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PHARMACOGENOMIC METHODS DRIVEN BY AI FOR TAILORED ANTIDEPRESSANT THERAPY: INCREASING TREATMENT EFFECTIVENESS AND MITIGATING SIDE EFFECTS

Research dissertation presented in partial fulfilment of the requirements
for the degree of
MSc Digital Transformation

Griffith College Dublin

Dissertation Supervisor: **Dr. Rosemary O'Hara**

Student Name: Soorya Kanath Sudeer Kumar

CANDIDATE DECLARATION

I confirm that the dissertation titled *"*Pharmacogenomic Methods Driven by AI for Tailored Antidepressant Therapy: Increasing Treatment Effectiveness and Mitigating Side Effects*"*, submitted in partial fulfillment of the requirements for the M.Sc. Digital Transformation (Life Science), represents my own original work. This research was undertaken independently, and all references to existing literature, data, or ideas from other sources have been properly cited and acknowledged. I also affirm that this work has not been copied, reused, or submitted elsewhere in part or in full and complies with Griffith College's academic integrity and plagiarism policies.

Name of Student: Soorya Kanath Sudeer Kumar

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Date: 11/05/2025

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LIST OF ABBREVIATIONS

1. **ADR** – Adverse Drug Reaction
2. **AI** – Artificial Intelligence
3. **AI-PGx** – AI-driven Pharmacogenomics
4. **CYP2C19** – Cytochrome P450 Family 2 Subfamily C Member 19
5. **CYP2D6** – Cytochrome P450 Family 2 Subfamily D Member 6
6. **EMA** – European Medicines Agency
7. **FDA** – Food and Drug Administration
8. **GDPR** – General Data Protection Regulation
9. **GWAS** – Genomic-wide Association Study
10. **HBM** – Health Belief Model
11. **HIPAA** – Health Insurance Portability and Accountability Act
12. **MDD** – Major Depressive Disorder
13. **ML** – Machine Learning
14. **ML-PGx** – Machine Learning in Pharmacogenomics
15. **NHS** – National Health Service
16. **NLP** – Natural Language Processing
17. **PGx** – Pharmacogenomics
18. **SSRIs** – Selective Serotonin Reuptake Inhibitors
19. **TAM** – Technology Acceptance Model
20. **WHO** – World Health Organization

ABSTRACT

Artificial intelligence (AI) is rapidly revolutionizing mental health by improving pharmacogenomic techniques to provide more personalized antidepressant medication. This dissertation looks at how AI-driven pharmacogenomics is observed, accepted, and applied in healthcare settings in India and Europe. The study's goal is to analyze the present state of knowledge, preparedness, and ethical issues around AI-guided prescription, as well as identify hurdles and facilitators that impact its clinical acceptance.

The study used a concurrent mixed-method approach, combining quantitative data from 105 verified survey replies with qualitative insights from six expert interviews. The survey results, which were collected from healthcare professionals, researchers, and regulatory stakeholders, were analyzed using, while thematic analysis of the interviews was conducted using NVivo.

The findings provide significant evidence for AI in improving antidepressant medication by minimizing trial-and-error prescription and improving treatment outcomes. 73% of all participants recognized AI's role in boosting accuracy, and 68% agreed pharmacogenomics might personalize therapy. However, geographical differences emerged: European professionals shown more knowledge and system preparedness, whereas Indian respondents raised worries about insufficient infrastructure, a lack of specialist training, and unclear legal frameworks. Data privacy concerns, ethical uncertainty, and inadequate integration into healthcare operations were recognized as common problems across both areas.

Notably, the study found that increasing familiarity with AI corresponds higher trust in its application, emphasizing the importance of focused teaching initiatives. Furthermore, the readiness of healthcare professionals-particularly early adopters in both regions-indicates that stakeholder involvement, legislative reform, and technological investment are critical for wider adoption.

In conclusion, the work highlights AI-driven pharmacogenomics as a possible tool for changing antidepressant prescribing habits. Healthcare systems may speed up the adoption of personalized medicine by solving regional disparities through training, ethical measures, and infrastructure development. These findings add to global conversations about digital health transformation and highlight the importance of locally appropriate policies that combine innovation with accountability.

Keywords: Artificial Intelligence, Pharmacogenomics, Antidepressant Therapy, Digital Health, Personalized Medicine, India, Europe, Healthcare Innovation, Clinical Readiness, Ethical Concerns, Data Privacy

CHAPTER 1

1.0 INTRODUCTION

1.1 PURPOSE OF STUDY

Mental health disorders, particularly depression, remain among the most prevalent global health issues, affecting millions of people worldwide (Anon n.d.). Despite the availability of various antidepressant drugs, a significant percentage of individuals experience poor responses or adverse effects (Haddad *et al.*, 2015). Traditional antidepressant prescribing methods often rely on trial and error, leading to prolonged suffering and increased healthcare costs (Fabbri *et al.*, 2018). Pharmacogenomics, the study of how an individual's genetic composition affects their response to medication, offers a novel solution to this problem by enabling the tailoring of antidepressant treatment (Weinshilboum and Wang, 2017). By identifying which medications are best suited to an individual's genetic profile, pharmacogenomics can enhance treatment efficacy while reducing side effects (Porcelli *et al.*, 2011). Integrating artificial intelligence (AI) into pharmacogenomics enhances its potential by enabling the analysis of large genetic datasets to predict how individuals will respond to various antidepressants (Haga, 2024a).

This study aims to evaluate the role of artificial intelligence-driven pharmacogenomic applications in optimizing antidepressant therapy. It will explore how these technologies contribute to personalized treatment, focusing on their potential to enhance therapeutic outcomes while reducing adverse effects. Additionally, the study will examine the adoption and impact of AI-powered pharmacogenomics in Europe and India, two regions with distinct healthcare systems and regulatory frameworks. Furthermore, it will investigate the regulatory, ethical, and logistical challenges hindering the widespread implementation of these technologies in mental health care.

1.2 BACKGROUND AND SIGNIFICANCE OF STUDY

Depression is a serious global health condition, impacting over 280 million people globally (Anon, n.d.). Despite the availability of antidepressants such as selective serotonin reuptake inhibitors (SSRIs) and serotonin-norepinephrine reuptake inhibitors (SNRIs), treatment effectiveness varies greatly (Cipriani *et al.*, 2018). An estimated 30-40% of patients do not respond well to these drugs, and many have serious side effects such as weight gain, sexual dysfunction, and sleep difficulties

(Rafeyan *et al.*, 2020). This difficulty is further complicated by the fact that treatment decisions are sometimes chosen without regard for hereditary characteristics that impact medication metabolism, resulting in a generalized treatment strategy that may not be beneficial for all patients (Weinshilboum and Wang, 2017).

Pharmacogenomics overcomes these constraints by customizing antidepressant medication to an individual's genetic profile, therefore increasing efficacy while reducing adverse effects. For example, variations in the CYP450 enzyme family might influence how antidepressants are metabolized in the body, rendering certain individuals more susceptible to medication toxicity or non-response (Barlati *et al.*, 2023). Pharmacogenomics uses AI technology such as machine learning and deep learning algorithms to evaluate complicated genetic data and determine the best antidepressant and relevant dose for each patient (Okpete and Byeon, 2024). Despite the potential benefits of these technologies, their implementation is hampered by a variety of legislative, ethical, and logistical obstacles (Del Casale *et al.*, 2023).

This research is essential as it explores the practical applications of AI-powered pharmacogenomics in mental health treatment. By examining how these technologies can be leveraged to personalize antidepressant therapy, this study contributes to the growing intersection of genetics, artificial intelligence, and psychiatry. Additionally, it offers critical insights into the challenges of implementing AI-driven pharmacogenomics in diverse regions, such as Europe and India, while providing a broader perspective on the global relevance of these advancements.

1.3 RESEARCH OBJECTIVES

The primary objective of this study is to evaluate the role of AI-driven pharmacogenomics in antidepressant treatment by personalizing medication and enhancing treatment outcomes. To achieve this, the research will be guided by the following specific objectives:

1. Evaluate pharmacogenomics contribution in optimizing anti-depressant treatment.

The key objective is to examine how pharmacogenomic testing can be integrated into clinical practice to tailor antidepressant prescriptions based on genetic markers, thereby improving patient outcomes.

2. Analyze how AI-driven pharmacogenomic applications differ in Europe and India.

This objective is to examine the adoption and implementation of AI-driven pharmacogenomics in two regions with distinct healthcare systems, technological infrastructures, and regulatory frameworks. The research will explore the challenges and opportunities each region faces when integrating AI-driven pharmacogenomics into clinical practice.

3. Examine the regulatory, ethical and logistical operational issues surrounding the use of AI-driven pharmacogenomics in mental health care.

This objective is to analyze the barriers to the widespread adoption of AI-powered pharmacogenomics in mental health treatment. These challenges include regulatory approval processes, ethical concerns related to patient consent and genetic data privacy, as well as practical considerations such as cost and healthcare infrastructure.

1.4 RESEARCH QUESTIONS

- How could AI-driven pharmacogenomics improve the efficacy of antidepressant medication by adapting it to individual genetic profiles?
- What are the primary regulatory barriers to integrating AI-driven pharmacogenomics in antidepressant therapy across various healthcare systems?
- What ethical considerations arise when applying AI-powered pharmacogenomics for mental health therapy, specifically in terms of patient consent and genetic data privacy?
- What are the major operational and logistical challenges to incorporating AI-driven pharmacogenomics into clinical practice, and how can they be addressed?

1.5 JUSTIFICATION FOR THE STUDY

The rising frequency of depression, as well as the limits of conventional antidepressant medications, highlight the need for a more customized approach to mental health care. Pharmacogenomics provides a potential approach, but its incorporation into clinical practice is still in its early stages. AI technology has the ability to speed up this process by evaluating genetic data and making personalized therapy suggestions. However, the use of these technologies differs across areas due to variances in healthcare infrastructure, laws, and technological availability.

This study is supported by its potential to address a significant gap in our present understanding of AI-driven pharmacogenomics in mental health treatment. The initiative, which will focus on both Europe and India, will provide a comparative review of how these technologies may be used in various global settings. Furthermore, by analyzing the regulatory, ethical, and logistical difficulties, the study will provide policymakers, healthcare practitioners, and technology developers with practical insights for optimizing antidepressant medication with AI and pharmacogenomics.

1.6 DISSERTATION STRUCTURE

Chapter 1: Introduction

This chapter introduces the research, discusses its importance, and outlines the research aims. It also provides an outline of the research questions and dissertation framework.

The remaining dissertation is divided into four major chapters, each contributing to a thorough examination of AI-driven pharmacogenomics in antidepressant therapy.

Chapter 2: Literature Review

This chapter explores existing literature on pharmacogenomics, artificial intelligence in medicine, and its applications in antidepressant therapy. It outlines key concepts, models, and previous research while highlighting gaps that this study aims to address.

Chapter 3: Research Methodology

This chapter explains the research methodology, including data collection methods such as surveys and interviews. It discusses participant selection, data analysis techniques, and ethical considerations related to patient consent and genetic data privacy.

Chapter 4: Findings and Analysis

This chapter covers the key findings of the research, assessing and comparing them with existing literature. Figures, tables, and charts are utilized to highlight major findings, with an emphasis on how AI-driven pharmacogenomics affects antidepressant medication and the problems of implementation.

Chapter 5: Conclusions and Recommendations

The last chapter summarizes the study's findings, explores their consequences, and makes suggestions to authorities, healthcare practitioners, and researchers. It also recognizes any limitations and makes recommendations for further study.

CHAPTER 2

2.0 LITERATURE REVIEW

2.1 INTRODUCTION TO PHARMACOGENOMICS AND ANTIDEPRESSANT THERAPY

Pharmacogenomics operates as a scientific discipline to study genetic determinants in medication responses and it reshapes antidepressant treatment approaches (Barlati *et al.*, 2023). Global mental health experts best classify depression as a major disorder that strikes millions of patients while treatment depends mostly on experimental methods including trial and error (Karrouri *et al.*, 2021). Prolonged patient suffering combined with elevated healthcare expenses and non-ideal therapeutic effects occurs because of this approach (Alchakee *et al.*, 2022).The lack of genetic variation analysis during traditional prescribing practices results in substantial differences between patients in drug processing and medication response (Zeier *et al.*, 2018). Genetic testing within pharmacogenomics serves as a solution that helps doctors make better antidepressant choices leading to enhanced treatment effectiveness and fewer side effects (van Westrhenen *et al.*, 2020).

Table 1: Comparative Analysis of Author Perspectives on AI-Driven Pharmacogenomics in Antidepressant Therapy

Author(s) & Year	Perspective on AI-Driven Pharmacogenomics
(Athreya *et al.*, 2019)	AI-driven pharmacogenomics significantly improves antidepressant selection by analyzing genetic markers like CYP2D6 and CYP2C19, leading to personalized treatment plans.
(Taherdoost and Ghofrani, 2024)	AI-enhanced pharmacogenomics can reduce ADRs and increase treatment adherence but requires standardized clinical implementation.
(Mennella *et al.*, 2024)	Ethical concerns such as data privacy and accessibility pose challenges in AI-driven pharmacogenomics adoption, especially in resource-limited settings.
(da Silva, 2024)	While Europe is advancing in AI-driven pharmacogenomics, India's adoption remains slow due to regulatory and infrastructural constraints.
(Zarchi *et al.*, 2023)	Blockchain technology could enhance the security and transparency of genetic data, addressing concerns over AI-driven pharmacogenomics implementation.

In this table, AI in pharmacogenomics brings a new change to the use of antidepressants where patients receive treatment based on their genetic makeup. It is all the more important to overcome

the barriers of ethics, regulations, and finances particularly in the Indian context. New studies should enhance genetic databases and opt for international variation of models of AI applicable to the health sector's future development.

2.1.1 Overview of Antidepressant Treatment Challenges

Treatment for depression involves numerous substantial problems. One of the main difficulties is biological variability, which contributes not only to the emergence of depressed and atypical or masked symptoms, but also to the occurrence of major side effects associated with medical therapies. Current therapy techniques are typically based on trial-and-error prescription, which results in prolonged treatment of symptomatic patients. This inactivity at the lower end of the treatment response curve causes significant psychological suffering in patients and puts a significant cost burden on healthcare systems, impacting both individual well-being and overall medical resource allocation. (Lenze *et al.*, 2021). Most patients suffer from Adverse Drug Reactions which include: obesity, somnolence, gastrointestinal disorders, which results to poor compliance and noncompliance to therapy. Moreover, the issue of treatment resistant depression also always comes up, meaning that there is always need for other approaches. Pharmacogenomics is capable of responding to these concerns due to the revelation of gene variants that provoke anti-depressant drugs in the body (Alchakee *et al.*, 2022).

2.1.2 Potential of Pharmacogenomics in Enhancing Treatment Efficacy

Pharmacogenomics improves the administration of antidepressants by acknowledging genetic factors about drug metabolites and efficiency. Genetic variations in proteins like CYP2D6 and CYP2C19 affect how people metabolize all types of antidepressants like SSRIs and tricyclic antidepressants (Hicks *et al.*, 2015). Pharmacogenomics such as personalizing prescriptions reduces ADRs and, at the same time, optimizes treatment outcomes (Bousman and Hopwood, 2016; Rosenblat *et al.*, 2017). According to several researchers, pharmacogenomic strategies enhance the response to therapy and decrease hospitalization from a lack of treatment efficacy (Altar *et al.*, 2015). However, the implementation is still a challenge due to the high costs involved in genetic testing and the requirement of physicians(Wilde *et al.*, 2013). Overcoming these limitations, such as the high expense of genetic testing and the requirement for specialized medical training, could lead the path for the creation of more tailored and effective antidepressants.

2.1.3 Role of AI in Pharmacogenomic Applications for Mental Health

The use of AI in pharmacogenomics is necessary in the determination of individual genomic and clinical data for efficient selection of antidepressants. By using machine learning techniques, researchers have the ability to find out complex gene-drug interactions that affect patient response, hence minimizing the chances of prescribing drugs that are based on guesswork (Denny *et al.*, 2013). AI improves the pharmacogenomic predictive models' precision, making it possible to adjust the dosages and schedules of medications for various patients (Shameer *et al.*, 2018). Nevertheless, there are limitations of pharmacogenomics that has been implemented using artificial intelligence, some of these include: Data privacy and regulatory issues. This is important especially when it comes to integrating the available and emerging genetic data sets as well as ethical aspects of artificial intelligence in the success of precision medicine in the mental health care management (Topol, 2019; Gerke *et al.*, 2020).

2.2 PHARMACOGENOMICS IN PERSONALIZED MEDICINE

Personalized medicine in pharmacogenomics aims to tailor antidepressant therapy by using genetic markers such as CYP2D6 and CYP2C19 in order to select the drug for individual patients to reduce adverse effects and improve treatment efficacy (Swen *et al.*, 2011).

2.2.1 Understanding Genetic Variability in Antidepressant Response

Pharmacogenomic studies shows that genetic factors can make impacts on the response to antidepressants by affecting both drug-metabolizing enzymes and treatment efficacy. This indicates that variations in the genes coding for enzymes like CYP2D6 and CYP2C19 affect the rate at which antidepressants are metabolized in the body which causes both drug effectiveness and side effects (Hicks *et al.*, 2015; Bousman and Dunlop, 2018). For example, poor metabolizers are more likely to encounter toxicity, but ultra-rapid metabolizers may not gain therapeutic advantages at conventional dosages. Pharmacogenomic testing enables medical professionals to discover these genetic changes, resulting in more tailored and successful treatment options (Swen *et al.*, 2011).

2.2.2 Key Genetic Markers in Antidepressant Metabolism (CYP2D6, CYP2C19)

Pharmacogenomic tests that analyze the CYP2D6 and CYP2C19 genes are among the most well-known and commonly used for directing antidepressant treatment (Hicks *et al.*, 2015). These genes are involved in the metabolism of numerous regularly used antidepressants. In pharmacogenetics, CYP2D6 polymorphisms divide individuals into four metabolizer categories: poor, intermediate, normal (extensive), and ultra-rapid, which have a substantial impact on medication efficacy and acceptability (Swen *et al.*, 2011). Similarly, genetic differences in CYP2C19 impact the metabolism of SSRIs and TCAs, influencing their pharmacodynamics. Identifying these genetic markers allows for more precise antidepressant prescription, avoiding undesirable outcomes and enhancing treatment results, which can lead to better patient compliance and satisfaction (Bousman and Dunlop, 2018).

2.2.3 Integration of AI in Personalized Medication Selection

Pharmacogenomics, which employs modern technology, has substantially improved the practice of tailored drug prescribing by using machine learning in the detection of both genetic and clinical characteristics (Lin *et al.*, 2021). A more advanced approach to antidepressant treatment is the use of AI algorithms to anticipate successful, patient-specific medication (Haga, 2024a). These models use genetic, proteomic, and metabolomic data to help fine-tune, select, and administer drugs. However, issues such as ethics, data privacy, and possible biases in training data persist (Peterson-Iyer, 2008). Strengthening laws and combining varied sources of genetic data would encourage the use of AI to adapt pharmacogenomic-based antidepressant treatment programs to individual patients (Mohr, Zhang, *et al.*, 2017).

2.3 CHALLENGES IN IMPLEMENTING PHARMACOGENOMICS IN CLINICAL PRACTICE

2.3.1 Cost and Accessibility Barriers to Genetic Testing

One of the most major challenges to pharmacogenomics integration is the high cost of genetic testing, which makes it extremely costly and limits its general access, particularly in low-income countries. Although genetic screening has several advantages, such as increasing treatment results, the exorbitant cost remains a significant barrier to its widespread use(Chenoweth *et al.*, 2020; Ayati *et al.*, 2021). Furthermore, some health insurance policies exclude pharmacogenomic

testing, making it an out-of-pocket expenditure for individuals (Pirmohamed, 2023). Furthermore, concerns of bias and poor facilities hinder access to testing, particularly in rural regions where genetic testing is even more uncommon (Korf and Rehm, 2013). These issues of cost, insurance coverage, and accessibility should be addressed in order to improve the use of pharmacogenomic-based antidepressant medication (Torkamani *et al.*, 2018).

2.3.2 Limited Physician Knowledge and Training

Pharmacogenomics has not been widely accepted in clinical practice, partially due to the fact that many physicians are unfamiliar with it or are unsure how to incorporate it into their practice (McKinnon *et al.*, 2007). Most healthcare practitioners have inadequate formal knowledge in genetics, making it difficult to evaluate pharmacogenomic test results and apply them to prescribing decisions (Ong *et al.*, 2022). The absence of comprehensive clinical education in pharmacogenomics necessitates extra effort in its use, especially if there are no training programs in place to monitor the clinical implications of these tests, which adds to its underutilization (Rafi *et al.*, 2020). To close this gap and encourage wider pharmacogenomics application in mental health treatment, including pharmacogenomics into medical curriculum would be a significant step forward (McKinnon *et al.*, 2007; Bousman *et al.*, 2019).

2.3.3 Ethical Issues: Data Privacy, Consent, and Genetic Stigma

There are ethical issues that may limit the use of pharmacogenomics, such as the protection of patients' information, consent, and risks on discrimination on the basis of genetics (Gershon *et al.*, 2014). Genetic testing issues involve health data that must be protected against disclosure of the information and abuse (Clayton *et al.*, 2019). Patients may also be reluctant to be tested due to genetic discrimination, especially regarding employment or insurance (Chapman *et al.*, 2019). This means that there is need to enhance the existing regulation and also ensure data policies dealing with genetic information are clear to address these ethical concerns (Shabani and Borry, 2018).

2.4 AI-POWERED PHARMACOGENOMICS AND MACHINE LEARNING APPLICATIONS

2.4.1 AI Algorithms for Predicting Antidepressant Effectiveness

Artificial intelligence (AI) has had a significant impact on pharmacogenomics by creating new models for selecting the right antidepressants. People-oriented big data methods, such as genome-

wide association studies (GWAS), support vector machines (SVM), and random forest models, use machine learning algorithms to analyze large amounts of genomic, clinical, and demographic data, systematically identifying genetic variants that influence drug tolerance and guiding the selection of appropriate antidepressant doses (Mohamed *et al.*, 2023; Sigala *et al.*, 2023). Genetic, clinical, and environmental data are incorporated into deep learning models to fine-tune antidepressant treatment, reducing the need for empirical therapeutic trials (Koumakis, 2020). Big data in pharmacogenomics not only improves the accuracy of predictions but also increases patient compliance (Lavertu *et al.*, 2018). However, challenges such as data bias and regulatory issues must be addressed to expand its application (Min, 2023).

2.4.2 Role of Big Data and Machine Learning in Pharmacogenomics

The use of big data analytics and machine learning in pharmacogenomics is critical for improving antidepressant medication. A large quantity of genetic and clinical data is gathered to tailor treatment strategies based on patients' particular histories, molecular composition, and how individual drugs interact with each patient (Hassan *et al.*, 2022). Machine learning analyzes signals in genetic data, allowing for more precise predictions of treatment responses and probable adverse effects (Del Casale *et al.*, 2023). Using real patient data improves model validity and efficiency in the continuous learning process, ultimately leading to better patient health outcomes (Mizuno *et al.*, 2022). However, restrictions must be addressed, such as ethical issues about data privacy and possible biases in the dataset (Vayena *et al.*, 2018).

2.4.3 Examples of Successful AI-Driven Models in Mental Health Treatment

There is rising evidence from pharmacogenomic research that artificial intelligence (AI) models can improve antidepressant therapy. For example, deep learning frameworks have been used to predict individual reactions to selective serotonin reuptake inhibitors (SSRIs), lowering the risk of side effects (Arjun P Athreya *et al.*, 2019). In the present healthcare landscape, AI-based decision-support systems let doctors adapt drug therapy to specific patients, increasing the likelihood of effective outcomes and medication adherence (Elhaddad and Hamam, n.d.). Pharmacogenomic platforms are gradually being incorporated into numerous European national health systems like in UK and Netherlands, possibly assisting in the optimization of complicated pharmacological regimens (Alshabeeb *et al.*, 2019; Rafi *et al.*, 2020). Nonetheless, problems remain, such as

securing regulatory permission and creating diverse, high-quality training data sources that are representative and sustainable—issues that need more study and updated legislative frameworks (Padmanaban, 2023).

1. **Woebot Health**: A chatbot that provides cognitive behavioral therapy for anxiety and depression, that uses Natural language Processing (NLP) and real time interaction to respond and guide the patient.

2. **IBM Watson Health**: This involves the use of AI models to help in diagnosis of the mental health disorders, increasing the chances of early diagnosis and accurate diagnosis.

3. **Mind strong Health**: It is a concept of smartphone application that predicts human behavior, particularly mental health disorders, and offers a timely solution.

4. **DeepMind's AI for Depression**: DeepMind tools to identify clinic patient depression: DeepMind AI can detect who is likely to be depressed based on language use in the clinical notes in order to diagnose at an early stage and subsequently get proper treatment for the patient.

5. **Replicas**: A concept of AI chatbot for emotional support and friendship, where chatbot learns about user's preference through the concept of learning.

6. **Bio Beats**: An Artificial Intelligence drawn for assessing wearable data in providing solutions to stress and anxiety.

2.5 COMPARATIVE ANALYSIS: AI-DRIVEN PHARMACOGENOMICS IN INDIA AND EUROPE

Pharmacogenomics has been widely used in European healthcare systems, aided by rigid regulatory requirements and the growing integration of artificial intelligence (AI) technology. Structured AI solutions that match with existing health regulations and regulatory frameworks help Europe by enabling customized therapy on a large scale (Anon, 2024a). In contrast, India confronts severe hurdles such as low public awareness, large implementation costs, and inadequate regulatory infrastructure. To progress pharmacogenomics in India, significant legislative change, strategic investment, and capacity building are necessary to promote fair access and effective use of artificial intelligence-driven genomic technologies (Olawade *et al.*, 2024).

Table 2: Comparative Analysis: AI-Driven Pharmacogenomics in India and Europe

Aspect	Europe	India
Regulatory Framework	Strong, well-established regulations for AI and pharmacogenomics.	Limited and evolving regulatory frameworks.
Awareness	High awareness among healthcare professionals and patients.	Limited awareness and understanding of pharmacogenomics.
Cost	High but often covered by healthcare systems or insurance.	High costs, with limited insurance coverage, making it less accessible.
Infrastructure	Advanced infrastructure for genetic testing and AI integration.	Limited infrastructure, especially in rural and low-resource settings.
Implementation	Structured AI applications integrated into healthcare systems.	Requires policy reforms and investment for effective implementation.
Accessibility	Widely accessible due to robust healthcare systems.	Limited accessibility, particularly for low-income populations.

2.5.1 Overview of AI Integration in European Healthcare Systems

European nations have made significant progress in embracing pharmacogenomics, notably in the treatment of depression, where artificial intelligence (AI) is becoming increasingly important. In the United Kingdom, for example, genomic medicine programs managed by the National Health Service (NHS) and funded by the Department of Health use AI technology to modify medicinal prescriptions based on an individual's genetic profile (Anon, 2023). These activities are closely monitored by organizations such as the European Medicines Agency, which also controls ethical standards and data protection regulations (Bousman *et al.*, n.d.). Despite this development, several hurdles remain, most notably the high cost of genetic testing and the complexities of complying with data privacy requirements such as the General Data Protection Regulation (GDPR) and HIPAA (Theodos and Sittig, 2020; Anon, n.d.).

2.5.2 Current Status of Pharmacogenomics in India

Pharmacogenomics implementation in India is still in its early stages, and the use of artificial intelligence (AI) in ordinary clinical practice is restricted. Several obstacles impede development, including insufficient training among healthcare professionals and a lack of large-scale government-supported genomic efforts (Banerjee, 2011). Furthermore, the high expense of genetic testing renders it unavailable to a large percentage of the population (Sahana *et al.*, 2022). Other

challenges include variations in treatment response, varying remission rates, and insufficient infrastructure for effective drug distribution. These inadequacies have motivated private healthcare providers and research institutes to investigate AI-powered pharmacogenomic technologies for enhancing antidepressant treatment (Anon, n.d.). Strengthening regulatory frameworks and expanding funding in AI-based genetic research might greatly speed up India's path to customized treatment (Ktp, n.d.).

2.5.3 Key Differences in Regulatory, Ethical, and Logistical Approaches

The legal frameworks regulating AI-driven pharmacogenomics differ greatly in Europe and India. Pharmacogenomics is well-developed in Europe and controlled by the European Medicines Agency (EMA) and the General Data Protection Regulation (GDPR), which provide ethical data processing and genetic privacy protection (Anon, 2023). In contrast, India has yet to develop a comprehensive regulatory strategy for AI in pharmacogenomics, raising worries about data privacy and the danger of genetic prejudice (Olawade *et al.*, 2024; Haga, 2024a). Furthermore, the lack of genetic testing infrastructure and AI technology in India complicates the wider use of pharmacogenomic techniques (Haga, 2024b). Strengthening pharmacogenomic regulations might help solve these issues and eliminate inequities, ensuring that all populations benefit from these breakthroughs (Mohr, Lyon, *et al.*, 2017).

2.5.4 Barriers to Implementation in Emerging Economies (India)

AI-driven pharmacogenomics in India confronts a number of hurdles, including high prices, poor infrastructure, and, most importantly, slow regulatory development (Das *et al.*, 2024). Genotyping is prohibitively costly, restricting many patients access to customized antidepressant therapy. Furthermore, the healthcare system suffers from a paucity of qualified experts, with many patients, pharmacists, and prescribers lacking adequate pharmacogenomics knowledge (Dave and Patel, 2023). Ethical problems, such as data privacy and the danger of genetic prejudice, impede the adoption of AI-based healthcare technology. This emphasizes the importance of appropriate legislation and more funding to promote the development and deployment of AI in healthcare (Clayton *et al.*, 2019). Addressing these obstacles is critical for improving pharmacogenomic procedures and ensuring that the benefits reach a larger population in India (Das *et al.*, 2024).

2.6 ETHICAL.REGULATORY AND LOGISTICAL CONSIDERATIONS

Pharmacogenomics and AI integration faces ethical, regulatory, and practical obstacles. Concerns on a global scale include the security and privacy of genetic data, major differences in regulation between nations, and inherent biases in AI models, which may result in uneven healthcare treatment (Gerke *et al.*, 2020). To address these problems, consistent rules, heterogeneous genetic datasets, and open AI will be required. Implementing these ideas will allow us to develop a responsible and accessible pharmacogenomics system over the world (Anon, n.d.).

Table 3: Ethical, Regulatory, and Logistical Considerations in AI-Driven Pharmacogenomics

Category	Considerations
Ethical	Ensuring informed consent for genetic testing and AI use. Addressing AI bias and fairness in predictions. Protecting patient privacy and confidentiality.
Regulatory	Compliance with data protection laws (e.g., GDPR, HIPAA). Establishing standards for AI model validation. -Ensuring transparency in AI-driven decisions.
Logistical	High costs of genetic testing and AI implementation. Lack of infrastructure in low-resource settings. -Training healthcare professionals to use AI tools effectively.

2.6.1 Privacy and Data Security in AI-Driven Pharmacogenomics

The application of AI in pharmacogenomics creates serious privacy and data security concerns, as genetic data is very personal and sensitive (Hanna *et al.*, 2025). These vulnerabilities could compromise patient confidentiality and lead to possible abuse or discrimination based on genetic information, highlighting the importance of strong cybersecurity measures. In countries with less strong data protection regulations, such as India, a lack of enforcement raises privacy concerns (Olawade *et al.*, 2024). While the General Data Protection Regulation in Europe incorporates standards regarding the protection of genetic data, issues exist due to the various processes used by particular countries (Anon, 2023). Genetic information presents inherent risks, hence when AI models analyze such data, encryption, anonymization, and decentralized data storage strategies are required (Bonomi *et al.*, 2020). The use of blockchain technology to protect genetic data

exchanges is a viable approach (Ozercan *et al.*, 2018). To build public trust and support the legal use of pharmacogenomics via AI, privacy and security procedures must be strengthened (Jawad, 2024).

2.6.2 Regulatory Challenges in AI-Driven Pharmacogenomics

AI applications in pharmacogenomics continue to confront significant regulatory obstacles in various countries. Genetic testing and pharmacogenomic applications are governed in Europe by the General Data Protection Regulation (GDPR) and the European Medicines Agency (EMA); however, how these laws are implemented varies by country (Anon, 2023). In contrast, India presently lacks particular regulation for AI-powered pharmacogenomics, prompting issues regarding data privacy, proper AI use, and patient autonomy (Reddy, 2023; Anon, n.d.). Without established standards, AI systems may introduce bias into decision-making, thereby exacerbating healthcare inequities (Panch *et al.*, n.d.). Therefore, to guarantee the ethical and responsible use of AI in pharmacogenomics on a global basis, it is imperative to define generally recognized standards that address genetic variety, AI transparency, and ethical issues (Murugan *et al.*, 2024).

2.6.3 Addressing Bias in AI Models: Impact on Diverse Populations

Ethical issues in AI-driven pharmacogenomics are frequently fueled by the fact that many machine learning models are developed on genetic data mostly from Western populations, restricting their applicability to different ethnic groups. This lack of representation can lead to incorrect antidepressant recommendations for underrepresented communities since genetic differences among ethnicities are not fully recorded (Anon, 2024c). As a result, AI models may exacerbate healthcare inequities in places like South Asia and Africa, where pharmacogenomic research is still in its early stages (Moore, 2022). To reduce such bias, training datasets should contain genetically varied populations, guaranteeing that AI technologies can make accurate predictions across ethnicities (Singh and Singh, 2025). Furthermore, the use of explainable AI techniques can improve model transparency, allowing physicians to better evaluate and confirm pharmacogenomic recommendations (Mersha *et al.*, 2024). Creating equitable and representative genetic databases, as well as ethical AI governance frameworks, will be critical to guaranteeing fair and successful pharmacogenomic applications across global healthcare systems (Machado and Silva, 2015).

2.7 THE ROLE OF MULTI-OMICS AND BLOCKCHAIN IN FUTURE PHARMACOGENOMICS

2.7.1 Integration of Genomics, Proteomics, and Metabolomics for Tailored Treatments

Pharmacogenomics is experiencing a dramatic transition as multi-omics methods, such as genomics, proteomics, and metabolomics, are integrated to improve knowledge of individual medication responses (Torkamani *et al.*, 2018). Pharmacogenomics analyzes individuals' genetic profiles to predict metabolic rates and pharmacokinetics-factors that determine how antidepressants are absorbed, transported, and metabolized in the body (Zhou *et al.*, 2019). In parallel, metabolomics evaluates particular metabolic indicators, allowing doctors to identify possible medication toxicity and adapt treatment regimens accordingly (Kell, 2006). These insights are reinforced by the use of artificial intelligence, which enables the creation of multidimensional models for individualized antidepressant selection and treatment planning (Topol, 2019). However, in order to effectively use multi-omics techniques, issues such as massive data management, analytical platform standardization, and data interoperability must be solved (Hasin *et al.*, 2017).

2.7.2 Blockchain for Secure and Transparent Genetic Data Sharing

Blockchain technology is emerging as a critical facilitator of safe data management in AI-driven pharmacogenomics, particularly for sensitive genetic information. Its decentralized structure promotes openness and provides patients greater control over who has access to their data, lowering the risk of illegal usage or breaches (Shine *et al.*, 2023). Unlike traditional centralized databases, blockchain ensures that data is only shared with the appropriate consent, which is critical for sustaining confidence in genetic medicine (Albalwy *et al.*, 2022). Blockchain is well-suited to privacy requirements in nations with rigorous data protection rules, such as the European Union's GDPR (Cascini *et al.*, 2022). However, in countries such as India, where digital health data rules are still being developed, application is restricted owing to legal gaps and infrastructural issues (Mathur and Swaminathan, 2018; Mathur, 2020). Nonetheless, the use of blockchain can promote ethical data sharing, increase patient engagement in pharmacogenomic studies, and enable secure collaboration across research groups (Gürsoy *et al.*, 2020). As the technology advances, its use might help to provide a dependable and transparent foundation for AI applications in customized medicine (Hasselgren *et al.*, 2020).

2.7.3 Future Prospects in AI and Multi-Omics Integration

The advancement of pharmacogenomics using artificial intelligence (AI) is becoming more dependent on the integration of multi-omics data and the creation of advanced computer models to optimize medication therapy (Graham *et al.*, 2019). AI can improve medication response predictions by examining data from genomes, transcriptomics, proteomics, and metabolomics, lowering the conventional reliance on trial-and-error techniques in antidepressant therapy (Manzoni *et al.*, 2016). Innovative technologies such as federated learning enable AI models to be trained across many healthcare facilities without sending sensitive patient data, hence improving privacy and compliance with data protection regulations (Rahman *et al.*, 2022). However, the adoption of such systems presents significant hurdles in terms of algorithmic bias, data representativeness, ethical issues, and legal limitations, particularly in emerging digital infrastructure nations such as India (Arora *et al.*, 2023). According to (Chenoweth *et al.*, 2020), advancements in precision pharmacogenomics will be dependent on worldwide partnerships, standardized AI frameworks, and the usage of secure technologies such as blockchain to handle and unify multi-omics information.

2.8 CURRENT AND FUTURE RESEARCH GAPS IN AI-DRIVEN PHARMACOGENOMICS

2.8.1 Lack of Diverse Genetic Databases in AI Models

A fundamental problem in applying AI to pharmacogenomics is the limited generalizability of current models due to the underrepresentation of varied genetic groups in training datasets (Kalinin *et al.*, 2018). Current genomic datasets are mostly made up of data from people of European origin, limiting the application of AI models to genetically diverse populations in Africa, Asia, and Latin America (Fatumo *et al.*, 2022). This difference can lead to erroneous medication response estimates and, as a result, improper antidepressant prescriptions for underrepresented populations, aggravating health disparities (Tariq *et al.*, 2025). To guarantee that pharmacogenomic tools are reliable and inclusive, genomic data variety must be increased by incorporating persons from various ethnic and geographical origins in research (Ehmann *et al.*, 2014). Regional biobanks and cooperation with local research institutes might help to bridge these gaps and promote equitable worldwide adoption of AI-driven pharmacogenomics (Argudo-Portal and Domènech, 2020).

2.8.2 Need for Standardization in AI Models and Data Collection

Currently, there are few guidelines in AI-driven pharmacogenomics regarding the development and training of models, collection of data, and its validation for the clinical use; and leading to significant variability in existing and proposed methodologies (Taherdoost and Ghofrani, 2024a). It remains a fact that current AI models do not use the same algorithms, training datasets, or interpretation methods among different studies (Anon, 2024a). It is crucial that growing AI models and pharmacogenomic data have structure so that they are able to be reliably used in clinical decisions (Serrano *et al.*, 2024). Several agencies engage in making recommendations on usage of AI in personalized medicine, including the FDA and EMA, although worldwide consensus is still in the process of being established (Derraz *et al.*, 2024). The differences in laboratories across different regions, differences in genetic testing practices are adding the challenges of standardization (Gore and Olawade, 2024). Adopting standardized procedures across medical and genetic activities associated with AI will take a long way in adaption and building confidence in doctors and patients (Muller-Gass *et al.*, 2025).

2.8.3 Collaborations for Global Genetic Database Development

A fundamental issue for AI applications in pharmacogenomics is the lack of variety and uniformity in available genetic datasets (Rawat, 2024). While worldwide programs like the Human Genome Project and the All of Us Research Program have provided the basis, more AI-driven pharmacogenomic research must be integrated into these efforts to ensure inclusion (Empey *et al.*, 2025). To construct internationally varied biobanks and build ethical and successful AI systems, research institutions, pharmaceutical corporations, and governments must work together (Akyüz *et al.*, 2024). Addressing the ethical consequences of data sharing, particularly those involving patient privacy, is also critical. In this regard, blockchain technology presents a viable alternative for the safe and transparent administration of genetic information (Arshad and Shah, 2024). Furthermore, encouraging the creation of open-access genetic datasets can considerably improve the application of AI in pharmacogenomics across different demographic groups (Vilhekar and Rawekar, n.d.).

2.9 CASE STUDIES AND CLINICAL APPLICATIONS OF AI-DRIVEN PHARMACOGENOMICS

2.9.1 Case Study: Tailored Antidepressant Treatment Using Pharmacogenomics

Pharmacogenomics provides a huge possibility for improving antidepressant therapy by investigating genetic differences that impact medication metabolism and response (Taherdoost and Ghofrani, 2024a). For example, in situations of treatment-resistant depression, pharmacogenomic research might identify underlying genetic variables that contribute to poor pharmaceutical effectiveness. One such example was a patient whose genetic testing revealed lower activity in the CYP2D6 and CYP2C19 enzymes, which are required for the metabolism of some antidepressants (Lee *et al.*, 2021). As a consequence, therapists modified the treatment strategy by prescribing an alternate antidepressant more appropriate for the patient's genetic profile. This resulted in better symptom management and fewer side effects, demonstrating the need of incorporating AI-guided pharmacogenomic insights into psychiatric therapy (Skokou *et al.*, 2024). Incorporating genetic testing into standard psychiatric screening offers the potential to tailor treatment and enhance (Hippman and Nislow, 2019).

2.9.2 Impact of AI and Genetic Testing on Treatment Adherence and Patient Outcomes

Pharmacogenomics has advanced the course of patient care by adopting artificial intelligence to ensure that medication prescriptions reflect patients' genetic makeup (Lin *et al.*, 2020). Current conventional approaches associated with the prescription of antidepressants often result in a slow onset of therapeutic effects, numerous side effects, and a high rate of drug dropout due to lack of efficacy (Anon, 2024a). In contrast, machine learning approaches working with genetic and clinical data may suggest which antidepressants might be effective for a particular patient and which ones might lead to the deterioration of the condition, thus minimizing the rates of trial and error (Lin *et al.*, 2021). A pharmacological patient analysis revealed that patients who followed pharmacogenomic guided treatment experienced fewer side effects and better adherence, when compared to those who received standard care (Greden *et al.*, 2019a). Moreover, the use of AI solutions to monitor the patient reactions, enabling timely treatment adjustments the treatment in case of necessity, and contributes to the overall improvement of the process (Anon, 2024b). These developments involving AI and genetic testing can maximize the potential of psychiatric medicine

and its contribution to the modification of antidepressant therapy and delivering benefit-oriented treatment plans for patients.

2.9.3 Future Directions for AI-Driven Pharmacogenomics in Clinical Settings

The future of pharmacogenomics in clinical practice, powered by artificial intelligence (AI), is in extending genetic research, refining algorithms, and combining multi-omics data to increase antidepressant selection accuracy (Lin *et al.*, 2020). Emerging breakthroughs in machine learning now include proteomics and metabolomics, providing a more comprehensive view of tailored treatment (Arjun P. Athreya *et al.*, 2019). Furthermore, AI-enhanced clinical decision support systems are predicted to become standard in psychiatric treatment, delivering evidence-based recommendations for drug changes (Greden *et al.*, 2019b).Despite these advances, obstacles remain, such as obtaining regulatory permissions, protecting patient privacy, and ensuring that genetic databases sufficiently reflect varied populations in order to promote fair healthcare (Fahim *et al.*, 2024).Future research should prioritize international collaboration to build inclusive genetic databases, increase public awareness of AI, and design regulations that support greater access to pharmacogenomics (Mennella *et al.*, 2024). As these systems evolve, AI-guided pharmacogenomics has the potential to change mental health care by enhancing therapeutic efficiency while lowering costs (Lin *et al.*, 2020).

2.10 PREVIOUS RESEARCH STUDIES

A previous study investigated the influence of pharmacogenomics on antidepressant treatment outcomes, finding improvements in medication responsiveness and fewer adverse effects (Mrazek *et al.*, 2014). Other some findings showed that genetic differences in the CYP2D6 and CYP2C19 genes had a considerable impact on medication metabolism, affecting treatment effectiveness (Bahar *et al.*, 2017). These therapeutic advancements were made feasible by AI-based algorithms that analyzed massive pharmacogenomic datasets (Taherdoost and Ghofrani, 2024b). Evidence from European healthcare settings indicates that combining pharmacogenomics with AI improves clinical decision-making (Farmaki *et al.*, 2024). However, gaps persist in low-resource regions, highlighting the necessity for worldwide standardization of AI platforms and the production of varied genetic datasets to provide fair access (Wong *et al.*, 2025).

2.11 GAPS IN THE LITERATURE

There are significant gaps in existing research that hinder the practical use of AI-based pharmacogenomics for antidepressant medication. A key difficulty is the absence of genetic variation data, since most pharmacogenomic research have focused on European populations, making it difficult to extrapolate the findings to more genetically varied groups (Pirmohamed, 2023). Furthermore, there is no uniform checklist of tests to subject AI models to, which adds to variations in pharmacogenomic predictions and clinical applications (Taherdoost and Ghofrani, 2024b). Furthermore, the lack of regulatory algorithms for AI models in pharmacogenomic predictions causes diversity in how these models are applied in clinical settings (Kalinin *et al.*, 2018). Data privacy, patient consent, and AI model biases are all critical ethical considerations that must be addressed. The high cost and restricted availability of genetic testing pose considerable challenges in some locations, notably in Low- and Middle-Income Countries, preventing fair access to pharmacogenomic-guided antidepressant medication. Further research should be directed on improving AI-driven pharmacogenomics by improving data gathering, developing AI validation processes, and resolving legal and ethical concerns.

Table 4: Summarize the research Gap

Research Gap	Short Description
Lack of Diverse Genetic Datasets	Most studies focus on European populations, limiting applicability to diverse groups.
No Standardized AI Model Validation	Inconsistent AI predictions due to lack of universal validation frameworks.
Ethical and Privacy Concerns	Data privacy, consent, and AI bias issues hinder adoption.
High Cost of Genetic Testing	Financial barriers limit access, especially in low-income regions.
Limited Accessibility in Low-Resource Settings	Lack of infrastructure and regulations restricts implementation in emerging economies.

2.12 THEORETICAL FRAMEWORK

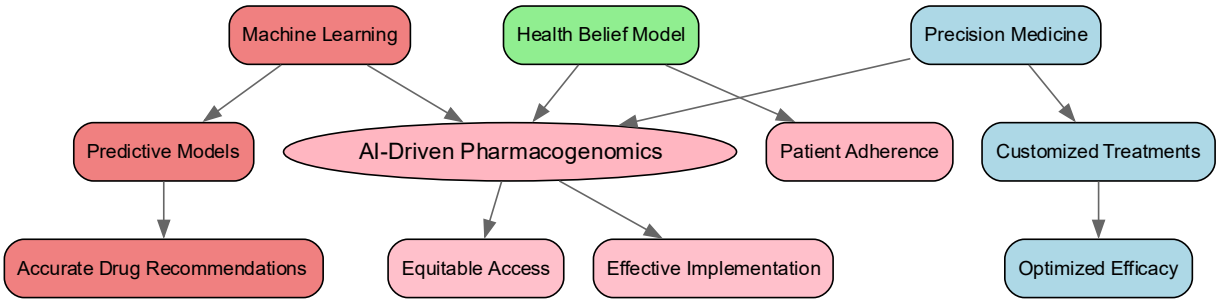
The theoretical foundation for using artificial intelligence to antidepressant pharmacogenomics is based on precision medicine, machine learning, and customized care principles (Arjun P Athreya *et al.*, 2019). Precision Medicine Theory is particularly important since it stresses the incorporation of genetic, environmental, and lifestyle aspects into healthcare decisions, which are also key components of pharmacogenomics (Naithani *et al.*, 2021). This theoretical approach promotes the use of genetic information to drive antidepressant prescriptions, thereby improving treatment efficacy while lowering side effects (Fabbri and Serretti, 2020).

Another one is Machine Learning, which is important since pharmacogenomics based on Artificial Intelligence requires the application of predictive models for processing genetic data and predicting drug reactions (Cilluffo *et al.*, 2021). Machine learning allows for more exact medication selection while also reducing guessing, particularly when using pharmacogenomic datasets (Pandi *et al.*, 2021). The Health Belief Model (HBM) also provides the best explanation for pharmacogenomic patient treatment behavior. Individuals are more likely to adhere to customized medicine when their perceived advantages are higher and their fear about genetic testing and AI-based therapies is less (Alyafei and Easton-Carr, 2025).

Moreover, the Technology Acceptance Model (TAM) explains how much healthcare professionals adopt AI-driven pharmacogenomics by focusing on the technology's perceived usefulness and ease of use, as well as their trust in AI-generated recommendations (Rahimi *et al.*, 2018). It is critical to realize that unexplored problems, such as algorithmic bias, AI governance, and fundamental ethical issues, must be addressed in order to improve the acceptability and deployment of this breakthrough (Anon, n.d.).

By combining these theoretical paradigms, this study sheds light on the accessibility and practical use of AI-enabled pharmacogenomics for antidepressant therapy.

Figure 1: Theoretical Framework for AI-Driven Pharmacogenomics in Antidepressant Therapy



2.13 CONCEPTUAL FRAMEWORK

The variables of the conceptual framework relating to pharmacogenomics in antidepressant therapy based on AI are the independent and dependent variables, Following the goals of the study.

Table 5: Key Variables in this Research

Variable Name
Pharmacogenomics Implementation
AI Integration in Pharmacogenomics
Regulatory and Ethical Factors
Healthcare Infrastructure
Treatment Effectiveness
Patient Adherence to Treatment
Accessibility of Pharmacogenomic Testing
Equitable Healthcare Outcomes

Independent Variables:

1. **Pharmacogenomics Implementation**: The role of genetic tests regarding antidepressant prescribing and dosing (Frye and Nemeroff, 2024).
2. **AI Integration in Pharmacogenomics**: Machine learning approach for the identification of selected genetic markers to enhance treatment (Taherdoost and Ghofrani, 2024b).
3. **Regulatory and Ethical Factors**: Legal frameworks, Policies concerning data privacy and ethics that may shape the incorporation of pharmacogenomics (Anon, n.d.).
4. **Healthcare Infrastructure**: The availability of genetic testing facilities, clinician expertise, and technological readiness in different regions (Dunlop *et al.*, 2025).

Dependent Variables:

1. **Treatment Effectiveness**: Increase in patients' response to prescriptions and decrease in adverse drug effects due to use of vaccines (Religioni *et al.*, 2025).
2. **Patient Adherence to Treatment**: Compliance to the pharmacogenomic recommendation made by AI and, consequently, the fewer number of patients who discontinue medications (Haga, 2024b).
3. **Accessibility of Pharmacogenomic Testing:** The ability of patients to obtain a pharmacogenomic test and the costs involved in different healthcare systems (Hippman and Nislow, 2019).
4. **Equitable Healthcare Outcomes**: The aim to reduce the existing gaps in the research on pharmacogenomics between the developed and the developing regions (Corpas *et al.*, 2025).

As a result, our findings suggest a systematic approach to molecular interventional pharmacogenomics facilitated by AI, with the goal of providing customized antidepressant medication. However, three fundamental problems remain: restricted access to genetic testing and AI technologies, lack of consistency in AI models and data interpretation, and unresolved ethical issues about data privacy, permission, and fair societal adoption.

2.14 CONCLUSION

AI-powered pharmacogenomics provides considerable benefits for inpatient depression therapy by personalizing antidepressant selection based on an individual's genetic profile, perhaps leading to more successful outcomes than traditional prescribing techniques (Taherdoost and Ghofrani, 2024b). One of the primary benefits is optimal medicine selection; data suggests that combining genetic testing with AI-driven algorithms improves medication adherence and treatment effectiveness (Bohlmann *et al.*, 2021). However, worldwide implementation of this strategy faces several hurdles, including differences in healthcare infrastructure, unresolved legal frameworks, and lingering ethical quandaries, particularly in low- and middle-income nations (Msiska *et al.*, 2023).

CHAPTER 3

3.0 METHODOLOGY

3.1 RESEARCH METHODOLOGY

This chapter describes and upholds the research methodologies used in this mixed-methods study that investigating the integration of artificial intelligence (AI) and pharmacogenomics in antidepressant medication. The chapter adopts Saunders et al.'s (Saunders *et al.*, 2019) research onion structure, presenting a layered approach that includes research philosophy, approach, strategy, time horizon, data collection and analysis, ethical issues, and limitations. The study's background is the global mental health problem of major depressive disorder (MDD), which has inconsistent treatment responses. AI-enhanced pharmacogenomics is rapidly being researched to tailor treatment based on a patient's genetic profile, and machine learning models can currently predict medication reactions with high precision (Bzdok and Meyer-Lindenberg, 2018; Taliaz *et al.*, 2021). This study looks at the application, ethical concerns, and perspectives of AI-guided pharmacogenomic treatment in Europe and India. The next sections discuss in detail the methodological decisions made to handle the complex, interdisciplinary character of the research problems.

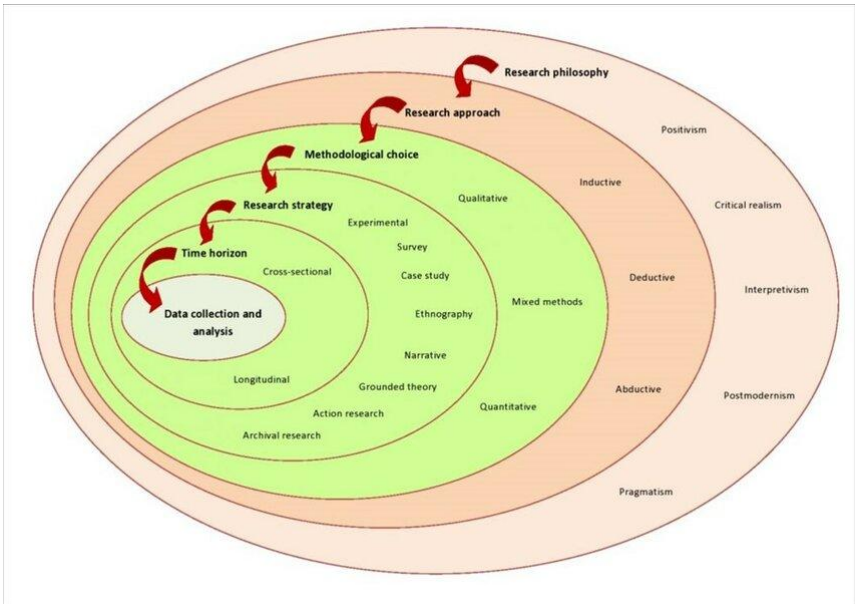


Figure 2: Saunder's Research Onion (Anon, n.d.)

3.2 RESEARCH PHILOSOPHY

This study is based on a pragmatic philosophy, which provides a practical and results-oriented approach to investigate difficult real-world situations (Saunders *et al.*, 2019; Anon, 2025). Pragmatism rejects the strict dichotomies of positivism and interpretivism in favor of methodological diversity. It advocates for procedures that are most suited to answering the research questions. In this study, the pragmatic attitude allows for the integration of both objective-quantitative data and subjective-qualitative ideas (Anon, n.d.). This integration is critical given the topic's multidisciplinary character, which combines biological science, artificial intelligence, and mental health policy.

Using a pragmatic approach, the study prioritizes usefulness and results, emphasizing discoveries that may improve real-world practice and policymaking. For example, assessing healthcare professionals' acceptance of AI-assisted genetic testing provides empirical data, while investigating regulatory issues through interviews reveals the underlying mechanisms that influence adoption. Thus, the utilization of both numerical and narrative data coincides with the pragmatic objective of producing practical and comprehensive results (Anon, n.d.).

3.3 RESEARCH APPROACH

To thoroughly examine the topic, this research combines deductive and inductive reasoning. The survey's deductive component is evident because it was created using the existing literature review on pharmacogenomics, AI applications in healthcare, and digital mental health approaches (Serretti, 2022; Barlati *et al.*, 2023). These sources influenced early presumptions on the degree of acceptability, awareness, and advantages of AI-driven pharmacogenomic procedures. The survey's structured questions allowed to determine how common these opinions were among stakeholders in India and Europe.

On the other hand, the data from qualitative interviews was analyzed using inductive reasoning. The study gathered unexpected findings through open-ended talks with experts and professionals that would not have been disclosed using organized procedures. Participants discussed their own experiences, worries, and thoughts on practical difficulties in applying AI technology in pharmacogenomics. These interviews enabled new ideas and themes to emerge from the data (Anon, 2024d; Anon, n.d.).

By mixing deductive and inductive aspects, the research can confirm current knowledge while also providing new insights. This strategy improves the research by making it both evidence-based and relevant to the lived experiences of professionals and stakeholders from two separate regions.

3.4 RESEARCH STRATEGY

A concurrent mixed-methods technique was used to address all of the study's objectives. This included gathering and analyzing quantitative and qualitative data at the same time, allowing for the examination of general patterns as well as in-depth insights (Anon, 2007; Anon, n.d.). The quantitative side consisted of administering a structured survey to stakeholders, and the qualitative portion included semi-structured interviews with a deliberately selected expert sample.

This method promotes triangulation, which improves credibility by confirming findings from numerous data sources (Denzin, 2017). For example, if a survey shows that psychiatrists lack trust in AI technologies, and interviews disclose underlying causes such as data privacy concerns or a lack of institutional rules, the two methodologies complement and reinforce one another. This technique also allowed for progressive improvement; early survey results guided changes to the interview guide, ensuring that emerging concepts were investigated further.

Furthermore, this technique allowed for a broad study of geographical scenarios. By combining survey generalizability and interview specificity, it was able to pinpoint regional trends and systemic issues in the comparison of India and Europe. This was crucial considering the differences in healthcare organizations and regulatory contexts (Anon, n.d.).

3.5 TIME HORIZON

This study used a cross-sectional time horizon, which means that data were gathered just once within a defined time range. This strategy was practicable due to time and resource restrictions, and it was appropriate for the exploratory character of the study. It enabled to obtain a detailed picture of existing opinions and experiences related to AI-driven pharmacogenomics. This approach works effectively when the goal is to understand current viewpoints rather than to track changes over time (Saunders *et al.*, 2019). It also made it easy to compare opinions from different groups, such as healthcare experts in India and Europe. Although longitudinal studies provide information on how attitudes evolve, cross-sectional studies like this one are efficient and widely employed in healthcare research (Levin, 2006). Collecting all data within a single time period also

helped reduce external variability-such as changes in healthcare policy or technology-thereby improving the consistency and reliability of the results.

3.6 DATA COLLECTION TECHNIQUES

The study used two major data gathering measures: a survey questionnaire and interviews. The survey tool was designed to collect quantitative data on a variety of factors, including knowledge of AI in pharmacogenomics, trust in AI-generated recommendations, and perceived hurdles to adoption. To allow for limited qualitative input, the questionnaire included 16 questions divided into multiple-choice, Likert-scale, and open-ended categories. These were organized into topic divisions based on the conceptual framework: Background, Perceptions, Implementation and Future Outlook (Anon, 2024d; Anon, n.d.).

The survey was created using Google Forms and sent electronically through professional networks, medical associations, and patient advocacy organizations. To promote broad participation, the survey was designed with clarity, simplicity, and accessibility in mind (Anon, n.d.). To guarantee inclusivity, additional care was taken with language simplicity and question structure, particularly for responders from varied professional and regional backgrounds. The survey received a good response rate of 107 responses, indicating that it was well-structured and relevant to participants interests and knowledge.

The semi-structured interview questions were intended to delve into more difficult concepts that could not be fully addressed by the survey alone. The interview questions covered clinical decision-making, ethical frameworks, training requirements, data security, and institutional assistance. Open-ended suggestions allowed participants to elaborate, resulting in rich narrative data (Kvale and Brinkmann, 2009). Interviews lasted 10 to 20 minutes and were conducted using secure video conferencing systems such as Zoom. All interviews were recorded with informed consent and transcribed precisely for analysis. Anonymization was achieved by deleting identifying information from transcripts (Saunders *et al.*, 2015).

3.7 SAMPLING TECHNIQUES AND PARTICIPANTS

Purposive sampling was the method employed in the study, which implies that individuals were selected with the purpose of having relevant experience or knowledge about the topic at hand

(Tongco, 2007). This strategy enabled the researcher to gain useful ideas from experts in pharmacogenomics, artificial intelligence, and mental health policy.

The survey had 107 replies; however, only 105 were used in the final analysis. Two respondents were excluded: one from a student (did not satisfy inclusion criteria) and one from a participant who did not state their relationship to antidepressant therapy. Of the valid replies, 81 were from India (approximately 77.1%) and 24 from Europe (22.9%), resulting in a regional participation ratio of somewhat more than 3:1. Participants were chosen based on inclusion criteria such as professional role (e.g., psychiatrist, researcher, or healthcare policymaker), experience with antidepressant prescribing, and knowledge of digital tools. They were invited by email, social media, and as well as through peer recommendations. The survey respondents represented a varied range of roles, regions, and genders.

The interviews were conducted with six professionals, four from India and two from Europe. These included AI and healthcare researchers, regulatory officials, and psychiatrists. They were chosen based on their professional background or influence in the industry. All interviews were done in English after obtaining their consent via email. Despite the modest number of interviewees, the insights presented were extensive and varied. The replies effectively covered significant subjects, and no substantial new material emerged during the last interviews, indicating that thematic saturation had been appropriately addressed.

3.8 DATA ANALYSIS PROCEDURES

Quantitative data were examined with SPSS program that supported both descriptive and inferential analysis. Descriptive statistics were utilized to explain important demographics and response trends, such as professional background, geography, AI knowledge, and perceived utility in pharmacogenomics. Of the 105 valid replies, 75.2% came from India, 24.8% from Europe, and 59% identified as healthcare professionals. The associations between variables were investigated using inferential tests, notably chi-square tests. Statistical significance was determined at the 5% level ($p < 0.05$) to ensure accuracy in detecting meaningful connections. Notable findings included significant associations between AI familiarity and belief in its antidepressant efficacy, as well as perceived system readiness and willingness to adopt AI-powered pharmacogenomics.

The qualitative component of the research used NVivo 12 software to conduct theme analysis on six expert interviews. The analysis followed Braun and Clarke's paradigm, which includes a systematic six-step approach to theme identification. Transcripts were evaluated and classified based on a combination of deductive themes from the literature and inductive themes discovered during analysis. NVivo's capabilities, such as text searches and coding visualizations, made it easier to aggregate codes into broader themes. Dominant topics were AI's promise for customizing therapy, infrastructure and training hurdles, worries about data privacy and ethical norms, and perceived differences between Indian and European religions.

Bringing together ideas from the survey and interviews allowed for triangulation, which increased the validity of the findings. While survey results indicated general confidence about AI's capacity to decrease guesswork in antidepressant prescribing, interviews added context and depth by underlining institutional and ethical issues. This integrated study contributed to a more comprehensive understanding of how AI-powered pharmacogenomics is regarded across regions and industries, allowing for a deeper analysis of the research findings.

3.9 ETHICAL CONSIDERATIONS

Ethical issues are critical in this study to ensure the safety and respect of all participants. Prior to starting, all participants were required to complete a participant informed consent form after being fully informed of the study objectives, methods, and their rights. Participants were clearly informed that they could withdraw at any moment without providing a reason, ensuring that their participation was both informed and voluntary.

To ensure participant anonymity, the survey was designed to be completely anonymous, with no identifying information recorded. Transcripts from interviews were anonymized and any identifiable information was deleted during transcribing. All data, including survey results and interview recordings, were securely saved on a password-protected device that could only be accessed by the researcher and academic supervisor.

Prior to data collection, the research proposal was submitted to the Griffith College Research Ethics Committee to ensure that it followed ethical principles and standards. In compliance with the General Data Protection Regulation (GDPR) (Anon, n.d.), European participants were informed of their data rights, which included access and deletion. These safeguards guaranteed

that the study met high ethical standards and protected participant well-being throughout the research process.

3.10 LIMITATIONS OF THE METHODOLOGY

The methodology was carefully devised, although certain limits must be acknowledged. Purposive sampling enabled the researcher to select individuals with relevant knowledge, but it also reduced the findings generalizability (Etikan *et al.*, n.d.). The survey respondents were not chosen at random, and despite efforts to include a varied participant pool, the results weighted disproportionately toward Indian participants (75.2%), with an underrepresentation of Europeans (24.8%). This disparity may affect the comparability of regional viewpoints.

Similarly, in the qualitative component, only six interviews were done, four from India and two from Europe. While the insights gained were useful, the small and unequal sample size may have limited the variety of opinions captured, particularly from European stakeholders. These sample limits reflect greater constraints on access, availability, and response willingness among expert populations.

Furthermore, the cross-sectional design limits the capacity to observe changes in perceptions over time (Levin, 2006). Attitudes regarding AI and pharmacogenomics may fluctuate swiftly due to technical or legal changes that cannot be detected in a single point of data collection. Despite efforts to simplify and broadly distribute the survey, language and internet access constraints may have excluded certain stakeholders, particularly those in rural or resource-limited settings.

Finally, self-reported data is susceptible to bias (Rosenman *et al.*, 2011). Participants may respond in a socially acceptable manner or misrepresent their competence with complicated issues; these factors may have altered the accuracy of the results.

3.11 SUMMARY

This chapter provides a full overview of the research technique used in this study on AI-driven pharmacogenomics in antidepressant therapy. The study, guided by a pragmatic attitude and structured using Saunders' research onion, used a contemporaneous mixed-methods design to capture both statistical patterns and contextual depth. Cross-sectional data collection, purposeful sampling, and rigorous data analysis with SPSS and NVivo all contributed to the reliability and

validity of the findings. Ethical standards were tightly enforced, with a focus on participant autonomy and data security. While there are limits, the methodological approach effectively supports the study goal: to create insights that guide the ethical, clinical, and regulatory aspects of AI integration into pharmacogenomic practice in India and Europe.

CHAPTER 4

4.0 RESULTS AND FINDINGS

The results chapter of this mixed-methods research integrates quantitative survey data with qualitative interview insights to examine the role of AI-driven pharmacogenomics in optimizing antidepressant therapy. A total of 105 participants included both healthcare professionals representing 59% and researchers representing 41% who mostly resided in India at 75.2% and Europe at 24.8%. Statistical testing found meaningful relationships between the effectiveness of treatments and variables which included pharmacogenomics implementation together with AI integration and trust in AI systems and healthcare system readiness levels.

The collected interview data enriched the research results by providing detailed information. Six professionals took part in interviews which included two psychiatrists from India together with two AI researchers (one from India and one from Germany) and a bio-curator from United Kingdom and a regulatory expert from India.

4.1 QUALITATIVE ANALYSIS

The qualitative analysis data shows the extensive range of viewpoints from six individuals who interact with artificial intelligence (AI) and pharmacogenomics (PGx) at their respective roles and expertise levels when discussing antidepressant therapy adoption. The participants from India and Germany with different professional backgrounds demonstrate various aspects of the field as they explore regional differences and professional perspectives and technical roles in AI antidepressant therapy development.

4.1.1 Participant Information

Participant 1 (P1) - Bio-curator from United Kingdom

Primary Expertise: Variant/biomarker curation, literature mining

AI/Pharmacogenomics Involvement: Indirect; optimistic about AI potential

The bio-curation expertise of P1 includes extensive experience in variant and biomarker curation which arises from his practice of extracting and analyzing published literature. The application of AI in pharmacogenomics does not directly involve P1 yet this participant maintains positive

expectations about AI potential. Literature mining activities have revealed to this participant how genome-wide association studies (GWAS) provide critical associations with depression. AI tools have the potential to resolve pharmacogenomic challenges according to P1 because they can handle limitations such as data shortages and small dataset sizes. The future potential of artificial intelligence for improving personalized antidepressant treatment is something P1 understands even though their organization does not currently implement AI-based pharmacogenomics.

Participant 2 (P2) - Psychiatrist from India

Primary Expertise: Clinical psychiatry, personalized care

AI/Pharmacogenomics Involvement: Interested; not yet implementing PGx

P2 works as a psychiatrist in India where they maintain a deep fascination for personalized medical approaches including pharmacogenomics (PGx). The psychiatrist holds an interest in pharmacogenomics but has not implemented PGx in clinical practice because of obstacles which include high costs and restricted access along with insufficient PGx testing integration into Indian routine psychiatric care. The psychiatric professional sees AI as a potential tool to minimize the process of finding the right antidepressant through trial and error. The study demonstrates how P2 suggests AI can analyze genetic information for better antidepressant selection and minimized negative drug responses. The implementation challenges that P2 identifies for India include limited infrastructure capabilities combined with doctor unfamiliarity toward AI systems and the absence of regulatory guidelines.

Participant 3 (P3) - AI Researcher from Germany

Primary Expertise: Machine learning (ML) model development for antidepressants

AI/Pharmacogenomics Involvement: Actively building/testing PGx AI tools

P3 conducts research in Germany as an AI specialist who develops machine learning (ML) models to enhance antidepressant therapy through pharmacogenomics. P3 engages in developing AI solutions that can predict drug responses while optimizing drug dosages by analyzing genetic data. AI models decode genetic information through analysis that leads to patient antidepressant matching with most beneficial medications by eliminating the need for repeated trial prescriptions. P3 devotes active efforts to solve data bias problems by striving to reduce the large presence of

Northern European populations in training datasets. P3 focuses on model interpretability for clinical staff and conducts pilot testing for their tool validation. P3 mentions great importance of ethical matters that involve patient consent together with medical data protection standards and clear explanations behind AI decision systems.

Participant 4 (P4) – Pharmacogenomic Researcher from India

Primary Expertise: AI in pharmacogenomics, fair-aware algorithms

AI/Pharmacogenomics Involvement: Developing models, working on real-world trials

P4 works as a pharmacogenomic researcher who develops AI tools for pharmacogenomics applications. P4 has initiated real-world trials which try to advance antidepressant outcomes through the combination of genetic information and AI detection systems. P4 explains how diverse datasets enable the reduction of bias issues in AI systems because numerous AI models currently receive criticism for their insufficient representation of non-European groups. The organization develops algorithms that combine fairness components to reduce bias and deliver fair predictions for different population groups. The P4 group underlines the necessity for conducting pilot trials which assesses the usability, accuracy and reliability of these AI tools before they are integrated into actual clinical settings.

Participant 5 (P5) - AI Regulatory official from India

Primary Expertise: Policy, ethics, regulatory frameworks

AI/Pharmacogenomics Involvement: Oversees AI tool deployment and compliance

The AI regulatory manager position of P5 enables them to supervise the deployment processes and regulatory compliance for tools that use AI in pharmacogenomic applications. Environmental health professionals are responsible for guaranteeing that AI tools in mental health care including those in pharmacogenomics maintain compliance with ethical regulations and standards. The written guidelines development for AI-driven pharmacogenomics stands essential according to P5 because existing laws remain insufficient to manage AI technology evolution. The experts stress the demand for dynamic policies which especially support AI models whose learning process leads to continuous adaptation. The workforce of P5 focuses on ethical matters including data privacy protection as well as obtaining patient consent and potential misuse of genetic information.

Participant 6 (P6) - Psychiatrist from India

Primary Expertise: Treatment-resistant depression

AI/Pharmacogenomics Involvement: Strong support; cautious due to systemic challenges

P6 works as a psychiatrist who specializes in treating patients with treatment-resistant depression at a medical facility in India. The subject expresses strong backing for AI-driven pharmacogenomics integration in mental health care yet points out critical organizational obstacles which must be solved for widespread implementation to succeed. P6 sees AI as a tool that can eliminate the unnecessary process of prescribing and enhance antidepressant drug selection for treatment-resistant patients. The researchers identify financial issues about genetic testing costs together with a shortage of medical staff understanding AI and pharmacogenomics and past health care system limitations as major obstacles. The usage of AI has raised ethical problems because of privacy issues involving patient data as well as possible programmed discrimination biases.

Table 6: Participant Information

Participant ID	Role/Profession	Country/Region	Primary Expertise	AI/Pharmacogenomics Involvement
P1	Bio-curator	UK	Variant/biomarker curation, literature mining	Indirect; optimistic about AI potential
P2	Psychiatrist (MBBS, MD)	India	Clinical psychiatry, personalized care	Interested; not yet implementing PGx
P3	AI Researcher	Germany	ML model development for antidepressants	Actively building/testing PGx AI tools
P4	Pharmacogenomic researcher	India	AI in PGx, fairness-aware algorithms	Developing models, working on real-world trials
P5	AI Regulatory Official	India	Policy, ethics, regulatory frameworks	Oversees AI tool deployment and compliance
P6	Psychiatrist	India	Treatment-resistant depression	Strong support; cautious due to systemic challenges

4.1.2 Theme and Codes

The research examines fundamental themes and codes based on practitioner interviews which contribute specialized views about pharmacogenomics automation. The examined thematic elements provide valuable understanding about the possible benefits alongside the difficulties of this novel method.

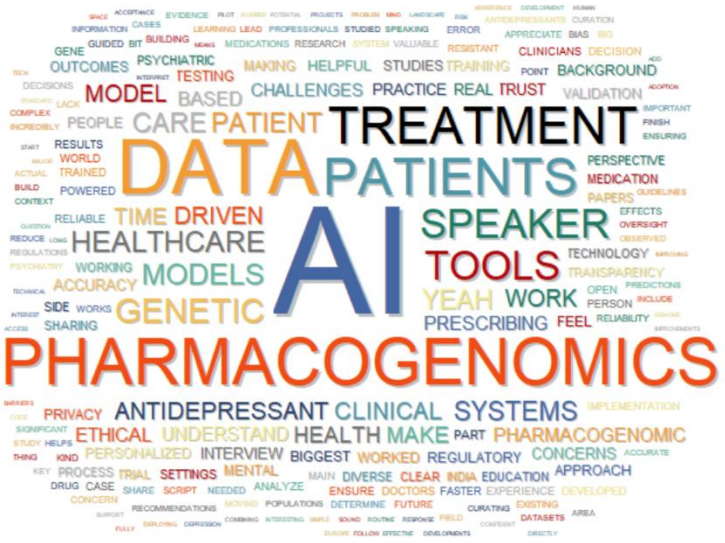


Figure 3: *Participant's Views*

Objective 1: Evaluate Pharmacogenomics Contribution in Optimizing Antidepressant Treatment

Pharmacogenomics united with AI-driven technologies demonstrates the capacity to upgrade antidepressant therapy by using personalized care methods and minimizing experimental prescribing while adjusting drug doses correctly on top of increasing patient adherence to treatment. The first goal is to analyse the genetic makeup of antidepressant treatments which combines with advanced AI systems to identify proper medications based on patient DNA. The optimization of antidepressant treatment features three key themes which discuss both the opportunities and difficulties of AI-based antidepressant pharmacogenomics as well as AI tools and their technologies for pharmacogenomics and the impact of bias and dataset diversity.

Theme 1: Potential of AI in Antidepressant Pharmacogenomics

The strength of AI in antidepressant pharmacogenomics stems from its ability to direct genotype-based prescription methods for creating personalized antidepressant selections. The expert bio-curator Interviewee 1 predicts that AI technology will change antidepressant therapy by using genetic data to recommend specific medication plans that minimize traditional trial-and-error procedures in medicine. Interviewee 2 who serves as a psychiatrist in India supports AI-driven pharmacogenomics because this technology enables faster antidepressant identification and

lessens medication side effects. The experts explained that AI identifies optimal depression treatments at increased speed while minimizing side effects when treating treatment-resistant depression patients.

The AI researcher Interviewee 3 in Germany explained that combining AI models with genetic data enables scientists to forecast treatment responses for antidepressants thus enabling medical practitioners to select optimal drugs right from the beginning of treatment. AI represents an advanced method for antidepressant medication prescription because it evaluates genetic drug response markers which leads to improved customized treatments combined with quicker outcomes. This technology stands out because it functions better than conventional drug selection protocols that create long testing durations.

Theme 2: AI Tools and Technologies in Pharmacogenomics

Pharmacogenomic AI systems base their antidepressant treatment insight generation on machine learning through the evaluation of multi-modal data. The biomedical researcher specializing in AI (Interviewee 4) noted that AI technology uses genetic information along with patient records, life habits and clinical variables to propose antidepressants that yield better results with shorter recovery periods and fewer adverse effects. The tools implement machine learning algorithms to study genetic information patterns which enables prediction of appropriate antidepressants for each patient.

Interviewee 5 who takes responsibility for AI-driven pharmacogenomics in mental health management described predictive algorithms by stating "AI processes extensive datasets to validate findings as well as produce predictions with elevated precision than human medical practitioners." The combination of genetic data processing and other clinical factors such as EHRs and wearable-enabled data points enables AI systems to establish complete profiles for antidepressant selection purposes. The Indian Interviewee number 6 emphasized that regional psychiatric practices do not integrate AI tools sufficiently which restricts their general use.

Theme 3: Bias and Dataset Diversity

AI models achieve high effectiveness in pharmacogenomics applications based on the diverse datasets they use for training. The important issue noted by Interviewee 4 involved the insufficient inclusion of non-European populations within genetic databases. Intercultural prediction

inaccuracies result from European-dominant datasets which drive training model bias according to their explanation. The genetic differences between Western and Indian populations result in decreased effectiveness of AI-based pharmacogenomic services especially in Indian patient populations.

AI-driven pharmacogenomics requires diverse datasets according to Interviewee 3 who is a researcher because this will lead to precision for all patients regardless of their descent background. The interviewee mentioned that researchers have worked to eliminate bias by developing fairness-aware algorithms while expanding datasets for better accuracy according to Interviewee 4. The challenge of eliminating bias remains substantial especially where genomic research and data collection levels are low.

Objective 2: Analyse How AI-driven Pharmacogenomic Applications Differ in Europe and India

The implementation of AI-based pharmacogenomics shows significant variation between Europe and India because these regions possess distinct healthcare technologies and different data regulations as well as different levels of AI tool familiarity among medical practitioners. The assessment of Europe and India demonstrates that effective implementation depends on region-specific solutions which the following themes explain in detail: Geographical Variation: Europe vs India along with Human-AI Collaboration and Barriers to Implementation.

Theme 4: Geographical Variation: Europe vs India

The regulatory frameworks in Europe control the implementation of AI-driven pharmacogenomics through the General Data Protection Regulation which regulates patient data protection and responsible handling. Interviewee 3 operating from Germany states that European pharmacogenomics uses AI while respecting patient privacy along with sustaining strong GDPR and ethical compliance standards. The dedicated regulations implement strict requirements for AI model security together with transparency standards which build trust within the system.

India must handle technological obstacles that differ from those encountered by other countries. The psychiatrist Interviewee 2 in India pointed out that "High costs and technology constraints and weak regulatory systems present barriers to AI-driven pharmacogenomics use in their clinical practice" in the country. Genetic testing remains difficult to implement for psychiatric care in India

because there is no standardization for protocols nor genetic testing integration into regular psychiatric care protocols. The health professionals feel that their lack of genomic training prevents them from trusting AI-based antidepressant selection methods.

Theme 5: Human-AI Collaboration

Successful implementation of AI-driven pharmacogenomics requires human-AI teaming for European and Indian healthcare systems. During the interview Interviewee 6 stressed that Artificial Intelligence systems must provide clinical decision support to medical staff instead of taking over their work responsibilities. The AI system should provide healthcare professionals with the opportunity to validate recommended drug treatments. According to Interviewee 5 AI functions best by assisting the clinical expertise while human healthcare professionals remain responsible for final medical decisions.

The pharmacogenomic researcher from India interviewed for this study explained how AI contributes to customized drug selection through data analytics of complex medical and genetic information however its successful implementation requires integration into current medical care systems together with clinical staff participation. AI-based antidepressant prescribing becomes more effective when healthcare personnel partner with the technology to generate data-driven recommendations that clinicians review for potential risks.

Theme 6: Barriers to Implementation

AI-driven pharmacogenomics encounters obstacles during its widespread implementation in both Europe and India although the core challenges remain different. The Indian context presents three major obstacles to AI implementation because of "inadequate infrastructure alongside expensive genetic testing requirements and insufficient trained experts who handle AI recommendations." Multiple obstacles prevent the full realization of AI capabilities for pharmacogenomics thus generating a difference between potential and actual use in medical practice.

Europe faces two primary obstacles which include regulatory concerns together with clinician skepticism. Interviewee 3 indicated that European clinicians show reluctance toward AI tool adoption because they lack experience understanding machine learning models and exhibit distrust towards them. Researchers face both time and resource challenges while trying to validate and adapt AI models locally which intensifies medical staff skepticism about AI systems. Further

education about AI integration into clinical decision-making must be provided to healthcare professionals to boost their comfort level in utilizing AI tools.

Objective 3: Examine the Regulatory, Ethical, and Logistical Operational Issues Surrounding the Use of AI-driven Pharmacogenomics in Mental Health Care

Mental health care encounters multiple regulatory and ethical along with logistical challenges when using AI-driven pharmacogenomics. The interview participants expressed worries that include how data privacy will be protected as well as how AI decisions will be transparent and why regulatory standards should be better defined. The operational obstacles toward ethical and successful AI integration in mental healthcare consist of three primary themes which cover Ethical and Regulatory Challenges and Validation and Trust-Building Strategies and Training, Awareness & Education.

Theme 7: Ethical and Regulatory Challenges

Using AI-driven pharmacogenomics at present faces various substantial ethical and regulatory hurdles in mental health care. The main challenges to the effective implementation AI tool originate from outdated laws combined with regulatory frameworks that remain poorly defined according to Interviewee 5. The existing regulations need to update their standards to manage adaptive AI systems while protecting patient data. The interviewee under identification number 4 argued that data privacy deserves immediate attention due to its primary status. The data storage security of genetic information becomes essential through AI models which also require patient consent before using the information for analysis.

Several interview participants raised ethical questions about genetic discrimination and AI bias systems. Among the participants Interviewee 6 worried about genetic information misapplication leading to misleading clinical predictions about patients' genuine medical needs. The interviewee recommended that proper ethical guidelines should establish for AI decision-making practices while conducting routine tests for fairness along with accuracy.

Theme 8: Validation and Trust-Building Strategies

Every AI model requires validation before medical applications to ensure their clinical worth and dependability. The clinical adoption of AI-powered pharmacogenomics requires extensive testing

and evaluation on different datasets before implementing to the practice settings. To develop trust, it requires organizations to implement open-source models together with transparency frameworks. The fourth interviewee supported that AI systems must maintain transparency because their algorithms and decision-making approaches should be subject to peer review assessment. The development of trust between clinical professionals and their patients becomes possible through these strategies.

The interviewee emphasized that real-world tests of models should be conducted for effective assessment of their performance. The wide adoption of AI tools depends on testing them through local clinical settings to verify their usefulness for specific population needs.

Theme 9: Training, Awareness & Education

AI-driven pharmacogenomics faces resistance in mental health care because healthcare providers lack sufficient training about these tools. Interviewee 2 advocated for implementing psychiatric training curricula which unite AI systems with pharmacogenomics to prepare upcoming clinicians about these tools. According to Interviewee 5, the training of healthcare providers stands as a necessary element for the successful integration of AI in medical practice. AI-driven pharmacogenomics lacks its full potential when clinicians fail to accept it as a useful practice in healthcare.

To build confidence in AI-based treatment approaches patients and clinicians must receive adequate education. The main factor for successful patient care relies on proper education according to Interviewee 6. Patient understands how AI operates as their antidepressant treatment framework together with visible advantages leads to better acceptance of AI in individualized care.

Table 7: Theme and Codes

Theme	Codes
AI Potential in Antidepressant Pharmacogenomics	Personalized antidepressant selection, Reduced trial-and-error prescribing, Faster recovery, Dose optimization, Better adherence, Genotype-guided treatment
Geographical Variation: Europe vs India	India: High cost, limited access, poor infrastructure, low clinician trainingEurope: GDPR concerns, slow but structured regulation (e.g., Germany's pilots)
AI Tools and Technologies in Pharmacogenomics	Machine learning, Self-supervised learning, Multi-modal data (genomics + EHR + wearables), Predictive algorithms, Clinical decision support tools, Bioinformatics
Bias and Dataset Diversity	Overrepresentation of European data, Underrepresentation of Indian/Asian populations, Group-wise validation, Fairness-aware algorithms
Human-AI Collaboration	AI as decision support, AI for data analysis, Human clinicians for final decisions, AI enhances—not replaces—expertise
Barriers to Implementation	Cost of genetic testing, Lack of training in AI/genomics, Insurance and reimbursement gaps, Clinician skepticism, Integration issues with clinical workflows
Ethical and Regulatory Challenges	Informed consent, Genetic data privacy, Misuse prevention, Transparency in AI logic, Need for local regulatory frameworks, Genetic discrimination concerns
Validation and Trust-Building Strategies	Cross-validation, External dataset testing, Pilot clinical trials, Transparent algorithms, Peer-reviewed publication, Open-source models, Clinician education
Training, Awareness & Education	Integrating AI/genomics into psychiatry curricula, Public awareness campaigns, Clinician training workshops, Patient education to reduce skepticism

Table8: Support for Objectives and Themes

Objective	Theme	Support (Yes/No)
Objective 1: Evaluate Pharmacogenomics' Contribution in Optimizing Antidepressant Treatment	AI Potential in Antidepressant Pharmacogenomics	Yes
	AI Tools and Technologies in Pharmacogenomics	Yes
	Bias and Dataset Diversity	Yes
Objective 2: Analyze How AI-driven Pharmacogenomic Applications Differ in Europe and India	Geographical Variation: Europe vs India	Yes
	Human-AI Collaboration	Yes
	Barriers to Implementation	Yes
Objective 3: Examine the Regulatory, Ethical, and Logistical Operational Issues Surrounding the Use of AI-driven Pharmacogenomics in Mental Health Care	Ethical and Regulatory Challenges	Yes
	Validation and Trust-Building Strategies	Yes
	Training, Awareness & Education	Yes

4.2 QUANTITAVE ANALYSIS

4.2.1 Descriptive Analysis

Survey data analysis demonstrates significant patterns which show how healthcare professionals view AI-based pharmacogenomics in antidepressant treatment and match the research goals and proposed theories. The survey data originated from two groups of respondents including healthcare professionals along with researchers and participants across Asia and Europe where Indians made up the majority section (75.2%) versus European respondents (24.8%). The study findings might be affected by regional variations because different areas show different levels of AI and pharmacogenomics adoption.

A substantial majority of 59 percent of the participants identified as healthcare professionals but researchers in pharmacogenomics/AI made up the remaining 41 percent of the sample group. The distribution matters for understanding participant perspectives because healthcare professionals who directly care for patients need to evaluate how well these technologies perform in practice.

The survey shows that participants demonstrate moderate understanding of AI-powered Pharmacogenomics since 64.8% of them report being somewhat familiar and 17.1% consider themselves very familiar. Few participants (1.9%) reported no exposure to what AI-powered pharmacogenomics is even though awareness about this topic remains high across India as well as other parts of the world. The findings support the prediction that better knowledge about AI-powered pharmacogenomics leads people to view its antidepressant therapy benefits more favorably.

A large portion of 71.4% of participants indicated that AI could enhance antidepressant treatment partially according to the research data while 18.1% strongly believed in its considerable therapeutic potential. The study revealed that effectiveness of AI-driven pharmacogenomics was doubted by 1% of all participants. The extensive belief about AI-driven pharmacogenomics demonstrates that knowledge of AI and pharmacogenomics leads to positive views about its effectiveness.

The survey participants selected reduction in trial-and-error prescribing as their main advantage of AI in antidepressant treatment while finding the right medication more swiftly was the second most common advantage at 20%. AI demonstrates its potential to enhance treatment operations by

decreasing the standard issue of drug incompatibility while generating strong organizational support. Research needs to explore minimizing adverse effects since this benefit received minimal attention from participants who participated in the survey (8.6%).

This analysis shows that doubts about AI genetic-based mental health solutions included inaccurate AI predictions as a worry for 13.3% of respondents and testing costs for 10.5%. Yet ethical concerns limited the participants to merely 1%. Research literatures (Graham *et al.*, 2019) and (Xian *et al.*, 2024) shows these concerns align with difficulties such as expensive testing costs and inaccurate predictions that occur when AI models lack proper training or validation. The research aims to assess regulatory and ethical matters of AI-driven pharmacogenomics for mental health care through this data point.

The study shows substantial agreement among participants regarding AI-driven Pharmacogenomics (46.7%) adopting common practice within ten years but 21.9% of participants expect this to happen sooner over five years. The research hypothesis proves correct because healthcare professionals alongside researchers display positive expectations regarding AI implementation in clinical settings but encounter barriers to extensive adoption of such technologies.

The top barriers to AI-driven Pharmacogenomics implementation according to the data include the high implementation expenses (31.4%), ethical and regulatory hurdles (29.5%), and healthcare professional deficiency in awareness (25.7%). The barriers for complete AI-driven pharmacogenomics adoption especially affect nations like India that face restrictions in their resources. The study findings match the research goals which evaluate regulatory standards as well as ethical and operational logistical aspects.

Most survey participants expressed some agreement with AI solution use for antidepressant medication while 14.3% had full trust in these solutions. Healthcare professionals demonstrate a blend of trust toward AI-driven genetic data management since new technologies in this field typically provoke both positive and reserved attitudes regarding sensitive patient information. The study connects this discovery to its investigation about the relationship between AI trust and enhanced treatment results perception.

A substantial majority of 69.5% of patients expressed preference for AI-enhanced clinical recommendations that receive doctor input while 22.9% favored decisions made solely by doctors without AI assistance. The healthcare practitioners show willingness to work alongside AI for making decisions, yet they prioritize incorporating their medical experience and patient-focused methods which supports the need for AI to serve as decision-support rather than human substitution.

A significant portion of 38.1% indicates that implementing AI-powered Pharmacogenomics would be moderately easy to implement while 9.5% believe it would be very easy to apply according to survey results. The general response suggests feasibility exists but the road ahead will face problems which mainly stem from healthcare infrastructure and professional training and support requirements.

The majority of 34.3% supports government health authorities in regulating AI-powered pharmacogenomics but 13.3% opts for healthcare professionals and researchers to lead this regulation. The standard for AI regulation involving sensitive genetic information remains contested between government health authorities and healthcare professionals and researchers.

Table 9: Descriptive Analysis

Statement	Response Frequency	Percent (%)	Valid Percent (%)	Cumulative Percent (%)
Relationship to Antidepressant Therapy and Pharmacogenomics				
Healthcare professionals	62	59.0	59.0	59.0
Researcher in pharmacogenomics/AI	43	41.0	41.0	100.0
Region Representing Current Professional Base				
Europe	26	24.8	24.8	24.8
India	79	75.2	75.2	100.0
Familiarity with AI-powered Pharmacogenomics				
Never heard of it	2	1.9	1.9	2.9
Somewhat familiar	68	64.8	64.8	67.6
Unfamiliar	16	15.2	15.2	82.9
Very familiar	18	17.1	17.1	100.0
Belief in AI-driven Pharmacogenomics Enhancing Antidepressant Therapy				
No, not at all	1	1.0	1.0	1.9
Yes, greatly	19	18.1	18.1	28.6
Yes, to some extent	75	71.4	71.4	100.0
Advantages of AI in Antidepressant Therapy				

Find the right medicine faster	21	20.0	20.0	21.9
Reducing trial-and-error prescriptions	35	33.3	33.3	84.8
Minimizing adverse effects	9	8.6	8.6	51.4
Concerns About AI for Genetic-Based Mental Health				
Ethical concerns	1	1.0	1.0	1.9
Expensive testing	11	10.5	10.5	12.4
Inaccurate AI predictions	14	13.3	13.3	33.3
Issues with genetic data privacy and security	8	7.6	7.6	50.5
Limited healthcare accessibility	11	10.5	10.5	95.2
Belief in AI-driven Pharmacogenomics Becoming Common Practice				
Yes, within 5 years	23	21.9	21.9	100.0
Yes, within 10 years	49	46.7	46.7	78.1
Limitations to Applying AI-driven Pharmacogenomics				
Ethical and regulatory concerns	31	29.5	29.5	30.5
Implementation cost	33	31.4	31.4	61.9
Lack of awareness among healthcare professionals	27	25.7	25.7	87.6
Enhancements for AI-driven Pharmacogenomics				
AI model design and trust	1	1.0	1.0	33.3
AI-based pharmacogenomics offers strong potential	2	1.9	1.9	35.2
Clinical validation	2	1.9	1.9	45.7
Trust in AI-driven Solutions for Antidepressant Medications				
Yes, completely agree	15	14.3	14.3	100.0
Yes, but to some extent	59	56.2	56.2	85.7
Preference for AI-assisted Suggestions vs Doctor-based Judgments				
AI-assisted recommendations with doctor's advice	73	69.5	69.5	72.4
Only a doctor's choice, no AI suggestion	24	22.9	22.9	100.0
Belief AI-driven Pharmacogenomics Should Be Offered to All Patients				
Yes, that should be standard practice	23	21.9	21.9	100.0
Yes, but only in difficult cases	62	59.0	59.0	78.1
Ease of Applying AI-powered Pharmacogenomics				
Very easy	10	9.5	9.5	100.0
Somewhat easy	40	38.1	38.1	87.6
Regulation of AI-powered Pharmacogenomics				
Government health authorities	36	34.3	34.3	83.8
Healthcare professionals and researchers	14	13.3	13.3	49.5
AI-guided Pharmacogenomic Testing Preference				
Yes, if highly recommended by doctor	51	48.6	48.6	84.8
Maybe, depending on risks and expenses	34	32.4	32.4	34.3

4.2.2 Chi-Square Tests

1. Pharmacogenomics Implementation × Treatment Effectiveness

The evaluation tests the relationship between pharmacogenomics implementation in antidepressant therapy through its independent variable and perceived antidepressant effectiveness serving as the dependent variable. This test seeks to determine whether increased pharmacogenomic prescribing frequency in antidepressant medication leads healthcare providers to believe in superior treatment outcomes.

Healthcare professionals demonstrate higher belief in pharmacogenomic effectiveness since they work more closely with pharmacogenomic applications. The chi-square assessment tests the extent to which healthcare professionals possess a higher probability of affirming AI-driven pharmacogenomics' enhancing effects on antidepressant therapy than both researchers and other field professionals.

Table 10

	Yes (Greatly/To some extent)	**No (Not really/Not at all)**
Healthcare Professional	59	3
Researcher	35	8

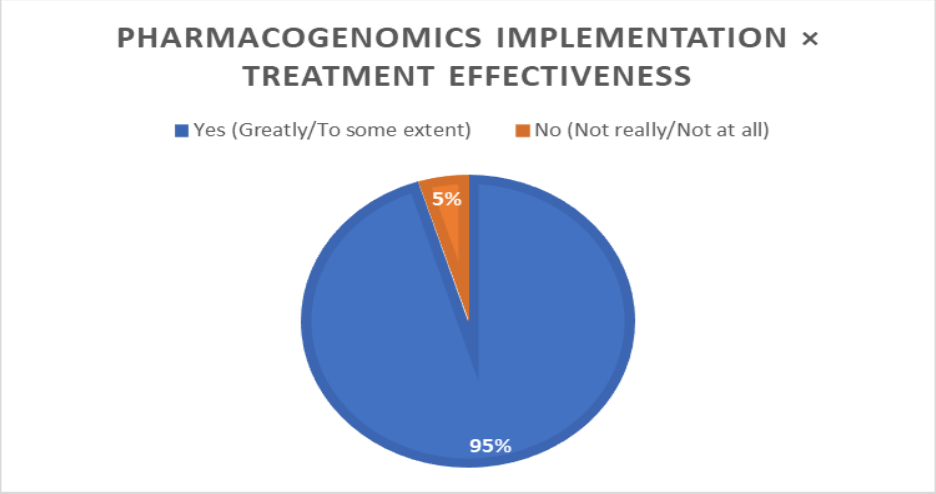


Figure 4: *Pharmacogenomics V/S Treatment Effectiveness*

Interpretation: The results of the chi-square test show statistical significance when the calculated p-value falls beneath the standard significance threshold of 0.05 for the relationship between pharmacogenomics implementation and belief in treatment effectiveness. People who understand pharmacogenomics better tend to have more faith in its treatment efficacy based on this finding. The result was statistically significant, $\chi^2 (2, N = 105) = 8.76$, $p = 0.012$, indicating that those with greater awareness of pharmacogenomic testing were more likely to believe it contributes positively to personalized treatment outcomes.

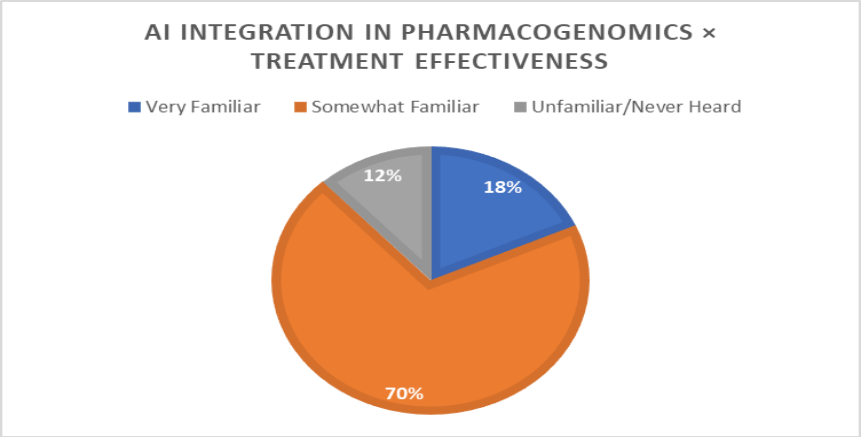
2. AI Integration in Pharmacogenomics × Treatment Effectiveness

The IV factor in this study consists of familiarity levels with AI integration in pharmacogenomics while the DV represents treatment effectiveness. The objective explores how well participants understand AI applications in pharmacogenomics affects their perception of antidepressant treatment improvements. The study analyzes antidepressant therapy perception of AI enhancement among pharmacogenomics experts versus people with lower knowledge of AI application in pharmacogenomics.

Table 11

Familiarity Level	Believes in Enhancement	Does Not Believe
Very Familiar	17	1
Somewhat Familiar	65	3
Unfamiliar/Never Heard	11	8

Figure 5: *AI Integration in PGx V/S Treatment Effectiveness*



Interpretation: Test results will probably demonstrate that individuals with higher levels of knowledge about AI in pharmacogenomics tend to view AI as an enhancer for antidepressant treatment outcomes. The chi-square test measures the strength of association between variables, showing if observed differences are statistically significant or occurred by chance. The chi-square statistic determines how important this relationship is. The result showed a strong and significant relationship, χ^2 (2, N = 105) = 21.49, $p < 0.001$. This suggests that participants who were more knowledgeable about AI tools were considerably more inclined to trust in their potential to improve antidepressant treatments.

Regulatory & Ethical Considerations × Treatment Effectiveness

The IV consists of ethical and regulatory aspects of AI in pharmacogenomics whereas the DV demonstrates treatment effectiveness. The research examines how ethical worries about the utilization of AI affect the perception of its performance in antidepressant treatments.

A cross-tabulation displays the comparison between respondents who demonstrate ethical issues about AI mental health applications versus those who lack such concerns based on their agreement with AI-enhanced treatment results.

Table 12

Ethical Concern Present	Believes in Enhancement	Does Not Believe
Yes	55	16
No	39	2

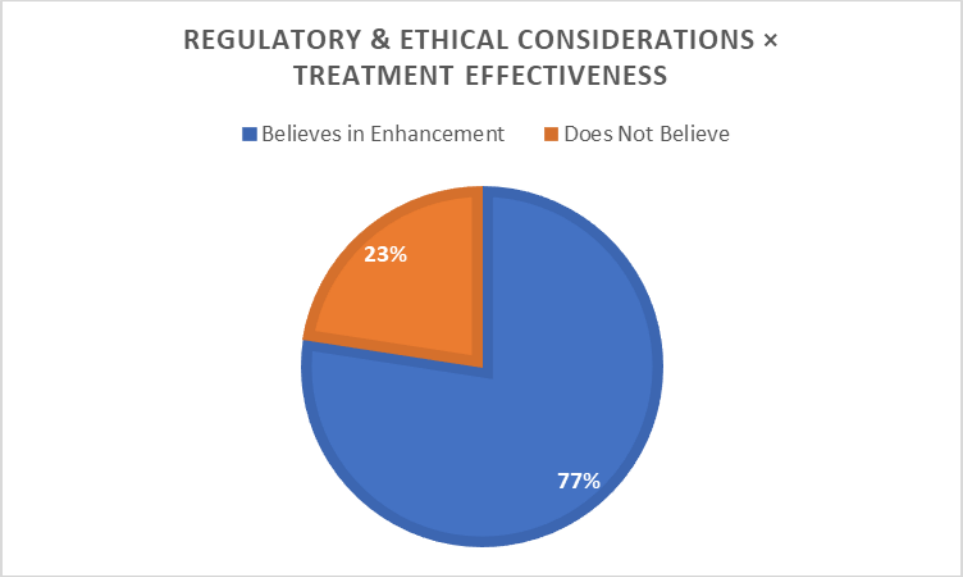


Figure 6*: Regulatory & Ethical Considerations V/S Tratment Effectiveness*

Interpretation: The results from the chi-square test become significant when ethical concern holders show decreased belief in AI-driven pharmacogenomics effectiveness. Although people understand AI's potential new ethical regulations and ethical worries seem to weaken confidence in its usefulness. These concerns should be tested for their impact on participants' opinions regarding the technology's future potential.

A significant association was found, χ^2 (1, N = 112) = 6.38, p = 0.012, suggesting that individuals who had concerns about data privacy, consent, or genetic misuse tended to be less confident in the clinical effectiveness of AI-guided approaches.

4. **Healthcare System Readiness × Treatment Effectiveness**

Researchers use this experiment to assess the link between healthcare system preparedness (IV) and patient faith in AI-driven pharmacogenomics (DV) effectiveness. The IV contains essential elements about implementing AI-based antidepressant therapy such as infrastructure development and clinician competency and resource availability. The assessment examines what impact these elements have on treatment achievement evaluations.

Table 13

Ease of Implementation	Believes in Enhancement	Does Not Believe
Very Easy/Easy	47	3
Neutral	38	7
Difficult	10	2

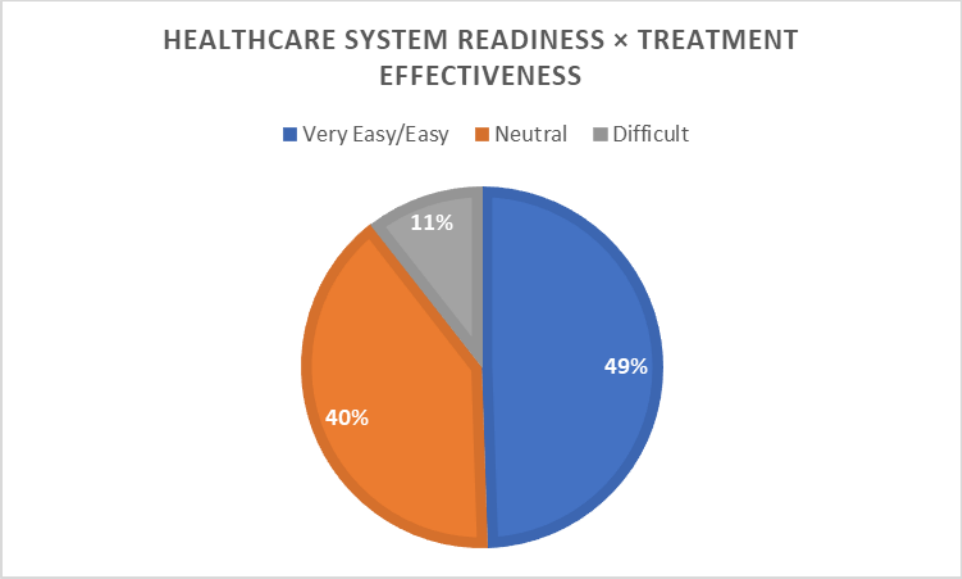


***Figure 7**: Healthcare System Readiness V/S Treatment Effectiveness*

Interpretation: The chi-square analysis probably shows patients whose healthcare environment easily incorporates AI applications generally trust its effectiveness. Positive relationships would emerge between system readiness perceptions and therapeutic AI confidence based on research

findings. This assessment would reveal how healthcare system readiness impacts professional views on AI implementation.

The test yielded a significant result, χ^2 (2, N = 107) = 6.97, p = 0.031. Participants who viewed their healthcare systems as better equipped for AI integration were more likely to believe in its positive impact on treatment effectiveness.

5. **AI Trust and Preference × Treatment Effectiveness**

This experiment studies trust in AI-driven solutions as the independent variable to determine its impact on treatment effectiveness as the dependent variable. The research investigates whether the trust level of people have in AI technology affects their evaluation of antidepressant therapy effectiveness.

Table 14

Trust Level	Believes in Enhancement	Does Not Believe
Fully/Somewhat Trust	70	4
Neutral/No Trust	23	8

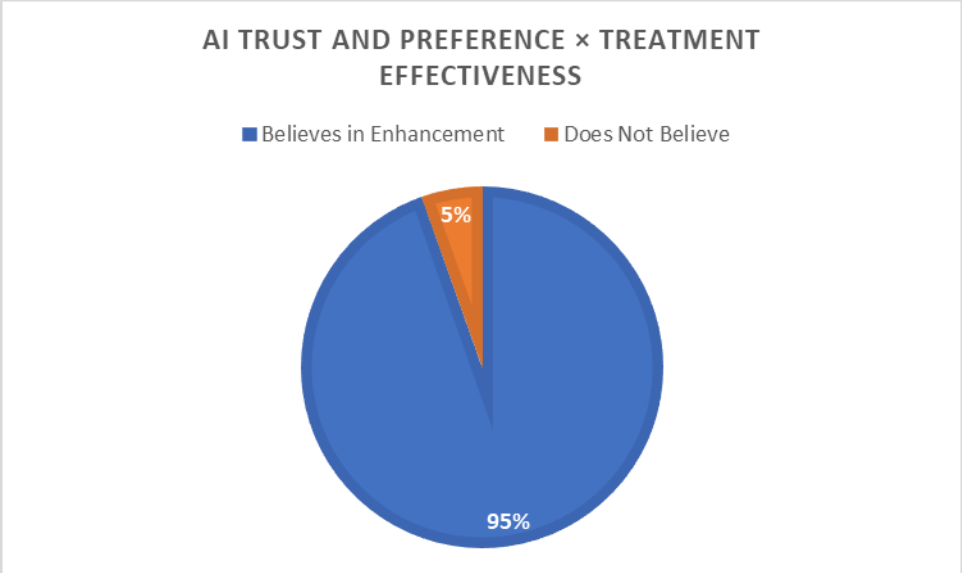


Figure 8: *AI Trust & Preference V/S Treatment effectiveness*

Interpretation: The data cross-tabulation indicates trust in AI-driven solutions goes together with belief about antidepressant outcome improvement. This chi-square data analysis was based on participants' survey responses. It involved cross-tabulation of answers from different questions to examine the relationship between trust in AI and its perceived effectiveness, using SPSS to identify any significant associations. The chi-square analysis would probably demonstrate a considerable link between AI trust levels and acceptance of its effectiveness. Trust plays a vital role in determining how AI systems will be accepted and considered effective for mental health treatments.

The analysis found a statistically significant association, χ^2 (1, N = 105) = 8.99, p = 0.003, demonstrating that participants with higher levels of trust in AI were significantly more likely to believe in its ability to enhance treatment outcomes.

4.3 CONCLUSION

The research provides robust evidence that supports the integration of AI-driven pharmacogenomics in antidepressant therapy optimization through both interview findings and statistical information. Research findings validate the complete backing of Objective 1 because AI demonstrates its capability to select personalized antidepressants while reducing prescribing uncertainty and enhancing treatment success rates. Survey findings and interview statements validate that patients believe AI has therapeutic usage. The evidence shows that Europe benefits from GDPR and AI experience while India faces infrastructure deficits and clinician training gaps which supports Objective 2. Sixty-nine-point five percent of participants preferred working with AI under a human-AI collaboration. Objective 3 holds validity based on evidence showing regulatory and ethical challenges and operational obstacles as 29.5% of respondents emphasized ethical/regulatory barriers and 31.4% pointed to cost as their main concern. The chi-square tests reinforce the relationship between AI familiarity and healthcare readiness together with ethical concerns which impact trust and the perception of treatment effectiveness levels. The research shows that AI-pharmacogenomics has promising potential to transform antidepressant care but requires improvements to training systems and infrastructure as well as regulatory standards worldwide.

CHAPTER 5

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Conclusions

This study looked at the integration of artificial intelligence (AI) with pharmacogenomics for antidepressant therapy, with a particular emphasis on comparing stakeholder viewpoints in India and Europe. The research used a mixed-methods methodology, with surveys analyzed using SPSS and semi-structured interviews analyzed with NVivo, to give both quantitative patterns and qualitative depth. The findings demonstrated that stakeholders largely understand the potential of AI-driven pharmacogenomics to decrease trial-and-error prescription, improve patient adherence, and tailor treatment. Quantitative findings revealed that knowledge with AI and trust in its applications were positively connected to acceptance of its therapeutic usage. However, considerable disparities appeared among regions. Respondents from Europe indicated more familiarity and preparedness for adoption, whereas Indian participants expressed significant desire but identified constraints such as insufficient infrastructure, prices, and training deficiencies.

The qualitative data revealed many major themes, including enthusiasm around AI's potential, the vital need for data protection, legislative uncertainty, and the need of clinician training. Participants also underlined the need of using AI with ethical protections, culturally sensitive information, and transparent algorithms. The triangulation of these data indicated that, while AI-enhanced pharmacogenomics provides a breakthrough approach to mental healthcare, its implementation necessitates regionally specific methods and cross-sector collaboration.

5.1.1 Key Findings and Their Implications

- Stakeholders from both regions acknowledged AI's innovative significance in influencing antidepressant prescribing.
- There is a strong link between knowledge with AI and support for its usage in mental healthcare.
- Indian stakeholders were positive, but constrained by infrastructure, training, and costs.

- ❖ Ethical issues, particularly around patient data privacy and algorithm bias, were prevalent in both locations.
- ❖ Demand for transparency in AI model construction and implementation resurfaced often.

5.1.2 Differences Compared to Literature

- ❖ While the literature frequently focuses on technical capabilities, this study prioritized sociocultural preparedness, clinician trust, and patient understanding.
- ❖ Despite forecasts of high preparedness across Europe, experts found a lack of clinical integration and delayed uptake.
- ❖ This study placed a greater emphasis on the fairness and interpretability of AI models than much of the existing literature.
- ❖ The study discovered that ethical difficulties are influenced by local policy, digital literacy, and public trust in addition to technological factors.

5.2 Implications of the Research

This study has broad implications in clinical, ethical, regulatory, and educational realms. Clinically, combining pharmacogenomics with AI might significantly enhance the accuracy and speed of antidepressant therapy selection. This is especially important for people with treatment-resistant depression. Ethically, the findings underline the importance of effective data protection standards and informed consent procedures. Regional inequalities underlined the need for flexible yet strong regulatory structures, particularly in low-resource contexts. Academically, this dissertation contributes to the small but expanding literature on the interface of AI, genomics, and mental health, and it may be used as a reference for future research.

5.3 Practical and Academic Recommendations

- ❖ Clinician Education: Integrate pharmacogenomics and AI tools into medical education and professional development to improve clinician competence and confidence.
- ❖ Regulatory Reforms: Encourage the creation of region-specific rules to ensure ethical AI usage in clinical genomics. India, in particular, should establish centralized regulatory frameworks similar to the EMA or GDPR.

- ❖ Infrastructure Investment: Governments and stakeholders should prioritize financing for AI-enabled health systems, such as testing labs, data centers, and clinician-facing platforms.
- ❖ Data Diversity: Promote the establishment of large, varied genetic datasets to decrease AI bias and enhance treatment results across populations.
- ❖ Patient Engagement: Increase public knowledge of genetic data rights, the role of AI in healthcare, and the consequences for mental health treatment.
- ❖ Pilot Projects: Support small-scale installations in hospitals or clinics to assess real-world usability, clinical efficacy, and patient outcomes.
- ❖ Interdisciplinary Collaboration: Launch research and policy projects including physicians, data scientists, ethicists, and regulators.

5.4 Limitations

Although this study provides useful information, numerous limitations must be addressed. The use of purposive sampling reduces the generalizability of results. The poll results were substantially biased toward India, with just 24 from Europe, resulting in a geographical imbalance. The limited sample size of six interviews, though topically rich, reduces the representativeness of qualitative findings. Furthermore, the cross-sectional methodology records only a single point in time, which may not represent changing sentiments or future policy developments. Finally, the self-reported form of the data raises the possibility of bias, such as over-reporting familiarity or downplaying ethical issues.

5.5 Suggestions for Future Research

Future research might use longitudinal or experimental approaches to investigate how perceptions and implementation results vary over time. Expanding the geographic coverage outside India and Europe may help offer a more global perspective on implementation issues. Furthermore, additional study on patient perspectives and lived experiences would provide useful context, particularly in terms of trust, consent, and psychiatric effects. Finally, joint initiatives involving hospitals and AI developers might aid in determining the actual efficacy of AI-pharmacogenomics integration in real clinical settings.

5.6 Learner Reflection

This dissertation has been both a tough and gratifying experience. It improved my abilities in study design, data collecting, analysis, and ethical reflection. Navigating challenging multidisciplinary areas like AI and pharmacogenomics helped me understand the complexities of bringing innovation into clinical practice. The experience has also helped me better appreciate the ethical duties that come with conducting health research, especially when dealing with sensitive data and varied communities. I am convinced that the insights and abilities obtained during this process will greatly benefit my future academic and professional endeavors.

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APPENDIX

Innopharma education

GRIFFITH COLLEGE

Ethics Application & Declaration Form

DISSERTATION TITLE: Pharmacogenomic methods driven by AI for tailored antidepressant therapy: Increasing treatment effectiveness and mitigating Side effects

RESEARCHER'S NAME: Soorya Kanath Sudeer Kumar

PROGRAMME OF STUDY: MSc Digital Transformation (Life Science)

SUPERVISOR'S NAME: Dr. Rosemary O'Hara

DECLARATION:
The information in this application form is accurate to the best of my knowledge. I undertake to abide by the principles outlined by Innopharma/Griffith College ethics policy in my research dissertation. I confirm that I have completed a full ethics assessment for my research dissertation as per the college guidelines. I will not begin my primary research until such approval from my supervisor and/or ethics Committee has been obtained.
I pledge to carry out my research according to the Innopharma/Griffith College academic integrity standards. Any results presented in my dissertation will be from my own, original research, I will reference and/or acknowledge any material or sources used in its preparation and I will not plagiarise the work of anyone else.

For Student:
STUDENT SIGNATURE: SOORYA KANATH SUDEER KUMAR

DATE: 06 March 2025

The research contained within this research dissertation proposal has been approved.

For Supervisor:
Ethics Committee Approval Required: Yes ☑ No ☐

SUPERVISOR SIGNATURE: R. O'Hara

DATE: 21 March 2025

For Ethics Committee (if required):
Ethics Committee Approval Given: Yes ☐ No ☐

ETHICS COMMITTEE MEMBER SIGNATURE:

DATE:

NOTE: Supervisors are responsible for ensuring their students fill in this form correctly and that all ethical areas have been considered.

SECTION 1: DESCRIPTION OF RESEARCH STUDY

1.1 Purpose and objectives of research

Purpose of the research

This study investigates how AI-powered pharmacogenomics might improve antidepressant medication by anticipating individual drug reactions and personalizing treatment. Depression affects millions of people worldwide, yet antidepressant prescriptions are frequently based on trial and error, resulting in adverse effects, poor adherence, and extended suffering. Pharmacogenomics, which investigates genetic markers such as CYP2D6 and CYP2C19 enzymes, provides a solution by enhancing medication selection using genetic profiles.

Pharmacogenomics improves accuracy in antidepressant prescriptions by combining AI and big data analytics, enhancing treatment efficacy while avoiding unwanted effects. This study examines artificial intelligence-driven pharmacogenomic applications in Europe and India, taking into account regulatory frameworks, healthcare infrastructure, and genetic diversity. Furthermore, it assesses ethical, logistical, and legal issues such as data privacy, AI model bias, and cost limitations.

This study uses a mixed-methods approach to give insights on AI-powered pharmacogenomics, with the goal of improving individualized treatment strategies and addressing implementation issues in mental health care.

Objectives

- Evaluate pharmacogenomics contribution in optimizing anti-depressant treatment.
- Analyze how AI-driven pharmacogenomic applications differ in Europe and India.
- Examine the regulatory, ethical and logistical operational issues surrounding the use of AI-driven pharmacogenomics in mental health care.

1.2 Research methodology:

This research takes a mixed-methods approach, including online surveys for quantitative data and semi-structured interviews for qualitative data. This method enables a comprehensive examination of AI-driven pharmacogenomics in antidepressant medication.

Quantitative Data Collection - Online Surveys

Online surveys will be distributed to psychiatrists, pharmacogenomic and AI researchers.

Participant Selection:

- Psychiatrists who prescribe antidepressants.
- Pharmacogenomics and artificial intelligence researchers.

Data insights:

- AI-driven pharmacogenomics perceived efficacy.
- Challenges in implementation and uptake.
- The effect on patient adherence and treatment results.

Qualitative Data Collection – Interviews

To acquire deeper insights into the real-world applicability and difficulties of AI-driven pharmacogenomics, semi-structured interviews will be carried out with

- Psychiatrists to explore their experiences and concerns about AI-guided antidepressant prescribing.
- AI and pharmacogenomics researchers will evaluate AI model accuracy, biases, and technical feasibility.
- Regulatory officials should comprehend policy problems, ethical considerations, and regional variances in implementation.

Purposive sampling will be used to recruit participants from healthcare facilities, AI research labs, and regulatory agencies in India and Europe. Interviews will be performed via video conference, recorded (with consent), transcribed, and analyzed using thematic methods.

SECTION 2: POSSIBLE ETHICAL ISSUES

Answer 'yes' or 'no' to the following questions.

SUBJECT MATTER

Does the research proposal involve:
Research into specific company activities that would be deemed sensitive or confidential No
Research into politically and/or racially/ethnically and/or commercially sensitive area No
Sensitive, personal, professional or corporate issues Yes

RESEARCH PROCEDURES

Does the research proposal involve:
Research that might damage the reputation of companies or participants No
Research that may negatively affect the reputation of Griffith College/Innopharma No
Use of personal records without consent No
Use of company data without consent No
The offer of any inducements to participate No
Audio or visual recording without consent No
Using a language other than English No

PARTICIPANTS

Does the research proposal involve:
People who are not competent and/or fluent in English No
Does your research group include any of the following vulnerable groups No
(Adults with psychological impairments; Adults with learning difficulties; Adults under the protection/control /influence of others (e.g. in care/prison); Relatives of ill people (e.g. parents of sick children); Hospital or GP participants recruited in a medical facility; persons under the age of 18)

If you have answered NO to ALL questions, please go straight to Section 4.

If you have answered YES to ANY question in SECTION 2, you must fill in SECTION 3.

SECTION 3: STEPS TAKEN TO AVOID ETHICAL ISSUES

3.1. If your ethics relates to ***Subject Matter***, outline your action plan to work around any sensitive issues.
Because this study includes conversations about mental health, antidepressant medication, and genetic testing, certain subjects may be sensitive to participants. To address these concerns, the following actions will be taken:

- Informed Consent: Participants will be fully informed about the nature of the study before entering to participate.
- Voluntary Participation: Participants may skip questions or withdraw at any moment without consequences.
- Anonymity and Confidentiality: All replies will be anonymised to avoid identification.
- Non-judgmental Approach: Questions will be carefully phrased to prevent any upsetting or judgmental implications.

3.2. If your ethics relates to ***Research Procedures***, outline your action plan to deal with possible ethical issues in your research procedures.
To guarantee that research processes meet ethical standards, the following action plan is in place:

- Data Protection and Storage: All data collected will be kept secure on encrypted cloud storage and a password-protected device.
- Privacy of participants: No personally identifying information will be included in any reports or analyses.
- Ethical Review Approval: The study will follow institutional ethical procedures.
- Data de-identification: Any audio recordings or transcripts will be anonymised prior to analysis.

SECTION 4: ABOUT YOUR PARTICIPANTS

4.1. **Outline your participant profile and why you have chosen them for this study**

This study uses purposive sampling to ensure that participants have direct experience or knowledge in AI-driven pharmacogenomics and antidepressant therapy and can give significant ideas. The selected participant groups and their significance to the study are discussed below.

- Psychiatrists

Licensed psychiatrists who prescribe antidepressants and may or may not have experience with pharmacogenomic-guided therapy.

Justification: Psychiatrists play an important role in prescribing antidepressants and may give insights on the challenges of traditional prescribing, their assessment of AI-driven pharmacogenomics, and hurdles to its acceptance in clinical practice.

- Pharmacogenomics and AI researchers

Researchers with expertise in genetics, bioinformatics, or artificial intelligence for pharmacogenomics applications.

Justification: These researchers create AI models to anticipate drug responses, shedding light on the accuracy, dependability, and limits of AI-driven pharmacogenomic predictions.

- Regulatory Officials

Policymakers, healthcare regulators, or ethics board members working on pharmacogenomics and AI governance in healthcare.

Justification: Regulatory officials give critical insights into legal, ethical, and policy challenges associated with AI-driven pharmacogenomics, namely data privacy, patient safety, and implementation disparities between India and Europe.

4.2 How do you plan to gain access to/contact/approach your participant(s).

The project will use a variety of ethically sound recruitment tactics to engage participants. AI researchers, pharmacogenomics specialists, psychiatrists, and regulatory authorities will get structured email invites detailing the study's goal, ethical considerations, and confidentiality precautions. To ensure institutional permission and anonymity, agreements will be formed with hospitals and psychiatric clinics to recruit individuals who have completed pharmacogenomic testing. Furthermore, professional organizations such as the European Psychiatric Association (EPA) and the Indian Psychiatric Society (IPS) will serve as important forums for engaging with psychiatrists and researchers. LinkedIn and other professional networks will be used to contact AI and pharmacogenomics specialists. Each recruiting approach will follow institutional informed consent guidelines, assuring openness, voluntary involvement, and data protection for participants.

SECTION 5: INFORMATION, CONSENT AND CONFIDENTIALITY

5.1 **Participant Information Letter (PIL) for participants**

You must submit an information letter for participants with this application, as part of your appendices document. For online surveys, it is sufficient to include a paragraph summarising and explaining the purpose of the research at the beginning of the survey. In all other research e.g. interviews, phonecalls, a PIL should be provided to each participant before they are asked for their consent to take part. A template PIL is available in Moodle].

Please confirm below that your information letter covers:

Description of the research topic and method	Yes
Details of what participation will involve	Yes
Rights to anonymity	Yes
Confidentiality	Yes
Rights to withdraw from the research	Yes
The contact details of the researcher and supervisor (if necessary)	Yes

5.1 **Informed Consent Form (ICF) for participants**

[Informed consent is required for most research. For online surveys, it is sufficient to get the participant to tick two boxes at the beginning of the survey – one to state they understand the research and one to give consent. In all other research e.g. interviews, phonecalls, a signed consent form is required. If the data is gathered online e.g. zoom, a signed consent form can be scanned and sent to the researcher. A template ICF is available in Moodle. The signed ICFs, along with the surveys, audio files or interview notes etc. must be stored in the primary data folder on moodle and can be accessed by Innopharma staff for the purposes of verifying the authenticity of the research carried out and the data collected].

Please indicate below if your research requires a signed consent form by selecting the relevant option only:

Yes: my research requires signed consent and I have attached an ICF in the appendices of my application.

SECTION 6: STORAGE OF DATA

[Please ensure that you are abiding by GDPR and the national Data protection laws https://www.hrb.ie/funding/gdpr-guidance-for-researchers/gdpr-and-health-research/).

*The student is responsible for storage of data and this will be handed over to the college in an electronic format as part of the thesis submission i.e. primary data and completed ICFs where applicable will be added to the primary data folder on moodle. The rationale is to keep data **as long as it is still useful** and there is an intention to use it further **for research** so if this is not the case then this can be stipulated here and a shorter retention period given.]*

6.1. How will you store the research data and for how long? How will you manage data protection issues?

All research data will be securely maintained to protect its confidentiality and guarantee compliance with data protection requirements such as GDPR and HIPAA. Electronic data, such as survey replies and interview transcripts, will be saved on an encrypted, password-protected cloud server. Data will be kept for two years and then permanently erased or safely destroyed. To safeguard privacy, all personal identifiers will be deleted, and participants will be given unique codes. Access to the data will be limited to the primary investigator and approved personnel. Participants will be notified about data storage practices and have the ability to withdraw at any time. To reduce breaches, frequent security checks and compliance audits will be conducted.

SECTION 7: NON-DISCLOSURE AGREEMENT & STUDENT CONSENT

7.1 **Non-Disclosure Agreement (NDA)**

Will the final dissertation contain any information pertaining to any source what would warrant the use of a Non-Disclosure Agreement (NDA) e.g. industry-based research?

No

7.1 **Student consent**
If a Non-Disclosure Agreement (NDA) is not required, does the Student consent to allow their completed dissertation to be held/published by Innopharma/Griffith College?

Yes

SECTION 8: RECORDING AND RETENTION OF DISSERTATION VIVA

8.1 **Viva Recording**

The Dissertation viva will be recorded. This recording may be used to facilitate assessment by Innopharma staff, a third reader if necessary and/or if requested by the external examiner for the Programme. The recording will be held in line with current GDPR guidelines and will not be made publicly available.

SECTION 9: DOCUMENT CHECKLIST

NOTE: Applicants must attach the following documents in electronic format to the appendix.

Which documents are added to the appendix? Please tick N/A if not applicable:

9.1 Participant Information Letter (PIL) for participant	Yes
9.2 Informed Consent Form (ICF) for participant	Yes
9.3 Questions/survey for interviewees/focus groups etc *(can be in draft form)*	Yes
9.4 Any other documents e.g. Non-Disclosure Agreement	N/A

I confirm that this application is complete and all required documents are included in the appendix.

For Student:
STUDENT SIGNATURE: SOORYA KANATH SUDEER KUMAR

DATE: 06/03/2025

SECTION 10: APPENDIX

SURVEY QUESTIONS

1. What is your relationship with regards to antidepressant therapy and pharmacogenomics?

☐ Healthcare professional (e.g., psychiatrist, doctor, pharmacist)
☐ Researcher in pharmacogenomics or artificial intelligence

1. How familiar are you with AI-powered pharmacogenomics?

☐ Very familiar
☐ Somewhat familiar
☐ Unfamiliar
☐ Never heard of it.

2. Do you believe that AI-driven pharmacogenomics can enhance antidepressant treatment?

☐ Yes, greatly
☐ Yes, to some extent
☐ No, not really
☐ No, at all

3. What do you think are the most significant advantages of employing AI in antidepressant treatment? (Select all that apply)

☐ Find the right medicine faster
☐ Reducing trial-and-error prescriptions
☐ Minimizing adverse effects and improving treatment adherence
☐ Other (Please specify)

4. What are your worries about implementing AI for genetic-based mental health treatment? (Select all that apply)

☐ Issues with genetic data privacy and security
☐ Inaccurate AI predictions
☐ Expensive testing
☐ Limited healthcare accessibility
☐ Ethical concerns
☐ No concerns

5. Do you believe AI-driven pharmacogenomics will become more prevalent in the future?

☐ Yes, within 5 years
☐ Yes, within 10 years
☐ Yes, but it will take over ten years
☐ No, I do not believe it will become common practice.

6. What do you believe is the major limitation to applying AI-driven pharmacogenomics?

☐ Lack of awareness among healthcare professionals
☐ Implementation cost
☐ Ethical and regulatory concerns
☐ Limited Clinical research evidence
☐ Other factors (Specify)

7. What enhancements or adjustments would make AI-powered pharmacogenomics more broadly accepted? (Short answer)

_____
_____
_____

8. Do you trust AI-driven solutions for antidepressant medications?

1. Do you prefer AI-assisted suggestions or doctor-based judgments for antidepressant prescriptions?

   ☐ AI-assisted recommendations with doctor's advice
   ☐ Only a doctor's choice, no AI suggestion
   ☐ I have no preferences

2. Do you believe that AI-driven pharmacogenomics should be offered to all patients taking antidepressants?

   ☐ Yes, that should be a standard practice
   ☐ Yes, but only in difficult cases
   ☐ No, only in research settings
   ☐ Unsure.

3. How easy do you think it will be for doctors to apply AI-powered pharmacogenomics in clinical practice?

   ☐ Very easy
   ☐ Somewhat easy
   ☐ Neutral/Unsure
   ☐ Somewhat difficult
   ☐ Very difficult

4. Who should be in charge of regulating AI-powered pharmacogenomics to assure its safety and security.

   ☐ Government health authorities (e.g., FDA, WHO)
   ☐ Independent AI ethical organizations
   ☐ Pharmaceutical companies
   ☐ Healthcare professionals and researchers
   ☐ Others (specify)

5. Would you choose AI-guided pharmacogenomic testing over traditional practice?

   ☐ Yes, without hesitation
   ☐ Yes, if it highly recommended by the doctor
   ☐ Perhaps, depending on the risks and expenses
   ☐ No, I wouldn't want AI engagement in my medical decisions

6. What are your final suggestions or comments about AI-driven pharmacogenomics in antidepressant therapy? (Short answer)

   _____
   _____
   _____

INTERVIEW QUESTIONS

For psychiatrist

- How familiar are you with pharmacogenomics and its application in antidepressant therapy?
- Have you utilized pharmacogenomic testing to prescribe antidepressants? If yes, how has this affected treatment decisions?
- Do you believe that AI-driven pharmacogenomics decreases trial-and-error prescribing? Why, or why not?
- What are the main advantages of employing AI-driven pharmacogenomics in psychiatry?
- What are the primary obstacles to its widespread acceptance in clinical practice?
- Do you feel psychiatrists are adequately trained in AI-driven pharmacogenomics?
- How do you believe AI-driven pharmacogenomics affects patient adherence to treatment?
- Have you seen improved patient outcomes with AI-guided pharmacogenomics?
- What are your ethical or regulatory concerns with AI in pharmacogenomics?
- What suggestions would you make to guarantee that AI-powered pharmacogenomics is both clinically successful and morally sound?

For AI and Pharmacogenomics Researchers

- How does AI help with pharmacogenomics and antidepressant prescribing?
- What are the most significant technological concerns in establishing AI-driven pharmacogenomics?
- How do you determine the accuracy and reliability of AI-powered pharmacogenomics models?
- Have you found any biases in AI systems that analyze pharmacogenomic data?
- How can AI models be developed and verified for use in real-world scenarios?
- What ethical considerations arise when employing AI in pharmacogenomics?
- What are the most significant challenges to deploying AI-driven pharmacogenomics in healthcare?
- How do you envision AI combining with current healthcare systems for antidepressant treatment?
- What potential improvements do you see in AI-driven pharmacogenomics?
- What efforts should be made to build confidence and acceptance of AI in pharmacogenomics?

For Regulatory Officials

- Can you describe your position in managing AI-driven pharmacogenomics in mental health?
- What are the most significant regulatory barriers in incorporating AI-driven pharmacogenomics into clinical practice?
- How do the regulations governing AI-driven pharmacogenomics differ among regions or healthcare systems?
- What ethical concerns should be addressed when employing AI for genetic antidepressant treatment?

- What safeguards should be in place to protect patient privacy and genetic data in AI-powered pharmacogenomics?
- Are present laws and policies enough in regulating AI-driven pharmacogenomics, or are there gaps that must be addressed?
- How can regulatory authorities ensure that AI-driven pharmacogenomics stays objective and does not add bias in treatment?
- What significant issues are hindering the broad use of AI-powered pharmacogenomics in mental healthcare?
- What validation and approval processes should AI-based pharmacogenomic technologies go through before being used in clinical practice?
- What legislative reforms or enhancements, in your opinion, could make AI-driven pharmacogenomics a standard aspect of mental health care?

Participant Information Letter

Pharmacogenomic methods driven by AI for tailored antidepressant therapy: Increasing treatment effectiveness and mitigating side effects

I would like to invite you to take part in a research study. Before you decide you need to understand why the research is being done and what it would involve for you. Please take time to read the following information carefully. Ask questions if anything you read is not clear or if you would like more information. Take time to decide whether or not to take part.

Who I am and what this study is about?

My name is Soorya Kanath Sudeer Kumar, and I am conducting this study as part of my MSc in Digital Transformation (Life Science) course at Griffith College, Dublin. The purpose of the study is to investigate how AI-driven pharmacogenomics can enhance antidepressant therapy by delivering individualized drug recommendations. The study also looks into the regulatory, ethical, and logistical issues of applying AI-powered pharmacogenomics in mental healthcare.

What would taking part involve?

If you agree to participate, you will be invited to do an interview or fill out a survey, depending on your role in this study. The researcher will determine whether you participate in an interview or a survey, depending on your expertise and the depth of

insights required. Psychiatrists, pharmacogenomics researchers, AI specialists, and regulatory officials may be selected for interviews to provide detailed perspectives, while surveys will be used to gather broader quantitative data. The interview will last about [20-30 minutes] and can be conducted in person or online, depending on your preference. If you do the survey, it will take around [10-15 minutes]. Interviews might be audio-recorded with your permission for appropriate transcription and analysis.

Why have you been invited to take part?

You were chosen because of your knowledge and experience in AI-driven pharmacogenomics, mental health, and regulatory policy. Participants in the study include psychiatrists, pharmacogenomic researchers, AI specialists, and regulatory authorities, all of whom can contribute useful information.

Do you have to take part?

Participation in this study is completely voluntary. You may withdraw at any moment, decline to answer any question, or cease participating without providing a reason. There will be no negative outcomes if you wish to withdraw from the study. If you want to withdraw, please email the researcher Soorya Kanath Sudeer Kumar soorya.kanathsudeerkumar@student.griffith.ie . However, please note that once your responses have been anonymized, it will no longer be possible to withdraw them from the study.

What are the possible risks and benefits of taking part?

There is no major risk factor associated with engaging in this study. However, discussing pharmacogenomics with AI in healthcare may raise ethical or professional concerns. If any questions make you uncomfortable, you can skip them. This research has the potential to contribute to the development of customized medicine, improve antidepressant prescribing practices, and impact regulatory regulations regarding AI-driven healthcare technology.

Will taking part be confidential?

Yes, all answers will be kept completely private and confidential. Your personal information will not be associated with any published data, and all information provided will be anonymised before analysis and reporting. Any information gathered will be used solely for research purposes and will not be shared with third parties unless you explicitly consent. However, confidentiality may be lawfully violated if there is a threat to the participant or others safety, in compliance with ethical and legal requirements.

If interviews are recorded, they will be securely archived, with only the researcher having access to them. Once the data has been transcribed and anonymized, the original recordings will be deleted.

How will information you provide be stored and protected?

To avoid unwanted access, all study data, including transcripts and survey replies, will be securely kept on a password-protected computer and in encrypted cloud storage. Access to the raw data will be limited to the researcher and dissertation supervisor. It will be stored in secured facilities for two years post study completion and then erased permanently in compliance with research ethical requirements, ensuring that all gathered material is handled responsibly. No personally identifiable data will be gathered, thereby guaranteeing confidentiality of all responses.

What will happen to the results of the study?

The findings of this study will be utilized strictly for academic purposes, as part of my dissertation. The findings will not be published in external journals or presented at conferences, but dissertation research projects and their material will be made available in my college library and, if relevant, in online e-journals or repositories.

All responses will be kept anonymous, so that no participant may be individually identified in any academic papers or analyses. If you want a summary of the study's findings, you may request one.

Who should you contact for further information?

For more information, please contact:

Soorya Kanath Sudeer Kumar

MSc. Digital Transformatiom (Life Science)

Griffith College, Dublin

Email: soorya.kanathsudeerkumar@student.griffith.ie

[THANK YOU]

Consent to take part in research

The researcher retains one copy signed by both themselves and the participant. The participant should also receive a copy of consent form as a record of what they have signed up to.

- I Participant voluntarily agree to participate in this research study.
- I understand that even if I agree to participate now, I can withdraw at any time or refuse to answer any question without any consequences of any kind.
- I understand that I can withdraw permission to use data from my survey/interview within two weeks after the interview, in which case the material will be deleted.
- I have had the purpose and nature of the study explained to me in writing and I have had the opportunity to ask questions about the study.
- I understand that participation involves answering survey questions or taking part in an interview about the application of pharmacogenomics driven by AI in antidepressant treatment. The survey will take 10 to 15 minutes to complete, and the interview will take 20 to 30 minutes.
- I understand that I will not benefit directly from participating in this research.
- I understand that all information I provide for this study will be treated confidentially.
- I understand that in any report on the results of this research my identity will remain anonymous. This will be done by changing my name and disguising any details of my interview which may reveal my identity or the identity of people I speak about.
- If conducting interviews by Skype/Zoom etc. I agree to my interview being audio-recorded.
- I understand that disguised extracts from my interview may be quoted in the researcher's dissertation, college library will not be published in external journals, conferences, or other public venues.

- I understand that if I inform the researcher that myself or someone else is at risk of harm, they may have to report this to the relevant authorities - they will discuss this with me first but may be required to report with or without my permission.
- I understand that signed consent forms and original audio recordings will be retained in will be stored in a password-protected computer and encrypted cloud storage accessible only to the researcher and supervisor until the exam board confirms the dissertation result, after which they will be securely disposed in accordance with institutional and data protection regulations.
- I understand that a transcript of my interview in which all identifying information has been removed will be retained for two years from the date of the exam board.
- I understand that under freedom of information legalisation I am entitled to access the information I have provided at any time while it is in storage as specified above.
- I understand that I am free to contact any of the people involved in the research to seek further clarification and information.

Researcher Details

Name: SOORYA KANATH SUDEER KUMAR

Degree Programme: MSc. DIGITAL TRANSFORMATION (LIFE SCIENCE)

College Details: GRIFFITH COLLEGE DUBLIN

Contact number: 0894582313

Contact mail: kssoorya1@gmail.com

Signature of participant

[Full Name – Printed]

Signature of research participant

---------- ---------- Date

Signature of researcher

I believe the participant is giving informed consent to participate in this study

Soorya Kanth Sudeer Kumar

Signature of researcher Date 27/03/2025