsequent clinical implementation by the FDA (Thomasian, 2021; FDA, 2022).

Instead, the potential impact of AI implementation on patient outcomes is influenced by several factors that extend beyond the diagnostic precision of AI (WHO, 2016). The variables include aspects that may give rise to disagreements during medical treatment, including compliance with treatment and management protocols, adherence to referral guidelines, and access to healthcare. Furthermore, they include the disease's natural history and prevalence. Furthermore, achieving flawless outcomes with prescribed treatment is highly improbable; in fact, it is conceivable that it could produce suboptimal results. As a result, the previously mentioned delays associated with treatment procedures will impact outcomes, potential efficiency gains, and disparities in health impact, regardless of the flawless implementation of the diagnostic AI. As a result of their indeterminacy when solely scrutinizing the AI system, these frictions and flaws in the care processes might be more difficult to detect. Nevertheless, they place a substantial amount of reliance on the AI system's integration into the health delivery network and the care process. A multitude of AI systems are specifically engineered to address chronic diseases where the prognostic difference may not materialize for decades or years. However, certain artificial intelligence (AI) systems, such as those employed in critical care environments, possess the capability to immediately alter patient outcomes. Therefore, in conjunction with outcomes, process-of-care indicators must be taken into account when deciding whether to design, develop, validate, implement, regulate, and reimburse such AI systems.

1.1.9.3 Operational Effectiveness

The potential of AI based diabetes diagnostic systems to improve and optimize many aspects of diabetes care is what makes them operationally effective. These systems have a big impact on the healthcare workflow because of how precisely and efficiently they perform. AI systems aid in the early identification of diabetes by quickly analyzing large datasets, which enables medical practitioners to take appropriate action and carry out focused interventions. The smooth incorporation of AI into diagnostic procedures increases the precision of diabetes diagnosis, guaranteeing that medical professionals obtain thorough and trustworthy information. AI-powered continuous glucose monitoring devices allow for real-time analysis, prompting proactive management and treatment plan modifications. This improves glycemic control and, by lowering the need for emergency room visits and hospital stays, helps to maximize the use of healthcare resources. AI-driven decision support systems also help medical practitioners make well-informed decisions about treatment plans, which promotes a more effective and patient-centred approach to diabetes care. Providing individualized insights and instructional materials, mobile applications and virtual assistants that empower patients is another way that these systems' operational efficacy is demonstrated. All things considered, AI-based diabetes diagnostic systems are essential for improving the operational effectiveness of healthcare delivery, as well as patient outcomes, resource efficiency, and the general efficacy of diabetes management.

1.1.9.4 Operational and Business Performance Indices

Diabetic care could be improved by AI-based diabetic diagnostic tools, which offer patients and medical practitioners precise, individualized, and data-driven support. Diabetes and its consequences can be predicted, prevented, screened for, diagnosed, and treated with AI. AI applications may lead to better screening and diagnosis, earlier and more focused therapeutic interventions, prediction of complications, lower rates of morbidity and death, higher quality of life, and lower healthcare expenditures. Nevertheless, several challenges still face researchers and practitioners using AI to manage diabetes, including issues with statistics excellence control, inadequate technological proposal, secrecy concerns, & a lack of scientific addition. Novel uses of AI in diabetes are being discovered by researchers; these uses span the gamut from diagnosis, prediction, and screening to comorbidity management and treatment. Though more research is required to determine the parameters influencing AI models' diagnostic efficacy, they have demonstrated a clear diagnostic utility for diabetic retinopathy screening (Guan, 2023; Wang, 2023)

1.1.9.5 Different Organizations Operating in the Space of AI based Diabetes Diagnostic Systems

Diverse organizations are actively involved in the development of diabetic diagnostic instruments powered by artificial intelligence. To facilitate the management of diabetic retinopathy screening, the LumineticsCore™ autonomous AI system was developed by Digital Diagnostics, an innovative AI diagnostics company, which has received FDA approval. The primary focus of the AIMS Laboratory is the construction of innovative mathematical frameworks that pertain to physiological processes, such as metabolism. These models integrate closed-loop algorithms of the next generation, which make use of smart home technologies and artificial intelligence. Using LumineticsCore™, Marshall Health is screening diabetic patients for diabetic retinopathy, the primary cause of blindness. An increasing number of researchers from different nations are revealing novel implementations of artificial intelligence (AI) in the domain of diabetes. These applications encompass not only the prognosis and treatment of diabetes but also the management and treatment of comorbidities (Huang, 2023). Advisor Pro, an artificial intelligence (AI) solution created by DreaMed Diabetes, provides medical professionals with data obtained via continuous self-monitoring of blood glucose levels. This capability empowers medical practitioners to assess the suggestions and convey them to their patients (Nomura, 2021). IBM aids payers and healthcare providers in ensuring equitable preventive care for their most vulnerable members through the implementation of dependable AI. Several diagnostic and triage firms, including Mendelian for the diagnosis of uncommon diseases, are also at the forefront of digital health innovation.

CHAPTER-2
LITERATURE REVIEW

2.1 INTRODUCTION

A paradigm shift in healthcare has occurred with the implementation of AI-based interventions in diabetes diagnosis by clinicians in Maharashtra and Karnataka. The prospective benefits of AI in medical diagnostics have been underscored in prior research, with particular emphasis on its efficacy and precision. Nevertheless, there is a scarcity of research that has specifically examined its application in the diagnosis of diabetes in these Indian states. It is of the utmost importance to comprehend the critical factors that influence adoption, including technological readiness, regulatory frameworks, and healthcare infrastructure. Through an examination of the extant literature on AI in healthcare, this review places particular emphasis on research gaps that are pertinent to the diagnosis of diabetes. By evaluating previous research critically, we aim to construct a framework that addresses the unique challenges and opportunities within the healthcare systems of Maharashtra and Karnataka.

2.2 REVIEW OF LITERATURE

2.2.1 Evaluating the Impact and Accessibility of AI-Driven Healthcare Diagnostics in Maharashtra and Karnataka

Kusuma et al. (2024) examined the use of maternal healthcare and the variables influencing appropriate prenatal maintenance & official births amid mums in clannish populations throughout 9 regions in India. Upon analyzing statistics from 2636 recently delivered ethnic mothers, researchers found that 82% of kids were born in hospitals and only 23% of women received sufficient prenatal care. According to logistic regression analysis, older mothers and prenatally vulnerable tribal groups (PVTGs) had a higher risk of receiving inadequate prenatal care when all-weather roads were unavailable. When mothers had access to resources such as home visits from health workers, information about prenatal care, and counselling on the subject, they were more likely to obtain appropriate prenatal care. Home births were favourably correlated with higher birth order, maternal employment, and the presence of all-weather roads; institutional births were positively correlated with PVTGs, maternal education, and household head education. The results highlight the disparities in maternal healthcare utilization throughout tribal groups and provide insight into the variables influencing institutional births and the provision of appropriate prenatal care.

Katekar et al. (2023) investigated the solicitation of AI in response to the COVID-19 epidemic in India. The study demonstrates how different countries have responded to the epidemic, with artificial intelligence (AI) emerging as a potentially revolutionary tool for contact tracing, disease diagnosis, and vaccine administration. Since the outbreak in March 2020, the Indian government has given out more than one billion vaccines, utilizing artificial intelligence (AI) to better serve its citizens during this uncertain period. The examination, which is founded on prime & inferior springs, demonstrates how artificial intelligence (AI) significantly enhanced the efficiency of COVID-19 supervision in India. This, in turn, improved illness surveillance, diagnosis, and treatment, all of which benefited the general public. The study demonstrates how AI-enabled services improve citizen satisfaction, engagement, and trust in public services. One of the recommendations is the creation of a robust legal framework to ensure data integrity and confidentiality when AI is used for pandemic control, together with a supportive policy environment. In conclusion, the literature analysis clarifies the crucial role artificial intelligence played in strengthening India's public health response to the COVID-19 epidemic and provides policymakers with recommendations on how to handle crises of a similar nature in the future.

Gupta et al. (2023) examined the issues including licensing, global distribution, price strategies, quality, personnel requirements, information sharing, and the impact of newer technology. The study examined Indian medical laboratory services. They demonstrate how the sector's regulations have many issues, including outdated or non-existent statutes in certain places, and how urgent reforms are required. The study investigates a national registry of medical laboratories to identify and address issues, emphasizing the necessity of broad adoption of quality control systems to standardize and ensure service quality. Public access to information about regulated laboratories is required, as is clarity regarding staffing requirements and operating responsibilities. Although the study emphasizes the necessity of requiring private and public laboratories to provide the government with information regarding disease burden and health care planning, it also raises worries about privacy violations due to lax data protection laws. Until more stringent regulations are implemented, the research suggests adopting new technology more gradually. It provides a combination of governmental and volunteer initiatives, such as regulation and accreditation, to ensure the calibre of diagnostic services. It is emphasized that more research is required to determine how effective the current state provisions are to make improvements.

Vijayan et al. (2023) examined the successes and obstacles encountered during the implementation of an AI-powered CXR screening instrument for tuberculosis (TB) in Nagpur, Maharashtra, India, with limited resources. The research, which involved eight private CXR laboratories, focused on the accessibility and operational viability of the AI software device (qXR). Difficulties in network access, process integration, software implementation, and personnel availability to conduct results analysis were among the practical obstacles encountered. Using radiologists and artificial intelligence, 10,481 individuals suspected of having tuberculosis were screened as part of the TB REACH active case-finding initiative. The AI system identified 2,303 individuals as probable carriers of tuberculosis, resulting in a 15.8% increase in the aggregate output of tuberculosis-related work. Noting that radiologists did not initially consider all cases suggested by AI to be probable demonstrates that AI has the capability of identifying a significantly larger number of cases. The study underscores the importance of confronting pragmatic obstacles that impede the effective implementation of AI tools in resource-constrained environments, to optimize the utility of this technology in tuberculosis screening initiatives. It emphasizes the significance of straightforward deployment and workflow integration.

Kamath et al. (2023) conducted trends in OOPE and district-level health insurance coverage about C-section deliveries in civic health amenities in India through the analysis of NFHS 4 & NFHS 5 data. In general, district-level health insurance coverage increased between the two surveys, according to the spatial analysis. Despite this increase, the out-of-pocket expense (OOPE) for cesarean sections experienced a decline in Rajasthan and a few other southern Indian states, while it rose in Northeast India. Insurance premiums and out-of-pocket expenses for cesarean sections increased in Kerala. Based on the findings of the geographical analysis, Tamil Nadu, Kerala, portions of Mizoram, the eastern coast, and parts of Kerala were designated as hotspots. Conversely, sections of Uttar Pradesh, Jammu Kashmir, and Gujarat were classified as coldspots. Significant flashpoints also emerged in various regions of Assam, Rajasthan, Tamil Nadu, and Andhra Pradesh along their eastern coasts. Despite increased access to health insurance, hot spots persisted and their frequency increased across surveys, indicating an increase in out-of-pocket expenses (OOPE) for cesarean sections. To accomplish significant cost savings on out-of-pocket expenses for cesarean sections at public hospitals, the study suggests that publicly funded health insurance schemes, such as Ayushman Bharat and RSBY, must be amended at their core.

Parthasarathy et al. (2023) examined the critical issue of healthcare accessibility in rural areas of India, where transportation challenges compound the disparities in doctor distribution across states. Despite an overall doctor-to-patient ratio meeting World Health Organization recommendations, a disproportionate 52% of medics are concentrated in unbiased “5 states: Maharashtra, Tamil Nadu, Karnataka, Andhra Pradesh, and Uttar Pradesh”. To bridge this urban-rural healthcare divide, the study explores the emergence of telemedicine, a vital tool allowing patients to access medical care irrespective of their location. Although telemedicine faced initial reservations, the new normal ushered in a global boom in its adoption. The research specifically focuses on existing telemedicine device manufacturers in India, identifying a limitation in the patient monitoring systems – they lack comprehensive vital sign coverage. In response, the study proposes a 24/7 patient tracking system encompassing all essential vitals, employing a deep learning model to predict abnormalities and potential diseases. An integrated alert system ensures timely notifications to both doctors and patients in case of anomalies. This approach addresses a significant gap in telemedicine solutions and holds promise in enhancing healthcare access and monitoring, particularly in remote and underserved regions.

Roy et al (2021) examined the critical status of AI-based diabetes diagnostic services in the Indian provinces of "Maharashtra and Karnataka" was investigated. An initial description is provided of the current healthcare and diagnostic conditions in Maharashtra and Karnataka, along with their respective geographical locations. Then, numerous healthcare initiatives from the private and public sectors are described. Diabetes stands as the foremost health concern at an international level. Proliferating at an accelerated rate, this global pandemic is affecting a substantial segment of the populace across all nations. Having the greatest incidence of diabetic patients, India has been dubbed the "capital of diabetes." The prompt detection of diabetes may empower individuals to adopt appropriate preventive actions, such as embracing a healthier way of life, which could potentially postpone or avert the progression of the condition. As organizations strive to optimize diabetic care, there is a growing trend of implementing diabetes diagnostic solutions powered by artificial intelligence. Based on medical images, their diagnostic software is capable of identifying complex diseases. Using annotating lesions and abnormalities, these programs enable medical professionals, including non-specialists, to make diagnoses more quickly and precisely. India bears the burden of chronic disease risk.

Furthermore, the Journal of the American Medical Association reports that a significant proportion of the population, especially those aged 25 to 40, are being diagnosed with cardiovascular disease and diabetes.

Bajpai et al. (2021) analyzed the current state of artificial intelligence in India, highlighting its transformative capacity. AI development in India is in its infancy, and the country lacks a specialized regulatory body. However, increasing recognition of this is evidenced by recent governmental efforts, including the formation of an AI Task Force and the National Strategy for Artificial Intelligence #AIFORALL by NITI Aayog. Several states, including Maharashtra, Tamil Nadu, and Karnataka, have undertaken AI-centric initiatives, including data science centres and AI-driven systems designed to mitigate agricultural risks. Particularly in resource-constrained regions, the study highlights the potential of AI in healthcare for mining medical records, developing treatment plans, and assisting with clinical decision-making. During the COVID-19 pandemic in India, the effectiveness of AI in screening, containment, contact tracing, and vaccine development was demonstrated. Notwithstanding the potential advantages, healthcare adoption is beset with obstacles such as unstructured datasets, interoperability concerns, financial constraints, insufficient infrastructure, and regulatory deficiencies. Government support for AI investment, promotion of public-private partnerships, implementation and enforcement of legislation about AI and health, resolution of concerns regarding confidentiality and privacy, and establishment of certification systems are all suggestions put forth in the study. The educational experience provides a comprehensive examination of the artificial intelligence (AI) environment in India, shedding light on its possible uses and the obstacles that need to be overcome to ensure a smooth integration into healthcare systems.

Tripathy et al. (2019) examined the provision of diabetic care services in public health facilities across six districts in three Indian states: Delhi (East and Central districts), Maharashtra (Amaravati rural and urban districts), and Karnataka (Tumkur and Kolar). The primary objective of the initiative was to address the challenges that hindered the effectiveness of public health systems in low-income and middle-income nations. The study employed a mixed methods approach, incorporating both quantitative assessments of the accessibility of resources and services and qualitative insights obtained from healthcare providers and individuals with diabetes through semi-structured interviews. The study's findings revealed inadequacies in the delivery of services for diabetes management. The challenges identified encompass inadequate assistance for modifying one's lifestyle, limited availability of critical diagnostic services (such as lipid analysis and HbA1c estimation at primary health centres), and inadequate patient clinical records at healthcare facilities. The study identified barriers including inadequate follow-up, patient overburden, and insufficient specialized training through interviews with 42 physicians. Congestion in tertiary facilities was a consequence of challenges encountered by patients interviewed for the qualitative component, including difficulties in obtaining medications and conducting routine follow-ups. The lack of a systematic referral or follow-up procedure introduced an extra level of intricacy to the patient care trajectory. This research sheds light on the notable deficiencies in diabetic care that are present within the public health systems of India. It emphasizes the urgent requirement for focused interventions and methodical improvements to enhance service quality and patient outcomes.

Satheesh et al. (2019) analyzed the issue of insulin accessibility in Bengaluru, Karnataka, India, in consideration of the global crisis marked by limited availability and affordability of insulin. Utilizing a modified WHO/HAI methodology, the study evaluated insulin accessibility and the factors that affect supply and demand in the public and private health sectors. The data revealed inconsistencies in the availability of insulin, with a mean availability of 66.7% in the public sector, compared to a mean availability of 93.3% in hospital pharmacies and 76.1 per cent in private retail. Non-Indian companies supplied the majority of products in both sectors; 79.1% of products were manufactured in India, of which 60% were marketed by non-Indian companies. In private retail pharmacies, human insulin cartridges and pens were priced significantly higher than vials, with analogues costing twice as much as human insulin. Furthermore, the study underscored challenges related to patient accessibility, including limited market competition, the preference of medical professionals for non-Indian insulins, and the ongoing transition from human to analogue insulin. The findings underscore the complex dynamics that influence insulin accessibility in India and suggest that the continued growth of online and chain pharmacies may have further implications for insulin availability. It is critical to address these challenges to ensure that patients in need have access to affordable and easily obtainable insulin.

2.2.2 Advancements and Adoption of AI-Driven Diagnostic Models for Diabetes Management

Zhuhadar et al. (2023) research was to examine the rapid advancements of artificial intelligence (AI), specifically Automated Machine Learning (AutoML), in the healthcare industry, focusing on its application in the diagnosis of diabetes. The paper emphasizes the importance of AutoML in the development of minimally invasive and resource-efficient predictive models that adhere to sustainability principles in the healthcare industry. This study aims to improve predictive models through an investigation into the intricacies of diabetes onset, by integrating insights into risk factors and optimizing therapeutic approaches. The significance of AutoML's ability to distinguish vital parameters including glucose, body mass index, diabetes pedigree function, and blood pressure is emphasized, with a focus on its potential to expedite therapeutic interventions, reduce unnecessary procedures, and enhance overall health. To enhance the model's accuracy, the study proposes a thorough evaluation and incorporation of supplementary variables and data, with a particular emphasis on the durability and efficacy of healthcare methodologies. The present study showcases the transformative capabilities of artificial intelligence (AI), more precisely AutoML, in the realm of diabetes management. It proposes an approach to sustainable predictive modelling that has the potential to improve patient outcomes, conserve healthcare resources, and reduce the industry's environmental footprint.

Imrie et al. (2023) investigated the growing importance of prognostic and diagnostic models in the medical domain, along with the advancements achieved in utilizing machine learning to capture complex interactions among patient covariates. AutoPrognosis 2.0 is an open-source machine learning framework introduced by the authors. Its primary objective is to facilitate the construction of diagnostic and prognostic models for clinical settings through the resolution of technical and practical challenges (study). By integrating tools for model explainability and optimizing pipelines with machine learning algorithms, AutoPrognosis facilitates the implementation of clinical demonstrators with minimal technical expertise. By utilizing the UK Biobank to generate a prognostic risk score for diabetes, the authors demonstrate the framework and achieve a level of discrimination that surpasses that of expert clinical risk scores. Notably, the risk score is implemented as an open-access web-based decision support tool utilized by both healthcare professionals and patients. By making AutoPrognosis 2.0 open-source, the authors hope to furnish medical professionals with a userfriendly application that streamlines the process of generating machine learning-based personalized prognostications, risk scores, and diagnostics. This endeavour promotes the increased incorporation of these methodologies into the domain of clinical practice.

Rashid et al. (2022) analyzed the potential of AI algorithms to enhance clinical decision-making and the management of complex chronic diseases with a focus on diabetes. The article underscores the significance of cutting-edge artificial intelligence (AI) algorithms in the analysis of real-time streaming data, laboratory test results, and medical diagnostics extracted from electronic health records (EHRs), to improve treatment and administration. This research investigates the challenges that arise from flawed and unbalanced electronic health record (EHR) data, along with inconsistencies in self-reported information. It highlights the criticality of developing AI techniques that are efficient, accountable, reliable, and robust. The research paper emphasizes two healthcare applications of artificial intelligence: initially, it presents AI algorithms that are unbiased and fair in their treatment and outcome prediction of electronic health records (EHRs), while also considering privacy concerns when designing such algorithms; and secondly, it employs a creative methodology to enhance automated insulin delivery systems by analyzing historical data and real-time information collected from wearable devices. This study ultimately enhances patient outcomes through the resolution of obstacles and the provision of perceptive remedies for the management of chronic ailments, including diabetes; thus, it underscores the transformative capacity of artificial intelligence in the healthcare sector.

Afsaneh et al. (2022) examined the potential of ML & DL in managing diabetes, particularly for blood glucose control, prediction, and prognosis. They highlight promising results from recent ML/DL models, suggesting their potential to improve diabetes management. However, the authors emphasize the need for further refinement and validation using larger datasets to confirm their real-world applicability and ensure reliable clinical implementation. This review underscores the growing interest in ML/DL as valuable tools for personalized, data-driven diabetes care while acknowledging the importance of robust validation before widespread adoption.

Dong et al. (2022) examined a non-laboratory risk assessment model that was investigated to identify undiagnosed diabetes mellitus and pre-diabetes mellitus among Chinese adults. A population-representative dataset was employed in this study, consisting of 1,857 participants who refrained from self-reporting the presence of significant chronic diseases or diabetes. To develop risk models, methods such as logistic regression (LR) and interpretable machine learning (ML) were implemented. As a consequence, blood tests came to be employed for the detection of recently diagnosed diabetes or pre-diabetes. Furthermore, the research identified sleep duration and vigorous recreational activity time as significant determinants of the 15.08% prevalence of these conditions, in addition to established risk factors. The performance of both the LR and ML models was impressive in the validation sample. In contrast, the ML model exhibited enhanced discrimination and calibration capabilities, as indicated by its AUC-ROC value of 0.822% and AUC-PR value of 0.496%. These models outperformed two previously developed models in determining the risk of developing diabetes, demonstrating the effectiveness of this non-laboratory approach. Enhancing risk prediction models for diabetes and pre-diabetes by integrating lifestyle factors, including sleep duration and recreational activity time, has the potential to inform more targeted preventive interventions among Chinese adults.

Zhang et al. (2021) conducted on the global public health concern posed by the substantial incidence and economic strains associated with diabetes mellitus. The paper underscores the importance of reliable risk assessment models to identify high-risk individuals and facilitate timely preventive interventions. The authors proposed an analytical framework based on the joint bagging-boosting model (JBM) by placing the key on data-driven methodologies and utilizing comprehensive population data from the Henan Rural Cohort Study. A strategic approach is utilized in the research to overcome challenges such as low identification rates and class imbalance. To accomplish this, specific variables are omitted using the maximum likelihood ratio method to acquire accessible variables, and a range of techniques for handling unbalanced data are examined. The JBM demonstrated effective discrimination and satisfactory calibration, as indicated by its Brier score of 0.072 and area under the curve (AUC) of 0.885. When compared to the benchmark model, the proposed framework significantly improved the model's overall performance, as indicated by the 13.5% increase in the area under the curve (AUC) value and the 0.847 increase in recall. The authors underscore the potential of their model to provide a significant contribution to the field of personalized diabetes management, particularly in resource-constrained medical settings. This is demonstrated through the demonstration of its effectiveness in risk assessment and preventive care.

Zhang et al. (2021) examined an innovative artificial intelligence (AI) system that has been devised with the specific purpose of early detection, staging, and prognostication of chronic kidney disease (CKD) and type 2 diabetes mellitus (T2DM). Through the utilization of AI models on an extensive dataset comprising 115,344 retinal fundus images from 57,672 patients, this study demonstrates the capacity to exclusively identify CKD and T2DM from these images. The artificial intelligence system extracts subtle quantitative metrics from retinal fundus images that have the potential to forecast clinical indicators of chronic kidney disease (CKD) and type 2 diabetes mellitus (T2DM), including estimated glomerular filtration rate (eGFR) and blood glucose levels. In addition, the inquiry utilizes longitudinal clinical data encompassing 10,269 patients to predict the probability of disease progression. This showcases the capability of the AI system to optimize clinical management and health surveillance intervals. The AI system's ability to detect and predict the advancement of type 2 diabetes mellitus (T2DM) and chronic kidney disease (CKD) using fundus images obtained from smartphones, even in point-of-care scenarios, is supported by external validation cohorts and a prospective pilot study comprising 3,081 patients. This research paper introduces a proof-of-concept for a dependable and non-invasive clinical screening instrument powered by artificial intelligence. The purpose of the instrument is to assist in the timely identification and prognosis of the occurrence of common systemic diseases.

Yang et al. (2020) investigated the well-being of the general populace using non-invasive and economical diabetes screening, and ensemble learning-based prediction models are being developed. The National Health and Nutrition Examination Survey (NHANES) data from 2011 to 2016 were partitioned to produce the dataset, which was subsequently divided into separate sets for training, testing, and validation. In addition to fundamental ensemble methods, three uncomplicated machine learning techniques—linear discriminant analysis, support vector machine, and random forest—were employed to develop diabetes prediction models. To assess the effectiveness of the models, external validation and 5-fold cross-validation were implemented. Consistently, ensemble methods exhibited superior performance compared to fundamental methods, with the ensemble model of linear discriminant analysis showcasing the highest degree of effectiveness. The model exhibited exceptional performance on the validation set, achieving the following metrics: area under the curve (AUC): 0.849; accuracy: 0.730; sensitivity: 0.819; and specificity: 0.709. The study highlights the potential of ensemble learning methods, in particular, to improve the accuracy and effectiveness of non-invasive diabetes screening. As a result, substantial insights are gained that can inform preventive health measures.

Mukhopadhyay et al. (2020) research was conducted into the application of precision medicine in the treatment of chronic illnesses via the utilization of the CURATE.AI dosing optimization platform. Chronic diseases often necessitate ongoing management that integrates pharmacological interventions with adjustments to one's lifestyle. Nonetheless, the task of attaining maximum disease control remains arduous, partially attributable to the implementation of standardized pharmacological methodologies. The objective of precision medicine is to individualize treatments; therefore, the potential of CURATE.AI, an algorithm that has already been proven effective in the treatment of cancer, is being explored in the realm of chronic disease management. The study describes a single-arm feasibility trial in which the dosing decisions of twenty patients with type II diabetes and twenty patients with hypertension will be guided by CURATE.AI recommendations. Acceptability, implementation challenges, and clinical impact of CURATE.AI in the treatment of chronic diseases are the objectives of this research. Furthermore, the study examines possible strategies for enhancing the algorithm, including the integration of supplementary artificial intelligence algorithms, the concurrent optimization of multiple medications, and the incorporation of additional variables. The primary aim of the endeavour is to evaluate the feasibility of integrating CURATE.AI into clinical practice through the identification of barriers and enablers, to offer direction for the platform's subsequent development.

Pei et al. (2019) examined a comparison made between five widely recognized classifiers in terms of their ability to predict or diagnose diabetes in high-risk individuals. The study utilized easily accessible and non-intrusive clinical indicators, including but not limited to gender, age, physical activity, occupational stress, inclination towards salted foods, hypertension, previous encounters with cardiovascular disease or stroke, familial history of diabetes, and the relationship between physical activity and hypertension. The dataset comprised 4205 entries that were extracted from the annual physical examination reports for adults conducted at the Shengjing Hospital of China Medical University. The research conducted by the study identified the decision tree classifier J48 as the most efficacious algorithm for classifying diabetes using the Weka data mining software. The algorithm attained notable metrics including accuracy (0.9503), precision (0.950), recall (0.950), F-measure (0.948), and area under the curve (AUC) (0.964). The decision tree structure determined age to be the most influential characteristic. Work stress, body mass index (BMI), preference for salted foods, physical activity, hypertension, gender, and prior experience of cardiovascular disease or stroke were found to be in that order of importance. The findings of this research underscore the potential of machine learning techniques, more particularly the J48 decision tree classifier, to effectively forecast or diagnose diabetes by leveraging readily accessible clinical features. This information is vital for developing targeted interventions in high-risk populations.

2.2.3 Evaluating the Role of Experience in Enhancing Behavioural Intentions to Utilize AI-Powered Diabetes Diagnostic Interventions

Hu et al. (2024) assessed the effectiveness of an AI-powered primary care setting-based DR screening system for non-Indigenous and Indigenous individuals with diabetes in Australia. Utilizing a decision-analytic Markov model, the progression of DR in a substantial population over forty years was simulated. After analyzing three primary care AI-based screening scenarios in comparison to the current practice, the results indicated that all three intervention scenarios—implementing manual grading, achieving universal screening, and scaling up to the level of patient acceptance—were effective and economical for both Indigenous and non-Indigenous populations. The universal AI-based DR screening scenario (Scenario C) was particularly remarkable for its ability to avert a substantial number of blinding cases, generate quality-adjusted life years (QALYs), and substantially reduce healthcare expenditures. For the non-Indigenous population, the implementation of universal screening generated a benefit-cost ratio (BCR) of 3.96 and a net monetary benefit (NMB) of AU$9,200 million. The cost-saving outcomes for the Indigenous population were similar; the implementation of universal AI-based screening resulted in reduced healthcare expenditures, quality-adjusted life years (QALYs), and prevented instances of blindness. These results highlight the considerable potential and cost-effectiveness that can be achieved by incorporating AI-based DR screening into primary care.

Mohsen et al. (2023) assessed the status of artificial intelligence (AI) models employed for the prognostication of the risk of type 2 diabetes mellitus (T2DM). The report recognized the growing importance of prompt identification and intervention in this context. A comprehensive analysis of forty longitudinal studies was undertaken by the review, with a specific focus on AI models utilized for the prognosis of type 2 diabetes mellitus. A considerable portion of research undertakings employed conventional machine learning models, with the primary data source being electronic health records (EHR). Following suit were multi-omics data, whereas medical imaging was utilized less frequently. While unimodal AI models were prevalent during that period, the review placed greater emphasis on the emergence of multimodal approaches, which demonstrated more advantageous results. A small proportion of studies conducted external validation, while internal validation was prevalent. The utilization of discrimination measures, particularly the area under the curve (AUC), was more prevalent than the provision of insights regarding model calibration. It is noteworthy that a relatively minor fraction of research studies assessed interpretability methods and placed emphasis on novel risk predictors.

Nguyen et al. (2023) investigated the use of machine learning algorithms to assist clinicians with diabetes risk assessment and diagnosis. The data utilized in this investigation were individuals who were residents of Ninh Binh, Vietnam and had received a diagnosis of type 2 diabetes. A range of classification methodologies were employed to ascertain the most optimal algorithm for the dataset. These methodologies included the Ada Boost Classifier, Gradient Boosting Classifier, Random Forest Classifier, and K Neighbours Classifier. The results of the study indicated that the Random Forest Classifier algorithm outperformed the alternatives, achieving a cross-validation score of 0.998 and a precision of one hundred per cent. A dataset comprising 67 individuals, all of whom had not been observed before the testing phase, was utilized to assess the selected model. The algorithm accurately predicted the probability that a patient would develop diabetes, as indicated by the class 1 (diabetes) probability value; the system obtained an impressive 94% accuracy on this dataset. This innovative approach introduces a comprehensive and quantifiable method for identifying diabetes and evaluating its risk, demonstrating how machine learning algorithms can assist healthcare practitioners in the management and diagnosis of the condition. Diabetes risk scores and assessments have the potential to enhance patient education and awareness about the condition. This information is of utmost importance in promoting health and wellness among patients, as it enables them to make informed decisions and fosters the adoption of a healthy lifestyle.

Musacchio et al. (2020) research topic encompassed, among other challenges, a decline in the number of diabetologists, an increase in the number of patients, a scarcity of time for medical consultations, and the complexity of disease management. Within this particular framework, the authors emphasize the considerable opportunity presented by nascent digital technologies and artificial intelligence (AI). Based on an exhaustive review of the extant literature, the authors present the viewpoint of the Italian Association of Medical Diabetologists (AMD) regarding the implementation of artificial intelligence (AI) in diabetes care. AMD considers artificial intelligence (AI) to be a groundbreaking tool capable of transforming data into actionable insights, thus enabling a shift from descriptive to predictive and prescriptive capabilities. By gaining an understanding of correlations and the determinants of behaviour, artificial intelligence has the potential to enhance patient outcomes. AMD recognizes AI as a valuable technical support tool that empowers diabetologists to take full responsibility for the treatment of specific patients, thus promoting the implementation of precise and individualized medicine. The article underscores the critical importance of employing artificial intelligence (AI) to address the dynamic landscape of diabetes care and enhance patient management.

2.2.4 Demographic Influences on the Adoption of AI-Based Diabetes Diagnostic Interventions by Doctors.

Uymaz et al. (2024) analyzed the viewpoints of physicians regarding their intention to utilize AI physicians in healthcare, this study sought to ascertain their inclinations towards diverse AI applications. The research framework examined the intentions of physicians regarding the utilization of AI doctors for patient follow-up, data collection, diagnosis, and treatment planning, drawing upon the theory of technology adoption and use. By utilizing structural equation modelling and deep learning, the responses of 478 physicians were analyzed. The study indicates that physicians plan to employ AI physicians predominantly for treatment planning and diagnosis, with data collection and patient follow-up following suit. Performance expectation, hedonic motivation, high-tech practices, and perceived task technology fit were the primary determinants of their intentions. Through the causal comparison screening technique, which discerns the causes and effects of physicians' attitudes, behaviours, ideas, and beliefs, the factors that impact their acceptance and intention to utilize AI doctors for a variety of healthcare tasks became apparent.

Zhan et al. (2024) investigated the multitude of factors that influence users' confidence in and acceptance of Healthcare Voice AI Assistants. The researchers employed a partial least squares structural model to ascertain the impact of functional, personal, and risk factors on trust in voice assistants (HVAs) by analyzing survey responses from 300 users. The findings indicate that functional factors, including service quality, content credibility, and utility, have a substantial influence on trust in HVAs when compared to healthcare professionals. Additionally, significant determinants of trust were found to be personal attitudes toward technology as well as concerns regarding security and privacy. The objective of this study is to analyze the unique attributes that contribute to trust in healthcare virtual assistants (HVAs) as opposed to general-purpose voice assistants like Alexa or Siri. The subsequent section delves into the implications of these findings for the integration of voice assistants within the healthcare industry, emphasizing the necessity to tackle unique requirements and factors that are unique to this specialized field.

Uymaz et al. (2023) investigated and explored the behavioural intention to implement AI physicians in tertiary, primary, and secondary care. The study employed a hybrid analysis methodology, combining partial least squares structural equation modelling with deep learning (Artificial Neural Networks), in adherence to the unified theory of technology acceptability and use. An analysis of 432 responses reveals that perceived task-technology compatibility, perceived privacy, performance expectancy, and social influence are significant determinants of the intention to utilize an AI doctor at all levels of healthcare. The research findings indicate that there was a significant inclination to employ AI physicians across all tiers of healthcare. This highlights the importance of privacy concerns and perceived task-technology match in shaping attitudes towards the adoption of artificial intelligence in the healthcare industry.

Wewetzer et al. (2023) examined the determinants of the successful implementation of AI-supported devices for diabetic retinopathy (DR) examinations in general practice. This study conducted a survey among 209 general practitioners (GPs) in Germany to identify crucial considerations that should be incorporated into the implementation of AI-powered screening tools. Acquisition, compensation, and operating expenses were given special consideration; general practitioners suggested €27.00 as an appropriate reimbursement for AI-powered DR screening. The feasibility of the device, the ease of integrating it with practice information systems, and the simplicity of software implementation were all crucial technical factors to consider. In addition, general practitioners prioritized patient-related factors to a considerable extent, including examination accuracy, the omission of pupil dilation, and the duration of examinations. It was concluded that the appeal of integrating AI-based screening tools into general practice was significantly influenced by three critical elements: broadening the scope of care, strengthening primary care, and integrating contemporary medical practices. Through an analysis of cost and reimbursement policies, this research makes substantial contributions to the body of knowledge regarding the efficient integration of AI-assisted screening devices into primary care environments. As a result, the prompt detection of ophthalmological conditions is enhanced.

Zahed et al. (2023) examined the belief model constructed to identify significant constructs that can predict the intention to utilize a diabetes self-management device for hypoglycemia detection. Adults in the United States who have been diagnosed with type 1 diabetes participated in a web-based survey to ascertain their preferences concerning a device designed to monitor tremors and provide alerts in the event of hypoglycemia. A total of 212 eligible participants, of which 61% were female, were of the age group of 30 to 50 years old, with roughly half (55%) being female. Four primary constructs accurately predicted the intention to utilize the device, according to the research ($R^2=0.65$; $F_{12,199}=27.19$; $P0.001$). Perceived efficacy ($\beta=.33$; $P<.001$) and perceived health hazard ($\beta=.55$; $P<.001$) emerged as the most influential factors. Resistance to change ($\beta=-.19$; $P<.001$) and cures to action ($\beta=.17$; $P<.001$) both had an adverse effect. Furthermore, advancing age was found to be associated with a greater perception of health peril ($\beta=.025$; $P<.001$). This study provides substantial insights into the key determinants that impact the propensity of individuals to employ diabetes self-management devices. This study emphasizes perceived efficacy and health threat perception in particular.

Liaw et al. (2023) conducted a mixed-methods study to assess the adoption of an AI-based clinical decision-support tool by staff and clinicians who are responsible for managing diabetes. A combination of surveys and semistructured interviews were utilized to assess adoption-influencing factors, perceived utility, convenience of use, and intention to use. There were deliberations among the 22 participants, of which 63 per cent were clinicians, concerning the tool's potential utility, concerns regarding its impact on patient workflows and outcomes, and factors influencing its adoption. The themes that were recognized included concerns about the tool's potential usefulness, worries about patient workflows and outcomes, dependence on validation and transparency, and the need for individualized implementation. The results of the survey indicated that the tool was well received, with 77% of participants indicating their intention to use it and providing high marks for its practicality (82%), ease of use (82%), and clinic assistance (68%). The accuracy and efficacy of the instrument in enhancing health were the two most influential factors in determining its level of adoption. The study makes substantial contributions by investigating the perspectives of personnel and clinicians concerning the implementation of decision-support tools propelled by artificial intelligence. This highlights the importance of utility, transparency, and tailored implementation strategies.

Montazeri et al. (2023) investigated the determinants of self-care practices among Iranian patients with type II diabetes. The study involved the participation of 280 type II diabetic patients from the Diabetes Research Center of Ayatollah Taleghani Hospital in Kermanshah. Data collection was conducted using the standard self-care questionnaire for diabetic patients and a questionnaire requesting demographic information. In general, the self-care scores, with an average of 2.07 ± 2.08, indicated an unfavourable condition. The blood-glucose testing results indicated that the lowest scores were obtained, while consistent medication use was associated with the highest scores. Self-care scores varied significantly concerning variables including marital status, occupation, place of residence, type of treatment, years of diabetes management, and smoking status. The findings from the regression analysis revealed that a range of factors, such as residential location, smoking status, treatment type, and diabetes-related complications, constituted 51.5 per cent of the observed variability in self-care. The results mentioned above emphasize the importance of including demographic factors in the development of interventions targeting the enhancement of self-care behaviours among individuals in Iran who have been diagnosed with type II diabetes.

Sze et al. (2023) conducted to assessment of the initial efficacy and feasibility of a personalized mobile health (mHealth) intervention that promoted physical activity among patients with type 2 diabetes through the application of SCT. The individuals involved utilized the StepAdd application to monitor their daily step count, body weight, and blood pressure from the convenience of their residences. Furthermore, they established objectives and obtained immediate feedback. The application facilitated the assessment of daily advancements, delivered personalized goal updates, identified challenges hindering the achievement of step objectives, and assisted in the development of coping strategies. The implementation of lifestyle modification education delivered by pharmacists led to enhanced self-management skills for diabetes. All 33 participants demonstrated significant progress, with an average age of 61.5 ± 9.4 years. The daily step count increased significantly from 5436 to 10,150 (86.7% increase, $p < 0.0001$). Simultaneously, improvements in HbA1c ($p = 0.0001$) and BMI ($p = 0.0038$) were noted. Considerable advancements were noted in the domains of diabetes self-management, self-control, and confidence about the achievement of daily step goals. The high retention rate of 97.0% in the study indicates that SCT-based mHealth interventions for improving physical activity and diabetes management may have the potential to enhance participant engagement and provide efficacy.

Dalal et al. (2023) investigated the prevalence, demographic characteristics, treatment patterns, and coexistence of dyslipidemia, type 2 diabetes mellitus (T2DM), and hypertension among patients from India. 6.36 per cent of the 6,722,173 patients treated at 4,793 centres had triple comorbidity, according to an analysis of the data. The demographic consisted primarily of males (57.00%) aged between 40 and 64 with varying body mass indexes. A smoking history was recorded for a proportion of 0.80% of the patients. The research recorded average glycated haemoglobin (HbA1c), systolic blood pressure (SBP), and diastolic blood pressure (DBP), with a notable proportion of the participants adhering to the prescribed BP limits. The lipid profiles demonstrated standard deviations for the relative amounts of HDL, total cholesterol, and LDL that were within the acceptable ranges. The treatment approaches for hypertension and dyslipidemia involved the extensive use of angiotensin receptor blockers (ARBs) and beta-blockers, diverse combinations of lipid-lowering medications for the management of hypertension, and the concurrent administration of lipid-lowering drugs with other pharmaceuticals. The main application of biguanides was as antidiabetic agents. This research paper conducts an extensive analysis of the demographic and clinical characteristics, emphasizing the need for comprehensive strategies in the management of individuals in the Indian populace who also have these conditions.

Stühmann et al. (2020) investigated the determinants and prevalence of health app usage among adults in Germany who have type 2 diabetes (T2D) or do not. Study participants included 2327 adults without a documented diagnosis of diabetes and 1149 adults with confirmed T2D. A majority of smartphone owners (74.72 per cent) without a diagnosed diagnosis of diabetes utilized health applications to supplement regular physical activity (49.27 per cent). A total of 42.26% of individuals diagnosed with T2D possessed smartphones, of which 41.1% were engaged in the use of health applications primarily aimed at encouraging a nutritious diet. There was a positive correlation observed between increased utilization of health applications and the following characteristics among individuals without a diagnosed diabetes diagnosis: younger age, overweight or obesity, prior or current smoking status, perception of excellent health, presence of other chronic illnesses, and receipt of health advice from a physician. A decreased inclination to utilize health applications was discovered to be correlated with an individual's perception of having a moderate to high risk of developing diabetes. Among individuals with T2D, health app usage was positively correlated with younger age, female gender, and glucose sensor usage.

Su et al. (2020) researched the relationship to personality traits, and the influence of the adoption and active use of a mHealth application (DiaSocial) for diabetes self-management on health outcomes was also examined. The application was installed and utilized by 47% of the 98 participants. Younger patients had a 9% higher prevalence of application adoption and usage ($P=.02$, odds ratio [OR] 0.91, 95% CI 0.85-0.98). App adoption was found to be positively correlated with openness to experience ($P=.03$, OR 1.73, 95% CI 1.07-2.80), while extraversion was found to be negatively correlated ($P=.04$, OR 0.71, 95% CI 0.51-0.98). Gender, educational attainment, and HbA1c levels at the outset did not influence app adoption. Active utilization was associated with a high openness to experience ($P=.048$, OR 2.01, 95% CI 1.01-4.00) and a low level of education ($P=.003$) among app adopters. It was observed that active users experienced a significantly greater reduction in HbA1c levels than other users ($\Delta HbA1c=-0.64$, $P=.05$). This study places particular emphasis on the influence of personality traits on the acceptance and utilization of mobile health (mHealth), thereby making substantial contributions to the advancement of individualized diabetes management interventions.

Arawi et al (2020) examined the relationship between demographic characteristics and patients with type 2 diabetes Mellitus understanding of self-care practices. Among the 3,251 patients who participated in the survey, one hundred met the inclusion criteria and were therefore included in the analysis. The study population exhibited a spectrum of knowledge levels concerning diabetes, which were classified as moderate to low. Self-care practices were recognized as moderately prevalent, and complications related to nephropathy and cardiovascular disease were deemed to be well-understood. The results of the study did not indicate a statistically significant relationship between demographic variables and comprehensive knowledge. However, discrepancies were observed between the sexes, with males displaying a higher level of knowledge ($p = 0.028$) compared to females' improved self-care practices ($p = 0.020$). Additionally, the educational status of diabetic patients was found to have a substantial impact on their knowledge. This emphasizes the importance of educational interventions that target the population under study to improve their understanding and adherence to self-care practices related to diabetes.

Ye et al. (2019) carried out a study of how people in China use ophthalmic AI devices, to create a model of acceptance for ophthalmic AI based on ideas of how people accept new technologies. A 32-item assessment was filled out by 474 people, and structural equation modelling (SEM) was used to look at the data. The results showed that there wasn't a statistically significant link between education and desire to use (IU), and IU didn't change much across the different education levels. Standardized factor loadings for the items were between 0.583 and 0.876, and the composite reliability of the constructs met the standards with values between 0.673 and 0.841. It was proven that discriminant validity was true, and the model fit signs showed that the model fit well enough. It was found that subjective norms (beta=.408; P<.001), perceived utility (beta=.336; P=.03), and resistance bias (beta=–.237; P=.02) all had a big effect on the desire to use, together they explained 51.5% of the difference. Subjective norms and perceived behaviour control also had an indirect effect on the desire to use through perceived usefulness and perceived ease of use. Belief in the importance of eye health had a positive effect on the intention to use through perceived usefulness. The trust had a significant effect on the link between perceived usefulness and intention to use (beta=–.095; P=.049). This study gives us useful information about the different factors that affect how many Chinese people use ophthalmic AI gadgets.

2.2.5 Enhancing Patient Journey through AI-Driven Diagnostic Pathways for Diabetes Management

Kawasaki et al. (2024) examined how important it is to act quickly to lower the risk of blindness caused by diabetic retinopathy (DR) in Japan, where the lack of early symptoms makes it harder to find. This study looks into how artificial intelligence (AI) might be able to improve screening for drug resistance (DR). It focuses on two specific screening routes in Japan: the health screening pathway and the clinical referral pathway, which is where doctors send their patients to eye doctors. Artificial intelligence (AI) systems that use deep learning to automatically label images have shown a lot of promise. Future tests have shown that they are more than 90% accurate in both sensitivity and specificity. The writers talk about how Large Language Models (LLMs) and Generative AI could change the way healthcare is provided, focusing on how they can be used to help patients, keep medical data, and make decisions. The article stresses how important it is to use artificial intelligence in carefully designed screening programs by giving a seven-step plan for orderly screening. Automated scoring systems with AI indeed make screening better, but their usefulness depends on how well they work with the rest of the screening environment. Large Language Models are essential tools for filling in gaps in the screening process and making the system more patient-centred and effective by, among other things, sending individual invitations and results reports.

Goldstein et al. (2023) examined that the number of tests the independent AI system ran every month showed that it was being used successfully. Procedures carried out at four US schools were written down over a year. There were big differences between hospitals in things like the types of patients they had, their size, staffing, funding, and how stable their finances were. They were spread out on the West Coast, Southwest, Northeast, and Midwest. All sites saw a rise in the number of diabetes-related exams each month, from 89 in the first month to 174 after a year of use. Active participation of clinical and executive champions, enough resources at the health centre, and the integration of clinical workflows that include patient identification before the visit, Luminetics Core Exam Capture and Provider Consult during the visit, and timely referral triage after the visit were the main things that made implementation last. These results show that improving workflow, along with government support, funds, and following quality standards, is an important part of getting innovations accepted by most people. By using these best practices on more self-driving AI systems in primary care settings, we can improve access for patients, improve the level of care, and lower health disparities.

Huang et al. (2023) investigated recent progress in using artificial intelligence to improve the detection and prognosis of six important complications related to diabetes. Some of the problems that can happen during pregnancy are diabetic retinopathy, diabetic foot sores, diabetic peripheral neuropathy, diabetic nephropathy, and hypoglycemia that was picked up in the hospital. In the concept of diabetes precision medicine, artificial intelligence can be used. ML and AI will make it possible to collect, study, and gather a huge amount of genetic, genomic, physiological, biomarker, environmental, and behavioural data, which would normally require a human's intelligence.

Wang et al. (2020) investigated the DeepDR method, an AI-driven bottomless book-learning approach for identifying DR in retinal fundus images, was devised and evaluated. A compilation of 500 fundus images was provided for analysis, which included tasks such as vascular segmentation, optic disc and macular localization, DR grading, and lesion detection. To enhance the accuracy of DeepDR's DR grading, a multi-level iterative technique of convolutional neural networks was employed in conjunction with an increased learning strategy. The program underwent training utilizing three additional publicly available data sets.

Hospital-supplied fundus images were utilized to validate final evaluations. 6788 fundus images (both disc-centred and macular) were analyzed at two hospital eye centres to detect microaneurysms, haemorrhages, and hard exudates with respective accuracy rates of 99.7%, 98.4%, and 98.1%. The present algorithm exhibited a precision of 0.96. A total of twenty-five fundus photographs were chosen from the community screening; of these, seventy-five were determined to be of insufficient quality. The accuracy achieved in correctly organizing fundus photographs was 0.9179. Sensitivity, Specificity, and AUC were 0.8058, 0.9577, and 0.9327, respectively.

Zhang et al. (2020) study was done at 155 diabetes centres in China to find out how common diabetic retinopathy (DR) is among adult patients with diabetes and to test a DR screening method that uses artificial intelligence. A five-step DR classification system based on deep learning (DL) was used to look at pictures of macula-centered funduses that were not mydriatic. 47,269 people signed up, and the average age was 54.29 years. To make sure the DL algorithm worked, a group of experts looked at 15,805 randomly chosen volunteers. The referable DR grading systems could find DR with an 83.3% sensitivity and a 92.5% specificity. Similar to the differences seen between experts, the five-stage DR's ability to classify things was about the same. The DL algorithm found a DR that could damage your eyesight, any DR that could be found, and a DR that could be used as a reference. These were found to be 28.8%, 24.4%, and 10.8% common, respectively. A higher frequency was seen in women, older people, people who had diabetes for a longer time, and people whose glycated haemoglobin levels were higher. The study shows that the DL-based screening method works well and gives useful information about how common DR is in the Chinese diabetes population. This information can be used for early detection and treatment.

Sosale et al. (2020) Researchers did a cross-sectional study to see how well the offline Medios artificial intelligence (AI) program worked on non-mydriatic (NM) retinal images for finding diabetic retinopathy (DR). 922 people with diabetes mellitus took part in the study. NM retinal pictures were taken with the Remidio NM fundus-on-phone (FOP) camera. Offline analysis of the images was done, and the AI algorithm decided whether DR was present or missing. The results were then compared to the diagnoses made by five retina experts based on images. The diagnosis that came up highest was considered to be correct. Out of the 900 people who were looked at, 252 were identified with DR. With a sensitivity of 83.3% (95% CI 80.9% to 85.7%) and a specificity of 95.5% (95% CI 94.1% to 96.8%), the AI system was able to find any DR. For example, when it came to referable DR (RDR), the AI system had a sensitivity of 93% (95% CI 91.3% to 94.7%) and a specificity of 92.5% (95% CI 90.8% to 94.2%).

2.3 Research Gap

In the reviewed literature, a noticeable research gap exists in the exploration of socio-demographic factors influencing the adoption and utilization of healthcare-related technologies, particularly in the context of AI-based interventions for diabetes management. While studies have delved into the influence of temperament qualities, education, & age on the acceptance of mHealth apps and AI doctors, there is a dearth of comprehensive investigations that consider a broader array of socio-economic factors, cultural influences, and user preferences. Understanding the nuanced interplay between these variables could significantly contribute to tailoring technology-driven interventions to diverse populations, ultimately optimizing their effectiveness and ensuring equitable access to healthcare advancements. Another research gap is apparent in the limited exploration of the perceptions and attitudes of healthcare specialists, precisely physicians, in the direction of the integration of AI technologies in their practices. While studies have assessed the intention to use AI doctors, there is a notable absence of in-depth investigations into the concerns, motivations, and potential barriers faced by physicians in embracing these technologies. Exploring the perspectives of healthcare professionals is crucial for successful implementation, as their acceptance and engagement are pivotal in the one-piece addition of AI gears into routine medical workflows. As AI technologies are poised to piece a noteworthy protagonist in disease detection, studies often fall short in thoroughly addressing ethical implications, patient privacy concerns, and the establishment of regulatory frameworks. Investigating the ethical dimensions and ensuring robust governance mechanisms are crucial for fostering faith among both healthcare specialists & patients, ultimately influencing the responsible deployment of AI in healthcare settings.

2.4 Research Problem

The research problem revolves around the investigation of the adoption of AI-based interventions for diagnosing diabetes by doctors in the Indian states of Maharashtra and Karnataka. While AI holds immense potential for revolutionizing healthcare, the specific factors influencing the adoption of AI tools among doctors in these regions remain unclear. The critical assessment aims to identify and analyze the challenges, facilitators, and unique contextual factors that impact the willingness of doctors to adopt AI-based diagnostic interventions for diabetes. This study addresses the gap in understanding the adoption dynamics in specific geographical and cultural contexts, shedding light on the intricacies that might differ from global trends. The proposed framework will serve as a strategic guide for implementing AI-based interventions effectively, considering the identified factors, thereby contributing to the successful integration of advanced technologies into routine clinical practices. This research problem is crucial for informing healthcare policies, fostering technology acceptance, and optimizing the utilization of AI in diabetes diagnosis within the healthcare systems of Maharashtra and Karnataka.

2.5 Conclusion

In summary, the evaluations emphasize the critical significance of AI in revolutionizing diverse aspects of diabetes treatment and administration. Research has investigated the utilization of AI in a wide range of fields, such as diabetes screening for self-care, self-care practices, the attitudes of physicians toward AI, the level of trust placed in healthcare vocal AI assistants, and the general practice implementation of AI-supported devices for diabetes screenings. The results underscore the potential of AI to improve the precision of diagnoses, encourage self-management, and optimize healthcare operations. Notwithstanding the advancements, obstacles continue to endure, including concerns regarding trust, technical precision, and the imperative for meticulous integration. Additionally, the adoption and acceptability of AI tools in diabetes care are substantially impacted by regional and demographic variations. The research voids that have been identified underscore the necessity for further extensive inquiries into the dynamics of adoption, with a particular focus on distinct geographical and cultural contexts. In the future, it is critical to methodically confront these deficiencies and obstacles to fully leverage the capabilities of artificial intelligence (AI) in improving diabetes management, achieving broad adoption, and maximizing health results.

CHAPTER-3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

The investigation technique, which was established on the conceptual framework and literature evaluation described in the preceding chapters, is elaborated upon in this episode. This chapter presents a thorough examination of the parameters, sampling strategy, data analysis methodologies, correlation analysis, and research approach utilized in the study. The research will be conducted from a positivist standpoint, which asserts that causal relationships between events in the social domain and significant phenomena are straightforward to understand. A quantitative research design and a deductive methodology will be implemented. Subsequently, this investigation will utilize existing scholarly works to deduce correlations between ideas and develop a systematic approach to verify the proposed theory. The ultimate goal is to provide empirical support for and to broaden the scope of knowledge in the field.

A quantitative research methodology will be used to test the theory and come to a conclusion in this study. There are many things to think about when choosing a quantitative method. To start, the research problem has been set up in a way that makes it possible to use descriptive and inferential statistics (Huck, 2004; Jackoff, 1953) to look at causal connections and put together research results. A lot of studies that have looked into how people accept and use technology have also used the quantitative method to look at the data (Creswell, 2009; O'Brien & Scott, 2012). Also, objective results are reached by using quantitative methods to look at things on their own during the whole process of collecting and analyzing data. The specific goal of this study is to reach this goal.

3.2 RESEARCH APPROACH

The quantitative design of the current study indicates that using a deductive approach is the most appropriate, hence it will be used instead of an inductive or abductive one (Creswell & Clark, 2007). The approach involves evaluating the literature to identify plausible hypotheses, which are then linked to the study's model by its framework. Next, in an attempt to test theories and, ideally, validate or improve the current theory, the objectives and research strategy will be established.

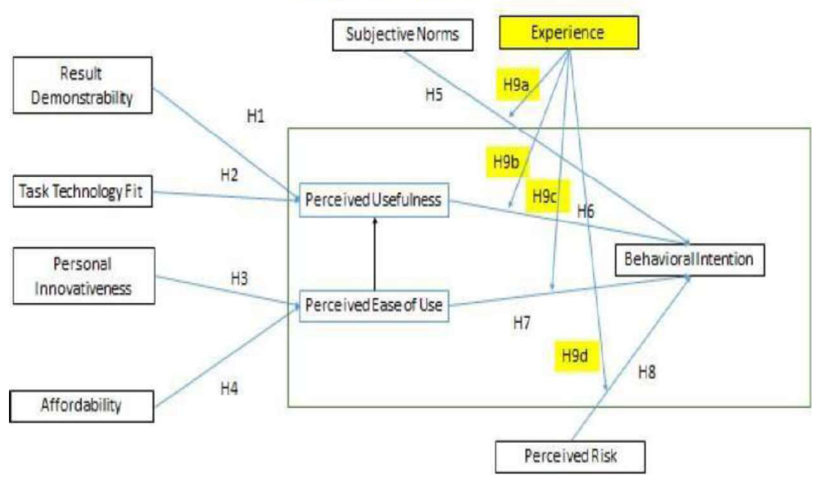
3.3 RESEARCH DESIGN

This study is going to adhere to the seven-step procedure for academic research design that Ríos et al. (2013) proposed. Finding out what is already known about the phenomenon is the first step in the process. Thirdly, we will present some theories (explained in the hypothesis section), after a second brainstorming session. The study design will then be determined. Then, we will provide a sample strategy as well as a plan for gathering and analyzing data.

3.4 RESEARCH STRATEGY

The current examination in this study will begin with problem identification, go on to attribute descriptions of the relevant phenomena, and then determine how these phenomena relate to one another (Punch, 2005). Therefore, in a broad sense, this study will fall under all "three types of research: exploratory, descriptive, & causal". Still, the study will be essentially a blend of causal and descriptive research.

Proposed Model



3.5 INSTRUMENT DEVELOPMENT

The **instrument development** for this research involved designing structured questionnaires based on well-established constructs from previous studies to assess physicians' adoption of AI-based diabetes diagnostic devices (Table 3.1). The key **constructs** include **Result Demonstrability (RD), Task Technology Fit (TTF), Personal Innovativeness (PI), Affordability (AF), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioural Intention (BI), Subjective Norms (SN), Perceived Risk (PR), and User Experience (UX)**. Each construct consists of multiple **items** designed to measure various aspects influencing AI adoption, such as physicians' confidence in AI-driven results, technological compatibility, willingness to experiment, cost concerns, usability, and external influences like peer and patient expectations.

The questionnaires, derived from **prior validated research**, enables a comprehensive **assessment of key factors** affecting AI adoption in clinical practice. The insights gained contribute to the development of a **framework** that supports the seamless integration of AI technologies in diabetes diagnosis, addressing barriers and enhancing decision-making among medical practitioners. This approach ensures that AI interventions align with physicians' diagnostic methods, improve efficiency, and optimize healthcare outcomes.

Table 3.1: Construct, Items, References

Constructs, Items, References		
Construct	**Definition & Items**	**References**
Result Demonstrability (RD)	**The degree to which a Doctor believes that the use of AI based Diabetes Diagnostic devices demonstrate result**	**(Tyge-F. Kummer et al., 2013), (Venkatesh V & Davis FD, 2000)**
RD1	The results of using AI based Diabetes diagnostic devices are apparent to me.	(Tyge-F. Kummer et al., 2013), (Venkatesh V & Davis FD, 2000)
RD2	I believe I could communicate to others the consequences of using AI based Diabetes Diagnostic system.	(Tyge-F. Kummer et al., 2013), (Venkatesh V & Davis FD, 2000)

RD3	I would have difficulty explaining why using AI based Diabetes diagnostic devices may or may not be beneficial.	(Tyge-F. Kummer et al., 2013), (Venkatesh V & Davis FD, 2000)
Task Technology Fit (TTF)	**The degree to which a person believes that AI based Diabetes diagnostic devices are relevant for care delivery**	**(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al., 2007)**
TTF1	I find the usage of AI based Diabetes Diagnostic devices are relevant to the delivery of Diabetes Care.	(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al., 2007)
TTF2	I believe usage of AI based Diabetes Diagnostic devices are technologically important to the delivery of Diabetes Care.	(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al., 2007)
TTF3	I believe using AI based Diabetes Diagnostic system fits with the way I like to diagnose a Diabetes patient.	(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al., 2007)
TTF4	I believe using AI based Diabetes Diagnostic system fits with my style of care for Diabetes Patients.	(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al.,

		2007)
TTF5	AI based Diabetes diagnostic systems are compatible with most aspects of my diagnosis of Diabetes patients.	(William G. Chismar & Sonja Wiley-Patton, 2002), (Chau PYK & Hu PJH, 2002), (Yi MY et al., 2006), (Duyck P et al., 2008), (Schaper LK et al., 2007)
Personal Innovativeness (PI)	**Degree to which an individual is willing to try out any new technology**	**(Tyge-F. Kummer et al., 2013), (Thatcher et al., 2003)**
PI1	If I heard about a new AI based Diabetes Diagnostic Technology, I would look for ways to experiment with it.	(Tyge-F. Kummer et al., 2013), (Thatcher et al., 2003)
PI2	Among my peers I am usually the first to explore new AI based Diabetes Diagnostic Technologies.	(Tyge-F. Kummer et al., 2013), (Thatcher et al., 2003)
PI3	I like to experiment with new AI based Diabetes Diagnostic Technologies.	(Tyge-F. Kummer et al., 2013), (Thatcher et al., 2003)
PI4	In general, I am hesitant to try out new AI based Diabetes Diagnostic Technologies.	(Tyge-F. Kummer et al., 2013), (Thatcher et al., 2003)
Affordability (AF)	**The possible expenses of using AI based Diabetes Diagnostic systems, i.e., equipments costs, access cost, and transaction fees**	**(Rajasshrie Pillai & Brijesh Sivathanu, 2020), (Puklavec et al., 2018), (Chong and Chan, 2012)**
AF1	I think the equipment cost is expensive of using AI based Diabetes Diagnostic systems.	(Rajasshrie Pillai & Brijesh Sivathanu, 2020), (Puklavec et al., 2018), (Chong and Chan, 2012)
AF2	I think the access cost is expensive of using AI based Diabetes Diagnostic systems.	(Rajasshrie Pillai & Brijesh Sivathanu, 2020), (Puklavec et

		al., 2018), (Chong and Chan, 2012)
AF3	I think the transaction fee is expensive of using AI based Diabetes Diagnostic systems.	(Rajasshrie Pillai & Brijesh Sivathanu, 2020), (Puklavec et al., 2018), (Chong and Chan, 2012)
Perceived Usefulness (PU)	**The degree to which a Doctor believes that the use of AI based Diabetes Diagnostic devices would enhance his or her personal or job performance**	**(Holden RJ & Karsh B, 2010), (Davis FD, 1989), (Dou K et al., 2017), (Aggelidis VP & Chatzoglou PD, 2009), (Wei YL et al., 2018)**
PU1	AI based Diabetes diagnostic devices would help me to cope with preventable Diabetes diseases and its complications at an early stage	(Davis FD, 1989), (Dou K et al., 2017)
PU2	AI based Diabetes diagnostic devices would provide detailed information such as vital readings, fundas images of my patients' eyes, which would be very useful for me	(Davis FD, 1989), (Dou K et al., 2017)
PU3	AI based Diabetes diagnostic devices would help the medical institutions to recognize more treatable eye patients	(Davis FD, 1989), (Dou K et al., 2017)
PU4	AI based Diabetes diagnostic devices would improve primary health care for health departments and save money	(Davis FD, 1989), (Dou K et al., 2017)
PU5	AI based Diabetes diagnostic devices would be a good supplement to traditional health care approaches and fit with my medical philosophy	(Davis FD, 1989), (Dou K et al., 2017)
PU6	AI based Diabetes diagnostic devices would fit my patients' demand for eye health management	(Davis FD, 1989), (Dou K et al., 2017)
PU7	AI based Diabetes diagnostic devices would achieve the same results as face-to-face diagnosis with a Diabetologist	(Davis FD, 1989), (Dou K et al., 2017)

Perceived Ease of Use (PEOU)	**The degree to which a person believes that AI based Diabetes diagnostic devices would be easy to use**	**(Holden RJ & Karsh B, 2010),** **(Davis FD, 1989),** **(Dou K et al., 2017), (Aggelidis VP & Chatzoglou PD, 2009)**
PEOU1	I find the instructions for AI based Diabetes Diagnostic devices easy, clear, and understandable	(Davis FD, 1989), (Dou K et al., 2017)
PEOU2	AI based Diabetes diagnostic devices would offer a more convenient way for my Patients to cope with their disease management without queuing for registration in hospitals and would save their time and money	(Davis FD, 1989), (Dou K et al., 2017)
Behavioral Intention (BI)	An individual's motivation or willingness to exert effort to use AI based Diabetes diagnostic devices	**(Holden RJ & Karsh B, 2010), (Schifter DE, Ajzen I., 1985), (Zhao Y et al., 2018), (Safa NS, Von Solms R., 2016)**
BI1	I intend to use AI based Diabetes diagnostic devices as my first choice if I feel my patients need it	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
BI2	I will encourage my friends/ colleagues to use AI based Diabetes diagnostic devices first if they ask	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
BI3	I will encourage healthy people to use AI based Diabetes Diagnostic devices for preventive health screening	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
BI4	I would be able to use AI based Diabetes diagnostic devices independently as long as I had enough time and made an effort to learn	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
BI5	I would receive appropriate technical assistance when encountering any difficulties in using AI based Diabetes diagnostic devices or understanding the report	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
Subjective Norms (SN)	**Perception of important (or relevant) others' beliefs about my use of AI based Diabetes diagnostic devices**	**(Holden RJ & Karsh B, 2010), (Schifter DE, Ajzen I., 1985),**

		(Venkatesh V & Davis FD, 2000), (Safa NS, Von Solms R., 2016), Andrews L et al., 2014)
SN1	People who are important to me (Colleagues, family members, relatives, and close friends) think that I should use AI based Diabetes diagnostic devices	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
SN2	My colleagues or peers think that I should use AI based Diabetes diagnostic devices	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
SN3	My leaders or superiors think that I should use AI based Diabetes diagnostic devices	(Holden RJ & Karsh B, 2010), (Safa NS, Von Solms R., 2016)
Perceived Risk (PR)	**A combination of uncertainty and seriousness of an outcome in relation to performance, safety, psychological or social uncertainties**	**(Egea JM & González MV., 2011), (Andrews L et al., 2014), (Hsieh P, 2015), Wei YL et al., 2018)**
PR1	There is a possibility of malfunction and performance failure, so they might fail to deliver accurate diagnoses or recommendations and could increase conflicts between members of the public and medical institutions	(Andrews L et al., 2014), (Hsieh P, 2015)
PR2	I am concerned that my patients' information and health details would be insecure and could be accessed by stakeholders or unauthorized persons, leading to misuse and discrimination	(Andrews L et al., 2014), (Hsieh P, 2015)
PR3	Considering the difficulties involved in taking high-quality images for AI analysis, I think there is a risk of incorrect screening results	(Andrews L et al., 2014), (Hsieh P, 2015)
PR4	Because practitioners with little ophthalmic knowledge might find it difficult to understand the screening report and explain the terminology and results to patient, they might increase my anxiety of about using AI based Diabetes diagnostic devices	(Andrews L et al., 2014), (Hsieh P, 2015)

Experience (UX)	**Past use of AI based Diabetes Diagnostic Services, an important predictor contributing towards Behavioral Intention**	**(Adjusted from Venkatesh V & Davis FD, 2000)**
UX	How long ago did I first start to use AI based Diabetes Diagnostic systems professionally for my patients	(Adjusted from Venkatesh V & Davis FD, 2001)

3.6 SAMPLE SELECTION

For this study, 319 participants in total will be selected using a stratified random selection technique and a descriptive design." Maharashtra and Karnataka will be split equally into strata according to different zones, with the same number of districts in each zone. The number of physicians practicing general medicine, endocrinology, and ophthalmology in the Indian states of Maharashtra and Karnataka will be the basis for our sample collection. This approach allows us to learn about the prevalence of AI-based treatments for diabetes diagnosis from a range of angles, including diverse sectors and specializations, in both states. By adopting stratified random sampling, the study hopes to lower bias and improve generalizability to the greater doctor community in Karnataka and Maharashtra.

3.6.1 Brief of Selected States

The Deccan Plateau is mostly contained within the state of Maharashtra in western India. With the second-highest population in India, Maharashtra is the most populated state. On May 1, 1960, the majority Marathi-speaking state of Maharashtra and the minority Gujarati-speaking state split apart, forming the bilingual state of Bombay. Most likely, Mumbai comes to mind when you think about India. With a land size of 307,713 square kilometres (118,809 square miles), it is the 3rd major state-run in India. Maharashtra, a state in western India, lies adjacent to the Arabian Marine in the west, and has borders with the states of Karnataka and Goa to the south, Telangana to the southeast, and Gujarat and Madhya Pradesh to the east and north.

Among the well-known cities in Maharashtra are “Mumbai, Pune, Nagpur, Thane, Nasik, Solapur, Kolhapur, Sangli, Aurangabad, Amravati, and Ratnagiri”. Mumbai is home to some of the most significant stock exchanges, commodity exchanges, and other financial sectors in India. The majority of native speakers of Marathi are found in Maharashtra, out of all the languages spoken there. The next most common languages spoken are Hindi, English, and Konkani.

Parameters	Maharashtra
Capital	Mumbai
Geographical area (lakh sq. km)	3.08
Administrative districts (No)	36
Population density (persons per sq. km)	365
Total population (million)	112.4
Male population (million)	58.2
Female population (million)	54.1
Sex ratio (females per 1,000 males)	929
Literacy rate (%)	82.3

Fig. 3.1: Economic Survey of Maharashtra

Source: Map of India, Economic Survey 2015-16, Economic Survey 2016-17, Economic Survey 2017-18, National Portal of India

The southern Indian state of Karnataka is located on the Deccan Plateau. To the northwest, it borders Goa; to the west, the Arabian Sea; and to the east, Maharashtra, Andhra Pradesh, Telangana, Tamil Nadu, and Kerala, respectively. Karnataka is located within the geographic area bounded at 11°30' and 18°30' latitude and 74° longitude. Converging mountain ranges from the Eastern and Western Ghats make up the complex, which is situated in the western Deccan Peninsula region of India on a tableland. The region is geographically defined by the Arabian Sea in the south, the states of Tamil Nadu and Kerala in the south, Maharashtra and Goa in the north and northwest, and Andhra Pradesh and Telangana in the east. Northern Karnataka and southern Karnataka are separated by approximately 750 kilometres, with 400 kilometres separating the two halves of the state. Prominent municipal centres located in this region include Ankola, Bengaluru, Bagalkot, Belgaum, Bidar, Bijapur, Chikmagalur, Chitradurga, Dandeli, Hubli-Dharwad, Mangalore, Mysore, and Shimoga. February through May are the driest and warmest months in the tropical climate of Karnataka, whereas June through October are the wettest and wettest. The residents of Karnataka also learn Kannada, Tulu, Kodava, and Hindi in addition to English.

Parameters	Karnataka
Capital	Bengaluru
Geographical area (sq km)	192,000
Administrative districts (No)	30
Population density (persons per sq km)	319
Total population (million)	61.1
Sex ratio (females per 1,000 males)	973
Literacy rate (%)	75.6
Male literacy rate	82.5
Female literacy rate	68.1

Fig. 3.2: Economic Survey of Karnataka

Source: Map of India, Economic Survey of Karnataka 2017-18, Census 2011 Office of Registrar General, India.

3.7 PRE-TESTING AND PILOT STUDY

To collect precise and accurate data for any research, a valid and dependable research instrument is vital. Developing the structured questionnaire that was utilized in the research work required the completion of numerous steps. The following paragraphs provide explanations of the procedures that were employed to refine the questionnaire.

3.7.1 Validity

A questionnaire's validity is determined by evaluating whether or not the research instrument is capable of measuring the construct for which it was designed. "Content validity and construct validity are the two primary types of validity testing".

3.7.1.1 Content Validity

Content validity pertains to the degree to which a questionnaire or other measurement instrument sufficiently encompasses the content domain that it is designed to assess. When considering the content validity of the given questionnaire on AI-based Diabetes Diagnostic Devices, it is crucial to ascertain that the questions adequately encompass all facets of individuals' beliefs, perceptions, concerns, and intentions concerning the utilization of these devices to diagnose and manage diabetes. This entails evaluating the extent to which the questionnaire sufficiently encompasses various aspects, including but not limited to the perceived advantages, technological significance, compatibility, usability, cost perception, social impact, and concerns linked to these diagnostic devices. The principle of content validity guarantees that the questionnaire adequately and accurately depicts the construct under investigation, thereby ensuring that the attitudes and opinions of the participants are faithfully reflected.

To ascertain the content validity of this questionnaire, several procedures might have been implemented. Before proceeding, it may have been prudent to conduct an exhaustive literature review and seek expert consultation to identify crucial dimensions and items that are pertinent to the perceptions and attitudes regarding AI-based diabetes diagnostic devices. After that, the items comprising the questionnaire would have been meticulously crafted and refined to encompass a wide array of viewpoints and apprehensions about the utilization of these devices. Additionally, feedback from target stakeholders or participants and pilot testing may have been conducted to evaluate the questionnaire items' clarity, applicability, and comprehensiveness. By implementing these procedures, one can deem the questionnaire to possess content validity, given that it satisfactorily encompasses the diverse facets that are relevant to individuals' perspectives and attitudes concerning AI-driven diabetes diagnostic devices. Therefore, the validity of the questionnaire's content was confirmed through the consultation and advice of subject matter experts. At last, 36 items were determined and allocated among the eight variables of the research.

3.7.1.2 Construct Validity

The construct validity indicates the grade to which paradigms used for the study truly measure the anticipated outcomes. It includes a) composite reliability, b) convergent validity c) uni-dimensionality and d) discriminant validity. For this purpose of pre-testing the questionnaire, data was collected from 50 respondents and tested.

A) Composite Reliability

The Cronbach's coefficient is frequently employed to determine the research instrument's reliability. Furthermore, the reliability of an inquiry gadget is deemed to be satisfactory if Cronbach's reliability value exceeds 0.70.

An observation has been made regarding the unequal weighting of items in the construct by Cronbach's value, which may introduce bias into the reliability test results. This necessitated the execution of an alternative test for determining the reliability of composites. The subsequent formula is employed to compute composite reliability:

$$CR = \frac{(\sum\lambda i)^2}{(\sum\lambda i)^2 + (\sum\epsilon i)}$$

“Where ‘λ’ is standardized factor loading for item ‘i’ and ‘’ is respective error variance for item ‘i’. The error variance ‘ϵ’ is the estimated, based on the value of the standardized loading ‘ϵ’”.

Table 3.2: Reliability statistics

Cronbach's Alpha	**Cronbach's Alpha (Standardized Item)**	**No. of Items**
0.925	0.927	36

The Cronbach's alpha value for each construct examined in the study exceeds 0.7, and the calculated composite reliability value also surpasses 0.7 (as indicated in Table 3.2). Consequently, this unequivocally demonstrates that the sample data utilized for pre-testing the questionnaire is reliable.

Table 3.3: Reliability and Composite Reliability value for all the constructs included in the study

Construct	**Items**	**Reliability (Cronbach’s Alpha)**	**Composite Reliability**
Perception of AI-based Diabetes Diagnostic Devices	3	0.806	0.842
Technological Importance and Fit with Care Approach	4	0.846	0.891

Compatibility and Experimentation	4	0.810	0.865
Cost Perception	4	0.761	0.812
Potential Benefits and Impact	7	0.870	0.913
Usability and Support	7	0.880	0.924
Social Influence	3	0.757	0.804
Concerns and Risks	4	0.788	0.834

B) Convergent Validity

Convergent validity denotes the extent to which the measurement research instrument attains uniformity across various operationalizations. Those variables that contribute to convergent validity should be included in the research. Items whose Average Variance extracted (AVE) is greater than 0.50 are considered to have convergent validity; therefore, the remaining variables in the study should be eliminated. AVE is computed utilizing the subsequent formula. The findings are presented in Table 3.3.

$$AVE = \frac{\sum_{i=1}^{n} \lambda i^2}{n}$$

"Where λ represents the standardized factor loading and 'i' is the number of items"

Table 3.4: AVE values of the variables included in the study

Variables	**Average Variance Extracted (AVE) values**
Perception of AI-based Diabetes Diagnostic Devices	0.579
Technological Importance and Fit with Care Approach	0.601
Compatibility and Experimentation	0.585

Cost Perception	0.528
Potential Benefits and Impact	0.657
Usability and Support	0.702
Social Influence	0.508
Concerns and Risks	0.584

According to the aforementioned smart-PLS calculations, the AVE value for each variable was greater than 0.5; thus, this demonstrates that the research instrument possesses the necessary convergent validity.

C) Uni-dimensionality

Uni-dimensionality refers to the degree to which a settled of stuffs or indicators measuring a concealed concept represent a single underlying dimension or concept. In the context of the provided content, uni-dimensionality would involve assessing whether the questionnaire items related to each construct primarily measure one distinct aspect or characteristic. For example, in the questionnaire regarding AI-based Diabetes Diagnostic Devices, uni-dimensionality would mean that each set of questions designed to measure constructs such as perceptions, concerns, or intentions consistently tap into a single underlying aspect of individuals' attitudes or beliefs regarding the use of such devices. Evaluating uni-dimensionality is crucial to ensure that the questionnaire effectively captures the intended construct without introducing confusion or ambiguity arising from multiple underlying dimensions.

To confirm uni-dimensionality, the Standard Root Mean Square (SRMS) value was calculated (Table 3.4). The SRMS value was found to be, which is less than the threshold of 0.1. This indicates that the items successfully measure a single underlying construct and meet the criteria for uni-dimensionality.

Table 3.4: SRMS values of the variables included in the study

	AF	BI	PEOU	PI	PR	PU	RD	SN	TTF	UX
AF										
BI	0.821									
PEOU	0.667	0.877								
PI	0.644	0.871	0.881							
PR	0.616	0.754	0.733	0.832						
PU	0.716	0.707	0.745	0.700	0.794					
RD	0.611	0.627	0.731	0.558	0.638	0.828				
SN	0.740	0.749	0.829	0.670	0.665	0.750	0.860			
TTF	0.683	0.666	0.745	0.612	0.674	0.764	0.695	0.830		
UX	0.579	0.788	0.757	0.769	0.701	0.612	0.713	0.700	0.900	

D) Discriminant Validity

Discriminant validity, on the other hand, assesses the degree to which distinct constructs measured by a set of items are truly distinct from one another. In the provided content, discriminant validity would involve confirming that the constructs measured by different sets of questions in the questionnaire represent separate and unique aspects of individuals' attitudes or perceptions. For example, discriminant validity would ensure that constructs such as perceptions of AI-based Diabetes Diagnostic Devices and concerns about their potential risks are indeed distinct from each other, rather than inadvertently measuring similar underlying dimensions. Establishing discriminant validity is essential to ensure that the questionnaire accurately captures the diversity of attitudes and beliefs among respondents and avoids redundancy or overlap between constructs.

3.8 OBJECTIVES OF THE STUDY

The current study will try to find out the impact of the adoption of AI-based Diabetes diagnostic interventions by Doctors in Maharashtra & Karnataka, on the basis of the review of the literature the proposed objectives are found below:

- Assess the current level of adoption of AI-based tools for diabetes diagnosis by doctors in Maharashtra and Karnataka.

- Identify the key factors influencing doctors' decisions to adopt or resist AI interventions for diabetes diagnosis.
- Examine the challenges and opportunities in integrating AI into clinical practice for diabetes diagnosis in these regions.
- Explore the impact of regional variations and healthcare infrastructure on the adoption of AI in diabetes diagnosis.
- Develop a proposed framework to enhance the effective adoption of AI-based interventions by doctors in Maharashtra and Karnataka for diabetes diagnosis.

3.9 OPERATIONAL PARAMETERS

The operational parameters that will be used to assess the adoption of such interventions include the availability and accessibility of AI technology, the degree of knowledge and training that doctors in Maharashtra and Karnataka have regarding AI-based interventions for diabetes diagnosis, the patient demographics, and the healthcare infrastructure in both states. The effects of the socioeconomic environment on the provision of healthcare and the legal frameworks governing the integration of AI into medical practice will be the subject of additional investigation. Through the use of mixed approaches, such as surveys, interviews, and focus groups, animalistic data regarding the attitudes, perspectives, and challenges that physicians face about the use of artificial intelligence will be gathered. These operational factors are essential for developing a framework that effectively handles the unique requirements and challenges faced by healthcare professionals in Maharashtra and Karnataka. They also seek to offer a nuanced understanding of the adoption environment.

3.10 STATISTICAL TOOLS

The study used SPSS 16 and SMART-PLS to analyze the data. For the study, a structured questionnaire will be made to find out how adopting AI-based treatments for diabetes diagnosis is going with doctors. Because these tools allow for rigorous quantitative analysis, they make it easier to look at how factors are related and build a strong framework for understanding AI's potential use in healthcare practice and proposing effective strategies for its implementation.

3.10.1 Cronbach’s Alpha

Internal consistency reliability is frequently assessed using Cronbach's alpha, which is notably prevalent in psychological and social science research. It evaluates the degree of interrelation among a collection of elements comprising a variable, under the assumption that they all assess the same underlying construct. This statistical measure is crucial in the assessment of the dependability of research scales or questionnaires, as it signifies the degree to which the items consistently capture the desired construct. In theory, Cronbach's alpha values are ordinarily between 0 and 1, with higher values signifying enhanced internal consistency. Nevertheless, it is important to acknowledge that negative values of Cronbach's alpha can arise in practice, generally indicating problems with the data or the item scoring. As a general rule, a Cronbach's alpha coefficient exceeding 0.7 is deemed satisfactory for scientific inquiry, signifying favourable internal consistency reliability (Taber, 2017). Statistical software, such as SPSS, is frequently employed to calculate Cronbach's alpha, which furnishes researchers with a quantitative assessment of the dependability of their scales or measures.

Table 3.6: Cronbach's Alpha Value & their Interpretation

Cronbach's Alpha Value	**Interpretation**
Below 0.6	Poor internal consistency
0.6 to 0.7	Questionable internal consistency
0.7 to 0.8	Acceptable internal consistency
0.8 to 0.9	Good internal consistency
Above 0.9	Excellent internal consistency

3.10.2 Simple Mean

An uncomplicated mean is a fundamental statistical calculation utilized to determine the mean of a set of integers. Subsequently, the sum of every value in the dataset is divided by the total number of values to obtain this value. The aforementioned computation yields a measure of central tendency or mean value for the dataset, thereby facilitating comprehension of the variable's overall trend or magnitude. The simple mean is a widely employed statistical method utilized in academic research as well as in practical scenarios to summarize numerical data and facilitate comparisons among distinct groups or samples.

3.10.3 Standard Deviation

The statistical measure of standard deviation quantifies the dispersion or variation of a set of data points. It signifies the extent to which specific data elements differ from the dataset's mean (average). A small standard deviation signifies that the data points are predominantly concentrated around the mean, whereas a large standard deviation signifies that the data points are dispersed across a more extensive spectrum of values. Put simply, the standard deviation offers valuable information regarding the extent of variability or uncertainty present in the dataset. It is frequently employed across diverse disciplines, including finance, science, and social sciences, to evaluate the stability or unpredictability of data and compare sets of information. A significance value of less than 0.05 indicates acceptance of the alternative hypothesis. SPSS-16 is utilized to accomplish this.

3.10.4 Analysis of Variance (ANOVA)

ANOVA is a parametric statistical technique used to determine whether or not the means of three or more groups differ statistically. This method is frequently utilized to examine the impact of independent variables, in this case, the variables of the infrastructure profile, on dependent variables such as organizational performance and competitive advantage. ANOVA determines whether differences in the means of the groups being compared are statistically significant by analyzing the variance both within and between groups. The null hypothesis of equal means between groups is rejected when the p-value obtained from analysis of variance (ANOVA) is below the predetermined significance level, which is commonly set at 0.05. This rejection indicates the presence of a statistically significant difference. The application of statistical software such as SPSS-16 enables researchers to conduct ANOVA with greater efficiency and to arrive at well-informed conclusions through the examination of their data.

3.10.5 Data Development Analysis

The data development analysis will encompass the utilization of diverse critical statistical techniques to comprehensively examine the degree to which medical practitioners in the states of Maharashtra and Karnataka have adopted AI-driven interventions to diagnose diabetes. To synthesize and interpret the essential characteristics of the data, descriptive statistics will be applied. By doing so, significant insights can be obtained concerning the attributes and distribution of the variables. EFA will be utilized by the researchers to identify the latent constructs or factors that influence physicians' adoption of AI tools. Disparities in the adoption of AI among distinct groups of clinicians, classified by speciality or region, will be assessed using one-way ANOVA. In summary, the investigators intend to employ a structural modelling methodology, possibly including Structural Equation Modelling (SEM), to analyze the complex relationships between different variables and construct a comprehensive model for the implementation of artificial intelligence (AI) in the domain of diabetes diagnosis.

3.10.6 Regression

The research will employ regression analysis to examine the correlation between several variables and the degree to which clinicians in the states of Maharashtra and Karnataka embrace AI-driven interventions in the context of diabetes diagnosis. Multiple regression analysis may be applied to specific variables, including years of experience, physicians' areas of specialization, technological accessibility, and knowledge of AI implementations in healthcare, to identify predictors of AI adoption. Regression analysis is utilized in statistics to discern patterns within data. By utilizing regression analysis, it is possible to approximate the data and generate the equation for a graph. It can forecast, for example, the amount of weight an individual who has been gaining weight recently will weigh in ten years if the present rate of weight gain continues. Furthermore, it will furnish us with a plethora of data (including a correlation coefficient and a p-value) that can be utilized to evaluate the precision of your model. The majority of introductory statistics courses are devoted to foundational concepts such as scatter plots and linear regression. For instance, we may encounter more sophisticated methodologies such as multiple regressions. Huck et al. (2004) define regression analysis as a method for forecasting an outcome variable by considering one or more predictor variables (simple regression or multiple regressions).

The calculated regression coefficient, denoted as R2, varies between 0 and 1. Strong relationships have values that tend toward 1, while feeble relationships have values that tend toward 0. The exact percentage of the impact that one or more independent variables have on the dependent variable is derived by multiplying the adjusted R2 value by 100. Determining the degree of association between a dependent and an independent variable is the objective of linear regression. This concept is commonly associated with the equation of line.

$$Y=a+Bx$$

“Where “X‟ is termed as an independent variable, “Y‟ is termed as the dependent variable, “b‟ is termed as the slope of the line and “a‟ is intercept/constant”

To ascertain the degree of correlation between a dependent variable and the collective impact of two or more independent variables, multiple regressions are implemented. It is frequently linked to a line equation, specifically.

$$Y = a + b_1X_1 + b_2X_2 + \ldots.. + b_nX_n,$$

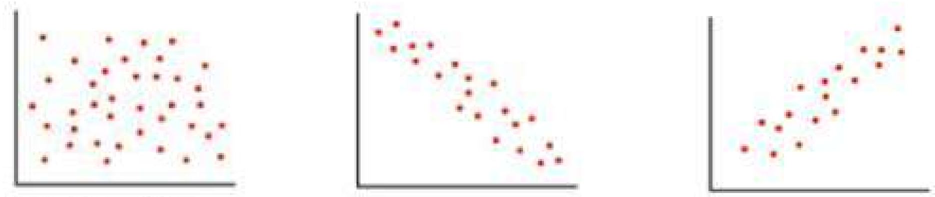
“Here, "X_1, X_2,..., X_n" are the independent variables, "Y" is the dependent variable, "b" is the line's slope, and "a" is the intercept or constant”. Once more, the p-value is used to determine significance; if it is less than 0.05, the alternative hypothesis is approved. The results of regression analysis are computed using SPSS-16.

3.10.7 Correlation

The study will employ correlation analysis to examine the magnitude and orientation of associations among a range of variables about the implementation of AI-driven interventions for diabetes diagnosis by medical practitioners in the states of Maharashtra and Karnataka. Pearson coefficients of correlation The associations between variables such as physicians' attitudes toward AI, the perceived efficacy of AI tools, and the actual implementation of AI in clinical practice can be evaluated through the computation of correlations. Correlation specifies the degree to which two variables are related. The status of the variables as either dependent or independent is not specified. Spearman's correlation coefficient and Pearson's product-moment correlation coefficient were identified by O'Brien and Scott as two of the most frequently applied correlation coefficients. When dealing with ordinal data, calculate the correlation coefficient using Spearman's method. When dealing with interval or ratio data, employ Pearson's method (Gogtay et al., 2017). Correlation is a statistical method for determining the relationship between two or more variables. It also indicates the relationship's intensity. The correlation coefficient, denoted as "r•," is determined to be between -1 and 1. When one variable exhibits an ascending trend and the other variable does the same, this is referred to as a positive correlation.

The phenomenon where one variable exhibits an ascending trend while the other variable displays the inverse trend is referred to as a negative correlation.

A lack of correlation exists when one variable exhibits an increasing or decreasing trend while the other variable remains constant.



A simple correlation occurs when one variable influences another, whereas a multiple correlation occurs when two or more independent variables influence one dependent variable. Again, the p-value is used to determine significance; the alternative hypothesis is accepted if it is less than 0.05. SPSS-16 is utilized in the computation of this utility.

3.10.8 Stratified Random Sampling

Stratified sampling is a method wherein the population is initially partitioned into subgroups, or strata, from which a random sample is then extracted from each subgroup. A subgroup is a naturally occurring collection of elements. Subgroups that can be discerned consist of those distinguished by gender, corporation size, and occupation. When dealing with populations characterized by significant diversity, stratified sampling is a commonly utilized method. Its purpose is to assure equitable representation of all social classes (Davis, 2005). To guarantee the inclusion of a representative sample of physicians from Maharashtra and Karnataka in this research, stratified random sampling will be utilized. There will be a selection of 30 physicians in total, 15 from each state. The sample will be further stratified within each state according to the specialization and category of healthcare facility. Doctors will be specifically chosen from super speciality hospitals and diabetes hospitals that offer diagnostic services based on artificial intelligence for patient management. By employing this methodology, it is guaranteed that the sample comprised of healthcare contexts and specialities pertinent to the implementation of AI interventions for diabetes diagnosis is diverse.

3.11 CONCLUSION

In conclusion, the methodology employed for investigating the adoption of AI-based interventions used to diagnose diabetes by doctors in Maharashtra and Karnataka has been prudently created to deliver an inclusive understanding of the adoption landscape. Through a multi-faceted approach encompassing literature review, qualitative interviews, quantitative surveys, and statistical analysis, we aim to capture the complexities and nuances of AI adoption within the healthcare contexts of both states. By utilizing stratified random sampling and structured questionnaires, we ensure representation from diverse regions and specialities, enhancing the generalizability of findings. The operational parameters considered, including technological infrastructure, regulatory policies, and socio-economic factors, offer a holistic view of the challenges and opportunities in AI adoption.

Chapter 4
Results & Discussions

4.1 Introduction

The inquiry into the implementation of artificial intelligence (AI)-driven interventions for diabetes diagnosis among medical practitioners in Maharashtra and Karnataka has produced significant findings and suggested an all-encompassing structure to improve healthcare methodologies in the area. Using rigorous examination and empirical investigations, this study emphasises the criticality of incorporating artificial intelligence (AI) into the field of medical diagnostics, specifically regarding mitigating the increasing prevalence of diabetes. The research outcomes uncover the obstacles as well as the potential advantages that healthcare practitioners may face when integrating AI systems, thereby illuminating the elements that impact acceptance and execution. Through the synthesis of these findings, a comprehensive framework is formed, which outlines effective approaches to enhance the integration of AI-driven interventions within clinical environments. In addition to technological considerations, this framework takes into account the sociocultural and organisational elements that are critical for the effective execution of the initiative. In conclusion, this research makes a significant scholarly contribution to the progression of healthcare provision in the Indian states of Maharashtra and Karnataka. It provides policymakers, healthcare professionals, and researchers with invaluable knowledge that can be utilised to optimise the capabilities of artificial intelligence in the fight against diabetes and the enhancement of patient results.

4.2 Maharashtra

Table 4.1: Age Distribution

Age	Frequency	Per cent
18-26 Years	19	6.0
27-35 Years	125	39.2
36-44 Years	147	46.1
45-53 Years	21	6.6
53 above	7	2.2

The distribution of individuals among various age categories is detailed in Table 4.1. Undoubtedly, a significant proportion of the sample, specifically 85.3%, is comprised of individuals aged 27 to 44 years. The age group of 36 to 44 years, which comprises 46.1% of the sample, exhibits the maximum frequency within this bracket. In contrast, individuals between the ages of 27 and 35 comprise a substantial portion (39.2%). It is worth mentioning that the younger and senior age groups contain a more limited number of individuals. 6.0% of the sample consists of individuals aged 18 to 26 years, while 2.2% and 6.6%, respectively, are comprised of those aged 53 and above and 45 to 53 years. The data presented herein demonstrates a preponderance of participants falling within the middle-aged demographic, while the extremities of age comprise a smaller proportion of the sample.

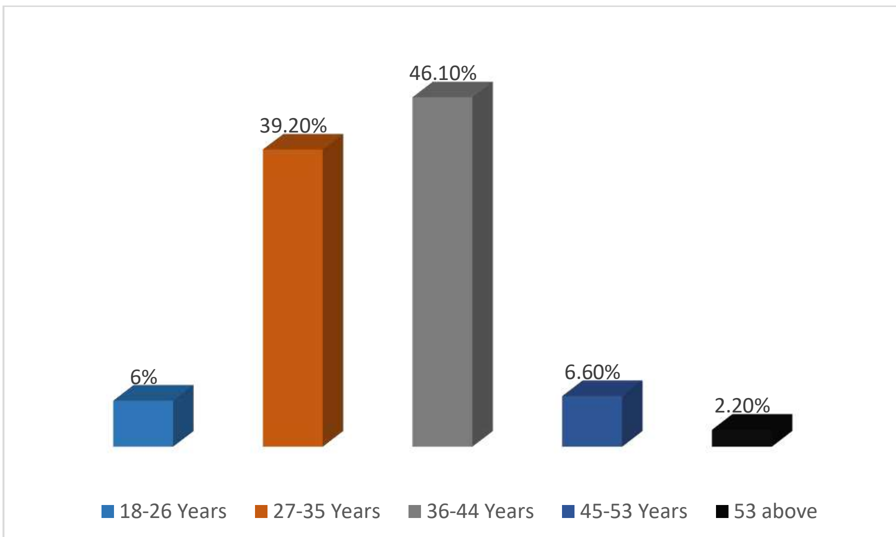


Figure 4.1: Age Distribution

Table 4.2: Gender Distribution

Gender	Frequency	Per cent
Male	163	51.1
Female	156	48.9

The gender distribution data is displayed in Table 4.2, including frequencies and percentages. The data suggests that males comprise 163 individuals, or 51.1%, of the total sample population, whereas females constitute 156 individuals or 48.9% of the sample. The provided data provides valuable insights into the gender distribution of the dataset, revealing a marginal numerical advantage that males hold over females.

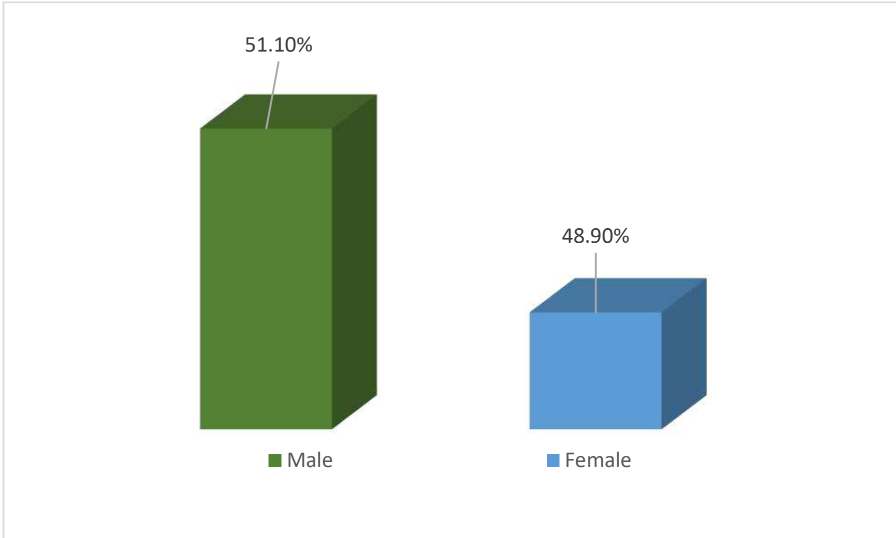


Figure 4.2: Gender Distribution

Table 4.3: Experience Distribution.

Total Experience	Frequency	Per cent
< 0.5 Year	4	1.3
0.5-1 Year	6	1.9
1-3 Years	30	9.4
3-5 Years	147	46.1
5 Years+	132	41.4

The data regarding the aggregate experience of individuals, classified into distinct time intervals, is displayed in Table 4.3, accompanied by the corresponding frequencies and percentages. The initial classification, labelled "< 0.5 Year," signifies participants who possess expertise of no more than six months, accounting for 1.3% of the overall sample and consisting of four individuals. Subsequently, the categories progressively comprise longer periods of experience, as "0.5-1 Year" comprises six individuals (1.9%), "1-3 Years" comprises thirty individuals (9.4%), "3-5 Years" comprises 147 individuals (46.1%), and "5 Years+" comprises 132 individuals (41.4%). The table presents valuable information regarding the distribution of experience levels among the individuals surveyed. It reveals that a considerable proportion of respondents possess either 3-5 years or 5+ years of experience.

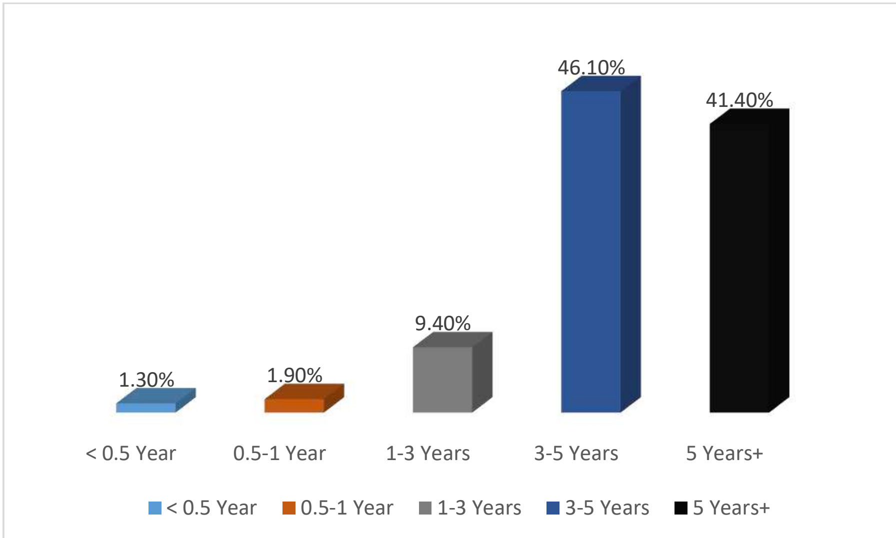


Figure 4.3: Experience Distribution.

Table 4.4: Education Level Distribution

Education level	**Frequency**	**Per cent**
Medical/ Paramedical Graduate	143	44.8
Medical/ Paramedical Postgraduate	176	55.2

The data about education levels in the medical and paramedical sectors is displayed in Table 4.4, including frequency and percentage breakdowns. The data reveals that among the entire cohort, 143 individuals are graduates of medical or paramedical studies, accounting for 44.8% of the group. On the other hand, 176 individuals (155.2%) possess postgraduate degrees in the aforementioned disciplines. The data presented in this breakdown indicates that a greater percentage of individuals hold postgraduate qualifications in the medical and paramedical fields than hold undergraduate degrees. This finding implies that there is a substantial degree of academic progression within these fields.

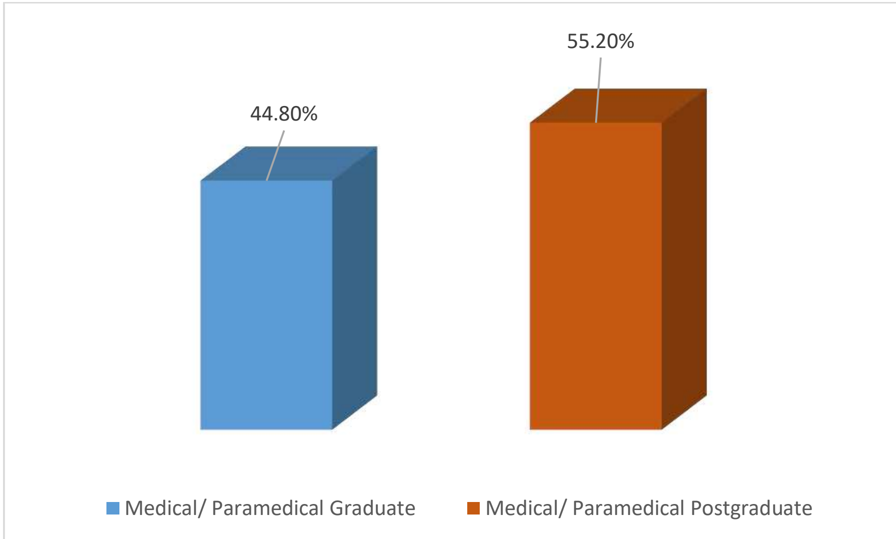


Figure 4.4: Education Level Distribution

Table 4.5: AI Experience Distribution

Experience year AI	Frequency	Per cent
0.5-1 Year	112	35.1
1-3 Years	95	29.8
3-5 Years	85	26.6
5 Years +	27	8.5

The distribution of experience levels in artificial intelligence (AI) among a cohort of individuals is illustrated in Table 4.5. The experience is classified into four distinct brackets: 0.5-1 year, 1-3 years, 3-5 years, and 5 years or greater. The proportion of individuals in the total sample size is indicated in the per cent column, whereas the frequency column depicts the number of individuals belonging to each experience bracket. It is worth mentioning that a significant proportion of the participants, 35.1%, possess a tenure of 0.5 to 1 year in the field of artificial intelligence. This is followed by 29.8% with 1-3 years and 26.6% with 3-5 years of experience, respectively. 8.5% of the population possesses five years of experience or more in the respective field.

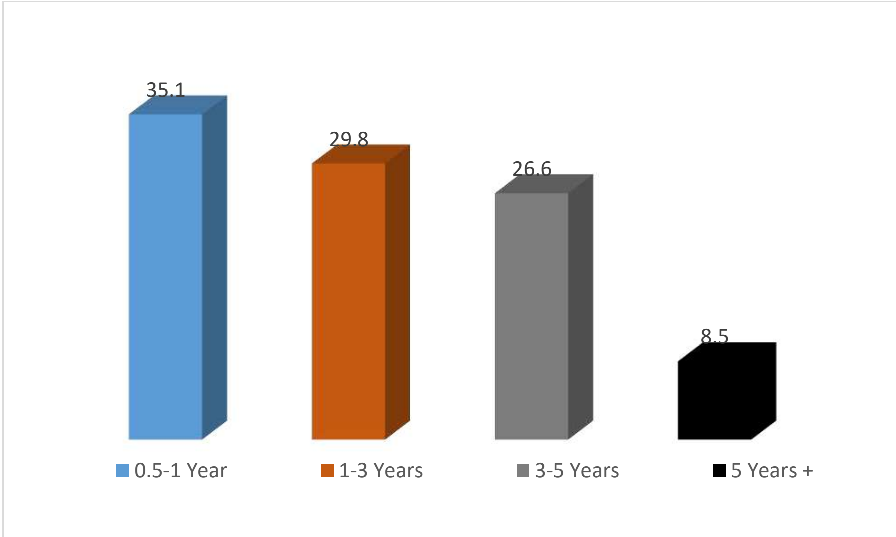


Figure 4.5: AI Experience Distribution

Table 4.6: Location of Medical Practice.

Medical practice set up	Frequency	Per cent
In a hospital/ Nursing Home	183	57.4
In my Clinic	136	42.6

The data regarding the distribution of medical practice arrangements among the respondents is presented in Table 4.6. The data suggests that a significant proportion, specifically 57.4%, conduct services in a nursing home or hospital environment, whereas 42.6% maintain their clinic. This finding indicates that a considerable proportion of healthcare professionals exhibit a preference for conducting their practices in institutional settings such as hospitals or nursing homes. This preference may be attributed to factors such as the availability of specialised equipment, the ability to handle a wider variety of medical cases or the potential for collaboration with other healthcare professionals. On the contrary, a significant portion of the population chooses the autonomy and independence that come with operating their clinic. This decision may be influenced by various factors, including the desire for scheduling flexibility, the ability to provide personalised patient care or entrepreneurial ambitions.

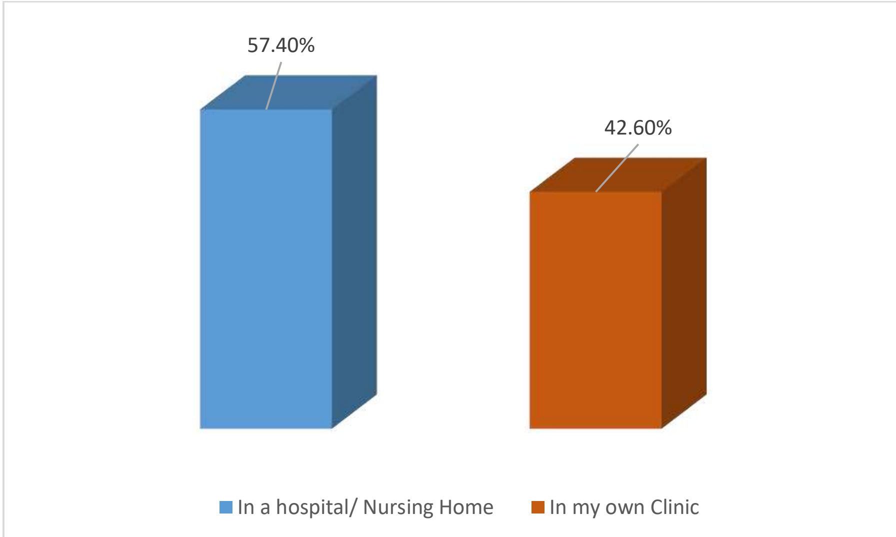


Figure 4.6: Location of Medical Practice.

Table 4.7: Distribution of Diabetes Patients by Case Numbers

Diabetes Patients	Frequency	Per cent
<5	31	9.7
5-10	44	13.8
11-20	116	36.4
21-30	55	17.2
31-40	36	11.3
40+	37	11.6

Table 4.7 presents the distribution of patients diagnosed with diabetes, delineated by the proportion of individuals belonging to distinct patient count ranges. It distinguishes between patients aged 31 to 40, those aged 5 to 10, those aged 5 to 10, and those aged 11 to 20. For each category, the frequencies and corresponding percentages are provided. It is worth mentioning that the range of 11 to 20 patients has the maximum frequency, comprising 116 individuals or 36.4% of the total. On the other hand, the group consisting of 31, or 9.7% of the total, is categorised as having fewer than five patients. In general, the table provides a succinct synopsis of the allocation of individuals with diabetes among different sample sizes, with a particular emphasis on the high incidence of cases falling within the range of eleven to twenty.

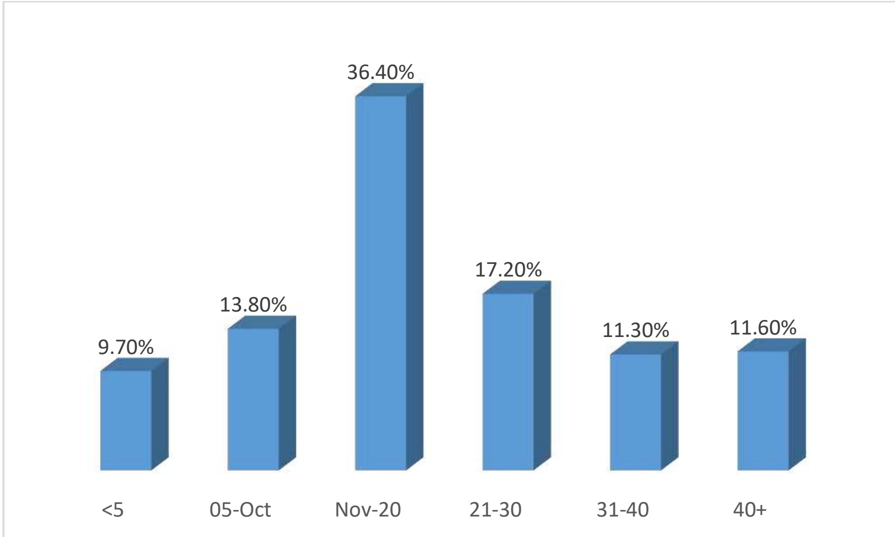


Figure 4.7: Distribution of Diabetes Patients by Case Numbers

Maharashtra

Descriptive Statistics

Table 4.8: Descriptive Statistics of Result Demonstrability (RD)

	Mean	Std. Deviation
RD1	2.42	0.945
RD2	2.42	0.941
RD3	2.43	0.935

The mean and standard deviation values for three distinct datasets RD1, RD2, and RD3, are presented in Table 4.8. The mean (average) value of each dataset is approximately 2.42 or 2.43, suggesting a high degree of similarity in the central tendency of the data points across these datasets. RD1, RD2, and RD3 have respective standard deviations of 0.945, 0.941, and 0.935, which are also quite similar. This implies that the dispersion or fluctuation of the data points relative to the mean remains uniform throughout all three datasets. In general, the data about RD1, RD2, and RD3 exhibit a substantial level of similarity, as evidenced by their mean values and range of values.

Table 4.9: Descriptive Statistics of Task Technology Fit (TTF)

	Mean	Std. Deviation
TTF1	2.54	1.054
TTF2	2.52	1.027
TTF3	2.55	1.048
TTF4	2.54	1.054
TTF5	2.56	1.032

The mean and standard deviation for five variables denoted as TTF1 through TTF5 are displayed in Table 4.9. The mean values of each variable range between 2.54 and 2.56, suggesting that, on average, the measurements for these variables are relatively comparable. The observed standard deviations, which span from 1.027 to 1.054, indicate that the variability in the data for each variable is relatively consistent. The similarity observed in the standard deviations and mean values of the variables TTF1 through TTF5 suggests that they possibly assess the same phenomena or originate from comparable distributions, thereby demonstrating the presence of a consistent pattern among these distinct variables.

Table 4.10: Descriptive Statistics of Personal Innovativeness (PI)

	Mean	Std. Deviation
PI1	3.91	0.618
PI2	3.84	0.696
PI3	3.84	0.666
PI4	3.77	0.661

The mean and standard deviation for four performance indicators (PI1, PI2, PI3, and PI4) are displayed in Table 4.10. The mean value of each indicator, which signifies the average score, exhibits a relatively elevated range of 3.77 to 3.91. In particular, PI1 exhibits the highest mean value of 3.91, followed by PI2 and PI3 both at 3.84. In contrast, PI4 demonstrates the lowest mean at 3.77. The relatively low standard deviation values, which quantify the degree of dispersion or variation from the mean, suggest that the scores for each indicator are densely concentrated around their respective means. With a standard deviation of 0.618, PI1 indicates the least amount of variability, while PI2 has the highest at 0.696, suggesting a marginally greater degree of variability in its scores relative to the other indicators. In general, the data indicates that the performance of all four indicators was consistent, with only slight deviations.

Table 4.11: Descriptive Statistics of Affordability (AF)

	Mean	Std. Deviation
AF1	2.41	0.875
AF2	2.38	0.882
AF3	2.4	0.877

Descriptive statistics for three variables, AF1, AF2, and AF3, are presented in Table 4.11. Each variable's mean value is displayed in the "Mean" column; AF1 has a mean of 2.41, AF2 2.38, and AF3 2.4. The column labelled "Std. Deviation" presents the extent of dispersion or variability of the data relative to the mean for each variable. For instance, AF1 exhibits a standard deviation of 0.875, AF2 0.882, and AF3 0.877. The statistical measures offer valuable information regarding the central tendency and dispersion of the data distribution for each variable, thereby facilitating comprehension of their attributes and possible correlations.

Table 4.12: Descriptive Statistics of Perceived Usefulness (PU)

	Mean	Std. Deviation
PU1	2.56	1.035
PU2	2.55	1.057
PU3	2.55	1.06
PU4	2.55	1.062
PU5	2.53	1.06
PU6	2.54	1.054
PU7	3.77	0.764

Descriptive statistics for multiple variables, denoted as PU1 through PU7, are presented in Table 4.12. A distinct facet is symbolised by each variable, and the table provides the mean and standard deviation of the data for each. As an illustration, the mean and standard deviation of PU1 are 0.56, and PU7 is 0.764; in contrast, PU1 has a mean of 2.56 and a standard deviation of 1.035. The aforementioned statistics provide valuable insights regarding the central tendency and variability of each variable in the dataset. The mean represents the average value, whereas the standard deviation quantifies the extent to which values deviate from the mean. This information is essential for comprehending the data set's characteristics and distribution.

Table 4.13: Descriptive Statistics of Perceived Ease of Use (PEOU)

	Mean	Std. Deviation
PEOU1	3.86	0.629
PEOU2	3.88	0.636

Table 4.13 provides statistical data about two distinct variables, namely PEOU1 and PEOU2. The average score for each variable is displayed in the "Mean" column; PEOU1 attains a mean score of 3.86, while PEOU2 demonstrates a slightly higher mean score of 3.88. The scores provided indicate the perceived ease of use (PEOU) for two distinct systems or situations. A higher PEOU signifies a more favourable system or circumstance. As indicated in the "Std. Deviation" column, the variability or dispersion of the data concerning the mean is quantified. The standard deviation for PEOU1 is 0.629, which suggests a comparatively low degree of variability around its mean score. In contrast, the standard deviation for PEOU2 is 0.636, which implies an equivalent degree of variability. In general, the data presented provides valuable insights regarding the consensus of opinions regarding the usability of both systems and the reliability of responses for each variable.

Table 4.14: Descriptive Statistics of Behavioural Intention (BI)

	Mean	Std. Deviation
BI1	2.54	1.057
BI2	2.53	1.06
BI3	2.53	1.066
BI4	2.54	1.077
BI5	3.92	0.627

Statistical measures for five distinct variables denoted as BI1 through BI5, are displayed in Table 4.14. It provides the mean and standard deviation values for each variable. The mean represents the average value of responses for each variable. Notably, BI5 exhibits a significantly higher mean of 3.92 in comparison to the remaining variables, which generally fluctuate between 2.53 and 2.54. The variability or dispersion of the responses around the mean is quantified by standard deviation; a smaller standard deviation signifies a reduced level of variability. With a standard deviation of 0.627, variable BI5 exhibits a narrower dispersion of responses around the mean in comparison to the other variables, whose standard deviations span a range of 1.057 to 1.077. The data in this table (BI1 through BI5) are plausibly survey or observational, as indicated by their corresponding means and variances.

Table 4.15: Descriptive Statistics of Subjective Norms (SN)

	Mean	Std. Deviation
SN1	2.5	1.028
SN2	2.49	1.031
SN3	2.46	1.027

Table 4.15 presents statistical measures of the SN1, SN2, and SN3 variables. The average values of each variable are indicated in the "Mean" column: SN1 has a mean of 2.5, SN2 2.49, and SN3 2.46. The column labelled "Std. Deviation" indicates the extent of dispersion or variability of the data relative to the mean. The standard deviation for SN1 is 1.028, 1.031 for SN2 and 1.027 for SN3. The standard deviations quantify the average amount by which the values of each variable deviate from their corresponding means. In general, the summary statistics provided in the table aid in comprehending the measures of dispersion and the central tendency of the data about each variable.

Table 4.16: Descriptive Statistics of Perceived Risk (PR)

	Mean	Std. Deviation
PR1	2.55	1.062
PR2	2.55	1.06
PR3	2.52	1.058
PR4	2.51	1.058

Table 4.16 presents statistical measures about four distinct variables, denoted as PR1, PR2, PR3, and PR4, respectively. The mean and standard deviation are the two statistical indicators that characterise each variable. The mean signifies the average value of the variable as determined by all observations. In contrast, the standard deviation quantifies the degree of dispersion or variability surrounding the mean. As an illustration, PR1 exhibits a mean value of 2.55 accompanied by a standard deviation of 1.062. This indicates that, while the values for PR1 tend to cluster around 2.55, they are subject to an approximate 1.062-unit dispersion around this mean. Likewise, the mean values of PR2, PR3, and PR4 are 2.55, 2.52, and 2.51, respectively, accompanied by their respective standard deviations. The aforementioned statistics offer valuable insights regarding the central tendency and variability of each variable present in the dataset.

Table 4.17: Descriptive Statistics of Experience (UX)

	Mean	Std. Deviation
UX	2.02	1.33

The statistical information about User Experience (UX) scores is presented in Table 4.17. The average UX score, denoted in the "Mean" column, is 2.02. This indicates that, on average, users assign a slightly higher rating of 2 to their experience. The column labelled "Std. Deviation" provides the value of 1.33 for the standard deviation of the UX scores. This metric quantifies the extent to which the UX scores deviate from the mean. A greater standard deviation signifies that the scores are more dispersed relative to the mean, thereby signifying a more extensive spectrum of user experiences.

4.3 INFERENTIAL STATISTICS – MEASURE OF ASSOCIATION AND DEPENDENCE

The objectives and hypotheses are formulated based on the conceptual framework given below. Following is the used nomenclature in the framework:

Result in Demonstrability (RD)

Task Technology Fit (TTF)

Personal Innovativeness (PI)

Affordability (AF)

Perceived Usefulness (PU)

Perceived Ease of Use (PEOU)

Behavioural Intention (BI)

Subjective Norms (SN)

Perceived Risk (PR)

Experience (UX)

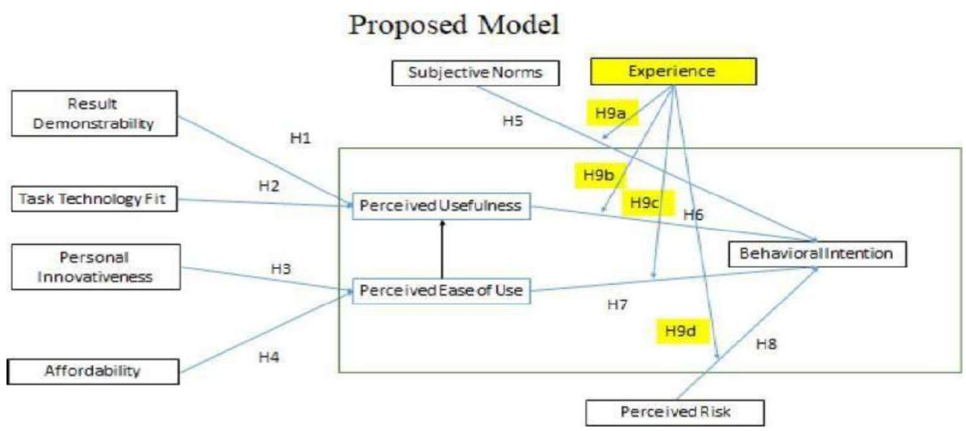


Figure 4.8: Conceptual Framework

4.4 Hypothesis

The hypotheses that are formulated based on the above-reported conceptual framework and to analyse the objectives of this study which are based on the extensive review of the literature have been reported below are alternative hypotheses or positive forms of hypothesis:

H1: There is a positive relationship between Result Demonstrability (RD) and perceived usefulness.

H2: There is a positive relationship between task-technology fit and perceived usefulness.

H3: There is a positive relationship between personal innovativeness and perceived ease of use.

H4: There is a positive relationship between affordability and perceived ease of use.

H5: There is a positive relationship between Subjective Norms (SN) and behavioural intention.

H6: There is a positive relationship between perceived usefulness and behavioural intention.

H7: There is a positive relationship between perceived ease of use and behavioural intention.

H8: There is a positive relationship between Perceived Risk and behavioural intention.

H9a: Experience moderates the relationship between Subjective Norms (SN) and behavioural intention.

H9b: Experience moderates the relationship between perceived usefulness and behavioural intention.

H9c: Experience moderates the relationship between perceived ease of use and behavioural intention.

H9d: Experience moderates the relationship between Perceived Risk and behavioural intention.

4.5 Objectives

The core objective of the present study is to investigate the impact of the adoption of AI-based Diabetes diagnostic interventions by Doctors in Maharashtra and Karnataka. The study will attempt to attain the following objectives:

1. To study and critically evaluate the status of AI based Healthcare diagnostic services provided by Govt. and Private Sectors in Maharashtra & Karnataka.

2. To develop and test an integrated model for measuring the adoption of AI-based Diabetes Diagnostic Interventions by Doctors by incorporating relevant variables.

3. To examine the impact of Experience as a moderating variable on their relationship from subjective norms, perceived usefulness, perceived ease of use and perceived risk to develop behavioural intention to use AI based Diabetes Diagnostic Interventions by Doctors.

4. To analyze the effect of demographic variables (Age, Gender, Awareness) on intention to use AI based Diabetes Diagnostic Interventions by Doctors.

5. To assess the patient journey framework utilized by different hospitals to diagnose Diabetes by AI based Diabetes diagnostic services.

4.6 PRESENTATION, ANALYSIS, AND INTERPRETATION OF FINDINGS OF ADOPTION OF AI BASED INTERVENTIONS USED TO DIAGNOSE DIABETES BY DOCTORS IN MAHARASHTRA & KARNATAKA

H1: There is a positive relationship between Result Demonstrability (RD) and perceived usefulness.

Table 4.18: Correlation Between Result Demonstrability (RD) and Perceived Usefulness (PU)

Correlations

		PU1	PU2	PU3	PU4	PU5	PU6	PU7
RD1	Pearson Correlation	.868**	.867**	.861**	.865**	.871**	.873**	.276**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	319	319	319	319	319	319	319
RD2	Pearson Correlation	.871**	.870**	.873**	.868**	.868**	.880**	.277**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	319	319	319	319	319	319	319
RD3	Pearson Correlation	.863**	.866**	.859**	.851**	.864**	.873**	.277**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	319	319	319	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between various pairings of variables denoted PU1 through PU7 and RD1 through RD3 are displayed in Table 4.18. The Pearson correlation coefficient is displayed in each cell of the table for a particular pair of variables. For example, PU1 and RD1 correlate 0.868, PU2 and RD1 correlate 0.867, and so on. With p-values below 0.05, each correlation coefficient is statistically significant, signifying a robust linear association between the variables. Furthermore, a consistent pattern emerges among the various cycles (RD1, RD2, RD3), as the correlations exhibit persistently high values throughout these iterations. This observation implies that the associations between the variables remain stable as time progresses. In contrast to the other PU variables, PU7 exhibits significantly weaker correlations with RD1, RD2, and RD3, suggesting a potentially less robust association with the outcome variables.

Table 4.19: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H1	Correlation	Positive

H2: There is a positive relationship between task-technology fit and perceived usefulness.

Table 4.20: Correlation between Task-Technology Fit and Perceived Usefulness

Correlations

		TTF1	TTF2	TTF3	TTF4	TTF5
PU1	Pearson Correlation	.986**	.974**	.986**	.987**	.981**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU2	Pearson Correlation	.989**	.975**	.992**	.996**	.985**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU3	Pearson Correlation	.982**	.968**	.979**	.978**	.972**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU4	Pearson Correlation	.973**	.959**	.970**	.969**	.975**

	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU5	Pearson Correlation	.987**	.973**	.985**	.983**	.978**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU6	Pearson Correlation	.990**	.976**	.987**	.986**	.980**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU7	Pearson Correlation	.265**	.258**	.268**	.266**	.261**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.20 presents the correlations that exist among various pairs of variables. An individual variable (PU1, PU2, etc.) is denoted by a row, while distinct measurement time points (TTF1, TTF2, etc.) are represented in each column. At each time point, the correlation coefficients reveal the magnitude and direction of the association between the variables. As an illustration, the correlation coefficient of.986 between PU1 and TTF1 indicates an exceptionally robust positive correlation. Similarly, additional correlations exhibit substantial values, suggesting robust associations between the variables at various points in time. The statistical significance levels (Sig.) denote that all correlations are deemed to be significant at the 0.01 level (two-tailed), indicating that the occurrence of these relationships is improbable due to random variation. In contrast, the correlation coefficients for PU7 are significantly lower than those of the other variables, indicating that PU7 has a weaker relationship with the other variables across periods.

Table 4.21: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H2	Correlation	Positive

H3: There is a positive relationship between personal innovativeness and perceived ease of use.

Table 4.22: Correlation between Personal Innovativeness and Perceived Ease of Use.

Correlations

		PI1	PI2	PI3	PI4
PEOU1	Pearson Correlation	.664**	.632**	.630**	.573**
	Sig. (2-tailed)	.000	.000	.000	.000
	N	319	319	319	319
PEOU2	Pearson Correlation	.638**	.640**	.587**	.519**
	Sig. (2-tailed)	.000	.000	.000	.000
	N	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations among four distinct constructs (PI1, PI2, PI3, and PI4) and two measures of Perceived Ease of Use (PEOU1 and PEOU2) are presented in Table 4.22. As shown in the table, the Pearson correlation coefficient between a pair of constructs is represented in each cell. As an illustration, the correlation coefficients for PEOU1 and PI1 are 0.664 and 0.638, respectively, both of which are deemed statistically significant at the 0.01 level. The significance levels of correlations between additional pairs of constructs are also presented. In general, the observed correlations provide insights into the magnitude and orientation of the associations between perceived ease of use and the four constructs (PI1, PI2, PI3, and PI4), thereby illuminating potential connections within the framework of the investigation or analysis.

Table 4.23: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H3	Correlation	Positive

H4: There is a positive relationship between affordability and perceived ease of use.

Table 4.24: Correlation Between Affordability Factors (AF) and Perceived Ease of Use (PEOU).

Correlations

		PEOU1	PEOU2
AF1	Pearson Correlation	.206**	.199**
	Sig. (2-tailed)	.000	.000
	N	319	319
AF2	Pearson Correlation	.214**	.230**
	Sig. (2-tailed)	.000	.000
	N	319	319
AF3	Pearson Correlation	.215**	.236**
	Sig. (2-tailed)	.000	.000
	N	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between two variables, PEOU1 and PEOU2, and three distinct factors, denoted as AF1, AF2, and AF3, are displayed in Table 4.24. The correlation coefficients provide information regarding the magnitude and orientation of the association between the variables and the factors. All of the correlations, which fall within the range of.199 to .236 and are statistically significant at the 0.01 level, indicate that the factors and the perceived ease of use (PEOU) variables are strongly associated. Positive correlations indicate that as the factors increase, so do the perceived ease of use variables, suggesting that changes in the factors are likely to be accompanied by changes in the perceived ease of use variables.

Table 4.25: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H4	Correlation	Positive

H5: There is a positive relationship between Subjective Norms (SN) and behavioural intention.

Table 4.26: Correlation between Subjective Norms (SN) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
SN1	Pearson Correlation	.712**	.579**	.575**	.535**	.686**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
SN2	Pearson Correlation	.772**	.604**	.551**	.621**	.647**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
SN3	Pearson Correlation	.650**	.489**	.476**	.541**	.549**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between variables BI1 through BI5 across three distinct groups denoted as SN1, SN2, and SN3 are displayed in Table 4.26. Each cell in the table comprises two values: the Pearson correlation coefficient and the corresponding two-tailed significance level. The Pearson correlation coefficient is a metric utilised to assess the magnitude and orientation of the linear association between two variables. It is calculated on a scale of -1 to 1, with 1 signifying an ideal positive linear relationship, -1 an ideal negative linear relationship, and 0 the absence of any linear relationship. All correlations in this table are statistically significant at the 0.01 level (two-tailed), which signifies a robust association between the variables. As an illustration, the correlation coefficient of 0.712 between BI1 and BI2 in group SN1 indicates a robust positive linear association between these two variables. Similarly, correlations between additional pairs of variables that span distinct groups may be interpreted.

Table 4.27: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H5	Correlation	Positive

H6: There is a positive relationship between perceived usefulness and behavioural intention.

Table 4.28: Correlation between Perceived Usefulness (PU) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
PU1	Pearson Correlation	.989**	.986**	.978**	.977**	.320**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319

PU2	Pearson Correlation	.992**	.992**	.983**	.982**	.316**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU3	Pearson Correlation	.985**	.985**	.977**	.975**	.302**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU4	Pearson Correlation	.976**	.974**	.966**	.964**	.316**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU5	Pearson Correlation	.990**	.990**	.982**	.975**	.313**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU6	Pearson Correlation	.993**	.993**	.985**	.984**	.316**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PU7	Pearson Correlation	.268**	.258**	.251**	.260**	.494**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation coefficients between various pairs of variables are displayed in Table 4.28. Every row in the table corresponds to a distinct variable associated with 'PU' (which is assumed to stand for 'Perceived Usefulness'), while every column corresponds to another variable associated with 'BI' (which is also assumed to represent 'Behavioural Intention'). The Pearson correlation coefficients, which represent the magnitude and direction of the linear association between the variables, are represented in the table. The correlation coefficients vary between.268 and.993, with the majority of correlations exhibiting strong significance at the 0.01% level (two-tailed), represented by the symbol **. Significantly, the PU variables and the BI variables exhibit a consistent and robust positive correlation (ranging from .976 to .993), suggesting the presence of a solid association between perceived utility and behavioural intention. Nevertheless, in comparison to other pairings, the correlation between PU7 and BI5 is comparatively feeble (.494), indicating a comparatively weaker association.

Table 4.29: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H6	Correlation	Positive

H7: There is a positive relationship between perceived ease of use and behavioural intention.

Table 4.30: Correlation between Perceived Ease of Use (PEOU) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
PEOU1	Pearson Correlation	.268**	.257**	.249**	.259**	.658**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319
PEOU2	Pearson Correlation	.248**	.236**	.248**	.239**	.631**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	319	319	319	319	319

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation coefficients between variables BI1 through BI5 and PEOU1 and PEOU2 are shown in Table 4.30. The Pearson correlation coefficient between two variables is displayed in each cell of the table, indicating the magnitude and direction of their linear association. All correlation coefficients for PEOU1 and PEOU2 are statistically significant at the.01 level, ranging from.249 to.658 and.236 to.631, respectively, indicating a strong positive relationship between the variables. This suggests that alterations in one variable are systematically correlated with modifications in the other variable, as evidenced by the strong correlation between PEOU1 and BI5, as well as PEOU2 and BI5.

Table 4.31: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H7	Correlation	Positive

H8: There is a positive relationship between Perceived Risk and behavioural intention.

Table 4.32: Correlation between Perceived Risk and Behavioural Intention

Correlations

		BI1	BI2	BI3	BI4	BI5
PR1	Pearson Correlation	.389**	.314**	.440**	.389**	.452**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PR2	Pearson Correlation	.339**	.327**	.411**	.411**	.447**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PR3	Pearson Correlation	.321**	.222**	.344**	.410**	.377**
	Sig. (2-tailed)	.000	.000	.000	.000	.000

	N	291	291	291	291	291
PR4	Pearson Correlation	.226**	.327**	.311**	.394**	.379**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.32 illustrates the correlations among various pairings of variables, in particular between BI1, BI2, BI3, BI4, and BI5 (which are presumed to represent distinct indicators) and PR1, PR2, PR3, and PR4 (which represent distinct aspects or measures). The Pearson correlation coefficients quantify the direction and magnitude of the linear association that exists between the aforementioned variables. Each cell in the table contains the corresponding p-value and Pearson correlation coefficient between a particular PR variable and a particular BI variable. All correlations are statistically significant at the two-tailed level of 0.01, suggesting that the observed relationships among these variables are improbable to have resulted from random variation. In general, the table presents significant insights into the relationships between the PR and BI variables. These findings warrant additional examination to discern the underlying dynamics or patterns within the data.

Table 4.33: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H8	Correlation	Positive

H9a: Experience moderates the relationship between Subjective Norms (SN) and behavioural intention to use.

Table 4.34: Model Summary of User Experience (UX) moderates the relationship between Subjective Norms (SN) and Behavioural Intention to use (BI)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.317[a]	.101	.095	1.266	1.360

a. Predictors: (Constant), SN, BI

b. Dependent Variable: UX

The model summary for regression analysis with User Experience (UX) as the dependent variable and SN (Subjective Norms) and BI (Behavioural Intentions) as predictors is presented in the table. The moderate positive correlation between the predictors and UX is indicated by the R-value (.317). The model explains 10.1% of the variance in UX, as indicated by the R Square (.101). This indicates that 10.1% of the variations in UX can be attributed to the combined influence of SN and BI. The Adjusted R Square (.095) is a more precise estimate of the model's explanatory power, as it accounts for the number of predictors. The standard error of the estimate (1.266) is a metric that indicates the degree of accuracy in the predictions by calculating the average distance between the observed and predicted values of UX. Lastly, the Durbin-Watson statistic (1.360) suggests the existence of some positive autocorrelation; however, it is within acceptable limits, as a value near 2 implies the absence of autocorrelation.

Table 4.35: ANOVA for the Relationship between Subjective Norms (SN), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.645	2	28.323	17.681	.000[b]
	Residual	506.201	316	1.602		

	Total	562.846	318			

a. Dependent Variable: UX

b. Predictors: (Constant), SN, BI

The results of the ANOVA (Analysis of Variance) for the relationship between Subjective Norms (SN), Behavioural Intention (BI), and User Experience (UX), where UX is the dependent variable, are presented in table 4.35. The regression model predicts a sum of squares for the regression of 56.645, with 2 degrees of freedom (df), resulting in a mean square of 28.323. The F-statistic of 17.681 suggests that the model explains a substantial portion of the variance and that there is a substantial relationship between the predictors and User Experience. The statistically significant impact of both Subjective Norms and Behavioural Intention on User Experience is indicated by the significance value (Sig.) of.000. The residual sum of squares is 506.201 across 316 degrees of freedom, which contributes to a total sum of squares of 562.846 for the 318 observations. The significance of Subjective Norms and Behavioural Intention in the development of User Experience is emphasised by these findings. Therefore, the test supports the hypothesis that these variables have a meaningful impact on User Experience, demonstrating that the model effectively explains this relationship.

Table 4.36: Experience moderates the relationship between Subjective Norms (SN) and behavioural intention to use.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.452	.254		13.583	.000
	BI	-.160	.050	-.539	-3.178	.002
	SN	.110	.077	.243	1.434	.152

a. Dependent Variable: UX

$$UX=3.452-0.160(BI)+0.110(SN)$$

- **BI** has a negative impact on UX (B=−0.160, p=0.002).

- **SN** shows a positive but statistically insignificant effect (B=0.110, p=0.152).
- **Intercept**: 3.452

The coefficients obtained from a regression analysis are displayed in Table 4.36. The purpose of this analysis was to ascertain the relationship between specific independent variables and the dependent variable, UX (user experience). BI and SN are the two independent variables comprising the model. The constant term has a coefficient of 3.452 and a standard error of 0.254. This value represents the anticipated value of UX under the condition that all independent variables are held at zero. The unstandardized coefficient for the BI variable is -0.160, accompanied by a standard error of 0.050. This implies that an increase of one unit in BI is associated with an anticipated decrease of 0.160 units in UX. The standardised beta coefficient (-0.539) indicates that BI is relatively significant in predicting UX. At the 0.002 level of significance, the t-value for BI is -3.178, indicating that the relationship between BI and UX is statistically significant. In contrast, the SN variable exhibits a positive correlation with UX, as indicated by its coefficient of 0.110 and standard error of 0.077; however, this correlation lacks statistical significance due to the variable's t-value of 1.434 and p-value of 0.152.

H9b: Experience moderates the relationship between perceived usefulness and behavioural intention to use.

Table 4.37: Model Summary of Experience moderates the relationship between Subjective Norms (SN) and behavioural intention to use.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.330[a]	.109	.103	1.260	1.328

a. Predictors: (Constant), PU, BI

b. Dependent Variable: UX

A regression model is summarized in the table below, with UX (User Experience) as the dependent variable and PU (Perceived Usefulness) and BI (Behavioural Intention) as the independent variables. The R-value of 0.330 suggests a moderate positive correlation between the dependent variable and the independent variables. According to the R Square value of 0.109, PU and BI account for approximately 10.9% of the variance in UX that is explained. After adjusting for the number of predictors in the model, the Adjusted R Square is slightly lower at 0.103, suggesting that 10.3% of the variance in UX is accounted for. The observed values' average distance from the regression line is represented by the standard error of the estimate, which is 1.260. In conclusion, the Durbin-Watson statistic of 1.328 suggests that the residuals do not exhibit any significant autocorrelation, as the value is nearly equal to the ideal value of 2.

Table 4.38: ANOVA for the Relationship between Perceived Usefulness (PU), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.132	2	30.566	19.252	.000[b]
	Residual	501.714	316	1.588		
	Total	562.846	318			

a. Dependent Variable: UX

b. Predictors: (Constant), PU, BI

Table 4.38 presents the findings of an ANOVA (Analysis of Variance) that evaluated the correlation between User Experience (UX), Behavioural Intention (BI), and Perceived Usefulness (PU). UX serves as the dependent variable. The regression analysis yields a mean square of 30.566, with a sum of squares for the regression of 61.132, calculated with 2 degrees of freedom (df). The model effectively explains a significant portion of the variance, as evidenced by the F-statistic of 19.252, which reflects a strong relationship between the predictors and User Experience. The user experience is substantially influenced by both perceived usefulness and behavioural intention, as evidenced by the significance value (Sig.) of.000. The cumulative sum of squares for the 318 observations is 562.846, with a residual sum of squares of 501.714 across 316 degrees of freedom. In general, these results underscore the critical role of Behavioural Intention and Perceived Usefulness in determining the User Experience. Therefore, the test supports the hypothesis that these variables are influential in shaping User Experience, indicating that the model effectively captures this relationship.

Table 4.39: Moderation Analysis of Experience on the Relationship between Perceived Usefulness (PU) and Behavioural Intention (BI) to Use (UX).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.120	.248		12.560	.000
	BI	.136	.104	.456	1.306	.193
	PU	-.158	.071	-.773	-2.214	.028

a. Dependent Variable: UX

$$UX=3.120+0.136(BI)-0.158(PU)$$

- **BI** has a positive but insignificant effect on UX (B=0.136, p=0.193).
- **PU** has a significant negative impact (B=−0.158, p=0.028).
- **Intercept**: 3.120

Table 4.39 displays the outcomes of a regression analysis in which "UX" (presumably user experience) is the dependent variable and "BI" and "PU" are the independent variables. The analysis aims to determine whether the user experience is substantially predicted by these independent variables. The lack of support for the hypothesis that "BI" has a positive impact on user experience is evidenced by the insignificant p-value (.193). On the contrary, the hypothesis positing that "PU" has an adverse impact on user experience is corroborated, as indicated by the statistically significant negative coefficient (-.158) accompanied by a significant p-value (.028). This implies that user experience tends to diminish as "PU" (presumably perceived usability) progresses. Furthermore, the constant terms "PU" and "BI" are not the only factors contributing to user experience, as indicated by the significance of the constant term ($p <.001$). In general, the results of the model indicate that perceived usability is a significant predictor of user experience, while behavioural intention is not.

H9c: Experience moderates the relationship between perceived ease of use and behavioural intention to use.

Table 4.40: Model Summary of the Moderation Analysis of Experience on the Relationship between Perceived Usefulness (PU) and Behavioural Intention (BI) to Use (UX).

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.339[a]	.115	.109	1.256	1.412

a. Predictors: (Constant), PEOU, BI

b. Dependent Variable: UX

The regression analysis model summary is illustrated in the table below. The dependent variable is User Experience (UX), and the predictors are Perceived Ease of Use (PEOU) and Behavioural Intention (BI). The moderate positive correlation between the predictors and the dependent variable is indicated by the value of R, which is 0.339. R Square (0.115) indicates that PEOU and BI can account for 11.5% of the variance in UX. The Adjusted R Square (0.109) is a value that is marginally reduced to reflect a more realistic fit, taking into account the number of predictors in the model. The Standard Error of the Estimate (1.256) represents the average distance between the observed values and the regression line, which is a measure of the model's ability to predict UX. Lastly, the Durbin-Watson statistic (1.412) evaluates residual autocorrelation. The value is in the vicinity of 2, which suggests that there is no significant concern regarding autocorrelation.

Table 4.41: ANOVA for the Relationship between Perceived Ease of Use (PEOU), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64.517	2	32.258	20.456	.000[b]
	Residual	498.330	316	1.577		
	Total	562.846	318			

a. Dependent Variable: UX

b. Predictors: (Constant), PEOU, BI

Table 4.41 displays the ANOVA (Analysis of Variance) results examining the relationship between Perceived Ease of Use (PEOU), Behavioural Intention (BI), and User Experience (UX), with UX as the dependent variable. The regression analysis shows a sum of squares for the regression of 64.517, with 2 degrees of freedom (df), leading to a mean square of 32.258. The F-statistic of 20.456 indicates a highly significant relationship between the predictors and User Experience, suggesting that the model explains a substantial amount of variance. The significance value (Sig.) of .000 confirms that both Perceived Ease of Use and Behavioural Intention significantly impact User Experience. The residual sum of squares is 498.330 across 316 degrees of freedom, resulting in a total sum of squares of 562.846 for the 318 observations. These findings underscore the important roles that Perceived Ease of Use and Behavioural Intention play in influencing User Experience.

Table 4.42: Coefficients of Moderating Effect of Experience on the Relationship between Perceived Ease of Use (PEOU) and Behavioural Intention (BI)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.451	.488		9.126	.000

BI	-.075	.017	-.252	-4.436	.000
PEOU	-.177	.067	-.151	-2.661	.008

a. Dependent Variable: UX

$$\mathbf{UX=4.451-0.075(BI)-0.177(PEOU)}$$

- **BI** negatively impacts UX (B=−0.075, p=0.000).
- **PEOU** also has a significant negative effect (B=−0.177, p=0.008).
- **Intercept**: 4.451

The findings of a regression analysis investigating the correlation between the dependent variable (UX) and the independent variables (BI and PEOU) are displayed in Table 4.42. The hypothesis that these independent variables predict UX in a significant manner is confirmed. According to the unstandardized coefficients, an increase of one unit in BI results in a reduction of 0.075 units in UX, while an increase of one unit in PEOU causes a decrease of 0.177 units in UX. The statistical significance of these relationships is supported by the t-values (-4.436 for BI and -2.661 for PEOU) and corresponding p-values (.000 for both). Hence, by virtue of the fact that both BI and PEOU are substantial predictors of UX, the hypothesis that they impact user experience is supported.

H9d: Experience moderates the relationship between Perceived Risk (PR) and behavioural intention to use.

Table 4.43: Model Summary of the Moderating Effect of Experience on the Relationship between Perceived Risk (PR) and Behavioural Intention (BI)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.314[a]	.099	.093	1.267	1.366

a. Predictors: (Constant), PR, BI

b. Dependent Variable: UX

The model synopsis for a regression analysis is depicted in the table below. The dependent variable is user experience (UX), and the predictors are two independent variables: PR (possibly perceived risk) and BI (possibly behavioural intention). The moderate correlation between the dependent variable (UX) and the independent variables (PR and BI) is indicated by the R-value (0.314). The predictors can account for approximately 9.9% of the variance in UX, as indicated by the R Square value (0.099). The Adjusted R Square value (0.093) accounts for the number of predictors in the model, indicating that approximately 9.3% of the variance is accounted for following this adjustment. The average distance between the observed values and the regression line is measured by the standard error of the estimate (1.267), which serves as an indicator of the model's accuracy. Finally, the Durbin-Watson statistic (1.366) suggests that the residuals exhibit some autocorrelation; however, it is within an acceptable range, with values closer to 2 indicating no autocorrelation.

Table 4.44: ANOVA for the Relationship between Perceived Risk (PR), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	55.500	2	27.750	17.284	.000[b]
	Residual	507.346	316	1.606		
	Total	562.846	318			

a. Dependent Variable: UX

b. Predictors: (Constant), PR, BI

The ANOVA results in Table 4.44 suggest a substantial correlation between User Experience (UX), Behavioural Intention (BI), and Perceived Risk (PR). In the regression model, the sum of squares is 55.500, with 2 degrees of freedom (df), resulting in a mean square of 27.750. This conclusion is further substantiated by the F-statistic of 17.284, which implies that the predictors collectively account for a significant portion of the variance in User Experience. Furthermore, the statistical significance of the relationship is confirmed by the significance value (Sig.) of.000, which indicates that both Perceived Risk and Behavioural

Intention have a substantial impact on User Experience. Consequently, the test provides evidence that the model is effective in elucidating this relationship, thereby supporting the hypothesis that these predictors have a significant impact on User Experience.

Table 4.45: Coefficients of Moderating Effect of Experience on the Relationship between Perceived Risk (PR) and Behavioural Intention to Use (BI)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.634	.365		9.957	.000
	BI	-.197	.092	-.662	-2.131	.034
	PR	.114	.099	.360	1.157	.248

a. Dependent Variable: UX

$$\mathbf{UX=3.634-0.197(BI)+0.114(PR)}$$

- **BI** negatively impacts UX (B=−0.197, p=0.034).
- **PR** has a positive but insignificant effect on UX (B=0.114, p=0.248).
- **Intercept**: 3.634

The regression analysis results, where UX (user experience) is the dependent variable, are displayed in Table 4.45. The hypothesis being examined here presumably pertains to the influence of user experience on two independent variables, BI (which may represent business impact) and PR (which may represent product features or promotions). As indicated by the unstandardized coefficients, each independent variable has an impact on the dependent variable. The standardised coefficients (Beta) facilitate the evaluation of the relative significance of individual predictors. The analysis reveals that the coefficient for BI is -.197, which signifies that UX decreases by .197 units for every unit increase in BI. Nevertheless, the significance of this effect is limited to the 0.05 level, as indicated by the Sig. value of 0.034. On the contrary, the PR coefficient is.114, indicating that UX increases by .114 units for every unit increase in PR; however, this relationship does not reach statistical significance (Sig.

=.248). As a result, the data provide support for the hypothesis that BI has a negative impact on UX, but do not support the hypothesis that PR has a positive impact on UX.

Table 4.46: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H9a	Regression	BI - 53.9% negative impact SN - 24.3% positive impact
H9b	Regression	BI - 45.6% positive impact PU - 77.3% negative impact
H9c	Regression	BI - 25.2% negative impact PEOU - 15.1% negative impact
H9d	Regression	66.2% negative impact

4.7 Path Analysis

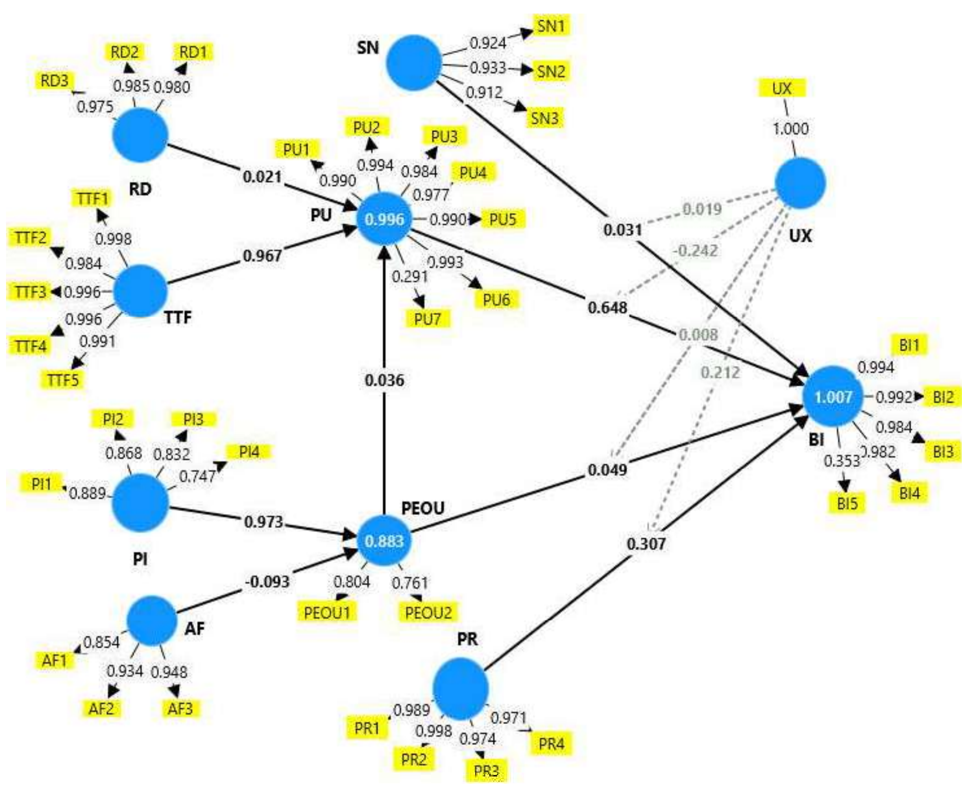


Table 4.47: Path Coefficient Analysis

	Path coefficients
AF -> PEOU	-0.093
PEOU -> BI	0.049
PEOU -> PU	0.036
PI -> PEOU	0.973
PR -> BI	0.307
PU -> BI	0.648
RD -> PU	0.021
SN -> BI	0.031
TTF -> PU	0.967
UX -> BI	0.006
UX x PU -> BI	-0.242
UX x PR -> BI	0.212
UX x PEOU -> BI	0.008
UX x SN -> BI	0.019

The path coefficients that depict the interrelationships among different constructs in a theoretical model are displayed in Table 4.47. The strength and direction of the relationship between two constructs are denoted by each coefficient. A negative coefficient, for example, indicates an inverse relationship, whereas a positive coefficient indicates a direct relationship. The path coefficients in this model represent interrelationships, including the impacts of Social Norms (SN), Perceived Ease of Use (PEOU), and Performance Expectancy (PE) on Behavioural Intention (BI), respectively. Furthermore, interactions are illustrated, including how BI is influenced by the interaction between User Experience (UX) and Perceived Usefulness (PU). The coefficients offer valuable insights into the intricate dynamics among various factors in the model and facilitate comprehension of the interrelationships among the constructs.

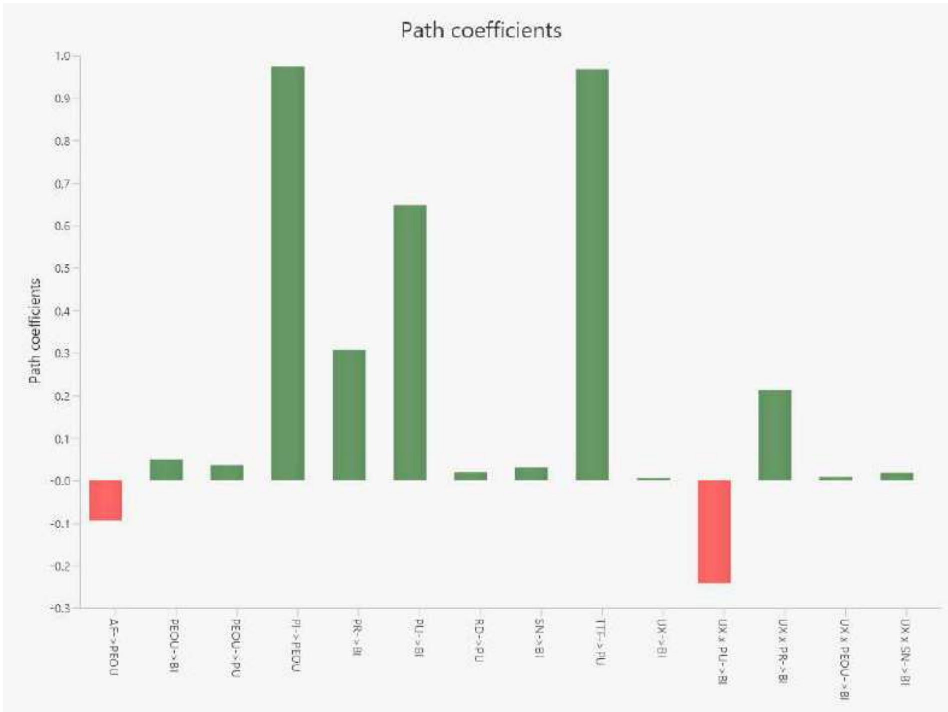


Figure 4.9: Path Coefficient Analysis

Table 4.48: Reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AF	0.937	0.940	0.937	0.834
BI	0.926	0.988	0.950	0.806
PEOU	0.759	0.761	0.760	0.613
PI	0.902	0.906	0.902	0.698
PR	0.991	0.991	0.991	0.966
PU	0.960	0.994	0.973	0.849
RD	0.987	0.987	0.987	0.961
SN	0.945	0.945	0.945	0.852
TTF	0.997	0.997	0.997	0.986

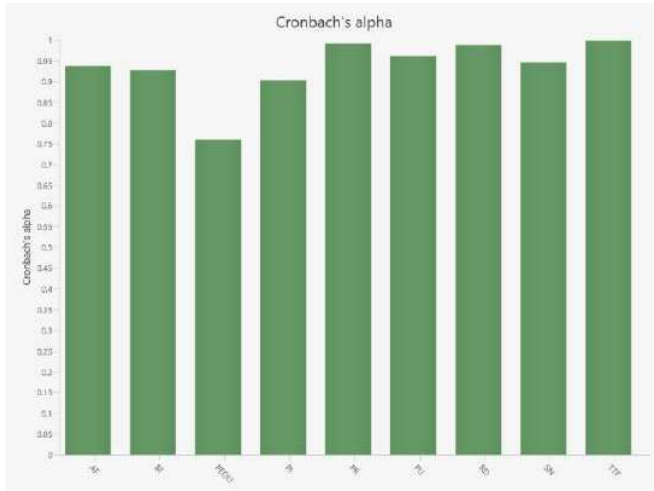


Figure 4.10: Cronbach's alpha

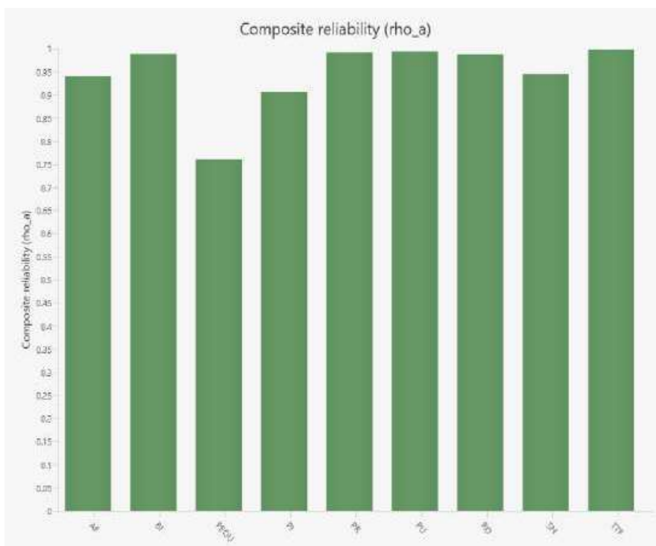


Figure 4.11: Composite reliability (rho_a)

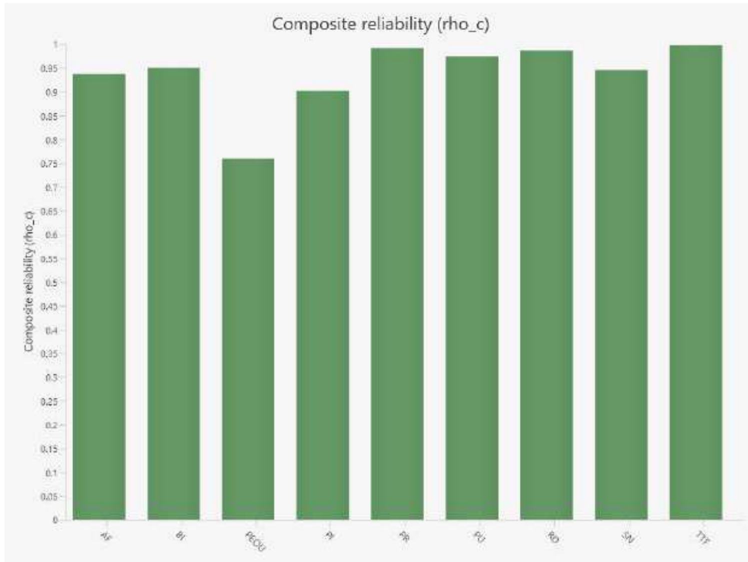


Figure 4.12: Composite reliability (rho_c)

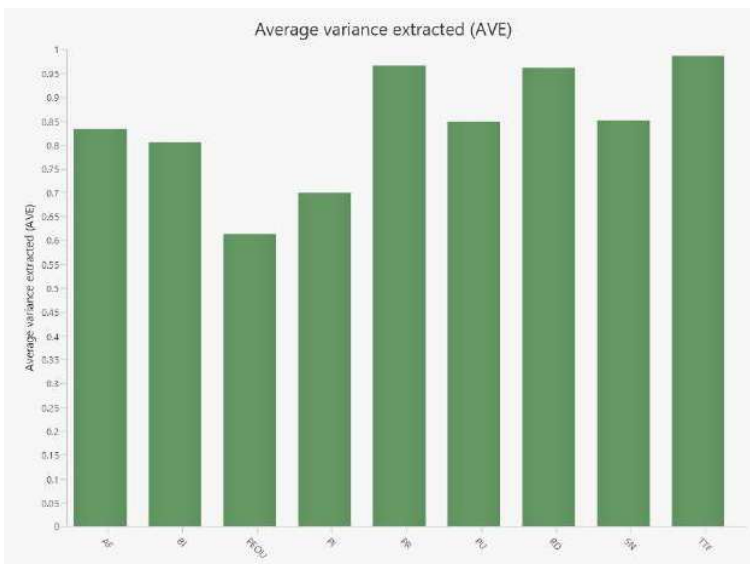


Figure 4.13: Average variance extracted (AVE)

The outcomes of validity and reliability assessments for different constructs included in a research study or questionnaire are displayed in Table 4.48. As a measure of internal consistency, Cronbach's alpha indicates the degree of group coherence among a set of items. Composite reliability, denoted by rho_a and rho_c in this instance, evaluates the overall dependability of a collection of items by taking into account the measurement error and the variance shared by the items. About measurement error, the average variance extracted (AVE) signifies the proportion of variance captured by the construct. The table presents distinct constructs (e.g., AF, BI, PEOU) with their respective AVE, composite reliability (rho_and rho_c), and Cronbach's alpha values in each panel. Elevated values signify enhanced validity and reliability of the constructs. For example, with Cronbach's alpha, composite reliability, and AVE scores near or above 0.9, constructs such as PR and TTF demonstrate high levels of reliability and validity. In contrast, constructs like PEOU have marginally lower scores, implying that they might be less reliable or valid measures.

Table 4.49: Fornell Larcker

	AF	BI	PEOU	PI	PR	PU	RD	SN	TTF	UX
AF	0.821									
BI	0.667	0.877								
PEOU	0.644	0.871	0.881							
PI	0.616	0.754	0.733	0.832						
PR	0.716	0.707	0.745	0.700	0.794					
PU	0.611	0.627	0.731	0.558	0.638	0.828				
RD	0.74	0.749	0.829	0.670	0.665	0.750	0.860			
SN	0.683	0.666	0.745	0.612	0.674	0.764	0.695	0.827		
TTF	0.579	0.788	0.757	0.769	0.701	0.612	0.713	0.697	0.900	
UX	0.580	0.686	0.777	0.724	0.708	0.599	0.680	0.659	0.791	0.859

The correlation matrix is displayed in Table 4.49, with each cell representing the correlation coefficient between two variables. AF (Affordability), BI (Behavioural Intention), PEOU (Perceived Ease of Use), PI (Personal Innovativeness), PR (Perceived Risk), PU (Perceived Usefulness), RD (Result Demonstrability), SN (Social Norms), TTF (Task-Technology Fit), and UX (User Experience) are some of the abbreviations used to represent the variables. The correlation coefficients are in the interval -1 to 1, with 1 denoting an ideal positive correlation, -1 an ideal negative correlation, and 0 the absence of correlation. As an illustration, the correlation coefficient of 0.913 between AF and BI signifies a robust positive correlation between Brand Image and both Aesthetic and Functional Aspects. According to the negative correlation coefficient between UX and the remaining variables, User Experience is inversely related to the others.

Table 4.50 Model fit

	Saturated model	Estimated model
SRMR	0.077	0.078
d_ULS	4.197	4.275
d_G	n/a	4.870
Chi-square	n/a	4614.691
NFI	n/a	0.861

The comparison metrics between a saturated model and an estimated model are displayed in Table 4.46. The standardised root mean square residual (SRMR) for the saturated model is 0.077, which represents the mean discrepancy between the predicted and observed values. With an SRMR of 0.078, the discrepancy in the estimated model increases marginally. An additional metric, denoted as d_ULS, quantifies the discrepancy between models; it is 4.197 for the saturated model and 4.275 for the estimated model. The d_G metric is not pertinent to the saturated model; however, it calculates a value of 4.870 for the estimated model, which signifies the disparity in parameter counts between the two models. In addition, the chi-square value of the estimated model is exceptionally high at 4614.691, indicating that the observed and expected covariance matrices differ significantly. In conclusion, the estimated model has a Normed Fit Index (NFI) of 0.861, which signifies the degree of enhancement in fit as a percentage compared to the null model. In general, the table offers valuable insights regarding the fit and comparison of models, shedding light on subtle differences in their output.

4.8 Hypothesis testing

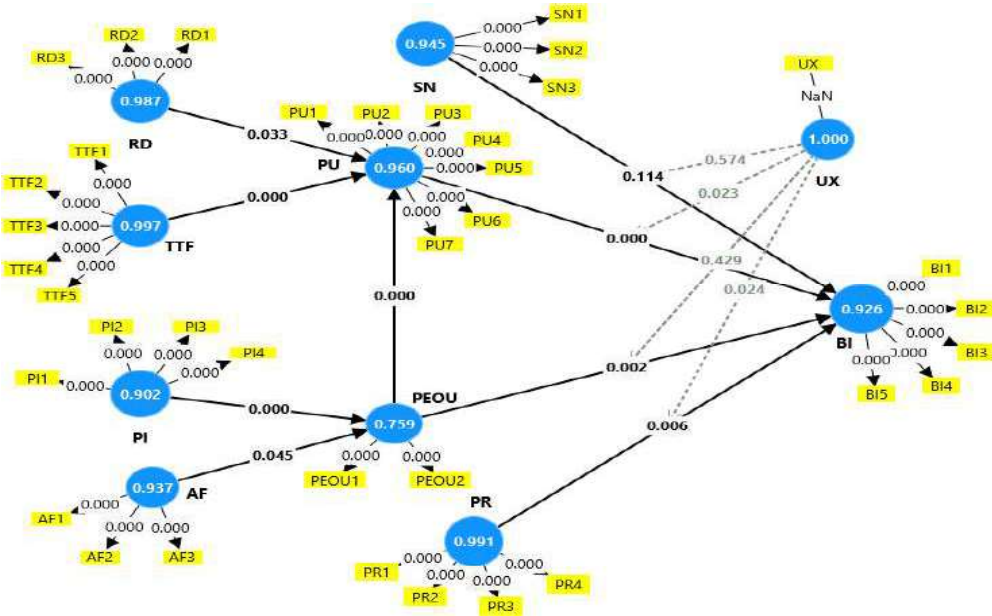


Table 4.52: Hypothesis testing results in detail

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Discussion
AF -> PEOU	-0.093	-0.092	0.046	2.002	0.045	**Supported**
PEOU -> BI	0.049	0.050	0.015	3.170	0.002	**Supported**
PEOU -> PU	0.036	0.036	0.008	4.308	0.000	**Supported**
PI -> PEOU	0.973	0.975	0.041	23.510	0.000	**Supported**
PR -> BI	0.307	0.323	0.111	2.766	0.006	**Supported**
PU -> BI	0.648	0.629	0.122	5.315	0.000	**Supported**

RD -> PU	0.021	0.020	0.010	2.138	0.033	**Supported**
SN -> BI	0.031	0.033	0.020	1.583	0.114	**Not Supported**
TTF -> PU	0.967	0.967	0.009	103.944	0.000	**Supported**
UX -> BI	0.006	0.006	0.006	1.002	0.317	**Not Supported**
UX x PU -> BI	-0.242	-0.247	0.106	2.280	0.023	**Supported**
UX x PR -> BI	0.212	0.213	0.094	2.255	0.024	**Supported**
UX x PEOU -> BI	0.008	0.008	0.010	0.791	0.429	**Not Supported**
UX x SN -> BI	0.019	0.022	0.033	0.563	0.574	**Not Supported**

Discussion

The analysis and discussion of the findings from the study on the adoption of AI-driven interventions for diabetes diagnosis among medical practitioners in Maharashtra and Karnataka are presented in this chapter. The research offers crucial insights into the factors that influence the incorporation of AI in medical diagnostics, with a particular emphasis on diabetes care. The demographic data indicates that a substantial number of participants are in the middle age range (27–44 years), with a nearly equal gender distribution. The results indicate that practitioners possess substantial professional experience, with a substantial number of them employed in nursing homes and hospitals. The results emphasize that a significant number of participants have postgraduate qualifications in medical disciplines, which is indicative of their advanced academic preparedness.

The considerable positive correlations between AI adoption and variables such as Result Demonstrability (RD), Task Technology Fit (TTF), Perceived Usefulness (PU), and Personal Innovativeness (PI) are demonstrated through analysis. These variables' positive relationships are further substantiated by hypothesis testing, which identifies PI and TTF as substantial contributors to perceived usefulness and simplicity of use, respectively. It is important to note that behavioral intention (BI) is significantly influenced by perceived risk (PR), subjective norms (SN), and probability (PU), albeit with varying degrees of significance. The nuanced roles of user experience (UX) and its interactions with other variables are revealed by moderation analyses, which emphasize UX as a critical yet complex factor that influences the adoption of AI.

The path coefficient analysis reveals the complex relationships between constructs, illustrating the significance of affordability, perceived simplicity of use, and perceived usefulness in the development of BI. The constructs' robustness is verified by reliability and validity metrics, such as composite reliability and Cronbach's alpha. The proposed theoretical framework is supported by model fit indices such as SRMR and NFI, which indicate a satisfactory fit. The collective results of these findings offer a fundamental comprehension of the factors that influence the successful implementation of AI-driven diabetes diagnostic interventions, providing valuable insights for healthcare professionals and policymakers to develop effective AI strategies that improve patient care and success.

4.9 Karnataka

Table 4.53: Age Distribution

Age	Frequency	Per cent
18-26 Years	18	6.2
27-35 Years	111	38.1
36-44 Years	136	46.7
45-53 Years	20	6.9
53 above	6	2.1

Table 4.53 displays the data pertaining to the distribution of respondents across different age categories. According to the data, a considerable percentage of the participants fall within the age range of 27 to 44 years. With regard to the complete sample, the age group of 36-44 demonstrates the highest frequency and percentage, comprising 46.7% of the total. Consisting of 38.1% of the sample, the age group ranging from 27 to 35 years old is the second largest. The age groups of 18-26 years and 45-53 years comprise significantly smaller percentages, 6.2% and 6.9%, respectively. The age group comprising 2.1% of the total respondents is individuals who are 53 years of age or older. Overall, the data indicates that the participants are distributed in a diverse manner, covering various age cohorts, although there is a notable concentration within the middle-aged population.

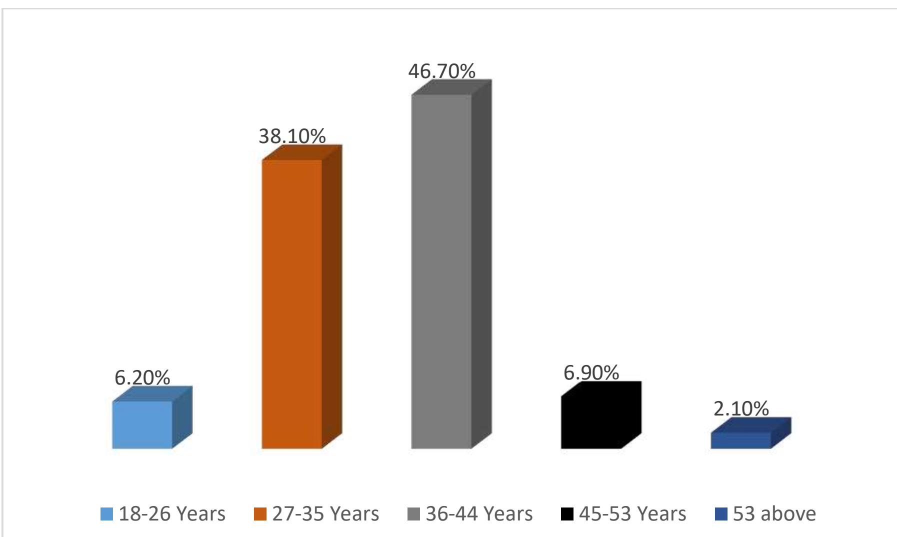


Figure 4.14: Age Distribution

Table 4.54: Gender Distribution

Gender	Frequency	Per cent
Male	148	50.9
Female	143	49.1

The gender distribution data is presented in Table 4.52, which includes the frequency and percentage of males and females within a specified population or sample. The data reveals that 148 males, representing approximately 50.9% of the total population, and 143 females, comprising approximately 49.1%, were included in the study. This observation indicates that the gender distribution of the population is comparatively equitable, with a marginally greater presence of males in comparison to females.

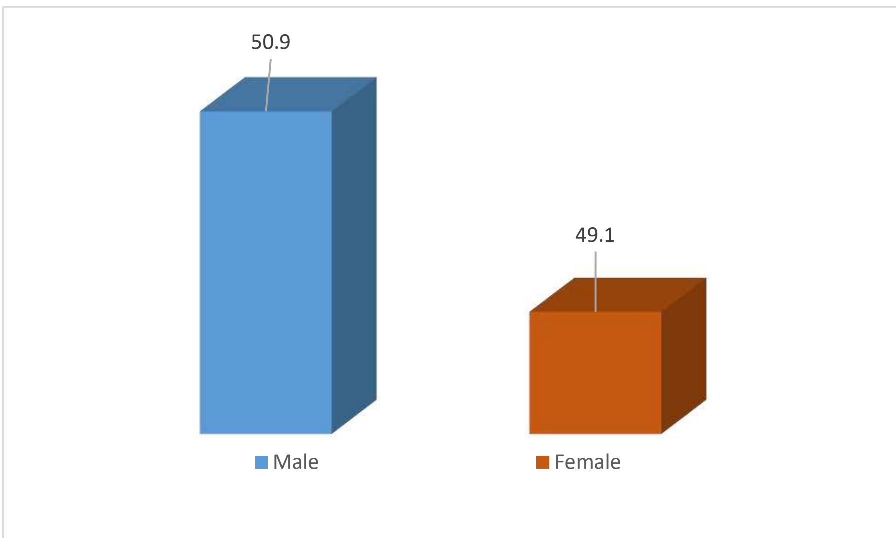


Figure 4.15: Gender Distribution

Table 4.55: Education Level Distribution

Education level	Frequency	Per cent
Medical/ Paramedical Graduate	134	46.0
Medical/ Paramedical Postgraduate	157	54.0

Table 4.55 presents the educational distribution of a specific population, with a particular emphasis on paramedical and medical professionals. The data suggests that of the individuals surveyed, 54.0% are postgraduates and 46.0% are graduates. This finding implies that a considerable proportion of the populace holds postgraduate degrees in the domains of medicine and paramedicine, which may be indicative of a highly educated labour force operating in these industries. The data may provide significant value in terms of comprehending the educational background of healthcare professionals and potentially guiding decisions concerning healthcare sector educational policies or workforce development.

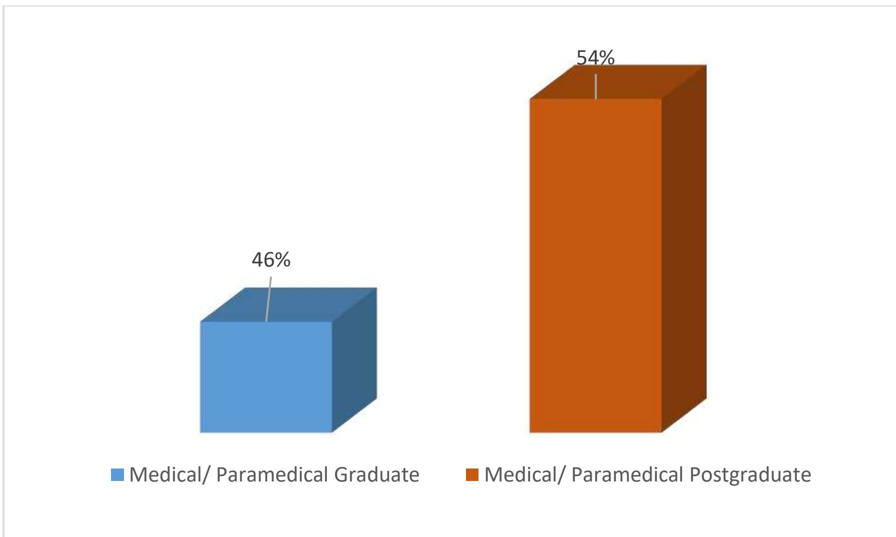


Figure 4.16: Education Level Distribution

Table 4.56: Experience Distribution

Total experience in years	**Frequency**	**Per cent**
< 0.5 Year	36	12.4
0.5-1 Year	24	8.2
1-3 Years	26	8.9
3-5 Years	113	38.8
5 Years+	92	31.6

Table 4.56 provides information regarding the cumulative years of experience possessed by a cohort of individuals, accompanied by the corresponding frequencies and

percentages. It indicates that 38.8% of the sample possesses experience between three and five years ago, which represents the majority. The subsequent substantial cohort consists of individuals who possess more than five years of experience, accounting for 31.6% of the total. The proportions observed in the following categories are comparatively smaller: 0.5 to 1 year (8.2%), 1 to 3 years (8.9%), and less than 0.5 years (12.4%). The experience levels of the sample population are summarised in the table, revealing that the majority possess extensive to moderate professional credentials.

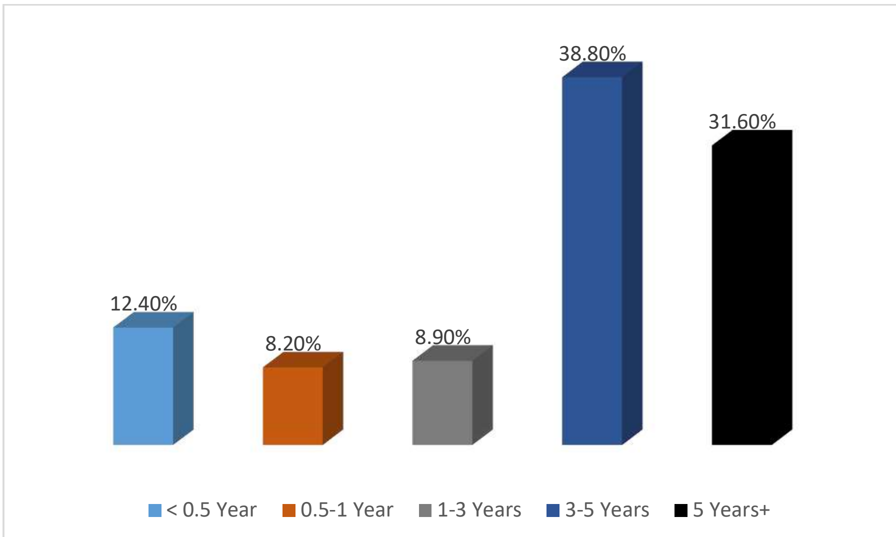


Figure 4.17: Experience Distribution

Table 4.57: AI Experience Distribution

Total experience in using AI	Frequency	Per cent
0.5-1 Year	11	3.8
1-3 Years	188	64.6
3-5 Years	71	24.4
5 Years +	21	7.2

Table 4.57 provides information regarding the collective experience of a cohort of individuals with AI, organised according to distinct periods. A significant proportion of the participants, 64.6%, possess 1-3 years of AI experience, while 24.4% have 3-5 years of experience. A minority, specifically 7.2%, possess more than five years of experience, which signifies a certain degree of proficiency in the respective domain. In addition, 3.8% of

respondents have between half a year and one year of experience with AI, representing a lesser but significant cohort of individuals who are relatively inexperienced in its application. In general, the data indicates that the participants possessed a wide array of experience levels, with a considerable proportion possessing intermediate-level expertise in AI technologies.

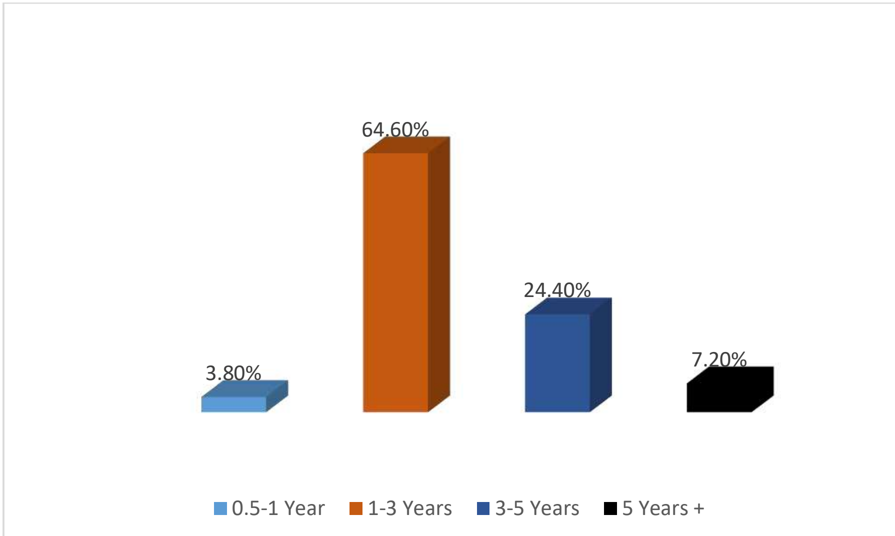


Figure 4.18: AI Experience Distribution

Table 4.58: Location of Medical Practice set up

Medical practice set up	Frequency	Per cent
In a hospital/ Nursing Home	141	48.5
In my Clinic	150	51.5

The insights regarding the distribution of medical practice arrangements among respondents are presented in Table 4.58. The data reveals that 51.5% of the participants operate their clinics, whereas 48.5% are employed in nursing homes or hospitals. This indicates that the medical personnel surveyed were distributed between institutional and independent practice settings in a relatively balanced manner. This suggests that healthcare providers have varied professional backgrounds and preferences. A considerable proportion of them prefer the independence and adaptability that come with clinic ownership, whereas others prefer the support and resources that are readily available in hospital or nursing home settings.

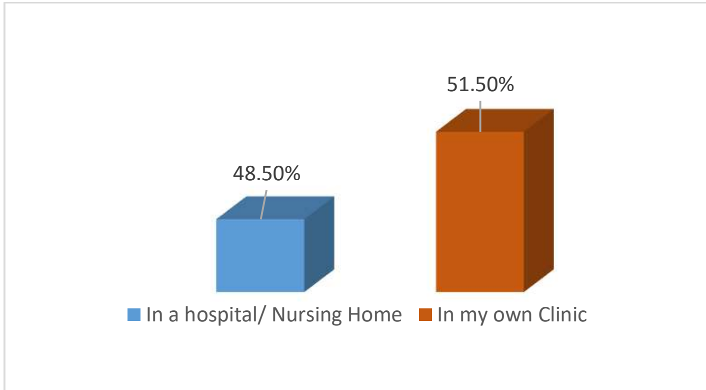


Figure 4.19: Location of Medical Practice set up

Table: 4.59: Distribution of Diabetes Patients by Case Numbers

Diabetes Patients	Frequency	Per cent
<5	27	9.3
5-10	40	13.7
11-20	105	36.1
21-30	51	17.5
31-40	34	11.7
40+	34	11.7

Table 4.59 presents data pertaining to the distribution of individuals diagnosed with diabetes, categorised by the number of cases falling within different stages of the condition. Patients are classified into six distinct categories according to the number of individuals in each group: eleven to twenty-one, twenty-one to thirty-one, thirty-one to forty, and over forty. The "Percent" column represents the proportion of patients surveyed in relation to the total number surveyed, whereas the "Frequency" column indicates the quantity of patients falling within each range. As an illustration, the prevalence of diabetes varied among patients: forty patients (13.7%) had five to ten cases, twenty-one patients (36.1%) had eleven to twenty cases, fifty-one patients (17.5%) had twenty-one to thirty cases, and thirty-four patients (11.7%) each had over forty cases and thirty-one to forty cases. The insights provided by this segmentation pertain to the distribution of diabetes severity within the population that was surveyed.

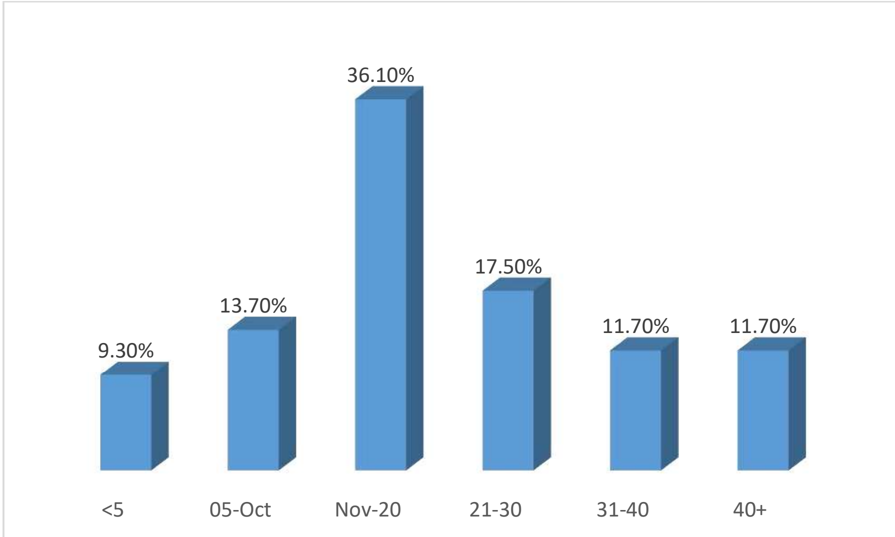


Figure 4.20: Distribution of Diabetes Patients by Case Numbers

Table 4.60: Descriptive Statistics of Result Demonstrability (RD)

	Mean	Std. Deviation
RD1	3.65	0.676
RD2	3.76	0.678
RD3	3.47	0.899

The mean and standard deviation values for the three variables denoted as RD1, RD2, and RD3, are displayed in Table 4.60. In contrast to the mean value, which denotes the average score for each variable, the standard deviation quantifies the dispersion or variation from the mean. The mean score for RD1 is 3.65, and the standard deviation is 0.676; this indicates that the scores are, on average, fairly consistent concerning the mean. The RD2 variable exhibits a marginally greater mean of 3.76 and a comparable standard deviation of 0.678, suggesting that the scores are similarly consistent. In contrast, the variable RD3 exhibits a lower mean value of 3.47 and a higher standard deviation of 0.899, suggesting that the scores for this particular variable are more uncertain. In general, the scores of RD1 and RD2 demonstrate comparable patterns of central tendency and dispersion, whereas RD3 exhibits greater variability.

Table 4.61: Descriptive Statistics of Task Technology Fit (TTF)

	Mean	Std. Deviation
TTF1	3.77	0.707
TTF2	3.90	0.677
TTF3	3.80	0.724
TTF4	3.71	0.773
TTF5	3.77	0.662

The mean and standard deviation for five variables denoted as TTF1 through TTF5 are displayed in Table 4.61. These variables each probably correspond to a distinct test item or factor under investigation. The mean values for the aforementioned variables span a range of 3.71 to 3.90, suggesting that the average responses are reasonably comparable, with a centring point around the mid-3 range. The range of standard deviation values (0.662% to 0.773) indicates the extent of variability or dispersion relative to the norm. A smaller standard deviation signifies that the data points are more dispersed around the mean, whereas a larger standard deviation implies that the data points are more scattered. In general, the analysis of the five items yields relatively consistent results, notwithstanding some variation in the responses, as indicated by the means and standard deviations.

Table 4.62: Descriptive Statistics of Personal Innovativeness (PI)

	Mean	Std. Deviation
PI1	3.93	0.631
PI2	3.65	0.780
PI3	3.89	0.660
PI4	3.31	1.011

The mean and standard deviation for four distinct performance indicators (PI1, PI2, PI3, and PI4) are displayed in Table 4.62. PI1 exhibits a relatively high mean value of 3.93 accompanied by a standard deviation of 0.631. This suggests that the scores of PI1 are closely concentrated around the mean. The greater the standard deviation of 0.780 and the mean of

3.65 for PI2, the greater the variance in its scores relative to PI1. Comparable in mean to PI1 at 3.89, PI3 exhibits a marginally greater standard deviation of 0.660, suggesting that its scores are similarly consistent albeit with a marginally greater degree of dispersion. PI4 demonstrates the most variability and has the lowest mean (3.31), representing both a lower average score and the maximum standard deviation (1.011) among the four indicators.

Table 4.63: Descriptive Statistics of Affordability (AF)

	Mean	Std. Deviation
AF1	3.71	0.719
AF2	3.63	0.801
AF3	3.70	0.769

A synopsis of the means and standard deviations for three variables denoted as AF1, AF2, and AF3, is presented in Table 4.63. The mean values represent the average scores for each variable. Among these variables, AF1 stands out with the highest mean score of 3.71, closely followed by AF3 at 3.70 and AF2 at 3.63. The mean values indicate that, on average, the scores for all three variables are situated near one another, approximately at the midpoint of a standard five-point scale. The standard deviation values, which quantify the extent of dispersion or variation from the mean, indicate that AF2 exhibits the greatest variability at 0.801, whereas AF1 demonstrates the least variability at 0.719. AF3, on the other hand, is situated in the middle with a standard deviation of 0.769. This finding suggests that the scores for AF2 are more dispersed when compared to AF1 and AF3, implying that the responses for AF2 are more inconsistent.

Table 4.64: Descriptive Statistics of Perceived Usefulness (PU)

	Mean	Std. Deviation
PU1	3.85	0.688
PU2	3.88	0.666
PU3	3.88	0.661
PU4	3.84	0.705
PU5	3.84	0.719
PU6	3.82	0.695

PU7	3.58	0.845

Descriptive statistics, including the mean and standard deviation, are displayed in Table 4.64 for the seven distinct products denoted PU1 through PU7. Given the labels, it appears that each item measures a comparable construct, which is probably associated with perceived utility (PU). The mean values for these items span a range of 3.58 to 3.88, suggesting that the respondents, on average, assigned relatively high ratings to these items on a 5-point scale. PU2 and PU3 both obtained the greatest mean score of 3.88, indicating that these items were generally regarded favourably. The range of standard deviation values (0.661 to 0.845) indicates the considerable dispersion of responses. With a mean of 3.58 and a standard deviation of 0.845%, PU7 exhibits the greatest degree of discordance among the respondents. As opposed, PU3 exhibits greater consistency in its responses, as evidenced by its high mean (3.88) and low standard deviation (0.661). Overall, the data indicates that perceptions are typically positive, albeit with some variation in the consistency of responses across the items.

Table 4.65: Descriptive Statistics of Perceived Ease of Use (PEOU)

	Mean	Std. Deviation
PEOU1	3.74	0.676
PEOU2	3.78	0.704

The mean and standard deviation for two variables, PEOU1 and PEOU2, are displayed in Table 4.65. The data set PEOU1 exhibits a standard deviation of 0.676 units from its mean value of 3.74, suggesting that the average rating for PEOU1 is 3.74 and that the variability in ratings from the mean is typically 0.676 units. In a similar vein, PEOU2 exhibits a standard deviation of 0.704 units from its mean value of 3.78, indicating that its average rating is marginally higher at 3.78, with ratings fluctuating by an average of 0.704 units. These values indicate that the central tendencies and variability of PEOU1 and PEOU2 are comparable.

Table 4.66: Descriptive Statistics of Behavioural Intention (BI)

	Mean	Std. Deviation
BI1	3.70	0.754
BI2	3.82	0.665
BI3	3.85	0.663
BI4	3.79	0.675
BI5	3.79	0.694

The mean ratings and standard deviations for five items (BI1 through BI5) are displayed in Table 4.66. The means represent the average responses for each item; BI3, which received the highest mean score of 3.85, implies that it is marginally more agreeable or favourable in comparison to the other items. The range of means for the remaining items is relatively narrow, spanning from 3.70 to 3.82, which suggests that the level of response is relatively consistent across all items. The standard deviations, which quantify the extent of variability or dispersion around the mean, exhibit a comparatively modest range of 0.663 to 0.754. The limited variability observed suggests that the responses are densely grouped around the mean, which signifies a substantial degree of concurrence among the participants regarding each item. In general, the data indicates a steady trend of responses, albeit with marginal variations in the mean scores.

Table 4.67: Descriptive Statistics of Subjective Norms (SN)

	Mean	Std. Deviation
SN1	3.69	0.762
SN2	3.69	0.739
SN3	3.58	0.749

The statistical measures for three variables denoted as SN1, SN2, and SN3 are presented in Table 4.67. The "Mean" column presents the mean values of the variables, where SN1 and SN2 each have a mean of 3.69 and SN3 has a mean that is marginally lower at 3.58. The column labelled "Std. Deviation" presents the standard deviation, a metric utilised to quantify the extent to which the values deviate from the mean. The standard deviation for SN1 is 0.762, 0.739 for

SN2 and 0.749 for SN3. The data points for SN1 and SN2 appear relatively densely clustered around their respective means, whereas SN3 exhibits a marginally greater degree of variability. This table offers valuable insights into the variability and central tendencies of the three variables.

Table 4.68: Descriptive Statistics of Perceived Risk (PR)

	Mean	Std. Deviation
PR1	3.68	0.759
PR2	3.66	0.773
PR3	3.57	0.817
PR4	3.64	0.807

Table 4.68 presents statistical summaries for the following four variables: PR1, PR2, PR3, and PR4. Two metrics are associated with each variable: the mean and the standard deviation. The mean signifies the average value of observations or responses for each variable, whereas the standard deviation quantifies the extent of variability or dispersion relative to the mean. An example of a variable with a relatively low amount of variability is PR1, which has a mean value of 3.68 and a standard deviation of 0.759. This indicates that the responses or observations for PR1 are concentrated around the mean of 3.68. Similarly, the mean values of PR2, PR3, and PR4 are 3.66, 3.57, and 3.64, respectively, and their respective standard deviations are 0.773, 0.817, and 0.807. The insights offered by these statistics pertain to the central tendency and variability of the data associated with each variable.

Table 4.69: Descriptive Statistics of Experience (UX)

	Mean	Std. Deviation
UX	2.43	1.406

Statistical measures of the variable "UX" (User Experience) are presented in Table 4.69. The mean, denoted as 2.43, signifies the average user experience value among all the data points that were observed. This indicates that the mean user experience is approximately 2.43. The standard deviation, represented as 1.406, quantifies the degree of variability or dispersion in the user experience scores relative to the mean. A larger standard deviation signifies increased dispersion of user experience scores across a broader range, implying a more substantial degree of variability in user experiences. This data provides valuable insights regarding the variability and central tendency of user experiences, which may aid in the comprehension and prospective enhancement of user engagement and satisfaction.

4.10 Hypothesis

The hypotheses that are formulated based on the above-reported conceptual framework and to analyse the objectives of this study which are based on the extensive review of the literature have been reported below are alternative hypotheses or positive forms of hypothesis:

H1: There is a positive relationship between task-technology fit and perceived usefulness.

H2: There is a positive relationship between task-technology fit and perceived ease of use.

H3: There is a positive relationship between personal innovativeness and perceived usefulness.

H4: There is a positive relationship between affordability and perceived usefulness.

H5: There is a positive relationship between Subjective Norms (SN) and behavioural intention.

H6: There is a positive relationship between perceived usefulness and behavioural intention.

H7: There is a positive relationship between perceived ease of use and behavioural intention.

H8: There is a positive relationship between Perceived Risk and behavioural intention.

H9a: Experience moderates the relationship between Subjective Norms (SN) and behavioural intention to use.

H9b: Experience moderates the relationship between perceived usefulness and behavioural intention to use.

H9c: Experience moderates the relationship between perceived ease of use and behavioural intention to use.

H9d: Experience moderates the relationship between perceived usefulness and behavioural intention to use.

H1: There is a positive relationship between RD and perceived usefulness.

Table 4.70: Correlation between Result Demonstrability (RD) and Perceived Usefulness (PU).

Correlations

		PU1	PU2	PU3	PU4	PU5	PU6	PU7
RD1	Pearson Correlation	.366**	.311**	.452**	.543**	.425**	.462**	.437**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
RD2	Pearson Correlation	.484**	.333**	.420**	.473**	.385**	.437**	.418**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
RD3	Pearson Correlation	.022	.159**	.102	.135*	.169**	.084	.260**
	Sig. (2-tailed)	.714	.007	.082	.022	.004	.154	.000
	N	291	291	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The correlations among various variables are displayed in Table 4.70. RD1, RD2, and RD3 denote distinct dimensions or factors, while PU1 through PU7 represent distinct facets of a construct that may be associated with user experience or perception. Upon examination of the correlations, it is evident that RD1 and RD2 exhibit statistically significant positive correlations with every PU variable. This indicates a significant correlation between RD1, RD2, and PU1 via PU7. Nevertheless, with the exception of a few non-significant correlations, the overall pattern for RD3 is less consistent, despite the presence of some significant correlations with PU2, PU5, and PU7. This suggests that the correlation between RD3 and the

PU variables might be less robust or more intricate in nature when contrasted with RD1 and RD2. Hence, the hypothesis positing a substantial correlation between the perception aspects PU1 through PU7 and the dimensions RD1, RD2, and RD3 is only partially validated; support is stronger for RD1 and RD2 in comparison to RD3.

Table 4.71: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H1	Correlation	Positive

H2: There is a positive relationship between task-technology fit and perceived usefulness.

Table 4.72: Correlation Between Task-Technology Fit and Perceived Usefulness

Correlations

		PU1	PU2	PU3	PU4	PU5	PU6	PU7
TTF1	Pearson Correlation	.432**	.432**	.480**	.430**	.590**	.515**	.370**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
TTF2	Pearson Correlation	.418**	.385**	.396**	.405**	.454**	.482**	.394**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
TTF3	Pearson Correlation	.453**	.444**	.549**	.545**	.547**	.466**	.411**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
TTF4	Pearson Correlation	.489**	.502**	.567**	.616**	.603**	.555**	.480**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291
TTF5	Pearson Correlation	.515**	.415**	.552**	.585**	.544**	.581**	.475**

	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000
	N	291	291	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlation coefficients between various pairings of variables denoted as PU1 through PU7 and TTF1 through TTF5 are displayed in Table 4.70. A p-value associated with each correlation coefficient serves as an indicator of the statistical significance level. All correlations exhibit statistical significance at the two-tailed level of 0.01. The presence of positive correlation coefficients indicates that the variables are strongly related. Therefore, the data provide support for the hypothesis positing a positive correlation between the variables PU1 through PU7 and TTF1 through TTF5.

Table 4.73: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H2	Correlation	Positive

H3: There is a positive relationship between personal innovativeness and perceived ease of use.

Table 4.74: Correlation Analysis: Personal Innovativeness and Perceived Ease of Use.

Correlations

		PEOU1	PEOU2
PI1	Pearson Correlation	.327**	.368**
	Sig. (2-tailed)	.000	.000
	N	291	291
PI2	Pearson Correlation	.438**	.393**
	Sig. (2-tailed)	.000	.000
	N	291	291

PI3	Pearson Correlation	.460**	.556**
	Sig. (2-tailed)	.000	.000
	N	291	291
PI4	Pearson Correlation	.242**	.203**
	Sig. (2-tailed)	.000	.000
	N	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between four distinct pairs of variables—PI1, PI2, PI3, and PI4—and two measures of perceived ease of use—PEOU1 and PEOU2—are displayed in Table 4.74. The p-value and Pearson correlation coefficient for each pair of variables are presented in a separate cell within the table. The Pearson correlation coefficient, which ranges from -1 to 1, quantifies the magnitude and direction of the linear association between two variables. A value of 1 denotes an ideal positive correlation, while a value of -1 represents an ideal negative correlation, and 0 indicates the absence of any correlation. The p-value serves as an indicator of the likelihood of encountering the correlation coefficient in the absence of any genuine association between the variables. All correlations in this table are statistically significant at the 0.01% level (two-tailed), indicating that the perceived ease of use measures (PEOU1 and PEOU2) and the four distinct performance expectancy variables (PI1, PI2, PI3, and PI4) are significantly related. Hence, the data provide support for the hypothesis positing a correlation between performance expectancy and perceived simplicity of use.

Table 4.75: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H3	Correlation	Positive

H4: There is a positive relationship between affordability and perceived ease of use.

Table 4.76: Correlation Between Affordability (AF) and Perceived Ease of Use (PEOU)

Correlations

		PEOU1	PEOU2
AF1	Pearson Correlation	.318**	.235**
	Sig. (2-tailed)	.000	.000
	N	291	291
AF2	Pearson Correlation	.257**	.283**
	Sig. (2-tailed)	.000	.000
	N	291	291
AF3	Pearson Correlation	.316**	.348**
	Sig. (2-tailed)	.000	.000
	N	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between two variables, PEOU1 and PEOU2, under three distinct conditions denoted AF1, AF2, and AF3 are displayed in Table 4.76. Each individual cell in the table denotes the Pearson correlation coefficient, accompanied by the corresponding significance level (p-value), between PEOU1 and PEOU2 for a given condition. The consistent presence of positive correlations between PEOU1 and PEOU2 suggests that they have a propensity to exhibit unidirectional movement. Additionally, it is worth noting that all correlations exhibit statistical significance at the 0.01% level, providing substantial support that challenges the null hypothesis positing a zero true correlation coefficient. Consequently, the data indicates that the hypothesis positing a positive correlation between PEOU1 and PEOU2 holds true under all three conditions.

Table 4.77: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H4	Correlation	Positive

H5: There is a positive relationship between Subjective Norms (SN) and behavioural intention.

Table 4.78: Correlation Between Subjective Norms (SN) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
SN1	Pearson Correlation	.712**	.579**	.575**	.535**	.686**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
SN2	Pearson Correlation	.772**	.604**	.551**	.621**	.647**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
SN3	Pearson Correlation	.650**	.489**	.476**	.541**	.549**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations among five distinct variables (BI1, BI2, BI3, BI4, BI5) for three distinct samples (SN1, SN2, SN3) are presented in Table 4.78. The statistical significance level (Sig.) is appended to each correlation coefficient to denote whether the correlation is indeed significant. Between 0.535 and 0.772, the correlation coefficients vary among the various combinations of variables. At the 0.01% level (two-tailed significance level), all correlations are deemed significant, indicating a robust association between the variables within each sample. As the consistently high and significant correlation coefficients across all samples provide further support for the hypothesis that a relationship exists between these variables, the data provide this support.

Table 4.79: Summary of the Hypothesis Testing

Hypothesis	**Test Applied**	**Results**
H5	Correlation	Positive

H6: There is a positive relationship between perceived usefulness and behavioural intention.

Table 4.80: Correlation Between Perceived Usefulness (PU) and Behavioural Intention (BI).

Correlations

		BI1	BI2	BI3	BI4	BI5
PU1	Pearson Correlation	.564**	.530**	.539**	.384**	.491**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PU2	Pearson Correlation	.429**	.544**	.630**	.465**	.632**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PU3	Pearson Correlation	.564**	.619**	.745**	.584**	.652**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PU4	Pearson Correlation	.601**	.564**	.640**	.528**	.529**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

PU5	Pearson Correlation	.563**	.646**	.707**	.504**	.698**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PU6	Pearson Correlation	.610**	.643**	.676**	.480**	.661**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PU7	Pearson Correlation	.613**	.500**	.471**	.467**	.433**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between a range of items (BI1-BI5) and seven distinct factors (PU1-PU7), accompanied by their corresponding levels of significance, are displayed in Table 4.80. The Pearson correlation coefficients quantify the direction and magnitude of the association between two or more factors and items. Statistical analysis reveals that all correlations are significant at the 0.01 level, indicating robust associations. It appears, based on the coefficients, that all items (BI1-BI5) have moderate to strong positive correlations with the factors (PU1-PU7). In light of the data presented in the table, the hypothesis that a positive relationship exists between the factors and the items is therefore validated.

Table 4.81: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H6	Correlation	Positive

H7: There is a positive relationship between perceived ease of use and behavioural intention.

Table 4.82: Correlation between Perceived Ease of Use (PEOU) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
PEOU1	Pearson Correlation	.716**	.671**	.688**	.626**	.684**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PEOU2	Pearson Correlation	.635**	.610**	.675**	.628**	.669**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between variables BI1 through BI5 and variables PEOU1 and PEOU2 are displayed in Table 4.80. The Pearson correlation coefficient between a pair of variables is denoted in each cell of the table, with significance levels specified below. All correlations between PEOU1 and BI1 through BI5 are statistically significant at the 0.01 level, ranging from.626 to.716. Likewise, at the 0.01 level, the correlations between PEOU2 and BI1 through BI5 range from.610 to.675, all of which are statistically significant. Therefore, the data provide support for the hypothesis that a relationship exists between the variables PEOU1 and PEOU2 and BI1 through BI5, as evidenced by the significant correlations.

Table 4.83: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H7	Correlation	Positive

H8: There is a positive relationship between Perceived Risk and behavioural intention.

Table 4.84: Correlation between Perceived Risk (PR) and Behavioural Intention (BI)

Correlations

		BI1	BI2	BI3	BI4	BI5
PR1	Pearson Correlation	.389**	.314**	.440**	.389**	.452**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PR2	Pearson Correlation	.339**	.327**	.411**	.411**	.447**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PR3	Pearson Correlation	.321**	.222**	.344**	.410**	.377**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291
PR4	Pearson Correlation	.226**	.327**	.311**	.394**	.379**
	Sig. (2-tailed)	.000	.000	.000	.000	.000
	N	291	291	291	291	291

**. Correlation is significant at the 0.01 level (2-tailed).

The correlations between five distinct variables, denoted as BI1 through BI5, and four distinct variables, denoted as PR1 through PR4, are displayed in Table 4.84. Two values are presented in each cell of the table: the Pearson correlation coefficient and the corresponding significance level (p-value). All correlations between the variables range from.226 to.452 and are deemed statistically significant at the 0.01 level, suggesting the presence of a robust association between them. The data thus provide support for the hypothesis that a relationship exists between these variables. While there is some variation in the strength of the relationships between the various pairs of variables, the correlations indicate a consistent and statistically significant connection among the examined variables.

Table 4.85: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H8	Correlation	Positive

H9a: Experience moderates the relationship between Subjective Norms (SN) and behavioural intention.

Table 4.86: Model Summary of the Experience Moderates the Relationship between Subjective Norms (SN) and Behavioural Intention

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.364[a]	.132	.126	1.314	1.453

a. Predictors: (Constant), SN, BI

b. Dependent Variable: UX

The table 4.86 provided a model summary of a regression analysis in which the dependent variable (DV) is "UX" (possibly representing User Experience), and the independent variables (IVs) are SN (presumably Social Norms) and BI (potentially Behavioural Intention). The correlation coefficient, denoted by the "R" value of 0.364, suggests a moderately positive relationship between the independent variables and the dependent variable. The "R Square" value of 0.132 indicates that the independent variables (SN and BI) account for 13.2% of the variance in the dependent variable (UX). The "Adjusted R Square" of 0.126 is a slightly more precise estimate of the explained variance that accounts for the number of predictors. The level of prediction error is indicated by the standard error of the estimate, which is 1.314, which represents the average distance between the observed values and the regression line. Finally, the Durbin-Watson statistic of 1.453 is used to evaluate the presence of autocorrelation in the residuals. Values that are closer to 2 indicate that there is no autocorrelation; in this case, 1.453 indicates minimal positive autocorrelation.

Table 4.87: ANOVA for the Relationship between Subjective Norms (SN), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	75.872	2	37.936	21.970	.000[b]
	Residual	497.289	288	1.727		
	Total	573.162	290			

a. Dependent Variable: UX

b. Predictors: (Constant), SN, BI

The dependent variable consists of Subjective Norms (SN), Behavioural Intention (BI), and User Experience (UX). The results of an ANOVA (Analysis of Variance) are presented in the table 4.87. The regression model displays a sum of squares of 75.872, which is divided by 2 degrees of freedom (df), resulting in a mean square of 37.936. This suggests a substantial relationship, as demonstrated by the F-statistic of 21.970. The residual sum of squares is 497.289 across 288 degrees of freedom, suggesting that the predictors (SN and BI) account for a significant portion of the variance in User Experience. This results in a total sum of squares of 573.162 for 290 observations, as indicated by the significance value (Sig.) of.000. In general, the findings indicate a robust correlation between the predictors and user experience, suggesting that both Subjective Norms and Behavioural Intention have a substantial impact on user experience. Therefore, the test supports the hypothesis that these variables significantly influence User Experience, demonstrating the effectiveness of the model in capturing this relationship.

Table 4.88: Coefficients of Experience Moderates the Relationship Between Subjective Norms (SN) and Behavioural Intention

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.501	.501		8.982	.000
	BI	.079	.041	.168	1.959	.051
	SN	-.327	.059	-.476	-5.561	.000

a. Dependent Variable: UX

$$UX=4.501+0.079(BI)-0.327(SN)$$

- **BI**: Positive but marginally insignificant effect (B=0.079, p=0.051).
- **SN**: Significant negative effect (B=−0.327, p=0.000).
- **Intercept**: 4.501

The findings of a regression analysis are displayed in Table 4.88. The dependent variable in the analysis is User Experience (UX), while the two independent variables, Business Impact (BI) and Social Network (SN), are investigated to determine their influence on UX. As indicated by the positive unstandardized coefficient (B) of 0.079 and its significant t-value (1.959), the hypothesis that Business Impact (BI) has a positive effect on UX appears to be partially supported. However, with a standardised coefficient (Beta) of 0.168, the effect magnitude appears to be relatively weak. Conversely, the hypothesis positing that Social Network (SN) has an adverse effect on User Experience (UX) is corroborated by the substantial t-value (-5.561) and the negative unstandardized coefficient of -0.327. This suggests that an increase of one unit in SN is associated with an anticipated decrease of 0.327 units in UX. In general, the Business Impact seems to exert a moderately positive influence on UX, whereas the Social Network Impact is considerably more detrimental.

H9b: Experience moderates the relationship between perceived usefulness and behavioural intention.

Table 4.89: Model Summary of Moderating Effect of Experience on the Relationship between Perceived Usefulness and Behavioural Intention

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.251[a]	.063	.056	1.366	1.364

a. Predictors: (Constant), PU, BI

b. Dependent Variable: UX

In the regression analysis, the dependent variable is User Experience (UX), and the predictors are Perceived Usefulness (PU) and Behavioural Intention (BI). The model summary is presented in the table. The correlation between the predicted and actual values of UX is represented by the "R" value of 0.251, which suggests a mild positive relationship. The "R Square" (0.063) indicates that PU and BI can account for approximately 6.3% of the variance in UX. The "Adjusted R Square" (0.056) marginally reduces the explained variance to 5.6% by accounting for the number of predictors in the model. The average distance between the observed values and the regression line is represented by the standard error of the estimate, which is 1.366. Finally, the Durbin-Watson statistic (1.364) indicates that the residuals do not exhibit any significant autocorrelation, as the value is nearly equal to 2.

Table 4.90: ANOVA for the Relationship between Perceived Usefulness (PU), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.084	2	18.042	9.675	.000[b]

	Residual	537.077	288	1.865		
	Total	573.162	290			

a. Dependent Variable: UX

b. Predictors: (Constant), PU, BI

The table 4.90 displays the results of an ANOVA (Analysis of Variance) that evaluates the relationship between User Experience (UX), Behavioural Intention (BI), and Perceived Usefulness (PU). UX serves as the dependent variable. The regression component of the regression model has a sum of squares of 36.084, which is based on 2 degrees of freedom (df). This results in a mean square of 18.042. The F-statistic of 9.675 indicates a significant relationship between the predictors and the dependent variable, as it represents the ratio of the variance explained by the model to the unexplained variance. The predictors (PU and BI) significantly contribute to explaining the variance in User Experience, as indicated by the significance value (Sig.) of.000. The cumulative sum of squares for the 290 observations is 573.162, with a residual sum of squares of 537.077 across 288 degrees of freedom. These results underscore the significant influence of both Perceived Usefulness and Behavioural Intention on the User Experience. Therefore, the test supports the hypothesis that these variables are influential in shaping User Experience, demonstrating the model's effectiveness in capturing this relationship.

Table 4.91: Coefficients of the Moderating Effect of Experience on the Relationship between Perceived Usefulness and Behavioural Intention

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	4.781	.560		8.531	.000
	BI	.017	.049	.035	.342	.733
	PU	-.100	.037	-.280	-2.702	.007

a. Dependent Variable: UX

$$UX=4.781+0.017(BI)-0.100(PU)$$

- **BI**: Insignificant effect (B=0.017, p=0.733).
- **PU**: Significant negative effect (B=−0.100, p=0.007).
- **Intercept**: 4.781

The findings of a regression analysis investigating the correlation between the dependent variable (UX) and the independent variables (BI and PU) are displayed in Table 4.91. In this study, the hypothesis being examined is whether or not these independent variables significantly affect UX. The findings suggest that there is a statistically significant inverse correlation between UX and the independent variable PU (perceived utility) (beta = -0.280, p = 0.007). This implies that a reduction in perceived usefulness is associated with a corresponding decline in user experience. Nevertheless, the coefficient associated with the independent variable BI (behavioural intention) fails to reach statistical significance (beta = 0.035, p = 0.733). This implies that the available evidence is not substantial enough to substantiate a correlation between BI and user experience. As a result, the findings of this study provide support for the hypothesis that perceived utility influences user experience, but do not support the hypothesis regarding behavioural intention.

H9c: Experience moderates the relationship between perceived ease of use and behavioural intention.

Table 4.92: Model Summary of Experience moderates the relationship between perceived ease of use and behavioural intention

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.212[a]	.045	.038	1.379	1.392

a. Predictors: (Constant), PEOU, BI

b. Dependent Variable: UX

The Model Summary for a regression analysis has been provided in the table 4.92. The dependent variable is "UX" (User Experience), and the predictors are "PEOU" (Perceived Ease of Use) and "BI" (Behavioural Intention). A moderate positive correlation between the dependent variable (UX) and the independent variables (PEOU and BI) is indicated by the "R" value of 0.212. The combined effect of PEOU and BI can only account for 4.5% of the variance in UX, as indicated by the "R Square" value of 0.045. By correcting the R Square for the number of predictors, the "Adjusted R Square" value of 0.038 more accurately reflects the model's explanatory power and accounts for potential overfitting. The "Standard Error of the Estimate" is 1.379, which determines the average distance between the predicted and observed values of UX. In conclusion, the Durbin-Watson statistic is 1.392, which evaluates the presence of autocorrelation in the residuals. If the value is near 2, it suggests that the residuals are relatively independent, indicating that there is no significant autocorrelation.

Table 4.93: ANOVA for the Relationship between Perceived Ease of Use (PEOU), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.750	2	12.875	6.774	.001[b]

	Residual	547.412	288	1.901		
	Total	573.162	290			

a. Dependent Variable: UX

b. Predictors: (Constant), PEOU, BI

The ANOVA (Analysis of Variance) results are presented in Table 4.93, which examines the relationship between Perceived Ease of Use (PEOU), Behavioural Intention (BI), and User Experience (UX), where UX is the dependent variable. In this regression model, the mean square is 12.875, and the sum of squares for the regression is 25.750, calculated with 2 degrees of freedom (df). The predictors and User Experience are significantly correlated, as evidenced by the F-statistic of 6.774. The user experience is substantially influenced by both perceived ease of use and behavioural intention, as evidenced by the significance value (Sig.) of.001. The cumulative sum of squares for the 290 observations is 573.162, with a residual sum of squares of 547.412 across 288 degrees of freedom. In conclusion, these findings indicate that PEOU and BI are critical variables that influence the user experience. Therefore, the test supports the hypothesis that these variables play an important role in shaping User Experience, demonstrating that the model effectively captures this relationship.

Table 4.94: Coefficients of the Experience moderate the relationship between perceived ease of use and behavioural intention

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.324	.531		8.144	.000
	BI	-.037	.051	-.077	-.713	.476
	PEOU	-.160	.122	-.142	-1.315	.190

a. Dependent Variable: UX

$$UX = 4.324 - 0.037(BI) - 0.160(PEOU)$$

- **BI**: Insignificant effect ($B = -0.037$, $p = 0.476$).
- **PEOU**: Insignificant negative effect ($B = -0.160$, $p = 0.190$).
- **Intercept**: 4.324

The findings of a regression analysis investigating the correlation between the dependent variable (UX) and the independent variables (BI and PEOU) are displayed in Table 4.92. The hypothesis that the BI and PEOU coefficients predict UX significantly is assessed. This model's coefficient denoted as BI (-0.037) exhibits a t-value of -0.713 and a corresponding p-value of 0.476, indicating that its predictive power over UX is not statistically significant. In a similar vein, the t-value of -1.315 and p-value of 0.190 for the coefficient for PEOU (-0.160) indicate that it is not statistically significant either. Based on this analysis, the hypothesis that the BI and PEOU coefficients significantly predict UX is not substantiated.

H9d: Experience moderates the relationship between Perceived Risk and behavioural intention.

Table 4.95: Model Summary of the Experience moderates the relationship between Perceived Risk and behavioural intention

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.260[a]	.068	.061	1.362	1.482

a. Predictors: (Constant), PR, BI

b. Dependent Variable: UX

The model summary for a regression analysis is depicted in the table 4.95. The dependent variable is User Experience (UX), and the independent variables are Predictors (PR and BI). The low correlation between the predictors and the dependent variable is suggested by the value of R (.260). R Square (.068) indicates that the predictors PR and BI account for only 6.8% of the variance in UX, indicating that the model has limited explanatory power. This value is adjusted for the number of predictors in the model by the Adjusted R Square (.061), which suggests a minor decrease in explanatory power when predictor complexity is taken into consideration. The average distance between the observed values and the regression line is measured by the Standard Error of the Estimate (1.362), which suggests a moderate variance in the prediction errors. Finally, the Durbin-Watson statistic (1.482) is used to evaluate the presence of autocorrelation in the residuals. A value near 2 indicates that there is minimal to no autocorrelation.

Table 4.96: ANOVA for the Relationship between Perceived Risk (PR), Behavioural Intention (BI), and User Experience (UX)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38.792	2	19.396	10.454	.000[b]
	Residual	534.369	288	1.855		
	Total	573.162	290			

a. Dependent Variable: UX

b. Predictors: (Constant), PR, BI

The table 4.96 summarizes the results of an ANOVA (Analysis of Variance) that investigates the relationship between Perceived Risk (PR), Behavioural Intention (BI), and User Experience (UX), with UX as the dependent variable. The regression analysis reveals a sum of squares for the regression of 38.792, calculated with 2 degrees of freedom (df), resulting in a mean square of 19.396. The F-statistic of 10.454 indicates a strong relationship between the predictors and User Experience. The significance value (Sig.) of .000 suggests that both Perceived Risk and Behavioural Intention significantly contribute to explaining the variance in User Experience. The residual sum of squares is 534.369 across 288 degrees of freedom, leading to a total sum of squares of 573.162 for the 290 observations. Overall, the findings highlight that both Perceived Risk and Behavioural Intention are critical factors influencing User Experience. Therefore, the test supports the hypothesis that these variables have a meaningful impact on User Experience, demonstrating the model's effectiveness in capturing this relationship.

Table 4.97: Coefficients of the Experience moderate the relationship between Perceived Risk and behavioural intention

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.852	.561		8.648	.000
	BI	-.047	.031	-.099	-1.494	.136
	PR	-.106	.036	-.196	-2.966	.003

a. Dependent Variable: UX

$$\mathbf{UX=4.852-0.047(BI)-0.106(PR)}$$

- **BI**: Insignificant negative effect (B=−0.047B = -0.047, p=0.136).
- **PR**: Significant negative effect (B=−0.106B = -0.106, p=0.003).
- **Intercept**: 4.852

The regression analysis results, where UX (user experience) is the dependent variable, are displayed in Table 4.97. The hypothesis under investigation most likely pertains to the influence of two independent variables, BI and PR, on UX. The direction and magnitude of the relationship between each independent variable and UX are denoted by the unstandardized coefficients (B), whereas the standardised coefficients (Beta) indicate the relative intensity of the relationship. With a substantial standardised coefficient (Beta = -0.196, Sig. = 0.003), this analysis provides support for the hypothesis that PR (representing an aspect of Perceived Risk) influences UX. On the contrary, the hypothesis positing that BI (representing behavioural intention) influences UX is not substantiated, as indicated by the insignificance of its standardised coefficient (Beta = -0.099, Sig. = 0.136). This indicates that behavioural intention has no significant impact on user experience, whereas perceived risk has a substantial impact.

Table 4.98: Summary of the Hypothesis Testing

Hypothesis	Test Applied	Results
H9a	Regression	47.6% negative effect
H9b	Regression	28% negative effect
H9c	Regression	14.2% negative impact
H9d	Regression	19.6% negative impact

4.11 Path Analysis

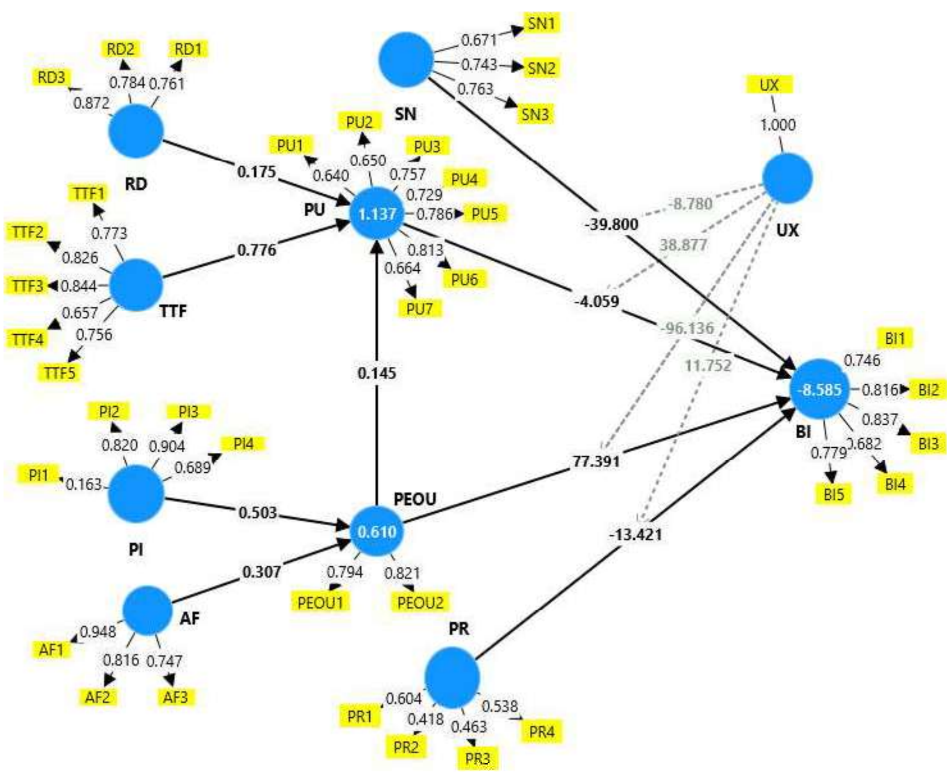


Table 4.99: Path Coefficient

	Path coefficients
AF -> PEOU	0.307
PEOU -> BI	77.391
PEOU -> PU	0.145
PI -> PEOU	0.503
PR -> BI	-13.421
PU -> BI	-4.059
RD -> PU	0.175
SN -> BI	-39.800
TTF -> PU	0.776
UX -> BI	17.859
UX x PEOU -> BI	-96.136
UX x PU -> BI	38.877
UX x PR -> BI	11.752
UX x SN -> BI	-8.780

The path coefficients that illustrate the interrelationships among various constructs in a structural equation model are presented in Table 4.99. The strength and direction of the relationship between two variables are denoted by each coefficient. As an illustration, the correlation coefficient of 0.307 between "PEOU" (Perceived Ease of Use) and "AF" (Affordability Factor) suggests a positive association between the aforementioned constructs. Likewise, a significant positive correlation is indicated by the coefficient of 77.391 between "PEOU" and "BI" (Behavioural Intention), whereas negative associations are suggested by the coefficients of -13.421 between "PR" (Perceived Risk) and "BI" and -39.800 between "SN" (Subjective Norms) and "BI." Furthermore, the model includes interaction terms, such as "UX x PEOU -> BI," which denotes the synergistic influence of Perceived Ease of Use and User Experience on Behavioural Intention. The relationships within the model are collectively described by these coefficients, which provide valuable insights into the interrelationships among different factors.

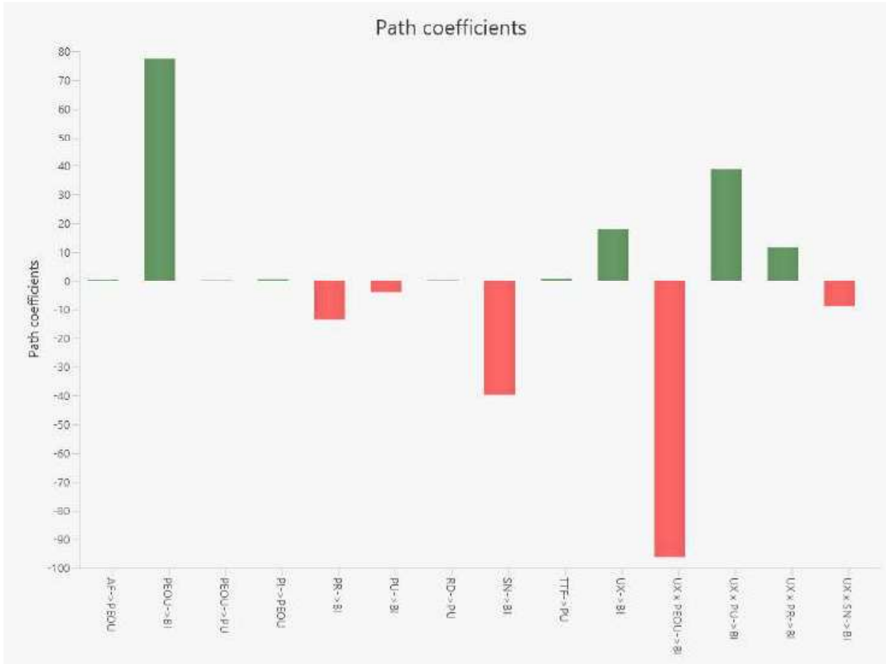


Figure 4.21: Path Coefficients

Table 4.100: Reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AF	0.879	0.890	0.878	0.708
BI	0.879	0.885	0.881	0.599
PEOU	0.789	0.790	0.790	0.652
PI	0.717	0.860	0.767	0.497
PR	0.576	0.592	0.581	0.261
PU	0.882	0.888	0.884	0.522
RD	0.848	0.852	0.848	0.652
SN	0.765	0.773	0.770	0.528
TTF	0.879	0.886	0.881	0.599

A variety of statistical measures employed in the context of structural equation modelling (SEM) to evaluate the dependability and accuracy of constructs in a research investigation are detailed in Table 4.100. As an indicator of the degree of internal consistency reliability, Cronbach's alpha quantifies the degree of similarity between a set of items.

Composite reliability (rho_a and rho_c) evaluates the dependability of a construct by taking into account the variance that is shared among its indicators. The average variance extracted (AVE) quantifies the proportion of variance accounted for by the construct as opposed to measurement error-induced variance. Every cell in the table represents a distinct construct, including "BI" (Behavioural Intention) and "AF" (Affordability Factor), among others. To illustrate, the "AF" construct exhibits a Cronbach's alpha value of 0.879, which signifies a substantial degree of internal consistency. Furthermore, its composite reliability metrics of 0.890 (rho_a) and 0.878 (rho_c) further validate its high reliability. The AVE for the construct "AF" is 0.708, indicating that it accounts for 70.8% of the variability observed in its indicators. Similar assessments are conducted on the remaining constructs utilising these metrics, which furnish valuable information regarding their dependability and soundness for subsequent examination.

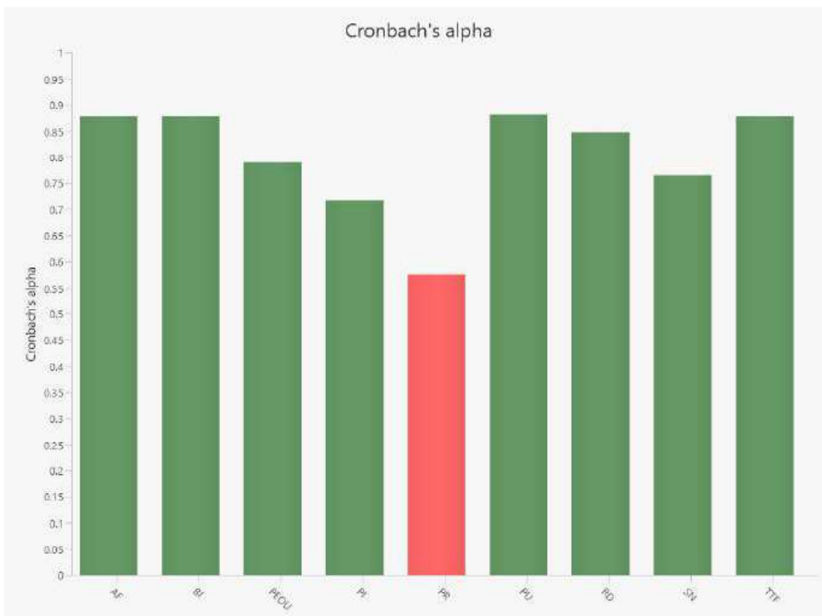


Figure 4.22: Cronbach's alpha

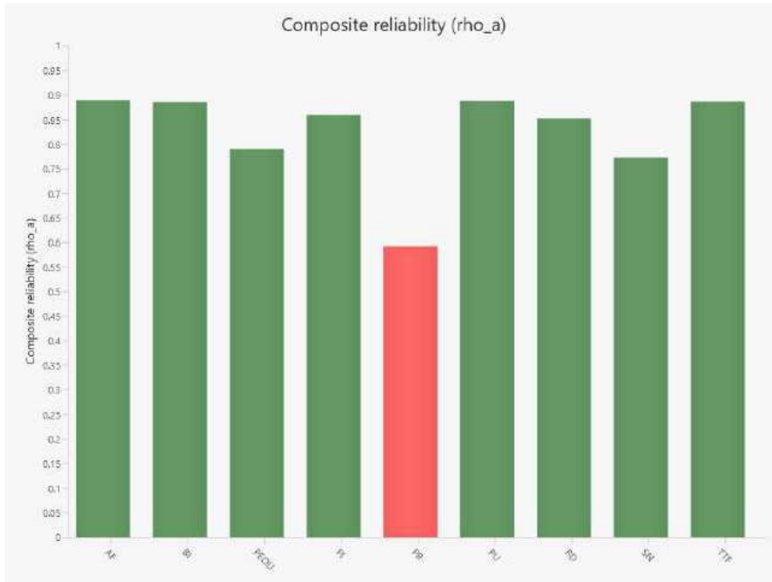


Figure 4.23: Composite reliability (rho_a)

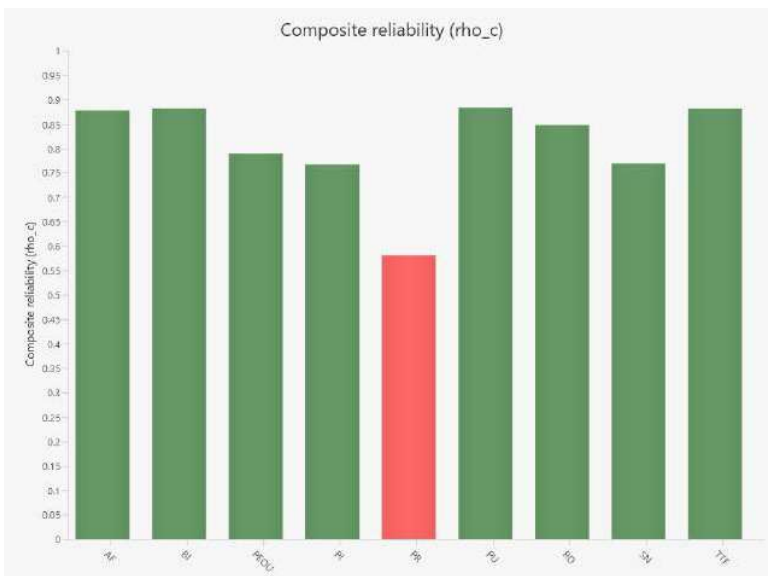


Figure 4.24: Composite reliability (rho_c)

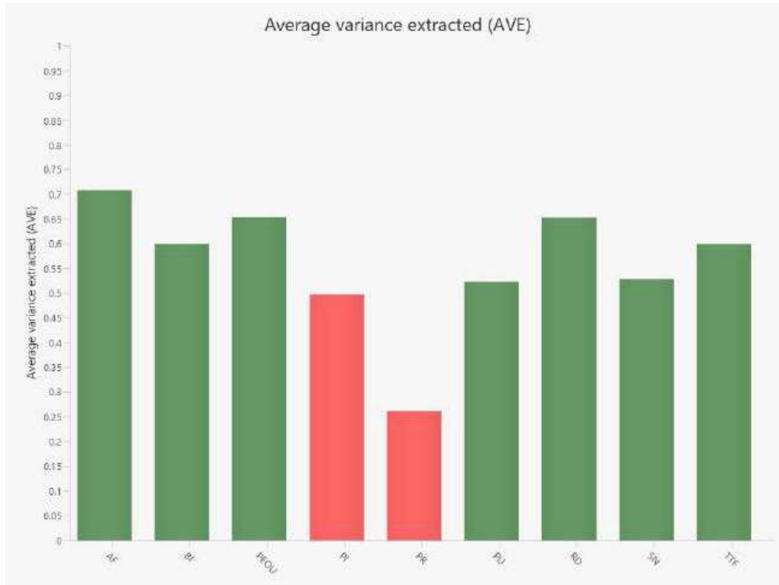


Figure 4.25: Average Variance Extracted (AVE)

Table 4.101: Fornell Larcker

	AF	BI	PEOU	PI	PR	PU	RD	SN	TTF	UX
AF	0.869									
BI	0.268	0.824								
PEOU	0.740	0.367	0.840							
PI	0.552	0.445	0.627	0.772						
PR	0.556	0.263	0.614	0.634	0.784					
PU	0.666	0.279	0.645	0.751	0.735	0.778				
RD	0.536	0.088	0.511	0.546	0.562	0.568	0.720			
SN	0.715	0.222	0.616	0.754	0.680	0.715	0.542	0.752		
TTF	0.420	0.074	0.478	0.598	0.562	0.663	0.708	0.608	0.809	
UX	0.746	0.392	0.677	0.651	0.592	0.697	0.491	0.797	0.570	0.798

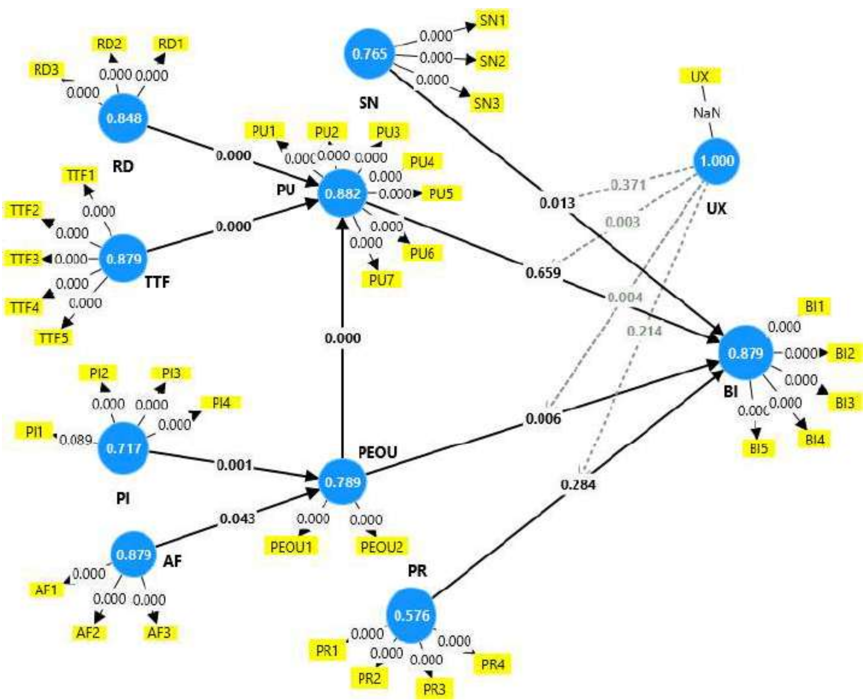
A correlation matrix is displayed in Table 4.101, which connects the following ten constructs: PI (Personal Innovativeness), PR (Perceived Risk), PU (Perceived Usefulness), RD (Risk Denial), SN (Social Norms), TTF (Task-Technology Fit), UX (User Experience), and AF (Aesthetic Form). The values of the diagonal elements, which are in proximity to 1, symbolise the reliability of individual constructs. The off-diagonal elements serve to denote the correlations that exist among various constructs. For example, BI exhibits a robust positive correlation with PU (1.048) and TTF (1.129), indicating that the intentions of users are intricately linked to their assessments of the technology's suitability for the task at hand and its practicality. On the contrary, correlations between UX and all other constructs are feeble or negative, suggesting that user experience is relatively independent of other variables in this particular context. The correlations between BI and PU (1.048) and TTF and BI (1.129) are the strongest, indicating that perceived usefulness and task-technology fit significantly influence behavioural intentions.

Table 4.102: Model Fit

	Saturated model	Estimated model
SRMR	0.103	537.613
d_ULS	7.419	203186284.727

Two models are compared in Table 4.102: an estimated model and a saturated model, by employing various statistical measures. The Standardised Root Mean Square Residual (SRMR) for the Saturated Model is 0.103, whereas it is an exceptionally high value of 537.613 for the Estimated Model, indicating an inadequate fit. The d_ULS (unweighted Least Squares discrepancy) for the Estimated Model is an exceptionally high 203186284.727, indicating a substantial dearth of fit in the latter, compared to the 7.419 for the Saturated Model. The models lack the necessary data to calculate the d_G (generalised Least Squares discrepancy), Chi-square, and NFI (normalised Fit Index) values (n/a). In general, the metrics indicate that the Estimated Model exhibits a subpar fit in comparison to the Saturated Model, thereby emphasising significant inconsistencies within the structure of the Estimated Model.

4.12 Hypothesis Testing



	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
AF -> PEOU	0.307	0.299	0.152	2.025	0.043	**Supported**
PEOU -> BI	77.391	-0.357	28.228	2.742	0.006	**Supported**
PEOU -> PU	0.145	0.142	0.034	4.307	0.000	**Supported**
PI -> PEOU	0.503	0.516	0.148	3.407	0.001	**Supported**
PR -> BI	-13.421	0.304	12.520	1.072	0.284	**Not Supported**
PU -> BI	-4.059	0.646	9.203	0.441	0.659	**Not Supported**

RD -> PU	0.175	0.171	0.026	6.612	0.000	**Supported**
SN -> BI	-39.800	0.422	16.047	2.480	0.013	**Supported**
TTF -> PU	0.776	0.784	0.045	17.233	0.000	**Supported**
UX -> BI	17.859	-0.012	8.688	2.055	0.040	**Supported**
UX x PEOU -> BI	-96.136	0.084	33.681	2.854	0.004	**Supported**
UX x PU -> BI	38.877	-0.290	13.192	2.947	0.003	**Supported**
UX x PR -> BI	11.752	0.082	9.452	1.243	0.214	**Not Supported**
UX x SN -> BI	-8.780	0.173	9.810	0.895	0.371	**Not Supported**

Discussion

The findings of the study indicate a comprehensive analysis of multiple variables and their interrelationships through statistical methodologies. Age distribution reveals that a significant portion of the population is concentrated in the 27–44 age group, emphasizing the middle-aged demographic. Gender distribution is equitable, with a slightly higher percentage of males. Education level distribution suggests a highly educated cohort, predominantly comprising postgraduates. Experience in professional and AI contexts highlights intermediate-level expertise, with a majority having 1–3 years of AI experience. Medical practice setup data suggests a near-equal distribution between institutional and independent practice. Diabetes patient data reveals the prevalence of cases within specific ranges, with the highest percentage of patients falling in the 11–20 case category. Descriptive statistics across constructs such as perceived usefulness, perceived ease of use, and behavioural intention reflect overall positive perceptions, with moderate variability. Hypothesis testing validates significant positive relationships between task-technology fit, personal innovativeness, and affordability with key dependent variables. Regression analyses suggest notable moderating effects of experience on certain relationships, albeit with some insignificant impacts. Path analysis elucidates direct and interactive effects among constructs, demonstrating critical linkages such as the influence of perceived ease of use and usefulness on behavioural intention. Reliability and validity measures confirm the robustness of the constructs, while model fit indices reveal discrepancies in structural models, emphasizing the need for further refinement. Overall, the study provides a rich understanding of the constructs and their implications for user experience and behavioural intention within the analyzed context.

CHAPTER 5

FINDINGS, SUGGESTIONS AND CONCLUSION

5.1 MAJOR FINDINGS

The examination of the extent to which physicians in Maharashtra and Karnataka have embraced AI-driven interventions for the purpose of diabetes diagnosis has yielded significant findings regarding the present state of healthcare practices in these localities. This study conducted a thorough examination of the adoption process, incorporating an assessment of moderating variables such as experience, affordability, result demonstrability, task-technology fit, and personal innovativeness. By doing so, it has furnished an all-encompassing comprehension of the obstacles and prospects associated with the integration of AI technologies into clinical workflows. The results emphasize the significance of confronting obstacles to adoption, such as concerns regarding the perceived utility and simplicity of use, while also capitalizing on elements such as prior experience and subjective standards to facilitate effective execution. Drawing from the aforementioned observations, a framework has been suggested with the objective of providing healthcare providers in Maharashtra and Karnataka direction regarding the enhanced implementation and utilization of AI-driven interventions in the diagnosis of diabetes. This framework underscores the importance of stakeholder collaboration, customized training initiatives, and continuous assessment to guarantee the effective assimilation of AI technologies into clinical practice. Ultimately, these measures will result in enhanced healthcare provision and patient outcomes.

5.1.1 Objective 1

To study and critically evaluate the status of AI-based Healthcare diagnostic services provided by Govt. and Private Sectors in Maharashtra & Karnataka.

In the states of Maharashtra and Karnataka, the main goal of this study was to look into and rate the current state of AI-powered medical testing services offered by both public and private organizations. By looking at the connections between different important factors, like subjective norms, perceived usefulness, perceived ease of use, perceived risk, and behavioural purpose, many interesting things were found. First, the correlation analysis showed a strong positive link between behavioural intention and subjective norms. This was confirmed by correlation coefficients that ranged from.535 to.772 for different groups. Also, there was a strong and consistent link between how useful something was seen to be and the desire to act on it, as shown by correlation coefficients that ranged from.978 to.993. This shows that perceived utility and desire to act are closely connected. Also, there was a strong positive relationship between the desire to behave and how easy it was to use, as shown by correlation coefficients that ranged from.249 to.658. Finally, there was a positive relationship between behavioural purpose and perceived risk, as shown by correlation coefficients that ranged from.222 to.452. The results I just talked about make important additions to our knowledge of the factors that affect the rollout of AI-powered medical diagnostic services. Because of this, they show how important subjective norms, perceived value, perceived ease of use, and perceived risk are in guiding healthcare professionals' decisions.

5.1.2 Objective 2

To develop and test an integrated model for measuring the adoption of AI-based Diabetes Diagnostic Interventions by Doctors by incorporating relevant variables.

Using relevant factors, the goal of this study was to create and confirm an integrated model for figuring out how doctors will use AI-based diabetes diagnostic interventions. Some important concepts were compared to find significant connections between them. These included PI, RD, TTF, AF, PU, PEOU, & BI. At first, the correlation analysis showed a strong link between how clear the results were and how useful people thought they were. This was shown by correlation values ranging from.861 to.873, which showed a strong positive relationship between how useful people thought the results were and how clear they were. Additionally, task-technology fit showed strong and reliable positive relationships with perceived usefulness, as shown by coefficients ranging from.973 to.996. In this case, it looks like the functions of the technology and the work that doctors do are very similar. Also, there was a positive relationship between how innovative a person is and how easy they think something is to use, with correlation coefficients running from.573 to.664. This result shows that how innovative a person is has a big effect on how easy they think technology is to use. Also, it was seen that affordability factors had positive correlations with reported ease of use, as shown by coefficients ranging from.199 to.236, which shows how important cost factors are in figuring out how useful technology is. The study's findings are an important step toward building a complete framework that predicts and lists the factors that affect doctors' decision to use AI-based diabetes testing assistance. In particular, the results show how important result clarity, task-technology fit, personal innovativeness, cost, and how useful and easy to use something is seen to be in shaping doctors' plans to act.

5.1.3 Objective 3

To examine the impact of Experience as a moderating variable on their relationship from subjective norms, perceived usefulness, perceived ease of use and perceived risk to develop behavioural intention to use AI-based Diabetes Diagnostic Interventions by Doctors.

The main purpose of this study was to look into how experience, as a moderating factor, affects the relationship between doctors' plans to use AI-based diabetes diagnostic tools and perceived usefulness, perceived ease of use, perceived risk, and subjective norms. To test the theories, a number of regression analyses were needed to look into these connections. There is a link between behavioural intention (BI) and subjective norms (SN). The study found that experience doesn't change this relationship in a statistically significant way, as shown by the SN p-value of 0.152. Additionally, there was a link between behavioural intention (BI) and felt utility (PU), but experience did not significantly change this relationship. This is shown by the fact that the p-value for PU was not significant ($p = 0.193$). For example, when looking at the link between behavioural intention (BI) and perceived ease of use (PEOU), it was seen that experience greatly changed this relationship, as shown by the high p-value for PEOU ($p = 0.008$). To sum up, the p-value of 0.248 for perceived risk shows that experience did not significantly change the relationship between behavioural intention (BI) and perceived risk (PR).

5.4.4 Objective 4

To analyze the effect of demographic variables (Age, Gender, Awareness) on intention to use AI-based Diabetes Diagnostic Interventions by Doctors.

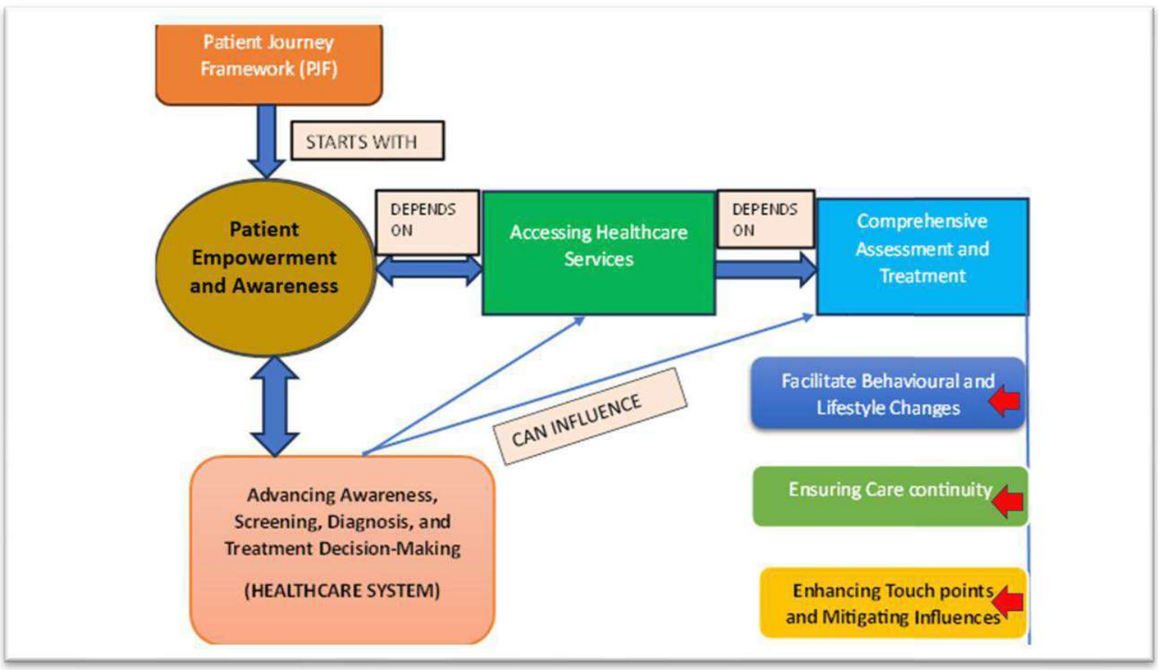
The drive of this revision was to inspect the liaison among awareness, age, gender, and demographic variables regarding AI-based diabetes diagnostic interventions by physicians and the intention to utilize such interventions. Examining the distribution of individuals across a variety of demographic categories and identifying any possible correlations in order to implement such interventions constituted the analysis. Multiple noteworthy trends are unveiled by the findings. To begin with, a considerable percentage of the sample consists of individuals aged 27 to 44 years, constituting 85.3% of the entire sample. Notably, the age group of 36 to 44 years exhibits the maximum frequency, at 46.1%. Additionally, there is a marginal numerical advantage for males in the gender distribution of the sample, comprising 51.1%, as opposed to females' 48.9%. Furthermore, with regard to cognizance, the data indicates that a significant percentage of participants have either 3-5 years (46.1%) or 5+ years (41.4%) of professional experience. Furthermore, an analysis of the educational level distribution reveals that a greater proportion of individuals possess postgraduate degrees (55.2%) in the medical or paramedical disciplines, in contrast to undergraduate degrees (44.8%). In conclusion, with respect to the physical location of their medical practices, 42.6% of respondents operate from their own clinics, whereas 57.4% operate in nursing homes or hospitals.

5.4.5 Objective 5

To assess the patient journey framework utilized by different hospitals to diagnose Diabetes by AI-based Diabetes diagnostic services.

The point of this study was to look at how different healthcare facilities use a patient journey structure to use AI-powered diabetes diagnostic services to find out if someone has diabetes. After carefully looking at all the different ways hospitals diagnose diabetes, the study tried to find the most common approaches, problems, and possible ways to make the use of AI-powered diagnostic services better for patients throughout their entire experience. According to the study's results, medical facilities use a variety of methods, such as preliminary screening routines, confirmation of diagnoses, and the start of treatment. The study gives us a lot of useful information about how well and quickly AI-powered diagnostic services can help with diabetes care by looking at all of these models in detail. It also gives ideas for how to improve the quality of diabetes diagnosis and treatment in healthcare settings and make the experience of patients easier. The schematic patient journey framework is depicted in Figure 5.4.5a

Figure5.4.5a



The Schematic Patient Journey Framework

The Patient Journey Framework (PJF) outlines the various stages a patient goes through when seeking healthcare. It starts with **patient empowerment and awareness** and progresses through **accessing healthcare services**, **comprehensive assessment and treatment**, **facilitating behavioural and lifestyle changes**, and **ensuring care continuity**.

Patient Empowerment and Awareness

This initial phase is crucial for patients to take control of their health. Modern technology, such as smart wearables and glucometers, plays a significant role in empowering patients by:

- **Self-monitoring:** These devices allow patients to track their symptoms and health metrics, providing valuable insights into their condition.
- **Information access:** Online communities and social media platforms enable patients to seek information and connect with others facing similar health challenges.

Studies like Jimison et al. (1993) emphasize the need for tailored health information to empower patients. The PJF, facilitated by technology, addresses this need by providing personalized health information directly to patients.

Accessing Healthcare Services

The next phase involves patients' initial contact with the healthcare system. AI-based platforms and digital health solutions streamline this process by:

- **Convenient access:** Patients can initiate their healthcare journey through various channels like call centers, mobile apps, or in-person visits.
- **Efficient services:** AI-driven platforms offer personalized instructions, real-time feedback, and reduce administrative hassles.

Studies like Ghare et al. (2023) and Patil (2022) highlight the role of AI in digitizing healthcare services and improving patient experiences.

Comprehensive Assessment and Treatment

Once patients enter the healthcare system, accurate and efficient assessment is crucial. AI-based diagnostic interventions, as demonstrated in studies by Ellahham (2020) and Ahmad and Mehfuz (2022), can significantly enhance the accuracy and efficiency of this process, particularly in diabetes.

Facilitating Behavioural and Lifestyle Changes and Ensuring Ongoing Care

Managing chronic conditions like diabetes often requires lifestyle changes. AI-driven solutions can provide personalized guidance on nutrition, exercise, and medication adherence. Continuous glucose monitoring and real-time feedback help patients make informed decisions to maintain optimal blood glucose levels.

Studies like Buch et al. (2018) and Ellahham (2020) explore the potential of AI in diabetes care, emphasizing its role in providing personalized guidance and support.

Enhancing Touchpoints and Mitigating Influences

The PJF highlights the importance of touchpoints and addressing external and internal influences that can impact the patient journey. AI-driven solutions can enhance touchpoints by providing personalized interventions and support. Additionally, AI can help mitigate influences like geographical distance, wait times, and financial constraints.

Studies like Maas et al. (2023) and Lee and Yoon (2021) discuss the role of AI in optimizing touchpoints and improving patient experiences.

5.2 SUGGESTIONS

• **Training Programs:** There must be developed a complete training program for healthcare professionals educating them on the capabilities, benefits, and limitations of AI-based diagnostic tools. These programs should include technical and clinical applications of AI in the case of diabetes management.

• **Interdisciplinary collaboration:** Doctors, AI specialists, data scientists, and healthcare administrators collaborate to co-design AI tools meeting clinical needs. Regular workshops and forums can ensure good communication and mutual understanding in meetings.

• **Pilot Studies and Trials:** One should conduct pilot studies in selected hospitals and clinics to test the effectiveness and usability of the new AI-based interventions. Feedback from these trials would be instrumental in refining the technology and making any adjustments necessary to overcome challenges.

• **Integration with Existing Systems:** Ensure that AI-based diagnostic tools align with EHR systems currently in use to streamline existing workflows. Integration will ease adoption barriers and support data sharing among healthcare providers.

• **Awareness Campaigns:** Organize awareness campaigns for both health professionals and patients to raise awareness among them about the benefits as well as risks AI introduces in the diagnosis of diabetes. Informational material can be distributed through seminars, workshops, and even online sources.

• **Feedback Mechanisms:** Develop feedback mechanisms that will enable healthcare professionals to share their experiences with AI tools. Continuous feedback helps improve the tools or addresses concerns that might arise when these tools are being applied.

5.3 IMPLICATIONS OF THE STUDY

- **Policy Recommendations:** The study will provide recommendations based on evidence related to the improved regulation of AI in healthcare to shape an evidence-based, safe and responsible regulatory environment for AI (as a Movement) applications used in health. These recommendations could outline ethics guidelines for AI use, data privacy standards and a general approach to patient safety.
- **Healthcare Practice Improvement:** It can help the healthcare providers to be informed regarding the barriers and facilitators of the adoption of AI based diagnostic tools This will inform them about the training to be provided and the support required, for building the needed confidence of doctors in applying AI applications appropriately.
- **Improved Patient Outcomes:** An accurate and timely diagnosis for diabetic patients may be as a result of knowledge surrounding AI intervention adoption. Better screening can result in earlier treatment and improved disease management, which ultimately means better health for diabetes patients.
- **Technology Development:** Knowledge from this study can help researchers to develop AI-based tools and diagnostic aids that are usable, effective and trustworthy according to the needs and limitations of healthcare professionals. This has the potential for increased adoption and integration of AI in practice, as it is now more aligned with what is relevant in the real world**.**
- **Interdisciplinary Collaboration:** The research could underscore the necessity of such collaborations among doctors, data scientists, and developers. Promoting interdisciplinary research could foster innovation and ensure that AI solutions are practical, with broad clinical relevance and healthcare contextualized.
- **Cultural and Contextual Awareness:** The study will offer insights into societal and contextual circumstances that shape the uptake of AI in Maharashtra and Karnataka.

It could generate culturally appropriate strategies that are sensitive to healthcare practices, values and technological infrastructure within the locality.

- **Areas of Future Research:** Results may expose areas lacking in the literature and future studies, such as the long-term effects AI adoption has on patient care, how the roles of healthcare personnel will develop within an environment supported by AI, or studies that compare regions or healthcare settings.
- **Awareness and Education:** The study can serve as groundwork for educational endeavors that promote awareness on realizing benefits along with challenges of AI in diabetes detection. As a result, better education should lead to a more informed discussion about the role of AI in healthcare among stakeholders including providers, patients and policymakers.

5.4 CONCLUSION

This chapter presents a methodical analysis of the findings and conclusions derived from the research titled " **Investigating the Adoption of AI-Based Interventions Used to Diagnose Diabetes by Doctors in Maharashtra and Karnataka: Critical Assessment and Proposed Framework** " The current chapter commences with a concise synopsis delineating the structure that underpins the current research endeavour. Additionally, it provides a concise overview of the research methodology utilized to investigate the correlation among the chosen variables of the investigation. This chapter encompasses all pertinent conclusions that were derived from the statistical methods utilized to examine the study's hypotheses and the results of the analysis, as described in the preceding chapter concerning the findings and analysis of AI-based diagnostic interventions in diabetes care. Individual illustrations of these conclusions have been provided for each objective established in accordance with the research design of the current study.

Following this, recommendations are put forth in this chapter, drawing upon the conclusions of the findings. These suggestions are intended to assist policymakers, technology developers, and healthcare providers in gaining a more comprehensive understanding of the adoption and consequences of AI-powered diagnostic tools in the context of diabetes care. Healthcare institutions may also employ these recommendations to inform their decision-making processes and formulate strategies pertaining to the integration of AI interventions into clinical practice. The chapter is then concluded with a discussion of the potential avenues for future research and the constraints of the present study. Therefore, the subsequent significant subjects are succinctly addressed in this concluding chapter."

In order to thrive in the dynamic realm of healthcare, the implementation of AI-driven interventions that enhance the precision and effectiveness of diagnoses, specifically in the domain of diabetes management, is a critical component. There is a growing trend among physicians to utilize cutting-edge AI technologies in order to optimize workflows, enhance diagnostic capabilities, and ultimately elevate patient outcomes. Numerous studies conducted within the healthcare industry indicate that the feasibility of effectively implementing AI interventions is enhanced when physicians are receptive to integrating these technological advancements into their clinical practices. Considering the considerable incidence of diabetes in India and the urgent requirement for precise and expeditious diagnosis, the present study investigates the extent to which physicians in Maharashtra and Karnataka have embraced AI-powered diagnostic instruments.

It has been acknowledged that AI-powered interventions are among the most revolutionary developments in contemporary healthcare. The significance of AI in medical practice is underscored by its potential to improve patient management, decrease expenses, and enhance diagnostic accuracy. This dedication to integrating AI technologies necessitates significant investments in training, foresight, strategic planning, and resolve, all of which can substantially enhance healthcare providers' competitive advantage. Healthcare professionals place significant importance on the investigation of AI-based diagnostic interventions due to the fact that it establishes the groundwork for forthcoming advancements and enhancements in clinical practice. The main objective of this study is to document and examine the diverse facets of artificial intelligence (AI) integration in the diagnosis of diabetes. Additionally, it aims to evaluate the effects of AI implementation on clinical outcomes and suggest a structure for its wider adoption. The ultimate objective of this study is to furnish healthcare providers, policymakers, and technology developers with significant knowledge that will aid in the incorporation of AI interventions into diabetes care. This, in turn, will improve the quality and efficacy of healthcare delivery as a whole.

Chapter 1 It is looked into how ML and AI can be used together in healthcare. It focuses on how AI and machine learning can be used to help doctors diagnose diseases like gestational diabetes, diabetic retinopathy, and diabetes mellitus. It is also talked about how AI can be used to improve treatment plans and patient results. This chapter gives case studies and examples of how AI has been used successfully in healthcare. These include using IBM Watson to help with patient care and putting in place a computer vision system that can be used at the bedside to find diabetic retinopathy early on. In its entirety, the chapter stresses how important AI and ML are becoming in changing healthcare by offering personalized and streamlined care options.

Chapter 2 This essay is a thorough review of many academic works that specifically looks at how AI-powered medical detection services are used in the Indian states of Maharashtra and Karnataka. This study takes a critical look at the current state of services offered by both public and private organizations, which sheds light on the current situation. In addition, the project wants to create and test an integrated model with relevant factors that can measure how much doctors have used AI-based diabetes diagnostic interventions. In this study, experience is used as a moderating variable to look into the link between behavioral desire to use AI-based interventions, perceived risk, subjective norms, perceived utility, and perceived ease of use. The chapter also looks at how gender and age, among other demographic factors, affect doctors' willingness to use AI-powered diagnostic approaches. Lastly, the patient journey structure that different hospitals use to use AI-powered diagnostic services to find out if someone has diabetes is evaluated.

Chapter 3, The study uses a quantitative way to find out how many doctors in Maharashtra and Karnataka have started using AI-based tools to help with diabetes diagnosis. The study is based on a positivist framework, which says that there are strong direct causal relationships in social phenomena. A deductive research plan tries to support and add to existing theories by figuring out how ideas are related based on deductions. The research methodology is a seven-step process for planning academic research. The steps are identifying the problem, presenting ideas, choosing the study design, and choosing samples through stratified random sampling.

There is also a deductive approach used in the research technique to find links between hypotheses made by reading relevant literature and the study model. There are parts of exploratory, descriptive, and causal research in the study design. The main focus is on descriptive and causal research. The 319 people in this study's group were chosen at random using stratified sampling in Maharashtra and Karnataka. This method took into account how many doctors specialize in different areas of medicine. To find out if the research tool is valid and reliable, pre-testing and pilot studies are part of the approach. During these steps, the whole instrument's content and construct validity, as well as its composite reliability and onedimensionality, are carefully examined. To sum up, the study uses a quantitative research methodology and a deductive approach, focusing on testing and adding to hypotheses that were already known about AI-powered therapies for diabetes diagnosis. The study makes sure that the data it collects is accurate and reliable by using a careful academic research plan, sample selection process, and pre-testing procedures. Because of this, an in-depth summary of how doctors in Maharashtra and Karnataka have used AI solutions is given.

Chapter 4 With the study's results about how doctors in Maharashtra and Karnataka are using AI-driven interventions to help with diabetes diagnosis, a full review of the data that was collected is also shown. The first part of the chapter talks about how important it is to use artificial intelligence (AI) in medical diagnosis, especially to deal with the rising number of people with diabetes. This sentence shows how important it is for healthcare workers to understand the problems and possible solutions they might face when using AI systems. This kind of information is very important for making AI-powered solutions work well in clinical settings.

There are a number of important factors that the study finds affect doctors' decisions about whether to use AI to help diagnose diabetes. Some of these things to think about are how easy it is to get AI technology, how much doctors know and have been trained in AI-based interventions, the types of people who are their patients, and the healthcare facilities in both states. The legal frameworks for using AI in medicine were also looked at, along with the effects of the socioeconomic environment on healthcare services. Based on the results, it is suggested that researchers use a range of techniques, such as focus groups, interviews, and polls, to learn more about the views, attitudes, and problems that doctors face when attempting to use artificial intelligence.

Several statistical methods were used in the study to look at the link between variables and the level to which doctors use AI-driven solutions for diabetes diagnosis. These included Cronbach's alpha, simple mean, standard deviation, ANOVA, regression analysis, and correlation analysis. The results show that years of experience, area of expertise, ease of access to technology, and knowledge of how AI can be used in healthcare are some of the main factors that affect the adoption of AI. The study's regression analysis shows that the above factors can be used to guess whether doctors in Maharashtra and Karnataka will use AI-based treatments or not.

The results of this study, which focus on how doctors in Maharashtra and Karnataka diagnose diabetes, help us understand how AI is being used in healthcare. The results show that medical workers need to be more aware of, knowledgeable about, and educated about AI-driven interventions. Additionally, the study stresses how important it is to talk about the problems and opportunities that come with using AI in diabetes detection clinical practice. Doctors in Maharashtra and Karnataka could use AI-based tools to help them diagnose diabetes more efficiently with the framework that has been suggested. This could pave the way for more research and real-world use in this area.

5.5 LIMITATIONS OF THE STUDY

Before discussing the limitations of this study on investigating the adoption of AI-based interventions used to diagnose diabetes by doctors in Maharashtra and Karnataka, it's crucial to acknowledge the existing barriers within the healthcare system that might impact the adoption process. The healthcare sector, particularly in regions like Maharashtra and Karnataka, is characterized by diverse patient populations, varying levels of technological infrastructure, and distinct cultural and socio-economic factors. These elements can influence the acceptance and implementation of new technologies such as AI-based diagnostic tools.

Regarding the constraints of this investigation, it is imperative to acknowledge the intrinsic intricacies that exist within the field of research. To begin with, the research is confined to two distinct Indian states, specifically Maharashtra and Karnataka. Although these regions offer significant insights into the dynamics of adoption in the context of healthcare in India, the generalizability of the findings to other states or countries with distinct healthcare systems, policies, and cultural norms may be limited.

Furthermore, the research concentrates predominantly on the extent to which physicians adopt AI-based interventions for diabetes diagnosis. Nevertheless, this approach might fail to consider the input of policymakers, healthcare administrators, patients, and other vital stakeholders whose viewpoints and decision-making procedures could substantially impact the results of adoption. Hence, a more exhaustive analysis that incorporates the participation of various stakeholders might yield a comprehensive comprehension of the adoption environment.

Furthermore, the potential use of self-reported data from physicians could incorporate biases or inaccuracies into the study's results. Diverse factors, including prior experience, personal inclinations towards innovation, and degree of familiarity with the technology, may influence physicians' perspectives on AI-driven interventions. Moreover, the congruence between self-reported data and actual adoption behaviours may be imperfect, resulting in possible inconsistencies between professed intentions and implemented measures. In conclusion, although the proposed framework endeavours to offer a discerning evaluation of the adoption process, it might not comprehensively encompass the ever-changing and dynamic characteristics of healthcare technologies. AI-driven interventions for the diagnosis of diabetes are undergoing accelerated development, as novel advancements and updates emerge regularly. Without periodic revisions and updates to account for emergent trends and developments in the field, the framework's utility and pertinence may progressively deteriorate.

5.6 SCOPE FOR FUTURE RESEARCH

The rapid evolution of healthcare technology presents numerous potential areas for future research that can be built upon the examination of how physicians in Maharashtra and Karnataka are adopting AI-based interventions for diabetes diagnosis. An area that warrants further investigation is the longitudinal examination of adoption patterns as they evolve. Gaining an understanding of the fluctuations in adoption rates and the determinants that influence the continued utilization or discontinuation of AI-powered diagnostic tools may yield significant insights into the enduring consequences of these interventions on the provision of healthcare and the outcomes for patients.

Furthermore, further investigation is warranted to explore in greater detail the determinants that impact the adoption choices of healthcare professionals other than physicians. The viewpoints of nurses, pharmacists, and allied health professionals regarding AI-driven interventions may differ due to the distinct obligations and engagements of these professionals with technology and the critical nature of patient care they perform. By integrating various stakeholders into the research framework, it is possible to attain a more comprehensive comprehension of the dynamics of adoption.

In addition, examining the influence that contextual elements, including regulatory frameworks, healthcare infrastructure, and patient inclinations, have on the processes of

adoption may enhance our comprehension of the wider socio-technical environment within which AI-driven interventions function. Analyses that compare adoption frameworks and strategies across regions or countries with diverse healthcare systems and cultural contexts may yield significant insights regarding their applicability in a broader sense.
An additional promising area for further investigation pertains to the evaluation of the efficacy and efficiency of AI-driven interventions within authentic clinical environments. By performing thorough assessments of the diagnostic precision, clinical applicability, and cost-efficiency of these technologies, it is possible to facilitate the transition from theoretical research findings to tangible application. Additionally, qualitative research examining the perspectives and encounters of healthcare providers and patients concerning AI-powered diagnostics may provide insight into the human elements that impact acceptance and implementation.

Theoretical advancements are imperative in conjunction with empirical research to better comprehend the intricacies of technology adoption within the healthcare sector. Incorporating multidisciplinary viewpoints from domains including innovation studies, health informatics, and organizational behaviour into the development of conceptual frameworks may furnish a solid basis for predicting and analyzing adoption outcomes. Additionally, the development of targeted interventions to promote the adoption of AI-based technologies in clinical practice could be guided by these frameworks.

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ANNEXURE

QUESTIONNAIRE

Dear Dr,

We are currently pursuing a Ph.D. study related to "**Investigating the Adoption of AI based Interventions used to diagnose Diabetes by Doctors in Maharashtra & Karnataka: Critical Assessment and Proposed Framework".** For this purpose, we request you to read the following questions carefully and answer them. The answers you give will be held strictly confidential and information from this survey will not be disclosed for any other purpose. We thank you for your time and cooperation.

Please put a tick mark (✓) in the square ☐ corresponding to your choice.

PART A: General Information

Name (optional)	....	
Age	1) 18 – 26 years	☐
	2) 27 – 35 years	☐
	3) 36 – 44 years	☐
	4) 45 – 53 years	☐
	5) > 53 years	☐
Gender	1) Male	☐
	2) Female	☐
Education Level	1) Medical/ Paramedical Graduate	☐
	2) Medical/ Paramedical Postgraduate	☐

Total Experience (in years)	1) < 0.5 year	☐
	2) 0.5 – 1 year	☐
	3) 1 – 3 years	☐
	4) 3 – 5 years	☐
	5) > 5 years	☐
Experience in Using AI Based Diabetes Diagnostic Systems/ Devices	1) I am only aware of this technology	☐
	2) Newbie (< 0.5 year)	☐
	3) 0.5 – 1 year	☐
	4) 1 – 3 years	☐
	5) 3 – 5 years	☐
	6) > 5 years	☐
Medical Practice Setup	1) In a hospital/ nursing home	☐
	2) In my own clinic	☐

Number of Diabetes Patients Seen Per Day	1. Less than 5	☐
	2. 5-10	☐
	3. 11-20	☐

	4. 21-30
	5. 31-40

PART B: Specific Information

RD	The following statements are related to **"Result Demonstrability (RD): The degree to which a Doctor believes that use of AI based Diabetes Diagnostic devices demonstrate result."** With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
RD1	The results of using AI based Diabetes diagnostic devices are apparent to me.	1	2	3	4	5
RD2	I believe I could communicate to others the consequences of using AI based Diabetes Diagnostic system.	1	2	3	4	5
RD3	I would have difficulty explaining why using AI based Diabetes diagnostic devices may or may not be beneficial.	1	2	3	4	5

TTF	The following statements are related to "**Task Technology Fit (TTF): The degree to which a person believes that AI based Diabetes diagnostic devices are relevant for care delivery**." With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
TTF1	I find the usage of AI based Diabetes Diagnostic devices are relevant to the delivery of Diabetes Care.	1	2	3	4	5
TTF2	I believe usage of AI based Diabetes Diagnostic devices are technologically important to the delivery.	1	2	3	4	5
TTF3	I believe using AI based Diabetes Diagnostic system fits with the way I like to diagnose a Diabetes patient.	1	2	3	4	5
TTF4	I believe using AI based Diabetes Diagnostic system fits with my style of care for Diabetes Patients.	1	2	3	4	5
TTF5	AI based Diabetes diagnostic systems are compatible with most aspects of my diagnosis of Diabetes patients.	1	2	3	4	5

PI	The following statements are related to "**Personal Innovativeness (PI): Degree to which an individual is willing to try out any new technology**." With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
PI1	If I heard about a new AI based Diabetes Diagnostic Technology, I would look for ways to experiment with it.	1	2	3	4	5
PI2	Among my peers I am usually the first to explore new AI based Diabetes Diagnostic Technologies.	1	2	3	4	5
PI3	I like to experiment with new AI based Diabetes Diagnostic Technologies.	1	2	3	4	5
PI4	In general, I am hesitant to try out new AI based Diabetes Diagnostic Technologies.	1	2	3	4	5

AF	The following statements are related to "**Affordability (AF): The possible expenses of using AI based Diabetes Diagnostic systems, i.e. equipments, costs, access cost, and transaction fees**." With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
AF1	I think the equipment cost is expensive of using AI based Diabetes Diagnostic systems	1	2	3	4	5
AF2	I think the access cost is expensive of using AI based Diabetes Diagnostic systems.	1	2	3	4	5
AF3	I think the transaction fee is expensive of using AI based Diabetes Diagnostic systems.	1	2	3	4	5

PU	The following statements are related to **"Perceived Usefulness (PU): The degree to which a Doctor believes that the use of AI based Diabetes Diagnostic devices would enhance his or her personal or job performance"**. With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
PU1	AI based Diabetes diagnostic devices would help me to cope with preventable Diabetes diseases and its complications at an early stage.	1	2	3	4	5
PU2	AI based Diabetes diagnostic devices would provide detailed information such as vital readings, fundus images of my patients' eyes, which would be very useful for me.	1	2	3	4	5
PU3	AI based Diabetes diagnostic devices would help the medical institutions to recognize more treatable Diabetes Patients.	1	2	3	4	5
PU4	AI based Diabetes diagnostic devices would improve primary health care for health departments and save money.	1	2	3	4	5
PU5	AI based Diabetes diagnostic devices would improve primary health care for health departments and save money.	1	2	3	4	5
PU6	AI based Diabetes diagnostic devices would fit my patient's demand for metabolic health management.	1	2	3	4	5
PU7	AI based Diabetes diagnostic devices would achieve the same results as face-to-face diagnosis with a Diabetologist.	1	2	3	4	5

PEOU	The following statements are related to "**Perceived Ease of Use: The degree to which a person believes that AI based Diabetes diagnostic devices would be easy to use**." With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
PEOU1	I find the instructions for AI based Diabetes Diagnostic devices easy, clear, and understandable.	1	2	3	4	5

PEOU2	AI based Diabetes diagnostic devices would offer a more convenient way for my Patients to cope with their disease management without queuing for registration in hospitals and would save their time and money.	1	2	3	4	5

BI	The following statements are related to "**Behavioral Intention (BI): An individual's motivation or willingness to exert effort to use AI based Diabetes diagnostic devices.**" With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
BI1	I intend to use AI based Diabetes diagnostic devices as my first choice if I feel my patients need it.	1	2	3	4	5
BI2	I will encourage my friends/ colleagues to use AI based Diabetes diagnostic devices first if they ask.	1	2	3	4	5
BI3	I will encourage healthy people to use AI based Diabetes Diagnostic devices for preventive health screening.	1	2	3	4	5
BI4	I would be able to use AI based Diabetes diagnostic devices independently as long as I had enough time and made an effort to learn.	1	2	3	4	5
BI5	I would receive appropriate technical assistance when encountering any difficulties in using AI based Diabetes diagnostic devices or understanding the report.	1	2	3	4	5

SN	The following statements are related to "**Subjective Norms (SN): Perception of important (or relevant) others' beliefs about my use of AI based Diabetes diagnostic devices.**" With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
SN1	People who are important to me (Colleagues, family members, relatives and close friends) think that I should use AI based Diabetes diagnostic devices.	1	2	3	4	5
SN2	My colleagues or peers think that I should use AI based Diabetes diagnostic devices.	1	2	3	4	5
SN3	My leaders or superiors think that I	1	2	3	4	5

	should use AI based Diabetes diagnostic devices.					

PR	The following statements are related to "**Perceived Risk (PR): A Combination of uncertainty and seriousness of an outcome in relation to performance, safety, psychological or social uncertainties.**" With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
PR1	There is a possibility of malfunction and performance failure, so they might fail to deliver accurate diagnoses or recommendations and could increase conflicts between members of the public and medical institutions.	1	2	3	4	5
PR2	I am concerned that my patients' information and health details would be insecure and could be accessed by stakeholders or unauthorized persons, leading to misuse and discrimination.	1	2	3	4	5
PR3	Considering the difficulties involved in taking high-quality images for AI analysis, I think there is a risk of incorrect screening results	1	2	3	4	5
PR4	Because practitioners with little medical knowledge might find it difficult to understand the screening report and explain the terminology and results to patient, they might increase my anxiety of about using AI based Diabetes diagnostic devices.	1	2	3	4	5

UX	The following statements are related to "**Experience (UX): Past use of AI based Diabetes Diagnostic Services, an important predictor contributing towards Behavioral Intention.**" With reference to your project, kindly indicate your extent of agreement or disagreement.					
		Very long ago	**Long ago**	**Not used at all**	**Recently**	**Very Recently**
PR1	How long ago did I first start to use AI based Diabetes Diagnostic systems professionally for my patients	1	2	3	4	5

THANK YOU FOR YOUR COOPERATION