PREVENTIVE & DECENTRALIZED HEALTH CARE WITH THE APPLICATION OF ARTIFICIAL INTELLIGENCE

by

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DISSERTATION

Presented to the SWISS SCHOOL OF BUSINESS AND MANAGEMENT

In Partial Fulfillment

Of the Requirements

For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SSBM GENEVA

2025

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ABSTRACT

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2024

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The emergence of novel medications has altered performance in the healthcare industry. Artificial intelligence (AI) has improved medical procedures by helping professionals make better decisions about disorders of complex and unpredictable systems. The application of artificial intelligence in preventive and decentralized health care is helpful in disease prevention. Information about disease prevention can be dispersed in the decentralized healthcare units and in the community to prevent disease outbreaks. For the health care system to integrate disparate systems and improve the accuracy of medical electronic records (ER) and a more patient-centric approach to care are direly needed. The current study was designed to apply artificial intelligence in decentralized healthcare settings to maintain electronic records, ensure patient privacy, and implement preventive measures. A total of 200 Patients, with diabetes (n=100) and Alzheimer (n=100), presented to the clinic and were assigned P_{id} and device D_{id} through which patients were screened. Data about the potential risk factors was collected through a predesigned questionnaire including open-ended and close-ended (di and trichotomous questions) specific to the disease condition. The collected information was organized in MS Excel and subjected to analysis through SPSS for evaluation of significant risk factors based on chi-square. The significantly associated risk factors ($p<0.05$) in both cases were age, gender, BMI, physical

activity, smoking, blood pressure, family history, alcohol consumption, stress, sleep disorder, and environmental factors. But specific to the disease condition, plasma levels of calcium and vitamins were significant in Alzheimer's patients while diet plan and risk score were significant in diabetes. In the case of Alzheimer's patient records, most of the infected age group was above 58 years as the mean value was 61.05 (S.E=1.304; SD=13.04) with median=60, mode=58 and that of diabetes was above 33 years with mean 42.93 (S.E=1.09; SD=10.94); median 43 and mode 33. Other numerical variables *Viz;* blood pressure (mean=142.93/89.01$\pm$12.97/4.25), risk score (mean=6.87$\pm$2), and BMI (mean=28.17$\pm$3.26) for diabetes but physical activity (2.56hrs$\pm$1.4), and cognitive activity (2.59hrs$\pm$1.98) for Alzheimer's patients were observed. The correlation analysis of quantitative variables for diabetes depicts the positive and strong association among blood pressure (diastolic), risk score, and BMI. While it was negative among age, systolic blood pressure, risk score, and BMI. Among Alzheimer patients' correlation analysis depicts the negative association of BMI and physical activity with age and cognitive activity. However, BMI and physical activity have a positive correlation with each. Cognitive activity has a negative correlation (inverse relation) with all the quantitative factors. The obtained information was dispersed to the public under decentralized conditions for disease prevention using AI. Further studies on other diseases can be performed for their prevention under a decentralized model for information dissemination and data collection at a large scale.

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CHAPTER I:

INTRODUCTION

1.1 Introduction

Artificial intelligence (AI) has been offered as a technology that can change medical practices to make better decisions in complicated and uncertain systems (Jiang et al., 2017; Tekkeşin, 2019). Humans are frequently forgotten while addressing the function of AI in practical applications. Just two of the many advantages (Buntin et al., 2011) of integrating information technology into the healthcare industry are electronic health records (EHRs) and clinical decision-making (Musen et al., 2021). However, data is being generated in various formats, such as pharmacy dispensations, digital sensors that are widely used in the population, lab results, electronic health records, diagnostic registries, patient registries, and so on. Typically, health regulators consider data as randomized clinical trials (Benneyan et al., 2017).

Medical data can be analyzed in many different ways and at different levels. Conventional alerting systems, for example, can help users become aware of an issue when values on heart electrocardiography (ECG) monitors deviate from the normal range. To input data into a system that delivers diagnostic and inference recommendations based on a priori rulesets, second-level processing entails combining and analyzing data from many sources. That makes it possible to use the outcome in a feedback loop to increase the system's accuracy. By building a tree-like hierarchy based on the input data, these kinds of systems can help identify a credible explanation for the symptoms that have been entered. These rule-based systems are referred to as "expert systems." Expert systems, which are computer programs, aim to imitate human decision-making processes by learning from past mistakes. Intelligence systems are currently being improved to enable them to reason more effectively and better use the data they gather. The objective is to let decision-making systems run ahead of schedule so they may provide an early diagnosis instead of the looking backward method, in which systems only deliver diagnoses and conclusions.

Several academics have recently concentrated on employing disruptive technologies like blockchain and artificial intelligence to prevent various diseases. Blocks of transactions are digitally recorded onto a distributed, peer-to-peer (P2P) collective ledger known as the blockchain. The blockchain network's nodes (miners) establish a chronological chain connecting each block. Blockchain nodes duplicate the collected data while keeping their network operational (Monrat et al., 2019). A blockchain thus delivers the complete history or attribution of data. In a blockchain digital ledger, test results, patient information, discharge summaries, and immunization statuses can all be stored. These will improve clinical laboratories, patients, hospitals, and government-funded healthcare organizations to manage healthcare information in a decentralized manner utilizing self-executing contracts referred to as "smart contracts" (Hölbl et al., 2018). In the blockchain network, smart contracts are computer programmers who, when specific conditions are satisfied, carry out the predefined terms of an agreement between participants (Griggs et al., 2018). The administration of the medical supply chain, tracking of outbreaks, and remote patient monitoring might all be automated using smart contracts built on the blockchain (Griggs et al., 2018)

In contrast to previous technologies, there is no precise explanation of how AI operates, performs, or its role (Siau & Wang, 2018). Trust in AI among patients and healthcare professionals [HCP] is correlated with security, privacy, and all three. If AI is to impact society positively, people must have confidence that their personal data will be utilized effectively and responsibly (Lords, 2018; Luxton, 2014; Mohandas, 2017). Patients can have confidence in the technology and make an informed decision about whether or not to consent or reject the use of their data by being given sufficient information about how it is being used (Bollier, 2017; Hengstler et al., 2016). In both human-to-human and AI interactions, trust plays a significant role. Understanding how AI and people establish trust is crucial in professions like medicine, where patients' lives are on the line. How many individuals trust technology is influenced by various factors, including human, environmental, and technological traits. Artificial intelligence (AI) technologies like machine learning (ML) and deep learning (DL) have been deployed as potent tools for improving disease diagnosis, drug/vaccine discovery, and carrying out substantial data analysis (Vaishya et al., 2020). Additionally, the federated learning paradigm has grown in popularity for healthcare purposes to overcome data privacy and governance challenges by training AI models collectively without sharing the raw information. As a result, by automating processes that are challenging to complete manually, AI can process large amounts of data in a fraction of the time and cost. The privacy and security of health data could be preserved while the blockchain supports secure data access and interoperability (Sharma et al., 2020). The advancement of the patient-centric strategy through the integration of blockchain and AI technology could alter healthcare centres (Chen et al., 2019; Jabarulla & Lee, 2020). For widespread dispersal of treatment and managing pandemic conditions, a patient-centred strategy might offer a workable response to the disease epidemic.

Furthermore, genetic data have independently surpassed data generated by other data-intensive industries, like networking sites and others. Blockchain and artificial intelligence have the potential to advance biomedical science and provide affordable networks. Blockchain and Artificial intelligence help keep the medical history and data provenances, patient laboratory tests, medical reports, and therapeutic measures and process a large amount of data in fractions of seconds. AI technologies like ML and DL have been deployed as potent tools for improving disease diagnosis, drug/vaccine discovery, and substantial data analysis. It can be concluded that research has been conducted on the use of blockchain and artificial intelligence in the medical field for data acquisition, storage, and analysis. But the application of artificial intelligence in the decentralized healthcare system for preventive measures is lacking.

1.2 Research Problem

A more centric approach to patient care is direly needed in the health care system for the connection of discrete systems and augmentation in the accuracy of health care electronic records (ER). The blockchain-based system develops and manages the data of ledgers (blocks) with automated data analysis. Blockchain-based algorithms are employed when healthcare researchers are concerned with clinical records' storage, security, and privacy maintenance.

Block chain and AI have potential benefits in integrated healthcare systems like personalized treatment, improved efficiency, and augmented patient care. But there are significant concerns about challenges and risks of ethical implications, prioritization of human rights and privacy protection. The challenges need to be addressed responsibly for the designing, deployment, and implication of AI tools in the health care system. Furthermore, there is a gap in practical appplication of AI techniques in clinical practices rather than in theoretical demonstration and research settings. Healthcare leaders and providers resist modern techniques, hamper the adaptation of AI techniques on a larger scale. Effective communication approaches are essential for addressing patient concerns and building trust in the implementation of AI tools in the healthcare system. It is direly needed to explore possible solutions for the implementation of potentially benefit AI techniques in healthcare system.

1.3 Purpose of Research

The current study was designed to apply artificial intelligence in decentralized healthcare settings to maintain electronic records, ensure patient privacy, and implement preventive measures. Further human rights were ensured while implementing AI tools in the healthcare system. Artificial intelligence in decentralized health care ensures real-time data collection and implementation of disease prevention measures at large scale.

1.4 Significance of the Study

AI can process large amounts of data in a fraction of the time and cost. The privacy and security of health data could be preserved while the blockchain supports secure data access and interoperability. Occurrence of disease epidemics urge to maintain the clinical records for future control of such outbreaks. The accurate maintainance of data with privacy in a decentralized healthcare system is only possible through AI tools. The real-time time data will be easily available to scientific community, stakeholders, and policymakers for early response towrds control of a disease.

1.5 Research Purpose and Questions

Artificial intelligence (AI) has developed at a very high pace these years and has impacted almost all the sectors including the healthcare sector. Preventive and decentralized healthcare seems to be one of the biggest areas of opportunity for practical implementation of AI, which could change disease prevention and control. Integrated artificial intelligence creates more effective methods to collect and analyze relevant real-time data of disease distribution and dynamics. This capability helps the healthcare providers and policymakers in early identification of potential diseases and to contain them, thereby minimizing disease burden to a society.

In addition, the e-Health records that are supported by Artificial intelligence provide valuable tools for public health and are able to provide a detailed picture of a disease state within a given community. From these records, the healthcare professionals will be in a position to know which groups should be targeted for prevention measures, the effectiveness of the current prevention measures and come up with more prevention measures that will prevent such risks in future. Self-service technologies with AI also enable the delivery of disease prevention information to the communities, especially in Decentralized communities. This means that vital information gets to the right people and those who require some knowledge to take positive measures of keeping themselves healthy are informed.

The aim of this research is to explore how AI can improve preventive healthcare systems; this include looking at how AI can support disease surveillance, how real-time data can be used and how information can be disseminated. This research also seeks to identify the extent to which solutions enabled by artificial intelligence may help fill the existing gaps in the implementation of health care solutions especially in decentralized or limited health care units and the overall disease preventing schemes.

To address these objectives, the following research questions are proposed:

1. What role does artificial intelligence play in specific preventive and decentralized healthcare that will help prevent diseases through better monitoring and data gathering?

2. The question one can formulate based on these findings is: What are the most efficient approaches to informing Disease Prevention using AI within Decentralized Healthcare Units and Communities and what will make it improbable for disease outbreaks to happen?

3. What strategies are relevant in enhancing the utilization of AI based systems in enhancing the availability, efficiency and the ability to expand the coverage of preventive measures in decentralized health care?

Answering these questions, this study aims to contribute to practical understanding of how AI technologies may help advance preventive care as a more effective, fair, and scalable solution in healthcare systems.

Business Implications of AI Implementation in Healthcare

The application of artificial intelligence in healthcare organization has many business implications which influence operation, revenue, and human capital.

1. **Operational Efficiency**

AI helps for improving the effectiveness of different processes in the healthcare sector due to the automation of the routine functions, optimization of the patient's information systems, and the optimization of the processes in general. For instance, decision-making based on big data can be done in real time, diagnosis and distribution of resources can be done efficiently in less time. This minimizes time taken before one is treated and in equal measure enhances the productive use of health facilities, hence improving service delivery with minimal hitches from within the core business function.

2. **Financial Impact**

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3. **Human Resources and Workforce Dynamics**

AI based systems require a radical change in the workforce. Automated technologies may diminish the need for particular administrative positions, at the same time generating a need for well-trained experts who can govern, analyze, and interpret automated solutions. The transition to AI cannot happen without training and investing in the upskilling of the existing human capital to optimally leverage the potential of integration. Another issue that needs to be solved is AI resistance in the organization and that is why its potential benefits should be explained with the new opportunities it offers.

4. **Change Management**

Successful Organizational change management is an imperative, when it comes to integration AI. In this respect, leadership has an important function of facilitating the development of culture for innovation, which focuses not only on change, but also on cooperation. Resistance is best handled by designing structured training programs, encouraging stakeholder involvement and communicating with them openly. Also, organizations have to pay attention to legal and ethical issues on ethical standards and data privacy concerning patients and other stakeholders.

Cost-Benefit Considerations

The use of AI in healthcare has both the direct and indirect costs and advantages. Tangible costs refer to the cost of acquiring hardware and software as well as costs of integrating the two and those pertaining to the continuous maintenance of systems. Other costs that have not been estimated quantitatively also need to be looked at, for example, the impact of disruption during the transitional phase and the time required to establish confidence in the AI system.

On the benefits side, AI improves predictive analysis outcomes, cuts costs of operations, and improves patients’ lives all of which have long-term, positive financial and image impacts on the healthcare industry.

CHAPTER II:

REVIEW OF LITERATURE

2.1 Theoretical Framework

2. Artificial Intelligence and Recent Advancements

Integrative analysis of this data is proving challenging, even though there are more large-scale global projects and health-related data than ever before. Even high-quality biomedical data is frequently complicated and varied, necessitating specialized preprocessing and analysis techniques (Marx, 2013). Pharmaceutical companies commonly incorporate computational biology tools into their pipelines and apply them in various healthcare settings. Among the most effective and promising computational analytic tools are machine learning approaches. Considerable advancement in the field of machine learning has been made possible by increased computer processing power and algorithmic advancements. Though machine learning techniques are now frequently employed in many research areas, such as the development of biomarkers and the discovery of new drugs (Alexander et al., 2017; D. Lee et al., 2017; Nielsen, 2017; Pretorius & Bester, 2016; Sotgia & Lisanti, 2017), Deep Neural Networks (DNNs)-based machine learning techniques are better able to identify high-level needs in data of healthcare system (Zhavoronkov et al., 2019). Recently, feedforward DNNs were effectively used to predict various drug features, including pharmacological action (Aliper et al., 2016) and toxicity (Gao et al., 2017). Another field in which DNNs have yielded notable successes is biomarker creation, which involves designing or searching for distinctive traits of healthy or sick diseases (Vandenberghe et al., 2017).

2.1. Generative adversarial networks

One of the highly promising recent advancements in deep learning is generative adversarial networks (GANs). Goodfellow et al. unveiled the GAN architecture in 2014, producing impressive text and image production results. Kadurin and colleagues extended comparable approaches to the production of molecules (Kadurin, Nikolenko, et al., 2017). An adversarial autoencoder (AAE), which incorporates the qualities of both the discriminator and the generator, was trained using a dataset of compounds with various levels of tumour growth inhibition (TGI) activity. The fingerprints of molecules with the desired attributes were then produced using the trained model. Additional examination of the produced compounds revealed that previously unidentified, extremely efficient anticancer medicines, such as anthracyclines, closely match the novel molecular fingerprints. An improved architecture has been introduced that allows the creation of more chemically varied molecules and incorporates other molecular properties, including solubility (Kadurin, Aliper, et al., 2017). The new model demonstrated enormous drug discovery potential, improving training and generation processes.

2.2. Recurrent neural networks

Clinical histories of patients are contained in electronic health records, which can be used to calculate a patient's risk of developing chronic disorders, including diabetes, cardiovascular disease, and others. One of the most promising time-series or text analysis methods is to use recurrent neural networks (RNNs), which are inherently used to analyze the sequence. Electronic medical record analysis is another of RNNs' most useful uses in the medical field. Based on clinical events found in patients' medical records, RNNs have recently been utilized to predict heart failure in those individuals (Choi et al., 2017). With an Area Under the Curve (AUC) of 0.883 and superior performance to the models, trained on a 12-month clinical history and assessed over six months. Interesting investigation of situations where the predictions were off revealed that networks frequently anticipate heart failure concerning the anamnesis of heart problems, such as hypertension. The suggested system can relate to devices that measure blood sugar and insulin levels and run automatically. A fascinating use of RNNs is the prediction of human activity using data from wearable devices, a recently emerging and intriguing topic of study. The recurrent neural network (RNN) model Deep Conv LSTM, which combines convolutional and recurrent networks with Long Short-Term Memory (LSTM) architecture, was used, for instance, to analyze recordings from on-body sensors to forecast gestures and movements. Concerning remote monitoring of chronic disorders like Parkinson's and cardiovascular conditions, such technologies have the most promise (Ordóñez & Roggen, 2016).

2.3. Transfer learning

Since most deep learning algorithms are extremely data-hungry, much data is needed to train and evaluate the system. Transfer learning is one of several solutions that have been suggested to deal with this issue. Transfer learning involves transferring knowledge gained from one domain to another with a smaller dataset. A trained neural network's fitted parameters can be transferred to another network thanks to the CNN design. Larger non-biological picture collections, like ImageNet, can be applied for fine-tuning a network first since the size of samples typically limits biomedical image datasets. To outline the organ's anatomy, a CNN that had already been trained on ImageNet underwent additional training on heart MRIs. The proposed model accomplished cutting-edge cardiac structure recognition (97.66% score). To forecast glioblastoma brain tumors, CNNs that had been fine-tuned on ImageNet were used (Ahmed et al., 2017).

2.4. One and zero-shot learning

Transfer learning methods that enable working with constrained datasets include one and zero-shot learning. One-shot learning seeks to identify new data points depending on a small number of samples from the training sets, considering that real-world data is sometimes unbalanced. Zero-shot learning aims to recognize new objects without having access to the training set's examples of those instances. The notions of transfer learning include both one-shot and zero-shot learning.

To solve this issue, Altae-Tran and co-workers suggested a one-shot learning strategy for predicting hazardous molecule potential (Altae-Tran et al., 2017). Medical chemistry is one of the domains with a lack of data. One-shot networks were compared to traditional models, including random forest with 100 trees, graph convolutional neural networks, and attention and refinement-based LSTMs. On the majority of the Tox21 tests and SIDER side effects, Iterative Refinement LSTMs fared better than other models. Additionally, networks trained on Tox21 data were examined on SIDER to assess the one-shot architecture's potential for translation.

3. Highly Distributed Storage Systems (HDSS)

Given the current data output and demand growth, finding improved data storage solutions is crucial. Among other things, storage systems for data should be more dependable, approachable, scalable, and affordable, resulting in enhanced availability. HDSS has been discovered to be a very beneficial and viable choice, even though there may be various solutions for optimizing these needs. Since the invention of computer systems, new technologies have been applied for data storage; nevertheless, as data demands and computational power have risen exponentially, solutions like HDSS have become crucial. HDSS essentially entails storing data over numerous nodes, such as host computers or databases. HDSS enables speedy access to data across this enormous number of nodes since the data stored on these nodes is typically replicated or redundant (Partap et al., 2017).

Reliability is one of the key criteria for storage systems since storage failures have become one of the more significant difficulties in data processing in recent years. It is now increasingly common to use HDSS, which enables data replication over several nodes or storage devices and protects it from failures.

3.1. Progress in HDSS

A remarkable degree of advancement in the optimization and applications of HDSS has been performed. However, preserving data consistency across numerous storage nodes and system costs are some of the major difficulties faced by HDSS applications. Recent HDSS solutions have addressed these issues, including allocated non-interpersonal databases and peer network node data storage. It illustrates a data store of a peer-to-peer node used in a blockchain. To maintain the consistency of the data, these records are divided into blocks that are then cryptographically locked. A peer-to-peer network of users typically maintains a blockchain by adhering to predetermined guidelines for accepting new blocks (which are secured by the program). A signature and a reference book to a preceding block in the chain are included in each record of the block. Blockchain technology is intended to guarantee data immutability (Y. Kumar & Singla, 2021; Sharma et al., 2020). As a result, once documented, amendments in blocks are impossible without alteration of all successive blocks and getting network members' approval. Due to its immutability and integrity, blockchain can be used as an open, distributed ledger and can effectively, verifiably, and permanently record transactions between various parties or networked database systems.

4. Data Privacy Issues and Regulatory Barriers

4.1. Data privacy issues

Privacy problems are among the most important issues in data collection and use. It is even more crucial in the healthcare industry, where a significant portion of the generated personal health data may be considered private. Regulations and guidelines have been established to ensure propriety in data management and to direct processes, including data collection, usage, transfer, access, and interchange. Although the General Declaration of Human Rights adopted by the United Nations General Assembly in 1948 declared privacy a basic human right, there is still no universal consensus on what privacy is. Because of this, privacy concerns and regulatory difficulties have frequently been the subject of significant but varying interpretations wherever data is collected and used (Kayaalp, 2018).

4.2. Regulatory barriers

A significant portion of the everyday data generated due to the invention of computing and ongoing technological improvements contains information that can be regarded as private. Some regulatory initiatives to guarantee the correct flow and application of these data may hinder productive improvement. Researchers and developers are typically eager to start working on analyzing, processing and exploiting data, and various obstacles could make doing so difficult (Evans & Jarvik, 2018).

While HIPAA and other legal obstacles are required to protect the proper usage of information, they could impede evolving efforts, particularly when work must be completed quickly. For example, HIPAA mandates that an institutional review board authorize data use, which could increase the complexity of data use. Patients typically want to know how their medical and other health information is handled because they generally believe this information is private and should be protected (Pope, 2020). The transition of medical records from paper (hard form) to electronic formats (soft form) may raise the likelihood that private health information will be accessed, used, or disclosed by unauthorized parties. The Department of Health and Human Services was compelled to create national standards for electronic healthcare transactions by HIPAA's administrative simplification requirements, which were implemented to increase the healthcare system's efficacy and efficiency. Congress became aware that changes and improvements in computer and electronic technology would impact the confidentiality of medical records. As a result, Congress included provisions in the HIPAA Act that made it mandatory for some types of individually identifiable health information to be covered by federal privacy laws. The HIPAA Privacy Rule provides national standards for protecting health information privacy (Standards for Privacy of Individually Identifiable Health Information). In essence, the Privacy Rule controls how specific organizations, sometimes called enclosed entities, use and disclose personally recognizable health evidence, also known as protected health information (PHI). PHI, which excludes specific school and employment records, is defined as individually identifiable health information transmitted or preserved in any format or medium (for example, oral, written, or electronic) (Schmeelk, 2019). The Privacy Rule, among other things, establishes appropriate safeguards that most healthcare providers and others must implement to protect the privacy of health information; 1. Gives patients more control over their health information; 2. Establishes limits on the use and release of health records; 3. Holds violators accountable with civil and criminal penalties that can be imposed if they violate patients' privacy rights; 4. Strikes a balance when Health data privacy and security must be maintained at all costs, and regulatory obstacles help to assure proper management and use of this sensitive information. But these obstacles' complexity and difficulties may prevent real advancement in data utilization (Mamoshina et al., 2018). Therefore, it is necessary to create systems and practices that ensure the proper processing and application of data and greatly promote its application for substantive advancements toward betterment in health.

5. Progress in Blockchain

In a disseminated database applying state machine replication, the blockchain ensures the reliability and tamper-endurance of the operation log through hash linkages between blocks. Atomic database changes, known as transactions, are grouped into blocks. The blockchain idea was first described for Bitcoin concerning dispersed electronic money (Swan, 2015). A globally verifiable proof of the presence or shortage of certain data or a state transition in the blockchain database can be provided using linked time-stamping, a feature of blockchain technology by design. Which are used to create these proofs are computationally secure, then no one other than a supermajority of the blockchain maintainers would be able to fabricate them. Additionally, accountability methods (such as proof of work or anchoring) can make it prohibitively expensive for anyone, including the maintainers themselves, to fabricate such proofs and offer long-term nonrepudiation. Such proofs for small portions of stored data could be concise and not require disclosing any further specific information.

Blockchain's consensus mechanism (Breitinger & Gipp, 2017) ensures that copies of the database that have not been compromised have identical perspectives on the state of the database. Consensus confirms that all non-compromised nodes finally receive notification of the changes made by the log of transactions, which are transmitted to them.

Applied cryptography procedures are used to decentralize authentication and authorization of network transactions, such as public key digital signatures (Dwork et al., 1988). In other words, transactions are generated independently of blockchain nodes, which reduces the impact of a compromised node. According to their roles, blockchain users are frequently split into three groups:

People who look after the blockchain infrastructure and make decisions about business logic. The maintainers actively participate in the blockchain's consensus procedure, which means they must write access to the blockchain and full read access to the full replica of all the data stored therein. They also decide on the guidelines for transaction processing. A formal or informal agreement between the maintainers and the other users that refers to the business logic contained in the blockchain is significant. The transaction processing rules cannot be changed or altered at the maintainers' discretion, and they even offer ways for outside users to check that the blockchain is operating following the regulations.

The blockchain's external auditors, such as law enforcement, non-governmental groups, and regulators, check the system's overall transaction processing accuracy in real time and/or after the fact. Auditors must retain a clone of the complete blockchain data to execute thorough audits. Auditors replicate the transaction log, but from a technological standpoint, they do not actively engage in consensus.

Every client has access only to a limited piece of the blockchain data, but their program may use cryptographic verifications to reasonably and accurately confirm the integrity of the blockchain data supplied by auditors and maintainers. According to the Bitcoin network's general taxonomy, full nodes, further separated into validator and auditor nodes following the above functions, have read access to the complete blockchain. Client software will be referred to as such. Blockchains could reduce participant trust and related counterparty risk by implementing cryptographic accountability and suitability safeguards (Stallings, 2006):

Blockchain reduces the dangers caused by the single point of failure provided by centralized authorization systems by having transactions cryptographically authorized by the logical originators.

Client-side data validation may make it possible to lower the dangers of man-in-the-middle attacks, even when carried out on the server. Additional secure user interfaces and key management techniques for client-side validation could be used. If the maintainers are compromised, the cryptographic soundness of the proofs allows for the conclusive restoration of the blockchain state.

The cost of auditing and monitoring procedures may be decreased by the availability of real-time and retrospective authorization instruments that assure the data's validity. In turn, this might make it possible for counterparties to evaluate contract risks with greater accuracy and/or for regulators to estimate systemic risks with greater accuracy. The degree of access to blockchain data could be used to categorize different types of blockchains:

6. Exonum Framework for Blockchain Projects

The open-source blockchain framework Exonum focuses on permissioned blockchain applications with broad read access to blockchain data (Stallings, 2006). Services are the framework's primary extension point and contain the business logic of blockchain applications. Multiple services may be available on an Exonum-powered blockchain, and multiple blockchains may use the same service (possibly with prior configuration). Because every single service is designed to provide the logically comprehensive and minimal performance required to fulfil a certain activity, services have some autonomy. In the context of blockchain, customer services provide termini for request reading that get continual data from the blockchain state and transaction processing. Clients implement the normal functionality; they are designed to be the main initiators of transactions and requests reader in the system and are accordingly given capabilities for forming transactions and verifying read request responses, including cryptographically.

Middleware offers the following features: transaction atomicity and ordering, interoperability between clients and services, services replica among network nodes (mend for fault-tolerance and auditing nodes-based audibility service), service lifecycle management, access control, data persistence, assistance in responses generation according to request, etc. In other words, from the perspective of service developers, middleware makes the system less complex. In comparison to other permissioned frameworks, Exonum has the following primary advantages for the application being described:

Exonum can do it simpler for auditors and clients, including those with limited read access to the data, system audit in real-time (including sporadically) as well as retrospectively, and thanks to the design of data storage structures for audibility. Additionally, the list of auditors may change when the blockchain is operational and may not be known in advance.

The application could quickly add and modify its services because it uses a service-oriented architecture, reuses services created for other Exonum apps, etc. Third-party apps could be more easily integrated into the Marketplace ecosystem because of common transports' direct usage and service orientation (like REST + JSON). In addition, service orientation could enable free interchange with other blockchains built on the Exonum protocol. (Although the Exonum framework does not yet take advantage of this capability, the middleware layer might significantly reduce the amount of interoperability work required of service creators.

Exonum offers significantly higher output capacity (more than 1,000 transactions in each second) and the capability to encode complex transactional logic, including external component interactions, in comparison with permissionless blockchains and domain-specific frameworks, and virtual machine language/indirection.

Exonum operates under pessimistic security hypotheses concerning validator node activity. Exonum's consensus approach prevents single points of failure from being introduced. Additionally, because the validator nodes set is restructured, it is possible to increase security by scaling the number of validators, changing the keys used by validators, locking out compromised validators, etc.

6.1. Blockchain storage

In Exonum, the blockchain state is a persistent key-value store (KVS), where the keys and values are typically byte sequences of any length that stated operations.

Add a value to the key given

A key based-eliminate of a key-value pair

Using collections as the components of top-level collections could result in the creation of additional hierarchical layers. Merkelization can be proclaimed for collections. Hash of the collection, a new procedure introduced by Merkelized collections, is the hash commitment to all its objects. With the help of this structure, it is possible to generate compact (logarithmic in terms of the collection's element count) cryptographic proofs of the presence, respectively, of collection items.

H state can be fixed on a non-permitted guarantee of strong accountability for blockchain (like Bitcoin) to lessen the risks of history modifications and ambiguity, and the proofs given to clients may be enhanced as a result. Refer to the Open Time stamps protocol's partial proofs concept (https://opentimestamps. org/). Keep in mind that the anchoring system would enable reliable assertions of blockchain status in the future.

6.2. Network

Services may engage with the outside world through two different types of interactions: The only way to alter the state of the blockchain is through transactions. The consensus algorithm running on the blockchain determines the sequence in which and the outcomes of each transaction's asynchronous execution. Incoming transactions are thereby disseminated among the network's entire nodes. Read requests enable data retrieval from the blockchain state, together with the appropriate evidence of presence or absence. Any full node can process local read requests.

6.3. Authentication and approval

Using public-key digital signatures, transactions must be authenticated by the parties that initiated them to guarantee their integrity and real-time and retrospective universal verifiability. If more comprehensive nonrepudiation and/or finely grained access control are required, public key infrastructure (PKI) can be added on the top.

The read requests are the local, authenticated permission for them and might be transported specifically. It could be accomplished, for example, with electronic signatures through web or by communication channel assisted authentication (voice detection protocol). Service endpoints could be marked as private to increase security further.

In the medical and healthcare industries, legacy systems frequently only allow for the internal sharing of healthcare data. Data, however, point to a number of important advantages of joining these networks for linked and enhanced healthcare, leading health informatics experts to call for links between various organizations. Since it requires that confidential data provided by a healthcare company be readily accessible to other organizations, multi-organizational data sharing is a significant barrier. Due to several characteristics of blockchains, such as their immutability, provenance, transparency, etc., distributed ledger technology is reinventing the process of data management and governance in the realm of the medical system. Numerous modern advancements in the healthcare industry depend on the blockchain (Lemieux, 2016).

There are now more choices for managing medical data and making it simpler for individuals to manage and share their individual medical data. Any business that relies on data must provide the safety, storage, transactions, and simple integration of their data. This is particularly true in the medical industry, where distributed ledger technology provides the capacity to address these crucial issues in a very efficient manner (Weber et al., 2016). The use of distributed ledger technology in healthcare advancements is multi-faceted, including its data sources and stakeholders. The discussion between Gordon and Catalini on using distributed ledger technology to make the entire system patient-centric rather than institution-focused was concluded. They examined how decentralized access rights, system-wide entity identification, and data immutability offered by distributed ledger technology could enhance the healthcare sector (Waseem et al., 2021).

For the management of digital assets related to healthcare, the blockchain framework Hyperledger Fabric was employed. The authors used mobile phone gadgets to gather the necessary medical data. Their goal was to use the Hyperledger framework to store medical data on the blockchain (Ichikawa et al., 2017).

The use of distributed ledger technology was investigated by the authors as a means of handling the medically related data effectively. They looked at the advantages and restrictions of using this technology in the medical field. The advantages include patient data privacy, security, and data flow transparency. Other restrictions include the high cost and difficulty of integrating this new technology with conventional infrastructure. Because it is a new field, there aren't as many highly qualified professionals. The authors also looked into the security implications of using this technology in conjunction with cloud computing for medical data (Hasan et al., 2021).

A model for overcoming the limitations of distributed ledger technology was put out by the authors. The Hyperledger framework was used to construct this approach for the administration of patient-focused medical data (Ahmad et al., 2021).

After conducting a survey of the healthcare industry, the authors developed two security solutions for networks. Distributed ledger technology was also marketed as the ideal way to maintain security and privacy (Sabir et al., 2021).

The authors proposed the MedChain system, which makes use of p-2-p networks and distributed ledger technologies to share healthcare data. The system was developed by the authors to gather patient data via medical tests, Voice over IP (VoIP), WiMAX, and other mobile apps as well as IoT sensors (Shen et al., 2019).

Khezr et al. investigated various issues with the healthcare management system and how blockchain technology might be used to address them. They presented a number of prospective medical use cases in which this technology might play an important role in speeding the procedure, as well as the most recent study on medical data utilizing this technology. A networking protocol-based IoMT delivery system has also been presented by them (Haque et al., 2021).

The writers looked at a variety of healthcare-related issues in addition to conducting a poll on healthcare difficulties. The authors considered blockchain-based methods to solve these challenges, including the confidentiality of patient medical data, the openness of conversations between various institutions, and data accessibility (Litchfield & Khan, 2019).

According to the authors, patient data breaches involving names, addresses, and other private information were frequent. They suggested developing a blockchain-based system to manage medical records. The main goal of their work was to analyze the system's effectiveness in order to determine how effectively their recommended framework met the needs of patients, doctors, and other stakeholders (Wei et al., 2020).

The authors suggested a book chapter in which they looked at several blockchain applications in the healthcare industry. They have emphasized the requirement for a blockchain-based healthcare system as well as the potential benefits of using this technology to construct medical systems (P. Zhang et al., 2018).

The authors talked about how operations could be made simpler by distributed ledger technology, which could benefit the medical sector. They noted in their study the importance of maintaining medical records and the capacity of technology to reduce data loss and prevent data fabrication by protecting information (Sodhro et al., 2021).

Jamil et al. looked into drug limits and how blockchain technology may be used to standardize drugs. In their study, they emphasized how challenging it is to identify fraudulent drugs and promoted the use of blockchain as a technique for doing so (Shuja et al., 2017).

A fingernail analysis management system was created by Lee and Yang using a blockchain and a microscope sensor. Unique human nails are a representation of a person's physiological make-up. In their study, they used tiny sensors to take pictures of the nails and preprocessing techniques to get crisp images. A deep neural network was used to track how well a feature extraction method worked. In order to protect user data, provide security and privacy, and track and record any system modifications via the ledger, blockchain technology was used (S. H. Lee & Yang, 2018).

The authors conducted a thorough investigation and study of already-existing blockchain applications in the healthcare industry. They found that many medical applications can benefit greatly from distributed ledger technology. They also stated that a deeper understanding of this technology might pave the way for fresh lines of inquiry in the field of healthcare. Inefficiency and onerous regulations have stymied healthcare innovation (Agbo et al., 2019).

The authors looked into the regulatory issues that lead to inefficiencies in the EMR system. To manage enormous amounts of medical data, they have offered a distributed-ledger backed system. They have demonstrated a novel and creative approach that includes a fair audit log mechanism for acquiring access to medical records. MedRec made it possible for patients and doctors to share medical information with third parties using distributed ledger technology. They give people like researchers and other medical experts incentives to participate in the mining process (Haider, Khan, et al., 2020).

The authors discussed how distributed ledger technology can be used to address a number of problems in the medical industry. With the use of this technology, numerous concerns regarding the security and privacy of medical data can be resolved. They continued by claiming that they could more successfully address healthcare concerns by developing blockchain-supported applications (Haider, Mehdi, et al., 2020).

The use cases of distributed ledger technology in the field of the healthcare industry were emphasized by the writers. The numerous barriers to the adoption of distributed ledger technology have been highlighted. For the management of medical systems, they also created smart contracts (T. Kumar et al., 2018).

The authors promoted distributed ledger technology as the most secure method of handling data in the healthcare industry. According to their survey, internet safety was a major issue because of the motivations of hackers and privacy intrusions. By implementing a number of laws that require the administration of patient data to go by a number of requirements while being available to legally authorized healthcare practitioners, it was made possible in the field of eHealth. Due to Bitcoin, distributed ledger technology's most well-known use in the payments sector, is generally known (Genestier et al., 2017).

Nofer et al. claim that the distributed ledger system has many benefits, including the preservation of private and secret data, eliminating intermediaries, etc. In contrast to centralized networks, the network continues to function even if one or more nodes fail. Since the reliability of the intermediary or other network members is not evaluated by individuals, this increases confidence. Because using middlemen might potentially result in data security breaches, the lack of intermediates also helped data security. Distributed ledger technology may render middlemen unnecessary, greatly enhancing user safety (Chowdhry et al., 2020).

A research from the MIT Media Lab that focused on all blockchain technology implementations also highlighted the security and confidentiality issues with managing personal information. Data processing is valuable because it is secure in the sense that it cannot be altered. Data security also included the protection and privacy of data. For instance, Enigma is a decentralized computing platform with blockchain innovation and guaranteed anonymity. Enigma's goal is to eliminate the need for middlemen so that developers can build peer-to-peer, decentralized applications that are "privacy by design."

The blockchain serves as a "operating system" for nodes in a network to undertake secure collaborative tasks. Given that computation and data storage are carried out outside of the blockchain, Enigma is an extension of distributed ledger technology (Boulos et al., 2018).

The blockchain was referred to be a secure location for handling all kinds of sensitive data. The distributed ledger was described as a decentralized system. This technology can address a wide range of commercial challenges. A blockchain transaction's records are protected by encryption, and the hashing algorithm links each block back to earlier blocks. Various consensus algorithms were used to validate transactions. Transparency will eventually be achieved through blockchains, enabling every user to view transaction history at any time. A secure way to avoid intermediary influence is with a smart contract. A public blockchain called Ethereum uses smart contracts to power it. On the basis of directives issued in the past, this helps creators build markets for the long-term movement of money.

The main characteristics of blockchains include decentralization, immutability, quick transfers, payment, and confirmation in real time (Khatoon, 2020).

Cloud computing enabled the authors to quickly identify user behaviours and gather data directly from the source. By incorporating historical data into distributed ledger transactions, they created and put into practise a methodology for the collection and authentication of data origins. The three key steps of the suggested paradigm were data collection, data validation using historical data, and data analysis. ProvChain enhanced security for cloud-based storage systems, including client confidentiality and minimal overhead dependability, according to performance evaluation findings (Thomas, 2009).

There are several problems with the existing healthcare system. Information that is sensitive and significant is kept in patients' medical records. Without an appropriate access control strategy, unauthorized people may misuse these records. It is difficult to establish data ownership using traditional methods. Second, it turns out that many of the "names" had various spellings and were not actually those of actual persons. Health insurance coverage is also a source of considerable worry. To begin with, exchanging information with numerous stakeholders takes time. Finding a false insurance claim is quite challenging when using the conventional method. The illegal drug market considerably contributes to the manufacture of fake and fraudulent drugs as participants add contaminated, improperly kept, and falsified ingredients. Due to a lack of technology and commercial solutions that enable accurate traceability and provenance, drug tracing is challenging. Another difficulty with the conventional systems is confidentiality. Once an unauthorized user gains access to the centralized databases of the conventional systems, the data are visible to them. By incorporating blockchain technology into the healthcare sector, these problems can be solved.

2.2 Theory of Reasoned Action

A social psychological theory called the Theory of Reasoned Action (TRA) can be used to comprehend human behavior, including the use and adoption of AI tools in healthcare. According to the TRA, a person's intentions, which are impacted by their attitudes and subjective norms, are what drive their conduct. The TRA can assist in determining the elements that influence healthcare professionals' and patients' intents to embrace and use these tools in the context of AI in healthcare.

The Theory of Reasoned Action has been applied in several research to better understand how AI is being used in healthcare. For instance, Chomutare et al. (2022) used empirical data from existing implementations to conduct a scoping review that looked at the facilitators and hurdles to deploying AI in healthcare (Chomutare et al., 2022). The review adopted a theoretical stance and pinpointed pertinent elements affecting the implementation procedure.

Gerardou et al. (2022) sought to discover the implementation frameworks utilized to comprehend the application of AI in healthcare practice in another scoping review (Gerardou et al., 2022). The theoretical frameworks that can direct the use of AI tools in healthcare settings are discussed in this paper.

In addition, Petersson et al. (2022) explored the difficulties in applying AI to the healthcare industry and emphasized the opposition that healthcare executives frequently experience when deploying cutting-edge technologies (Petersson et al., 2022). These difficulties can be explained by the Theory of Reasoned Action, which also offers a framework for methodically addressing them.

Even if the Theory of Reasoned Action has only a limited number of applications, understanding the intents and behaviors of those participating in the implementation process can benefit from the theory's concepts. Stakeholders can more effectively prepare and address the implementation challenges by taking attitudes, arbitrary norms, and other pertinent elements into consideration.

The Theory of Reasoned Action is just one of the theories and frameworks that may be used to comprehend and direct the adoption of AI in the healthcare industry, thus it's vital to keep that in mind. In this context, other theories have also been applied, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The theory used will rely on the precise study or implementation aims and the relevant factors.

In conclusion, by looking at the goals, attitudes, and subjective norms of healthcare providers and patients, the Theory of Reasoned Action can shed light on the application of AI tools in healthcare. To establish a thorough understanding of the variables influencing the effective application of AI in healthcare settings, it is necessary to consider a variety of theories and frameworks.

Healthcare Management and the Role of Artificial Intelligence

AI appears to be gradually emerging as a disruptive innovation in healthcare, reshaping managerial processes, organizations and care approaches. There are multifaceted issues for those in the healthcare administration including controlling resources, people, and high quality service while being cost effective. Computerized solutions present new approaches to these difficulties, making available quantitative analysis and increased productivity that were not earlier possible. Studying how AI helps manage healthcare, alters business models, and changes how care is delivered is the focus of this paper.

1. AI in Decision-Making

Many decisions in healthcare are complex, and healthcare managers are faced with numerous decisions that impact patients, organization finances and employees. AI tools can simplify and enhance decision-making processes in several ways:

1.1 Predictive Analytics

Automated business intelligence employs large datasets both historical and live data to unravel patterns, trends, and prognoses. For instance, predictive analytics can predict the density of the admitted patients so that the management can be warned or prepare for the increase during a particular season or increase the availability of resources needed during an emergency. This foresight brings out the implication of overcrowding and ensures appropriate investment on the available resource is made.

1.2 Scenario Simulation

AI models do analysis and prediction across different factors such as budget variation, staff changes or even resources reallocation. In any of these cases, the administrators can be in a position to make the right decisions regarding the changes on policy or any operation strategy.

1.3 Real-Time Monitoring

Popular examples of using AI include data from electronic health record systems, supply chain management systems, and patient feedback dashboards. These dashboards offer near real-time data so that instruction can detect problems, potential and actual, and address them before they worsen.

2. Resource Allocation

The prudent use of resources in satisfying the care needs of patients is important to the attainment of improved quality care while at the same time ensuring that costs are well controlled. AI tools enable healthcare managers to allocate resources more effectively through data-driven insights:

2.1 Equipment and Supplies

AI makes inventory better by predicting the demand of supplies and equipment used in hospitals. For instance, with a pandemic, an AI system can identify the usage pattern of different pathogens and, subsequently, estimate the demand for protective equipment such as gloves or masks, or the number of ventilators needed. It cuts costs and eliminates situations when resources are critically low.

2.2 Facility Management

Patient flow information is employed by the AI tools in the management of the number of beds occupied by patients, diagnostic equipment, and the operation theatre. For instance, it can recommend when surgeries should be done to optimize the use of operating theaters with regards to the patient’s waiting time.

2.3 Financial Resources

AI features in financial planning by offering areas of the organizations to reduce spending while improving on the quality of care. When studying the spending within a business, AI can suggest which specific areas require either automation or optimization to decrease spending.

3. Staffing and Workforce Management

The healthcare workforce is an important yet stressed out component. AI tools can significantly enhance staffing strategies and workforce management:

3.1 Staffing Optimization

AI is able to forecast the number of staff required by using data from previous years, and current number of patients. This means that adequate staff are available to cater for the patient turnover so that costs such as overtime payments are eliminated and staff fatigue is also avoided.

3.2 Skill Matching

It compares the skills of the staff members in relation to the needs of the patients. For instance, in a critical care surge situation, the AI capability can pinpoint providers with experience in a particular area and recommend them for assignment to areas requiring their services.

3.3 Recruitment and Retention

Human Resources management is made easier by use of AI in that, candidates are pre-selected depending on their qualifications. Besides, the AI-based tools for sentiment analysis can determine the level of worker satisfaction and areas that lead to staff turnover, allowing the administration to prevent staff turnover.

4. Impacts on Healthcare Business Models

AI technologies are becoming the norm in the healthcare business models through changing and providing efficiency and effective means for delivering care.

4.1 Transition to Value-Based Care

AI assists in transition to gain sharing instead of fee-for-service reimbursement options that pay doctors based on the outcomes rather than the amount of services they have provided. Healthcare applications track the progression of the patient, look for signs of adverse reactions, and offer treatments to guarantee the results to be optimal and timely.

4.2 Personalized Medicine

AI applies patient-specific data for treatment and diagnosis of diseases and health conditions. In detail, artificial intelligence, such as an AI system, can analyze clients' genes and recommend the precise treatment for them that they are more likely to recover from without experimenting with a variety of treatments and medicines. This precision care model is slowly emerging as a competitive tool in segmented healthcare markets.

4.3 Decentralized Care Models

Healthcare decentralization is made possible through AI in that it supports delivery care through use of remote and community settings. Through artificial intelligence, a symptom checker and initial categorization of patients are done to lessen the load on central locations and provide care closer to the patient.

5. AI-Driven Care Delivery Approaches

Though established as a tool in healthcare management, it is also notably redrafting the way through which care is being delivered.

5.1 Virtual Health Assistants

Virtual health assistants enabled by artificial intelligence help patients to self-manage, respond to knowledge-based inquiries, and book appointments. It enhances the interaction of patients and at the same time relieving the burden placed on the administrative employees.

5.2 Automated Diagnostics

In diagnostic studies, it is noteworthy that AI systems perform imaging analysis, pathological slides, and other diagnostic data with high efficiency. For example, there are AI in radiology in which the AI diagnose findings on X-rays and MRI scans quicker than radiologists, thus improving on diagnosis.

5.3 Chronic Disease Management

AI patient supervision in Chronic Diseases is accomplished by wearable devices and IoT sensors. These tools allow patients and healthcare professionals to quickly identify when interventions are needed, and help to prevent readmissions.

5.4 Population Health Management

AI uses demographic and health data to determine who may need help and about what and then it creates specific preventive solutions. Such approach helps to enhance public health and fundraise for various programs while the healthcare organizations can enhance the their health strategies to reflect the needs of the society.

6. Challenges and Considerations in AI Adoption

However the uptake of AI in the health sector is not without its challenges as shown in this paper.

6.1 Ethical and Privacy Concerns

AI in the operation has questions on the fundamental principles of patients' privacy, security of their data, and consent. Heath care organizations have to use proper frameworks to meet the requirements of the GDPR and the HIPAA.

6.2 Integration with Existing Systems

The integration of AI tools with the existing and often entrenched healthcare systems can be challenging as well as costly. It requires organizations to make investments in integrating technologies that can work with each other and the human resources to ensure the integration takes place.

6.3 Workforce Resistance

Some of the challenges in AI adoption may include resistance from the healthcare staff in that he or she may feel that the AI solution is likely to take over his or her job. These barriers can only be addressed through proper communication with the clients, and training programs that introduce the clients to VA.

6.4 Cost of Implementation

Although the use of AI in the long run reduces costs, the overall costs relating to infrastructure, software, and training are a significant barrier for some healthcare institutions. Another factor that can help to avoid the negative impact of the financial constraints is implementation of the strategies for CRM in phases, basing on the analysis of the impact areas.

Business-Oriented Metrics in AI-Driven Healthcare Management

Artificial Intelligence (AI) is no longer a clinically applied utility; the use of AI in managing healthcare organizations is increasingly measuring up to business performance indicators. The traditional goal of clinical outcomes like better patient care, lower mortality rates, and hospital readmissions must be coupled with goals like return on investment, increased operating efficiency, cost reduction, and revenue enhancement. The next part of the paper focuses on these metrics to understand how they can inform the utilisation of AI in healthcare.

1. Return on Investment (ROI)

1.1 Measuring ROI in AI Adoption

ROI is a significant tool for measuring the feasibility to implement AI systems. It compares the value realised with the use of the AI tools with the costs associated with their use.

- Investment Costs: It concerns investments in software and hardware, infrastructure, training and development, and system maintenance.

- Returns: Mention dollar values for the quantifiable benefits, such as lower labour expenses, an increased number of patients served, and higher accuacy of billing.

1.2 Examples of ROI in Healthcare AI

- **Diagnostic AI Tools**: AI-based diagnostic systems decrease the cases of misdiagnosis hence decreasing the chances of malpractice suits and increases billing accuracy.

- Administrative Automation: Replacing such routine procedures as patient appointments and claims as a result of automation eliminates potential cost waste and delivers positive ROI instantly.

- Predictive Analytics: Reducing avoidable readmissions or increase efficiency in the use of resources benefits at the same time both cost containment and revenue.

2. Operational Efficiency Gains

2.1 Workflow Optimization

AI is unsuitable for these tasks because it helps to eliminate existing inefficiencies in the work of health care organizations by automating routine activities and managing resources.

- Scheduling and Patient Flow: AI algorithms enhance appointment scheduling because it reduces patient’s waiting time as well as optimizing clinician’s time.

- Data Management: AI systems categorise and filter big amounts of data, such as frequent updates of medical records and insurance checks.

2.2 Real-Time Decision Support

Real-time data from AI-enabled dashboards and decision-support technologies deliver information that helps healthcare managers to adjust staffing, capacity, and supplies in response to increased demand or other disruptions in care processes.

2.3 Case Study: Robotic Process Automation (RPA)

Some of the healthcare organisations that have implemented RPA for claims processing have cut processing time by 80% enhancing organisational productivity.

3. Cost Savings

3.1 Labor Cost Reduction

Functions such as billing, coding, and record management are among the activities that are most depersonalized by automation. Chatbots for customer support also reduce the team's staffing needs, and AI tools in general do this less directly.

3.2 Reduced Waste and Errors

AI reduces wastage through the proper assessment of the demand rate hence avoiding a situation where there is excess stock or insufficient stock in the chain. On the same note, it eliminates wrong billing and coding that can cost the organisation a lot of money in fines.

3.3 Preventive Care Cost Benefits

Since AI-driven predictive analytics can help diagnose diseases at an early stage and alert healthcare practitioners to act before these diseases progress, they decrease the expense of managing diseases at their later stages. For example:

- HHS systems for chronic diseases reduce hospital expenses.
- Screening instruments reduce the need for costly, terminal treatments.

4. Revenue Growth and Profitability

4.1 Enhanced Patient Throughput

Healthcare AIs reduce the time it takes to diagnose and treat patients thus the ability of the healthcare facilities to treat a larger number of patients. Higher throughput, therefore, means higher revenue for the company.

4.2 New Revenue Streams

AI also increases opportunities to develop new care delivery models, for example, creative remote monitoring and telemedicine and build up new revenues. For example:

- Remote patient monitoring services that the patient pays a monthly fee for their use.

- Scheduled virtual consults that were priced cheaper than face-to-face appointments with an AI assistant.

4.3 Case Study: Telemedicine Expansion

A survey of the healthcare organisations, which have integrated AI-based telemedicine solutions for supporting healthcare, revealed an increase in revenues by 30–40% due to an increase in the range of provided services during the COVID-19 pandemic.

5. Patient Satisfaction and Retention Metrics

5.1 Improved Patient Experience

Virtual assistants, recommendation systems and many other applications of AI have the potential to make healthcare better for patients by making it easier and more personal.

- Net Promoter Score (NPS): The studies show that most of the patient satisfaction with AI-enabled services leads to a higher NPS score.

- Retention Rates: Happy clients are more willing to come back to the same doctor explaining why more healthcare providers provide long-term earnings.

5.2 Reduced Turnaround Times

AI fast tracks things such as diagnosis results and appointment and this can be satisfying to the patients hence leading to their loyalty.

6. Compliance and Risk Management

6.1 Regulatory Compliance

By automating documentation and reporting procedures compliance to healthcare regulations is facilitated by the use of AI tools. For instance, AI systems provide fully audited reports to cut the time consumed in this docket and avoid penalties on non-adherence to the legal requirement.

6.2 Malpractice Risk Reduction

Good diagnostic instruments and decision-support systems prevent medical mistakes and decrease malpractice suits and resulting costs.

7. Long-Term Financial Sustainability

7.1 Investment in Scalable Technologies

AI systems are also claw based, along with being modular, that means they can be adjusted to accommodate greater amounts of data or more complex problems. Investments in structures and tools give a foundation for development in the future without corresponding rises in expense, making it a financially feasible approach to organizational development.

7.2 Strategic Partnerships

One may partner with AI technology suppliers or research establishment to mitigate on the costs while at the same time gaining access to advanced innovations in the market to be at par with the competition in the long run.

Table 2.1. List of Healthcare Specific AI frameworks

Framework	Application
Convolutional neural network (Fiszman et al., 2000)	To accurately identify diseases, it combines AI-based features and natural language processing.
Skytree (J. Lee & Hwang, 2009)	More specifically, to process enormous structured and unorganized collected data without down sampling.
Apache Mahout (Walunj & Sadafale, 2013)	Provides procedures including clustering, regression, and grouping
Cognitive ML algorithm (Sengupta et al., 2016)	Using the master learning technique, echocardiology data are normalized to separate constricting pericarditis from restrictive cardiomyopathy.
ML algorithms (Narula et al., 2016)	Demonstrate the distinction between an athlete's heart and cardiomyopathy hypertrophy.
BigML (Nagwanshi & Dubey, 2018)	It combines cloud-based technology with AI-based characteristics to produce applications that are affordable, extremely precise, and scalable.
Phenotypic clustering (Lancaster et al., 2019)	Left ventricular dysfunction and high-risk phenotyping patterns can be identified by analyzing echocardiography clustering.

Tabel 2.2. **Role of digital assistants in improving patient care** (Colón, 2018)

Application	**Action**
Symptom triaging	Connect with patients and lead them through a series of inquiries about their past and present problems. Provide a report on the patient's symptoms and potential conditions to the patient's doctor so that the doctor can review it at a later appointment.
Reminders	In specific use cases include prompts to take prescribed prescriptions and notifications of forthcoming appointments.

Automated follow-up	Review the current condition of symptoms that were brought up during a previous appointment with the doctor (for instance, if the doctor notes that a patient had a cough or sore throat and was given the right treatment plan, a digital assistant automatically contacts them to ask how the plan is working out, such as "how has your cough been since starting your medication?").
Assessments and questionnaires	Automate popular tests, such as the PHQ-9 for depressive disorders, to collect data for intake forms and other papers in a more user-friendly way.
24-hour hotlines or emergency services	In times of emergency or when care teams are not accessible, direct patients. As soon as necessary, alert the patient's designated emergency contact, care teams, or both.
Automate preventive health measures	Send a real-time message to the patient recommending that he or she consult with the patient's care team if any data points significantly depart from the patient's average (for example, a decrease in step count, restricted movement, and reported feelings of sluggishness).

Table 2.3. List of available big data tools with their advantages and disadvantages (Chattu, 2021)

Sr No.	**Big Data Analytics Tools**	**Advantages**	**Disadvantages**
1.	**"Xplenty"** a platform based on cloud for integrating, processing, and getting data ready for analytics that runs on the cloud.	Scalability and elasticity	Billing can be done yearly only, no other option.
2.	**"Apache Cassandra"** a distributed NoSQL database administration solution that is open source and free. Large volumes of data can be handled by it with ease.	No failure at a single point	Extra maintenance and troubleshooting are needed.
3.	"MongoDB" a NoSQL database that focuses on documents	Variety of systems and technologies supported	Limited analysis can be performed only.
4.	Apache "Hadoop" a software framework for managing clustered file systems and massive amounts of data.	Beneficial for R&D purposes	Possibly runs out of storage space due to data redundancy
5.	"Datawrapper" a portable, open-source tool for data visualization	Equally effective on all devices including cell phone, desktop system, tablet, or laptop.	Color palettes are Limited.

6.	“Rapidminer” a solution that works across platforms that brings together predictive analytics and machine learning in one setting.	Excellency in Technical and Customer Services	There are needs to enhance the online data quality and services.
7.	“Tableau” a software program for analytics and business intelligence.	Perform fast lightning and has a slew of applicable characteristics.	Control of formatting should be advanced
8.	“KNIME” a free and open-source application called Konstanz Information	Working is very nice with various technologies and languages.	The data handling capabilities can be enhanced
9.	Apache “Storm” an array of platforms-based distributed stream analysis system	Tolerant to fault and extremely quick in performance	Difficult to use and learn.
10	“CDH” (Cloudera Distribution for Hadoop) is intended for use with enterprise-class Hadoop systems.	Highly secure and good governance.	Installation methods are multiple and create difficulties.

2.3 Human Society Theory

The application of AI to healthcare has broad ramifications for modern civilization. AI has the ability to completely change the way healthcare is provided, as well as patient outcomes and system efficiency. The following are some crucial points about the theory and application of AI technologies in healthcare:

1. The World Health Organization's (WHO) Global Report on AI in Health outlines six guiding principles for the development and application of AI in health. Unfortunately, the URL supplied could not be used to retrieve the report's exact content.
2. The Industrial Revolution and Its Effect on Society: The Fourth Industrial Revolution (IR4.0), often known as artificial intelligence (AI), is changing the way we live, interact, and perceive the world. AI has profound effects on 21st-century industrial, social, and economic transformations, making it necessary to establish guidelines for AI bioethics.
3. Advances in Computational and Data Sciences: Changes in healthcare are being driven by artificial intelligence as well as developments in computational and data sciences. Integrated health information systems, patient education, social media analytics, predictive modeling, and medical imaging are a few of the healthcare applications that use AI methodologies and models.
4. AI in Healthcare: Uses and Benefits AI is being utilized in healthcare to detect diseases, develop individualized treatment regimens, project patient survival probabilities, and automate numerous tasks. Improvements in accuracy, efficiency, and decision-making, as well as the potential to lower healthcare costs, are all advantages of AI in healthcare.
5. Compassion and AI in the Medical Field: There has been research on the relationship between AI technology and compassion in healthcare. While present AI theory falls short of comprehending the fundamental motivating mechanisms of human compassion, it is important to take into account how these systems may affect intricate societal healthcare systems.

6. The future of AI in healthcare: It is anticipated that by 2030, AI-enabled health systems will be able to provide proactive and predictive healthcare. This change is anticipated to improve the way healthcare is delivered while also enhancing patient outcomes.
7. AI-based Tools and Healthcare Delivery: AI-based tools have the potential to enhance clinical care in a number of ways, including prognosis, diagnostics, care planning, and more. Patients are significant benefactors and consumers of these applications, which are being funded by a large number of technology businesses and governmental organizations.
8. Perceptions of AI in Healthcare: Artificial intelligence has advanced significantly in recent years, and its applications are proliferating throughout society. To ensure the appropriate and efficient use of AI in healthcare, better understanding, education, and collaboration are required because healthcare professionals' and the general public's opinions of AI differ.
9. Interactive technologies in Online Health Care Communities: Interactive technologies are becoming more and more important, especially in light of the COVID-19 pandemic. Healthcare practitioners and patients can communicate more easily with one another because to internet-based medical platforms.
10. Humanizing Healthcare with AI: By enhancing effectiveness and efficiency, AI solutions are bringing a human touch to healthcare. These solutions have already demonstrated advantages in terms of improving diagnostic precision, lowering administrative burdens, and expediting healthcare procedures.

In conclusion, the theory and use of AI technologies in healthcare have the potential to completely change the way care is provided and enhance patient outcomes. But it's important to think about the ethical, social, and economic ramifications and make sure that artificial intelligence is used in healthcare in a responsible and equitable manner.

2.4 Summary

Artificial intelligence (AI) technologies are used in preventative and decentralized healthcare to strengthen preventive measures, improve healthcare delivery, and change the emphasis from reactive therapy to proactive and individualized care. Ethics and human rights are very important, and the World Health Organization (WHO) emphasizes that AI in healthcare should give ethics and human rights top priority in its development, implementation, and use. Even while AI has a great deal of potential to advance healthcare globally, it must be used in an ethical and responsible manner. Enhanced Preventive Measures, Diagnosis, and Treatment: AI in healthcare can help make preventive actions, diagnosis, and treatment more effective and efficient. AI systems can find patterns, forecast illness risks, and provide individualized suggestions for preventive therapy by analyzing enormous volumes of healthcare data. Better Decision Support: AI systems can give medical practitioners decision support capabilities to help them make accurate diagnoses, choose appropriate treatments, and improve patient care. To provide recommendations that are supported by the available evidence, AI algorithms can examine patient data, medical literature, and clinical guidelines. Remote Monitoring and Telehealth: AI-enabled gadgets and software make it possible to remotely monitor patients' vital signs, enabling medical professionals to keep tabs on their health and take appropriate action as required. AI-supported telehealth services can facilitate remote patient monitoring, virtual consultations, and prompt interventions. Early Detection and Predictive Analytics: AI algorithms may examine various healthcare data sources, such as electronic health records, medical imaging, genetic information, and lifestyle data, to spot early indications of diseases, forecast outcomes, and enable prompt interventions. This may result in better patient outcomes and lower medical expenses.

Delivery of Decentralized Care: AI in healthcare facilitates decentralized care by empowering people to track their own health, offering individualized health advice, and encouraging self-care. Mobile apps and wearables with AI capabilities can gather and analyze health data, enabling users to take an active role in their own well-being. Efficient Resource Allocation: By anticipating patient demand, maximizing bed occupancy, and expediting workflows, AI can improve resource allocation in healthcare organizations. This may result in increased effectiveness, shorter wait times, and more effective use of healthcare resources. Regulatory Guidelines: Regulatory bodies and organizations have created regulations to ensure the appropriate and safe use of AI in healthcare. To share best practices and reduce risks connected with AI implementation, the Ministry of Health in Singapore has collaborated on the MOH Artificial Intelligence in Healthcare Guidelines (AIHGle). In conclusion, the use of artificial intelligence in preventative and decentralized healthcare has the potential to improve decision-making, customize care, and boost prevention.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

In order to connect disparate systems and improve the accuracy of health care electronic records (ER), the healthcare system urgently needs to adopt a more centralized approach to patient care. Using automated data analysis, blockchain-based systems create and manage the data of ledgers (blocks). Block-based algorithms are used when healthcare researchers are concerned with the storage, security, and privacy management of clinical records.

In an integrated health care system, blockchain with AI may offer advantages, including augmented patient care and individualized treatment with increased efficacy. However, there are significant worries about difficulties, the possibility of ethical ramifications, and the importance of human rights and privacy protection. Responsible solutions must be found to the problems before designing, implementing, and integrating AI systems into the healthcare system. Additionally, there is a gap between the theoretical presentation, research settings, and clinical settings for the practical application of AI approaches. The use of AI approaches on a bigger scale is hampered by healthcare leaders' and providers' opposition to contemporary methods. Effective communication strategies are crucial for alleviating patient worries and fostering confidence in integrating AI tools into the healthcare system. Investigating options for implementing potentially useful AI technology in the healthcare sector is urgently needed.

AI can process large data sets in a small fraction of the time and expense. While the blockchain provides safe data access and interoperability, the privacy and security of health data may be preserved. The occurrence of illness epidemics encourages the preservation of clinical records for controlling similar outbreaks in the future. Only AI solutions allow for accurate and private data maintenance in a decentralized healthcare system. For an early response to the control of a disease, the scientific community, stakeholders, and policymakers will have easy access to real-time data.

3.2 Operationalization of Theoretical Constructs

The study was performed as described by (Walters & Kalinova, 2021) with modifications. In most cases, hospitals could access patients' medical records and offer healthcare services during emergencies and routine checkups. Hospitals do not trade or share patient information with third parties due to problems with trust, transparency, or ulterior motives. The patient's medical history is of utmost importance, particularly in an emergency, to provide the proper care at the appropriate moment and preserve life. In addition, people frequently choose to attend clinics rather than hospitals. Therefore, clinics and hospitals must work together in harmony. AI technology makes it possible to build trust, transparency, and data security between hospitals and clinics to address these problems. A rule-based AI smart contract for the hospital was represented. A smart contract node comprises four distinct sections: (1) Create P_{id}: The hospital node makes an authentication request with the deployed contract address and ABI. The AI network is where this information is verified. It generates the ack "True" if the arguments are correctly matched. The healthcare worker submits the patient's information for the P_{id}, which is kept on the AI and includes the patient's name, father's name, address, city, cellphone number, and pin code. A unique P_{id} was generated if this information or parameter cannot match the existing information. (2) Create Did: Using a smart contract, the healthcare worker enters the AI device's mac address, manufacturer, and sensor information to register it in the AI network. The blockchain network verifies the device parameters against the already-existing parameters as part of the verification process, and if the parameters were unique, D_{id} was generated. (3) Update of patient and device data: The initial stage in updating patient data was to provide the distinct P_{id} with the deployed contract address and ABI, then match the

P_{id} with the database already in the blockchain network. If IDs match, the network responds with "P_{id} matched." The hospital node sends an "update command" accompanied by updated data to update the patient's existing data and receives an acknowledgement that the information has been updated. Update patient information: Once the P_{id} matches are successful, the hospital node adds the new patient data to the AI network. The ack "Info updated" was generated when uploading was complete.

Identification of the patient and the equipment

The AI data is securely and effectively encrypted using the Merkle tree, which also speeds up data verification. Every completed transaction on the AI network has a hash associated with it. These hashes are often cached in a tree-like structure, connected to their parents in the shape of a tree, and demonstrate filial relation even though they are not aligned in a particular order in the blocks. Numerous transactions may be included in a single block, and each transaction may be hashed. In this study, P_{id} was registered using a mix of patient names, unique identification, contact information, and home address using the Merkle tree. P_{id} is the sum of the entered values for these parameters. In the case of the D_{id}, the entered item that transforms into a Merkle root is the device information and MAC address. Without revealing their identities, these parameters were maintained in the network. D_{id} with additional parameters like P_b, deployed contract address, and ABI at the validation time.

Data verification

Data authentication consists of two steps: (1) creating a signature and (2) message validation.

Creating a signature: The main building element of the AI network, cryptographic signatures, were used to verify ownership addresses without disclosing the secret key. This work uses the input message and private key (Pr) as input parameters to create a digital signature using the elliptic curve digital signature method (ECDSA). A mathematical technique called a digital signature is used to verify the authenticity of AI device authentication and the integrity of data transferred from the devices. This article's digital signature for AI devices is created using the ECDSA technique.

Verification:

The public key is retrieved from the elliptic curve recovery via input message during validation, and the message also includes a digital signature. AI networks allow communication to be authenticated if D_{id} and Pb match.

3.3 Research Purpose and Questions

The current project aims to use artificial intelligence in a decentralized healthcare setting to safeguard patient privacy and electronic data in order to take preventive measures. When AI tools were implemented in the healthcare system, further human rights were guaranteed. Artificial intelligence is used in decentralized health care to provide real-time data collection and widespread use of disease prevention strategies.

With real-time data collecting, artificial intelligence-based systems are more beneficial for illness prevention. The genuine picture of sickness in the community can be shown through disease surveillance based on AI-generated electronic data. Information about disease preventive measures distributed to the community is helpful for disease control. My research questions were:

1. The application of artificial intelligence in preventive and decentralized health care is helpful in disease prevention.
2. Information about disease prevention can be dispersed in the decentralized healthcare units and the community to prevent disease outbreaks.

3.4 Research Design

For the use of AI technologies in the healthcare system to prevent disease, a thorough framework was needed that guarantees patient safety, boosts system effectiveness, and handles ethical issues. In light of the information provided, including the pertinent sources, the following framework was proposed for using AI tools in healthcare:

Standards and regulations were established to ensure AI's secure development and application in healthcare. Relevant parties, such as governmental agencies, healthcare organizations, and AI developers, collaborated to produce these guidelines. For instance, the Singapore Ministry of Health (MOH) has collaborated with other organizations to establish the Artificial Intelligence in Healthcare Guidelines (AIHG) to share best practises with AI developers and implementers.

The system's workflow

The system's workflow is as follows:

Data Collection: Information regarding medical records, family history, lifestyle, body mass index, blood glucose and cholesterol level, cognitive assessments, genetic lineage, braining imaging, and other clinical manifestation was collected for early diagnosis and prevention of diabetes and Alzheimer's.

Data Processing: The data was processed just after collection to remove outliers, resolve missing values, and standardize. Ethical concerns were considered while handling and processing data.

Feature Engineering: Data regarding the most relevant features of each disease were preprocessed as blood glucose level and body mass index for diabetes and brain imaging and cognitive score for Alzheimer's. Data on lifestyle, family history or genetic lineage was used for bot the diseases.

Development of AI model: An algorithm model (logistic regression) was used to predict individuals at risk based on extracted features. For analysis of disease progression, a time series analysis was performed. Further, for Alzheimer a neural network was used for early detection of the disease.

Evaluation and Validation: The developed model was validated by analyzing various data sets to assess the accuracy, sensitivity, generalizability, and specificity.

Preventive Strategies: the AI model was deployed for early detection of developing signs and symptoms of both diabetes and Alzheimer's in individuals at risk. In parallel with risk factors, preventive strategies were developed for each individual. The mainly focussed preventive measures were modifications in lifestyle, dietary plan, and exercise routine specifically for diabetes and Alzheimer's cognitive training and use of potential therapeutic measures along with improvements in lifestyle.

Disease Progression Monitoring: The AI algorithm was implemented in diagnosed patients for real-time monitoring. Continuous monitoring was helpful in the evaluation of treatment and interventions. The biomedical data was also useful in discovering new drugs against both diseases.

Collaboration with Healthcare Professionals: The expertise of healthcare professionals were complemented with use of AI tool in the early detection and adaptation of preventive measures. Collaboration with these professionals was helpful in implementing the AI model and interpreting o results.

Ethical Considerations: Our main was to focus on the ethical aspects of maintaining data privacy, implementing ethical guidelines, and handling sensitive data.

Patient ID (P_{id}) creation. Step 1: The hospital node delivers the Application Binary Interface (ABI) and patient information (Pinf), which comprises the patient's name, unique identification number, contact information, and home address. The AI system recognizes the Pinf and determines whether or not it matches an existing one. Step 2: If the information is incompatible, it generates the P_{id}; if it is, it causes a system error.

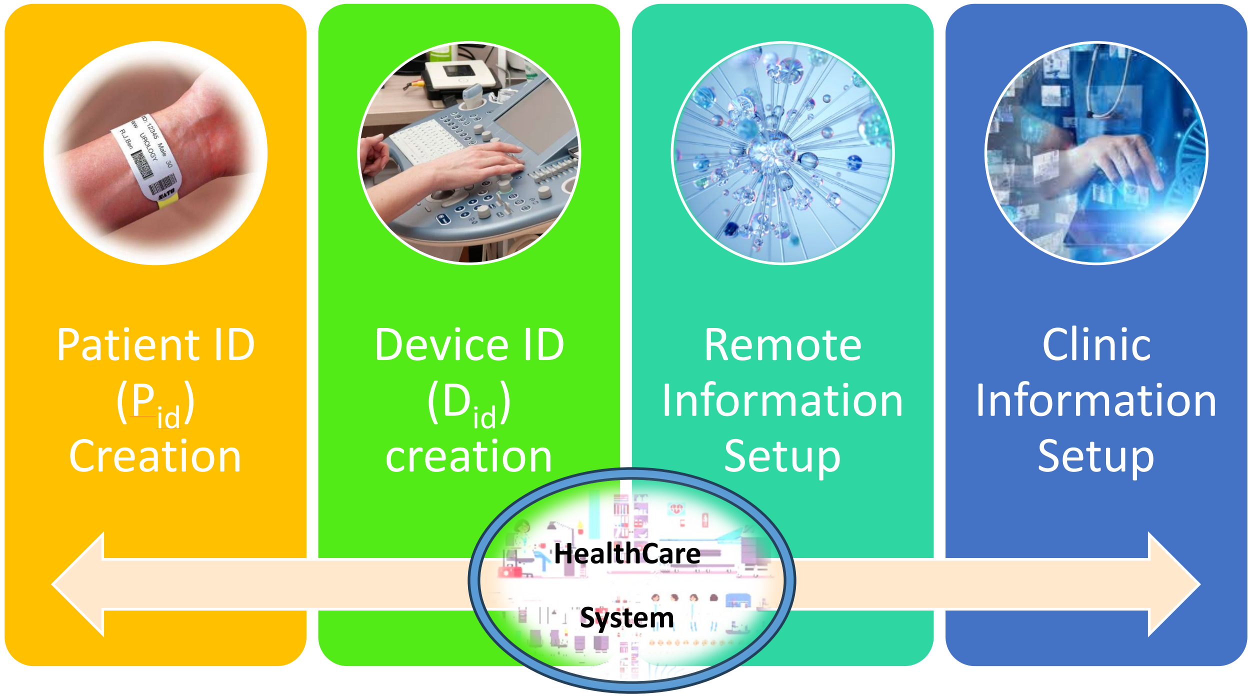
Device ID (D^{id}) creation. The D_{id}, and P_{id} are created using very similar processes. The hospital server provides the data generator's MAC address and device details for verification and device information. If the information is distinct, a new Did was created after that.

Remote information setup creation: Step 1: The device requests the centralized AI system (Hospital) with the D_{id}, deployed contract address, and ABI to authenticate the distant information set. The error "device was not registered or malicious" was generated because the device's D_{id} does not match the existing ID stored in the AI network.

Step 2: Following the $D_{id's}$ successful verification, the AI network permits a second request from a distant information set to access the data.

Clinical information setup creation: Step 1: The clinic data system makes an authentication request to the centralized AI network with Pid, contract address, and ABI to receive the patient's medical history. An AI system with rules is implemented to make a quick conclusion regarding authentication.

Step 2: Clinic information enables access to patient data following clinic authentication success. The AI rules layer was integrated into smart contracts with devices. P_{id} and patient data from the central network were used to update the patient information. As stated in the prior section, Pid and D_{id} are formed in Step 1. Step 2: The hospital node uses an AI rule-based smart contract to send Pid with the contract address. After successful authentication, devices were permitted to update information.



3.5 Population and Sample

The sentinel surveillance was performed on selected clinics and hospitals to collect data. One hundred patients were selected as per the convenience and screened for the parameters.

3.6 Participant Selection

Patients presented at the clinic or hospital with complaints of illness of diabetes or Alzheimer were included in the study and given a specific ID. There was no specific discrimination in the selection of participants, but these participants were divided into various groups based on ethnicity, race, age, gender, and occupation.

3.7 Instrumentation

The data was first entered into AI system through an electronic device (computer). The required instruments were blood glucose testing, genetic evaluation, and brain imaging devices. Along with these devices, a neural network was used to connect all of them with the main server to collect data for further maintenance and analysis. Data of each patient was regularly monitored for disease progression analysis and effectiveness of therapeutic measures.

3.8 Data Collection Procedures

The data about each was collected in collaboration with healthcare professionals. The patient presented to the hospital and presented his/her data to health care professionals that were recorded in the system of the hospital or clinic. That data was transferred to the main storage system through neural networks. The data was stored in an Excel sheet for further analysis.

3.9 Data Analysis

The collected data was earlier processed for the evaluation of any missing information. Earlier descriptive analysis was performed to assess qualitative risk factors, and quantitative analysis data were subjected to an AI analysis (Regression analysis) through SPSS software. The data was presented in the form of various tables and graphs.

3.9 Research Design Limitations

Data collection from susceptible patients not presented to any clinic or hospital was not fulfilled during the current study. Only two diseases were evaluated, need to explore other conditions. The SPSS algorithm was used for the analysis of stored data.

3.9 Conclusion

The current study used AI tools in a preventive decentralized healthcare system. The data was collected about patients (especially those with Alzheimer's and diabetes), equipment from clinics and hospitals, and earlier electronic health records. The data was shifted into a decentralized AI system for real-time monitoring of the patient's condition, and the impact of medication and other therapeutic interventions was noted. Further data about patient age, gender, diet plan, life activity, behaviour, body mass index, and ethnicity were also analyzed. The significant factors were evaluated, and recommendations were drawn based on the analysis.

CHAPTER IV:

RESULTS

4.1 Research Question One

4.1. Results question 1

A total of 100 diabetic patients presented to selected hospitals were subjected for evaluation of associated risk factors of the disease. During the current study thirteen risk factors were evaluated including age, gender, body mass index (BMI), diet plan, physical exercise, Blood pressure, Smoking, family history, alcohol consumption, sleep disorder, hormonal alterations, risk score, and hypertension. All the examined risk factors were found to be significantly associated with the occurrence of diabetes. For quantitative variables age, blood pressure, risk score, and body mass index mean value along with other parameters were calculated as mentioned in **Table 4.1**. The descriptive analysis of quantitative variables depicts the mean value along with standard error of mean (possible error), median (middle value), mode (most repeated value), standard deviation (dispersion of data), Variance (possible variation in data), range (range of data), minimum and maximum observed values for each variable. Among the observed diabetic patients, observed mean of age was 42.93±1.09, and that of blood pressure, risk score, and BMI were 142.93/89.01±1.3/0.43, 6.87±0.2, and 28.17±0.33 respectively. The most observed age was 33 years with blood pressure 135/90, risk score 7, and BMI 28. While the median age was 43 years with minimum 23 years, and maximum 63 years. The range that elaborates the deviation of data in between minimum and maximum value was 40, 50/15, 9, and 13 for age, blood pressure, risk score, and BMI respectively. The possible dispersion of observed individual data set from mean value was 119.74 years, 168.25/18.09, 3.99, and 10.65 for quantitative variables age, blood pressure, risk score, and BMI respectively.

Table 4.1. Statistical analysis of quantitative variables for diabetes

	Age (years)	Blood pressure Systolic	Blood Pressure Diastolic	Risk Score	BMI
Mean	42.93	142.93	89.01	6.87	28.17
Std. Error of Mean	1.09	1.30	0.43	0.20	0.33
Median	43	140	90	7	28
Mode	33	135	90	7	28
Std. Deviation	10.94	12.97	4.25	2.00	3.26
Variance	119.74	168.25	18.09	3.99	10.65
Range	40	50	15	9	13
Minimum	23	125	80	2	21
Maximum	63	175	95	11	34

4.1.1. Gender-based variability

Among the diabetic patient's large number of females were in infected in comparison to males as depicted in **Table 4.2 and Figure 4. 1.** The males were 32% out of all infected individuals. Higher number of infected females depict their higher susceptibility than males. There was significant difference in frequency of infected of male and female ($p<0.05$).

Table-4.2: Gender based frequency of individuals infected with diabetes.

	Frequency	Percent	Valid Percent	Cumulative Percent
Female	68	68.0	68.0	68.0
Male	32	32.0	32.0	100.0
Total	100	100.0	100.0	

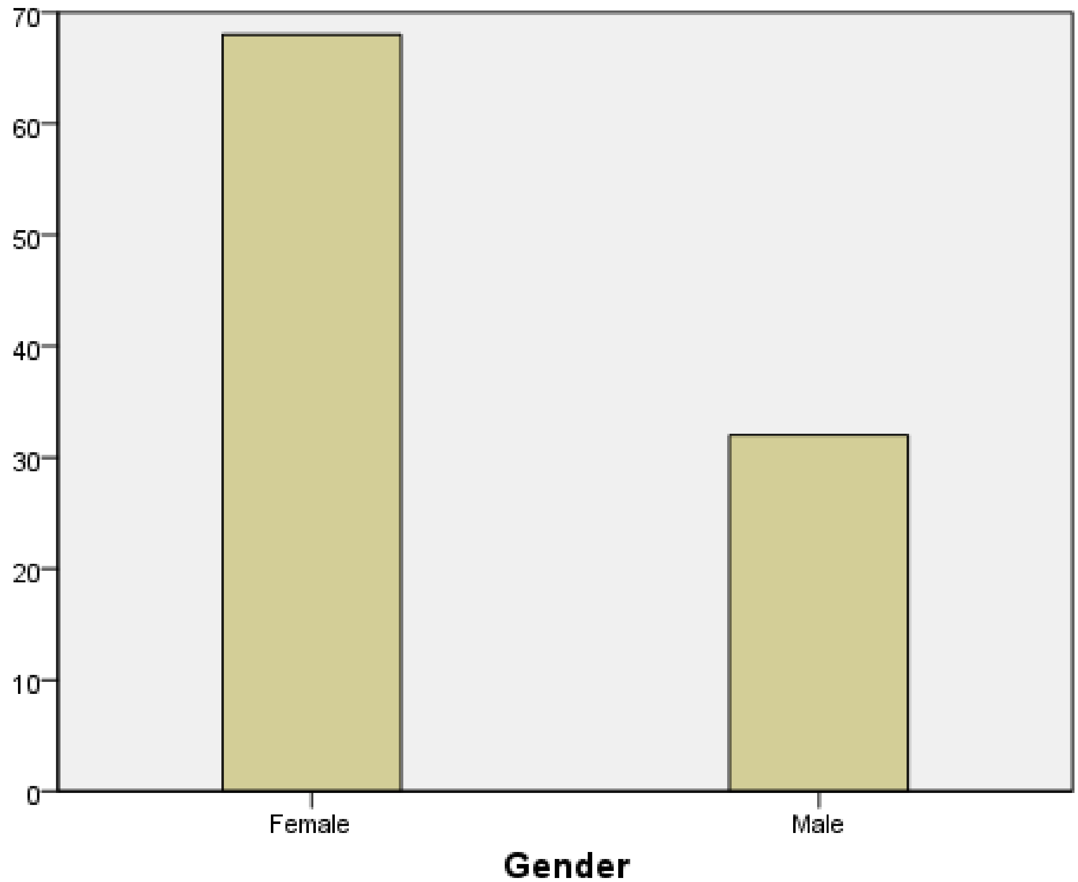


Figure 4.1. Gander-based variability among diabetes infected individuals

4.1.2. Age-based variability

The variable trend of diabetes in relation to the age of individuals is depicted in **Table 4.3** and **Figure 4.2**. The highest trend of diabetes occurrence was recorded in the individuals who are above 30 years of age, with several 8 cases in 33, and 7 cases in 45 years age. Individuals who are in their early age have a lower rate of diabetes and this trend also falls beyond fifty years of age.

Table 4.3: Age-based frequency of individuals infected with diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
	23.00	3	3.0	3.0	3.0
	25.00	3	3.0	3.0	6.0
	28.00	4	4.0	4.0	10.0
	29.00	7	7.0	7.0	17.0

	33.00	8	8.0	8.0	25.0
	35.00	7	7.0	7.0	32.0
	38.00	3	3.0	3.0	35.0
	39.00	3	3.0	3.0	38.0
	40.00	4	4.0	4.0	42.0
	41.00	4	4.0	4.0	46.0
	42.00	3	3.0	3.0	49.0
	43.00	4	4.0	4.0	53.0
	44.00	4	4.0	4.0	57.0
	45.00	7	7.0	7.0	64.0
	47.00	3	3.0	3.0	67.0
	49.00	3	3.0	3.0	70.0
	50.00	3	3.0	3.0	73.0
	53.00	4	4.0	4.0	77.0
	55.00	7	7.0	7.0	84.0
	56.00	3	3.0	3.0	87.0
	58.00	4	4.0	4.0	91.0
	59.00	3	3.0	3.0	94.0
	60.00	3	3.0	3.0	97.0
	63.00	3	3.0	3.0	100.0
	Total	100	100.0	100.0	

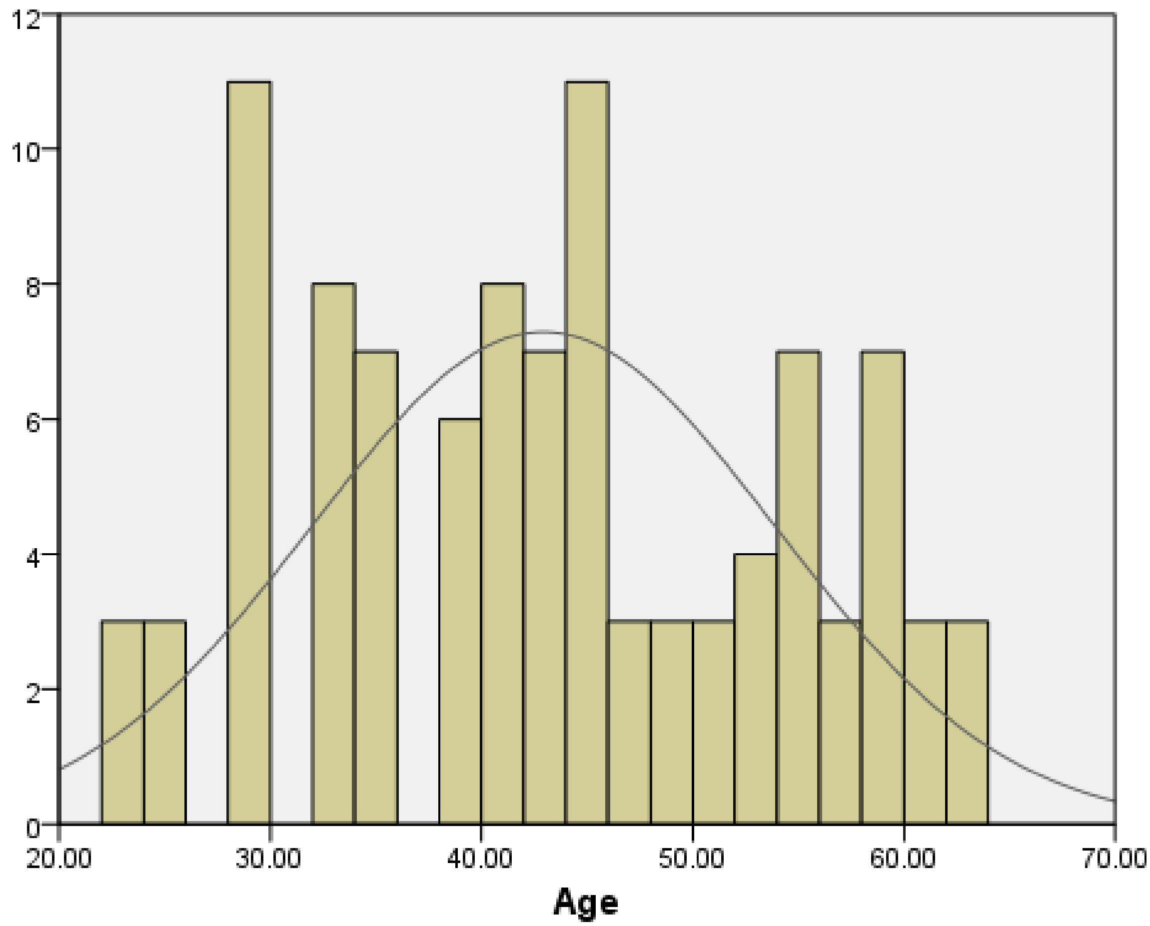


Figure 4.2. Age based variability in diabetic patients with higher number of cases in age range 35 to 55.

4.1.3. Role of family history in the occurrence of diabetes

For evaluation of genetic factors in the occurrence of diabetes, the data about family history was calculated and evaluated. The data depicted that patients having family history of diabetes were higher in number than patients do not have family history as shown in **Table 4.4** and **Figure 4.3**.

Table 4.4. Family history and diabetes

	Frequency	Percent	Valid Percent	Cumulative Percent
No	12	12.0	12.0	12.0
Yes	88	88.0	88.0	100.0
Total	100	100.0	100.0	

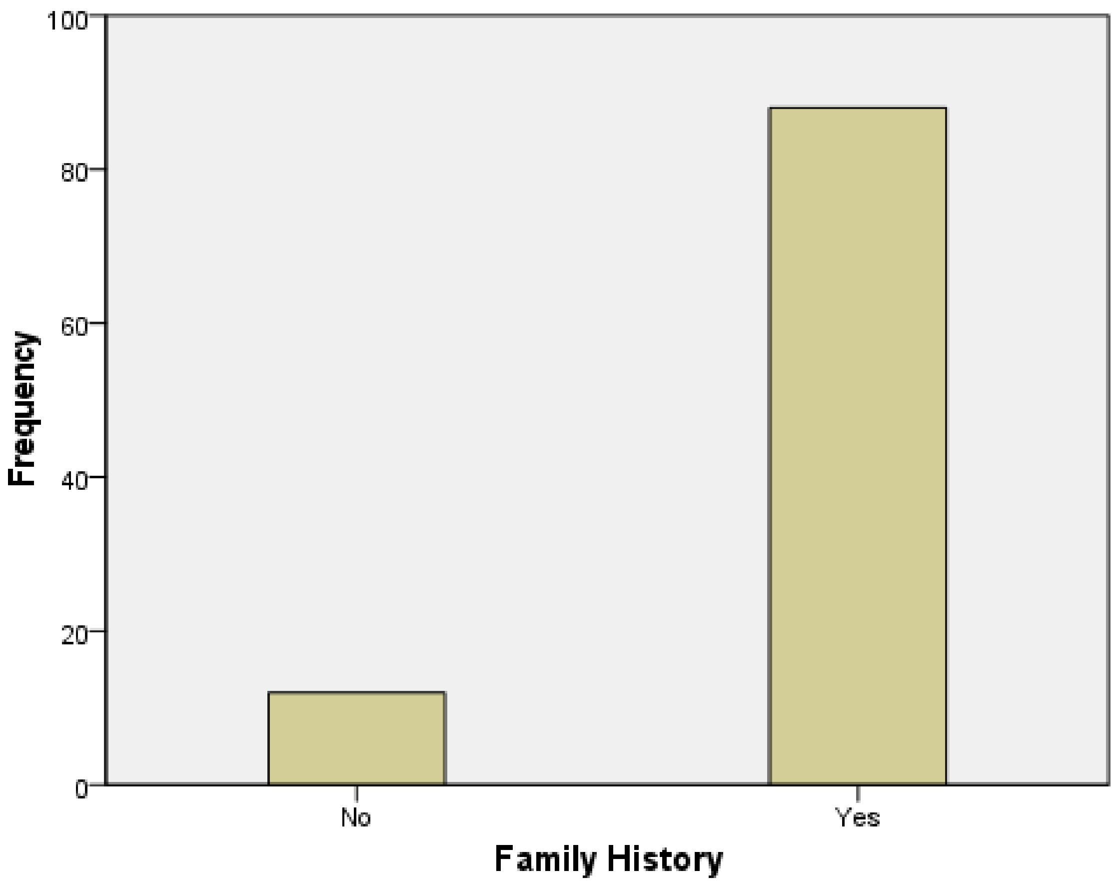


Figure 4.3. Family history and occurrence of diabetes among patients. Depicting an association of genetics with disease.

4.1.4. Role of blood pressure in diabetes.

The blood pressure was divided into systolic and diastolic data to evaluate their role in the occurrence of diabetes. The representative data for diabetes in relation to systolic blood pressure (BP) is given, highlighting the importance of blood pressure in the occurrence of diabetes. A total of 18 cases having 135 systolic blood pressure were reported with diabetes, twelve cases for 150 systolic blood pressure, and 11 for 140 & 145 systolic BP measurement as shown in **Table 4.5** and **Figure 4.4**. The tabular data depicts the relationship between diastolic blood pressure and the happening of diabetes in different age groups of people. At 90 diastolic blood pressure the 29 individual patients were found positive for diabetes. At 85 blood pressure 24 patients were diabetic, and at 95 diastolic BP there were 17 people reported for diabetes. Lower frequency of diabetes at 80 diastolic blood pressure was checked during the current study as shown in **Table 4.6.** and **Figure 4.5**.

Table 4.5. Systolic blood pressure and diabetic patients

		Frequency	Percent	Valid Percent	Cumulative Percent
	125.00	6	6.0	6.0	6.0
	128.00	7	7.0	7.0	13.0
	130.00	5	5.0	5.0	18.0
	132.00	6	6.0	6.0	24.0
	135.00	18	18.0	18.0	42.0
	140.00	11	11.0	11.0	53.0
	145.00	11	11.0	11.0	64.0
	148.00	6	6.0	6.0	70.0
	150.00	12	12.0	12.0	82.0
	152.00	6	6.0	6.0	88.0
	165.00	6	6.0	6.0	94.0
	175.00	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

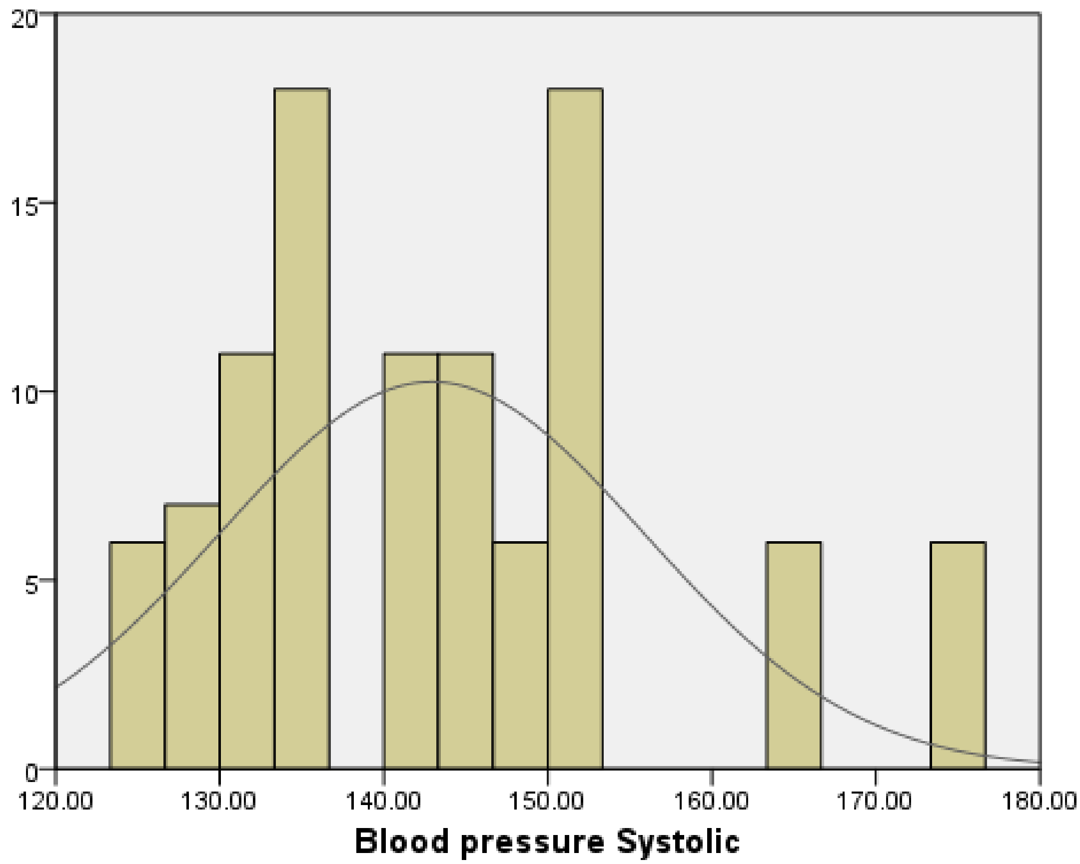


Figure 4.4. Role of Systolic blood pressure in the occurrence of diabetes

Table 4.6. Diastolic blood pressure and diabetic patients

	Frequency	Percent	Valid Percent	Cumulative Percent
80.00	5	5.0	5.0	5.0
84.00	6	6.0	6.0	11.0
85.00	24	24.0	24.0	35.0
88.00	7	7.0	7.0	42.0
90.00	29	29.0	29.0	71.0
92.00	6	6.0	6.0	77.0
94.00	6	6.0	6.0	83.0
95.00	17	17.0	17.0	100.0
Total	100	100.0	100.0	

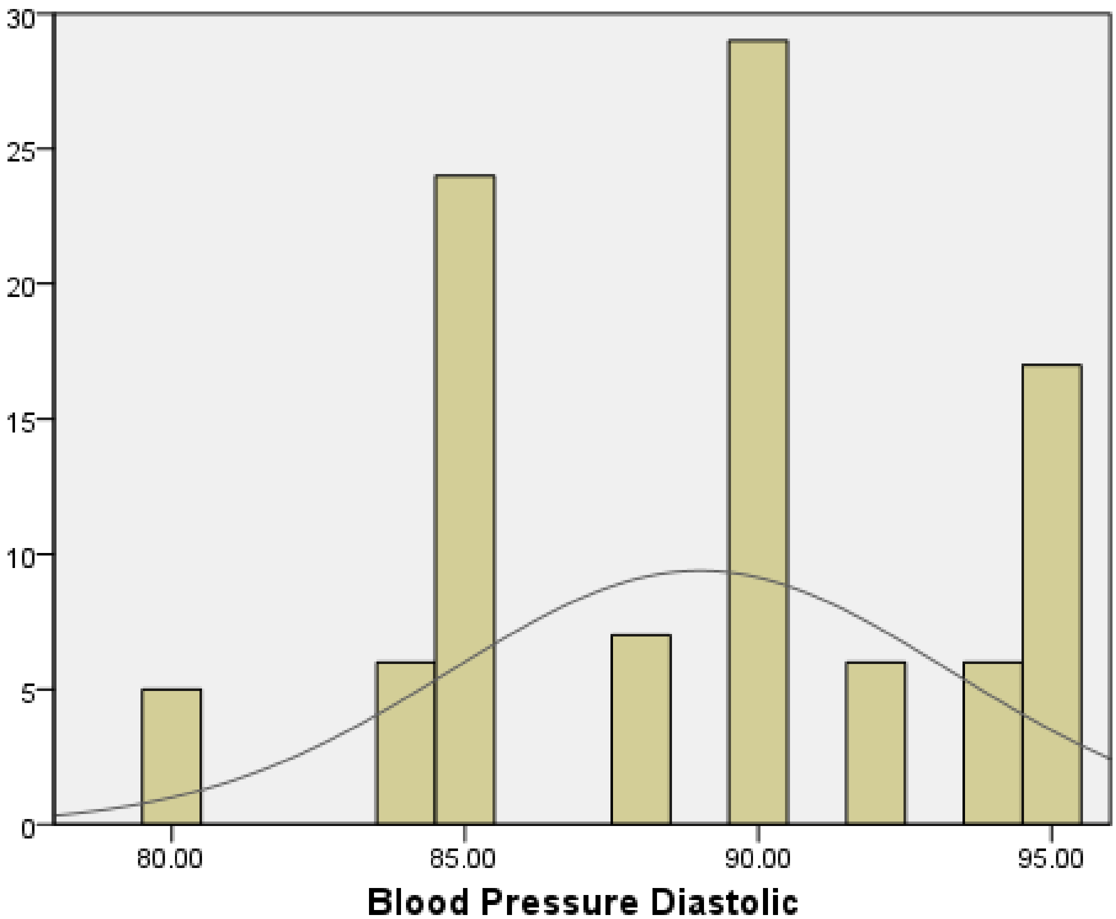


Figure 4.5. Role of Diastolic blood pressure in the occurrence of diabetes

4.1.5. Physical Activity and diabetes

The link between physical activity and the trend of diabetes has been highlighted in **Table 4.7** and **Figure 4.6**. The individuals having sedentary lifestyle were more positive for diabetes as compared to the individuals who were more active in their daily routine. A total of eighty-one cases were reported positive for diabetes who were sedentary and six cases of diabetes for active people and thirteen cases for moderate life styled people.

Table 4.7. Physical activity and diabetes

	Frequency	Percent	Valid Percent	Cumulative Percent
Active	6	6.0	6.0	6.0
Moderate	13	13.0	13.0	19.0
Sedentary	81	81.0	81.0	100.0
Total	100	100.0	100.0	

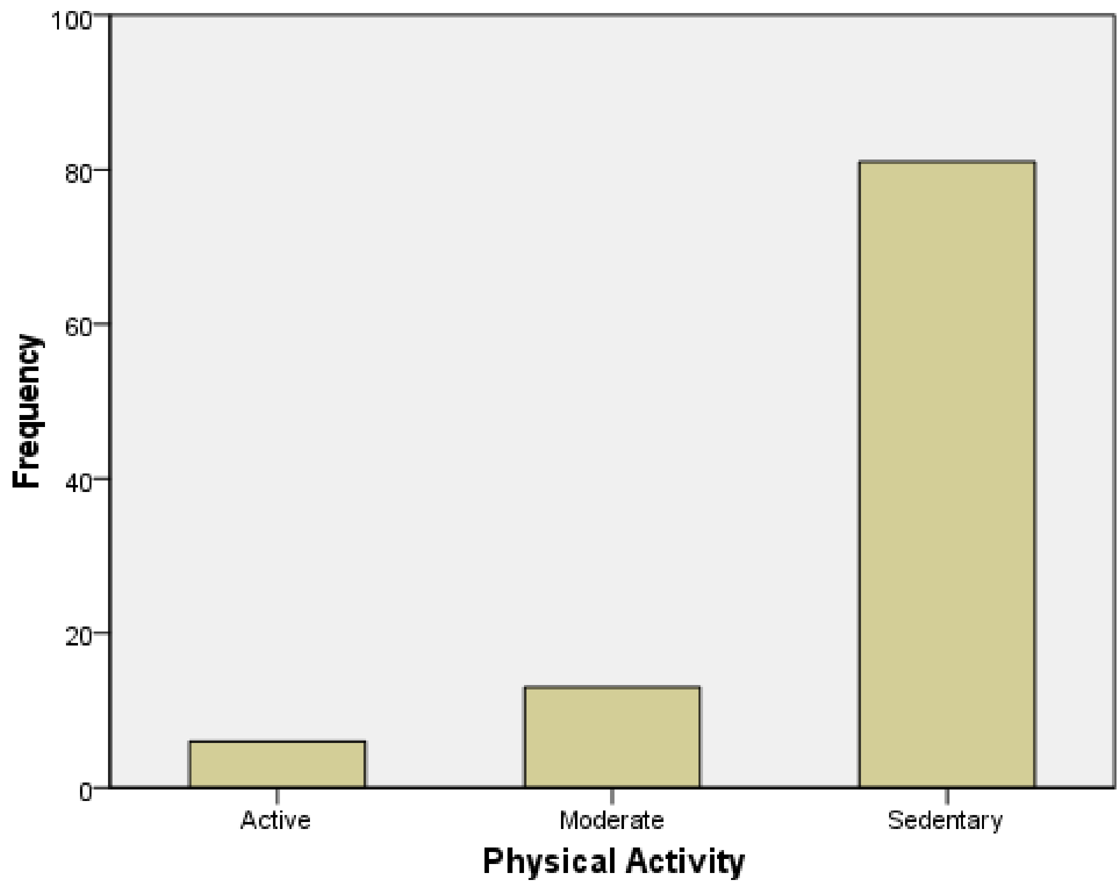


Figure 4.6. Physical activity and frequency of diabetes

4.1.6. Diet plan and diabetes.

The incidence of diabetes happening with a variety of diet taken by the individuals has been depicted in **Table 4.8** and **Figure 4.7**. The persons who are consuming high sugar have a high rate of diabetes as compared to the patients who are at low fat diet with several 86 cases and 6 cases respectively.

Table 4.8. Diet plan and diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Balanced	8	8.0	8.0	8.0
	High Sug	86	86.0	86.0	94.0
	Low Fat	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

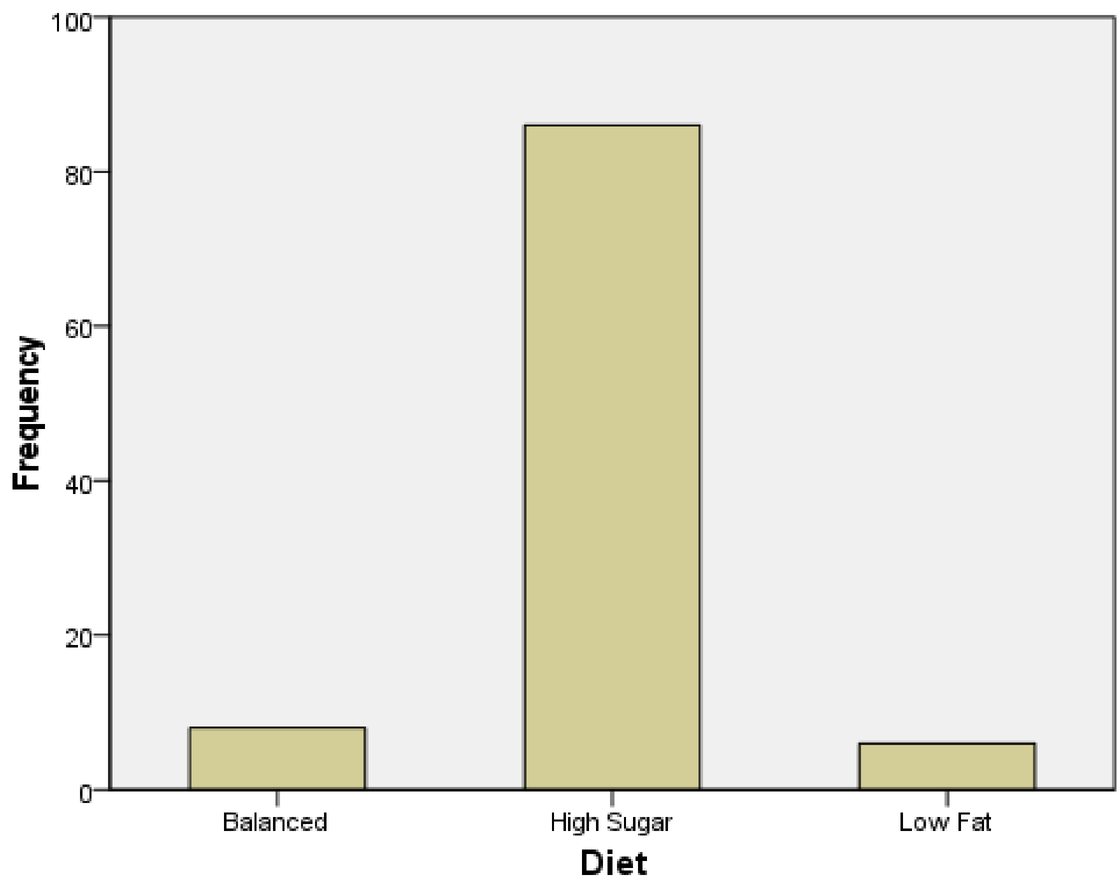


Figure 4.7. Diet variety and occurrence of diabetes among individuals.

4.1.7. Role of smoking in diabetes

The incidence of diabetes in relation to smoking has been depicted in **Table 4.9** and **Figure 4.8**. The patients who were smokers had a higher rate of diabetes as compared to the people who were not involved in smoking with several 78 and 22 respectively.

Table 4.9. Smoking and occurrence of diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	22	22.0	22.0	22.0
	Yes	78	78.0	78.0	100.0
	Total	100	100.0	100.0	

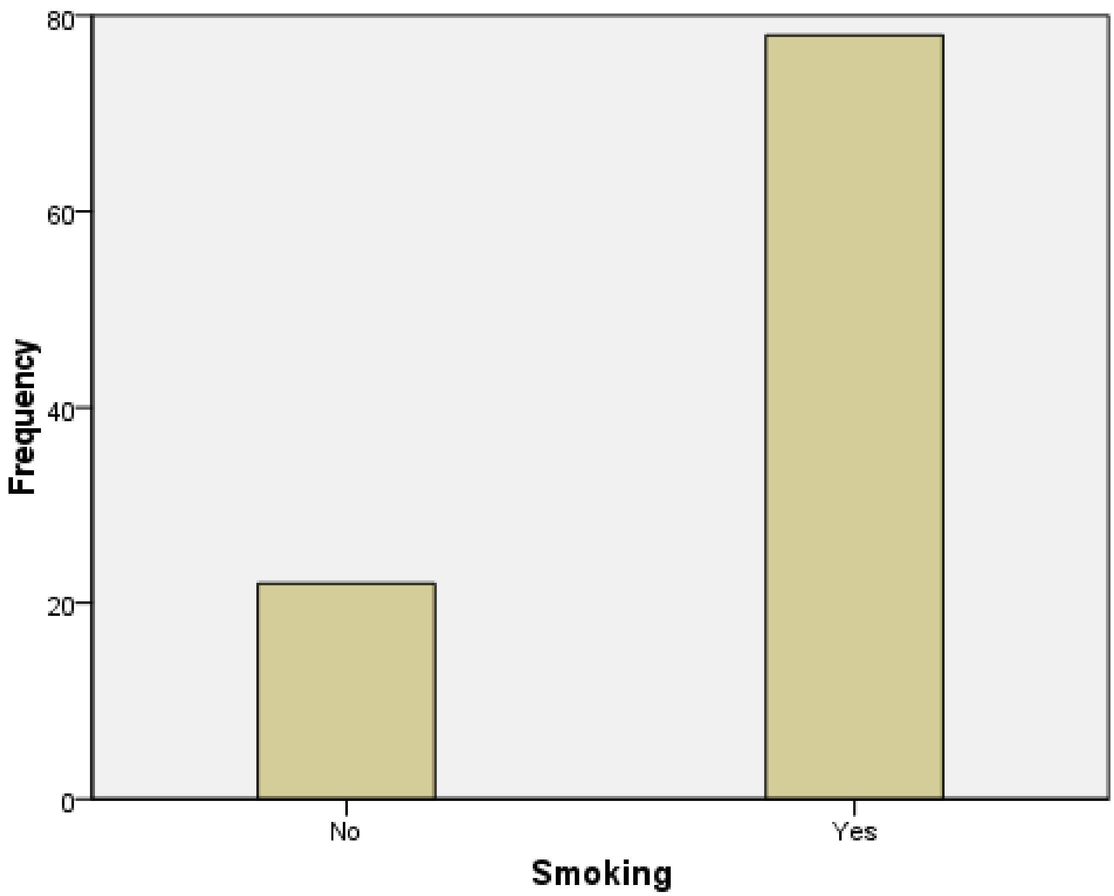


Figure 4.8. Frequency of diabetes with respect to smoking

4.1.8. Role of alcohol consumption and incidence of diabetes

The variable trend of alcohol consumption and diabetes was reported in the current study. The occasional alcoholic consumers showed 7 cases, 7 for people who consume a little alcohol, 8 for moderate consumers, and 6 cases for non-alcoholic individuals. Individuals consuming high alcohol have maximum diabetes than all others as shown in **Table 4.10** and **Figure 4.9**.

Table 4.10. Alcohol consumption and diabetic patients

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High	72	72.0	72.0	72.0
	Low	7	7.0	7.0	79.0
	Moderate	8	8.0	8.0	87.0
	No	6	6.0	6.0	93.0
	Occasional	7	7.0	7.0	100.0
	Total	100	100.0	100.0	

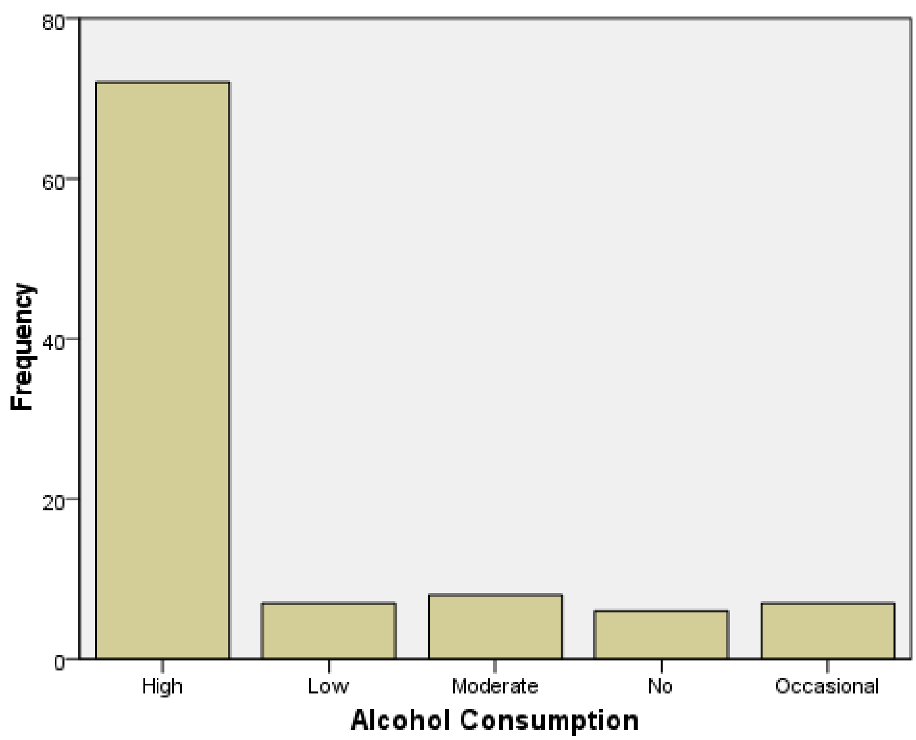


Figure 4.9. Role of alcohol consumption and diabetic patients

4.1.9. Role of stress in diabetes

Stress has a direct link with the occurrence of diabetes as shown in **Table 11** and **Figure 4.10**. A total of 83 cases from 100 people exhibits high stress. The incidence of diabetes is low with the decline in stress level (7 cases out of 100 cases for the individuals who have low stress level).

Table 4.11. Stress and variability in diabetic patients

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High	83	83.0	83.0	83.0
	Low	7	7.0	7.0	90.0
	Moderate	10	10.0	10.0	100.0
	Total	100	100.0	100.0	

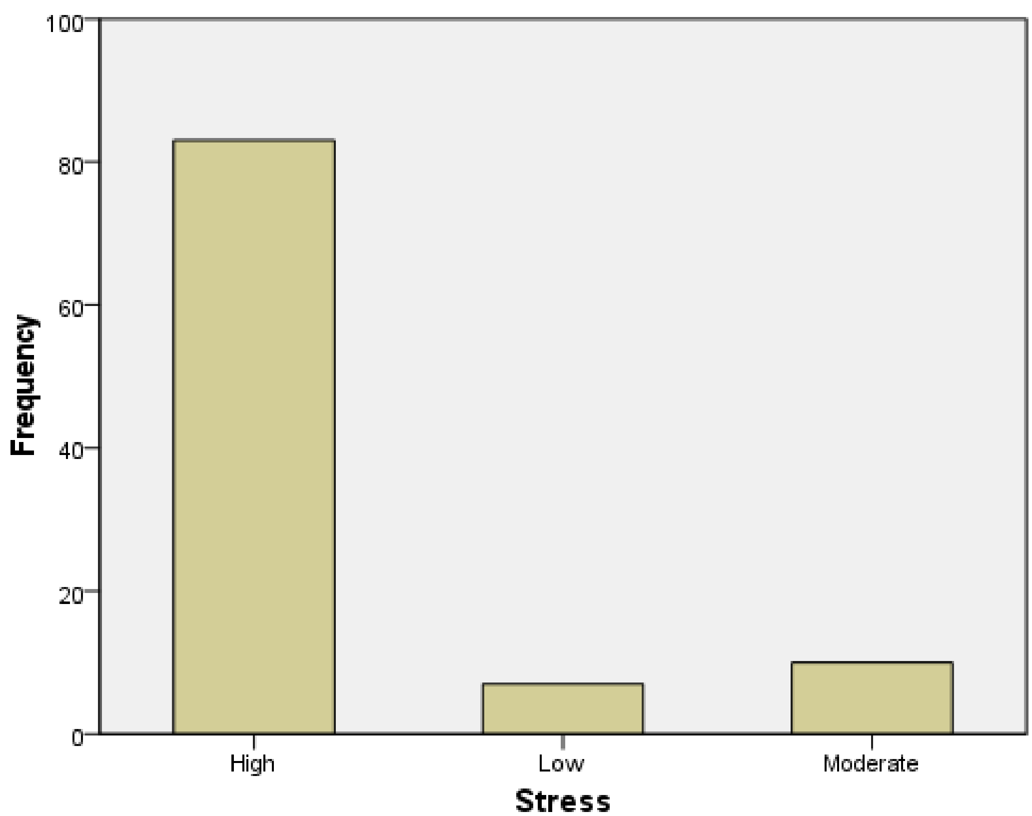


Figure 4.10. Stress level and incidence of diabetes.

4.1.10. Sleep disorder and incidence of diabetes.

There is a link between sleep disorder and incidence of diabetes as shown by **Table 4.12** and **Figure 4.11**. The persons having sleep disorder showed a high rate of diabetes (79 out of 100 individuals positive for diabetes), and the patients having no sleep disorder showed lower trend of diabetes in them.

Table 4.12. Sleep disorder and frequency of diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	21	21.0	21.0	21.0
	Yes	79	79.0	79.0	100.0
	Total	100	100.0	100.0	

Figure 4.11. Sleep disorder influences the occurrence of diabetes among individuals.

4.1.11. Impact of environmental factors on the occurrence diabetes

Environmental factors also have a strong impact on the occurrence of diabetes as revealed from the above data. A total of eighty individuals were positive for diabetes having impact of different environmental factors on them as compared to the people who were less exposed to the environmental factors as shown in **Table 4.13** and **Figure 4.12**.

Table 4.13. Environmental Factors and diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	20	20.0	20.0	20.0
	Yes	80	80.0	80.0	100.0
	Total	100	100.0	100.0	

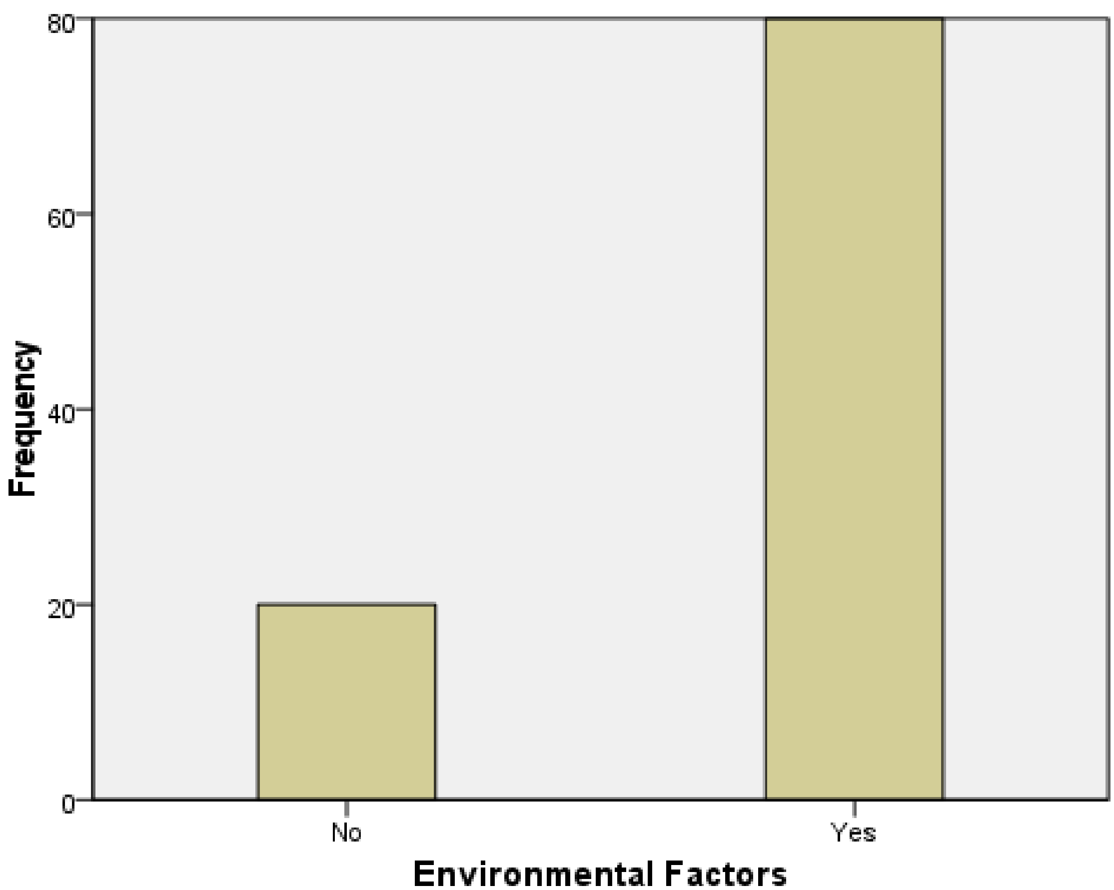


Figure 4.12. Role of environmental factors in the occurrence of diabetes

4.1.12. Hormonal imbalance and diabetes

The data showed a strong impact of hormones and diabetes. The patients with hormonal imbalance were at higher risk of diabetes as compared to the individuals who were not suffering from any hormonal imbalance as shown in **Table 4.14** and **Figure 4.13**.

Table 4.14. Hormonal imbalance and diabetes frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	43	43.0	43.0	43.0
	Yes	57	57.0	57.0	100.0
	Total	100	100.0	100.0	

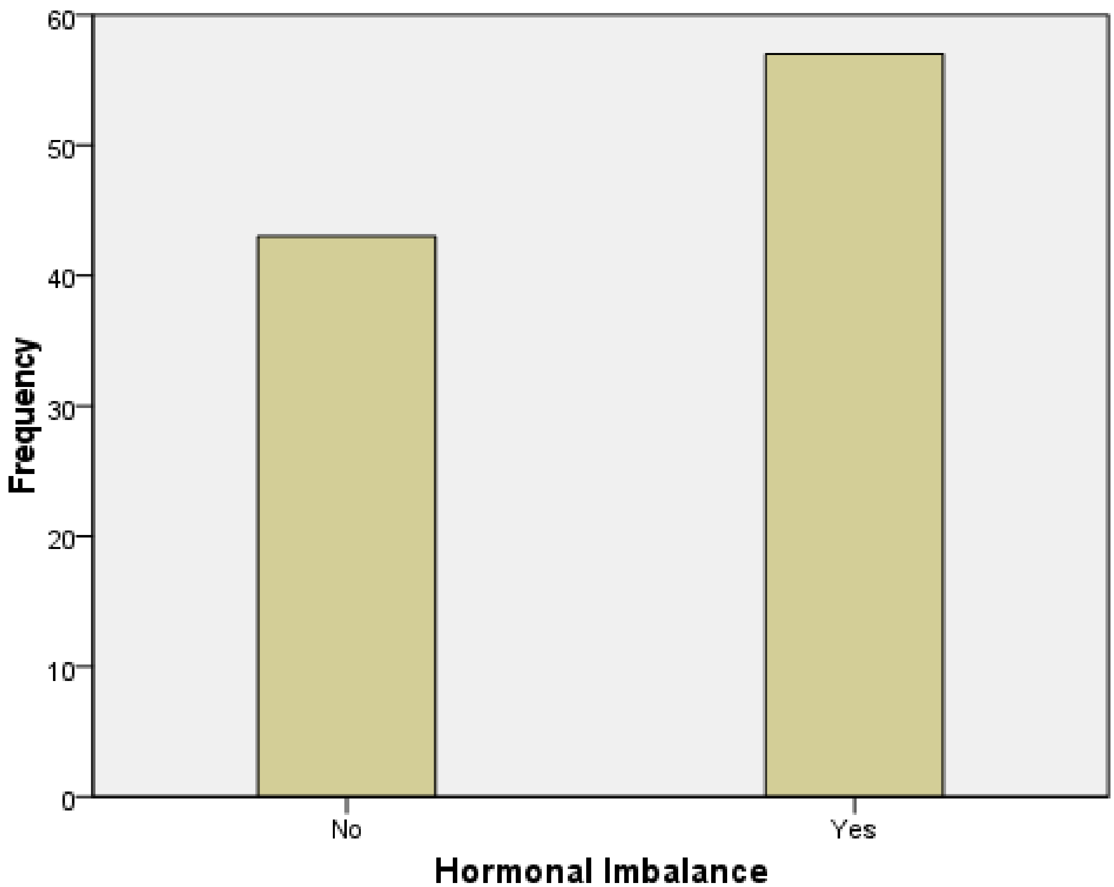


Figure 4.13. Frequency of diabetes with the hormonal imbalance

4.1.13. Diabetes and Risk Score

The risk score for type diabetes was evaluated, ranges from 1 to 11 and maximum frequency of risk score 7 was observed during the current study. The lowest frequency was 1 for risk score 11 as shown in **Table 4.15** and **Figure 4.14**. The risk scores 6,7,8, and 9 were found more frequent than others, while scores 2 and 11 were found least frequent.

Table 4.15. Risk score and occurrence of diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2.00	3	3.0	3.0	3.0
	3.00	5	5.0	5.0	8.0
	4.00	5	5.0	5.0	13.0
	5.00	8	8.0	8.0	21.0
	6.00	16	16.0	16.0	37.0
	7.00	24	24.0	24.0	61.0
	8.00	18	18.0	18.0	79.0
	9.00	13	13.0	13.0	92.0
	10.00	7	7.0	7.0	99.0
	11.00	1	1.0	1.0	100.0
	Total	100	100.0	100.0	

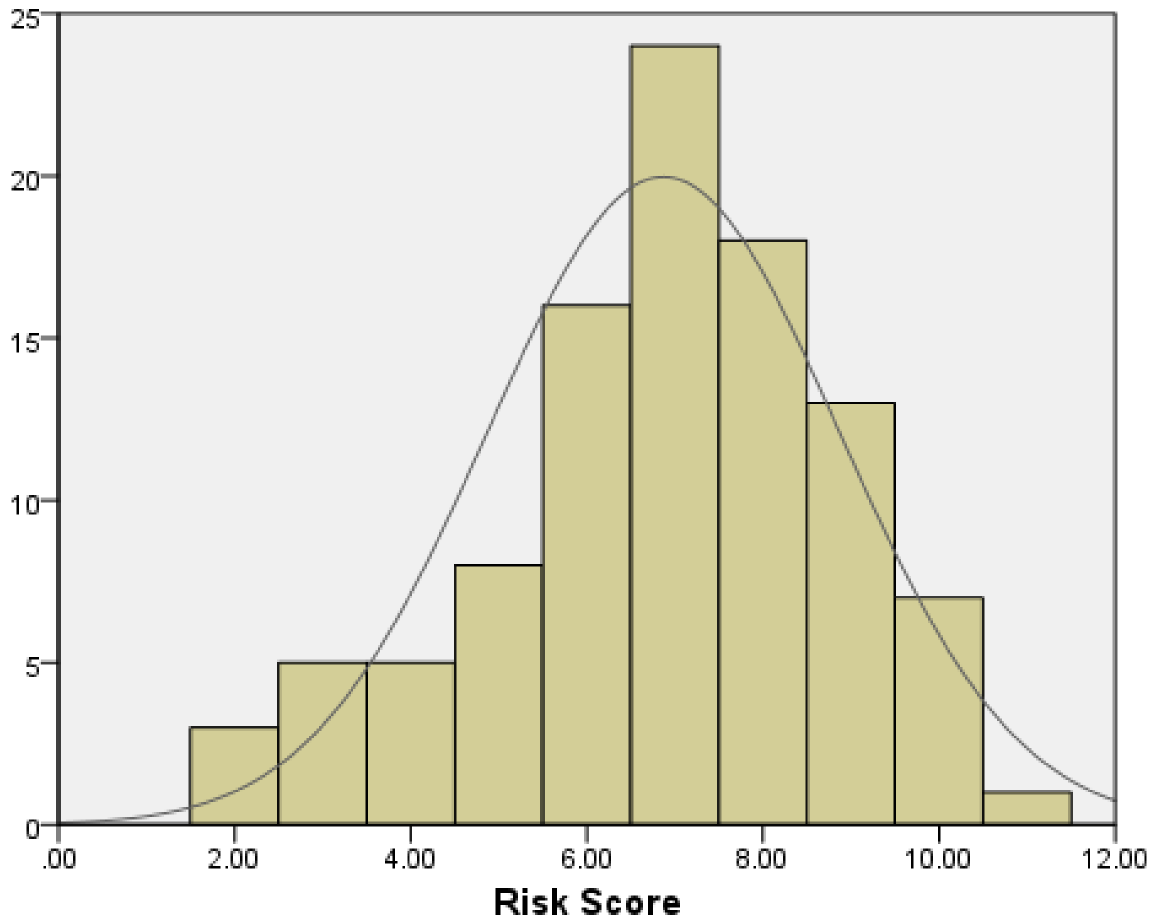


Figure 4.14. Risk score and occurrence of diabetes Maximum frequency for risk score 6 to 9 has been depicted here.

4.1.14. Diabetes and BMI

There is a relationship observed between different BMI and happening of diabetes, at BMI range above 25 the incidence of diabetes was recorded highest such as at BMI 28, the 16 individuals were diabetic, similarly at 31 BMI 16 individuals were again positive for diabetes as shown in **Table 4.16** and **Figure 4.15**.

Table 4.16. BMI and incidence of diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21.00	6	6.0	6.0	6.0
	24.00	5	5.0	5.0	11.0
	25.00	10	10.0	10.0	21.0
	26.00	10	10.0	10.0	31.0
	27.00	10	10.0	10.0	41.0
	28.00	16	16.0	16.0	57.0
	29.00	4	4.0	4.0	61.0
	30.00	10	10.0	10.0	71.0
	31.00	16	16.0	16.0	87.0
	32.00	4	4.0	4.0	91.0
	33.00	3	3.0	3.0	94.0
	34.00	6	6.0	6.0	100.0
	Total	100	100.0	100.0	

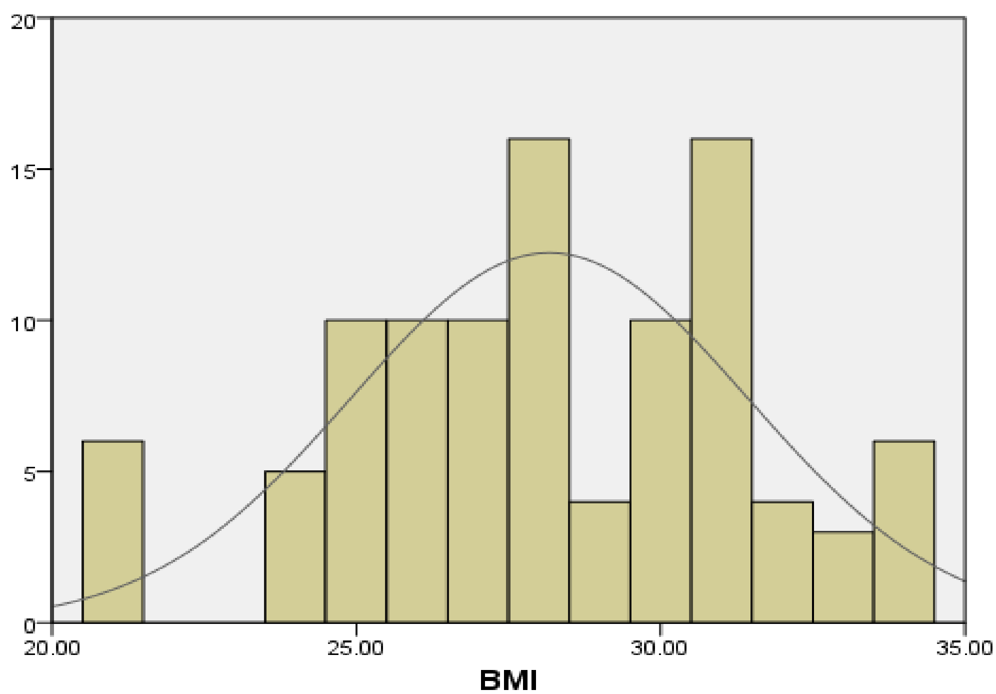


Figure 4.15. Diabetes and occurrence of BMI

4.1.15. Medication and occurrence of diabetes

Medication and diabetes were also linked together as observed from the above tabular figures. The patients who were on medication were positive for diabetes (85 out of 100 individuals), the lower incidence of diabetes was observed in the people who were not on any medication (15 out of 100) as shown in **Table 4.17** and **Figure 4.16**.

Table 4.17. Medication and Diabetes

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	15	15.0	15.0	15.0
	Yes	85	85.0	85.0	100.0
	Total	100	100.0	100.0	

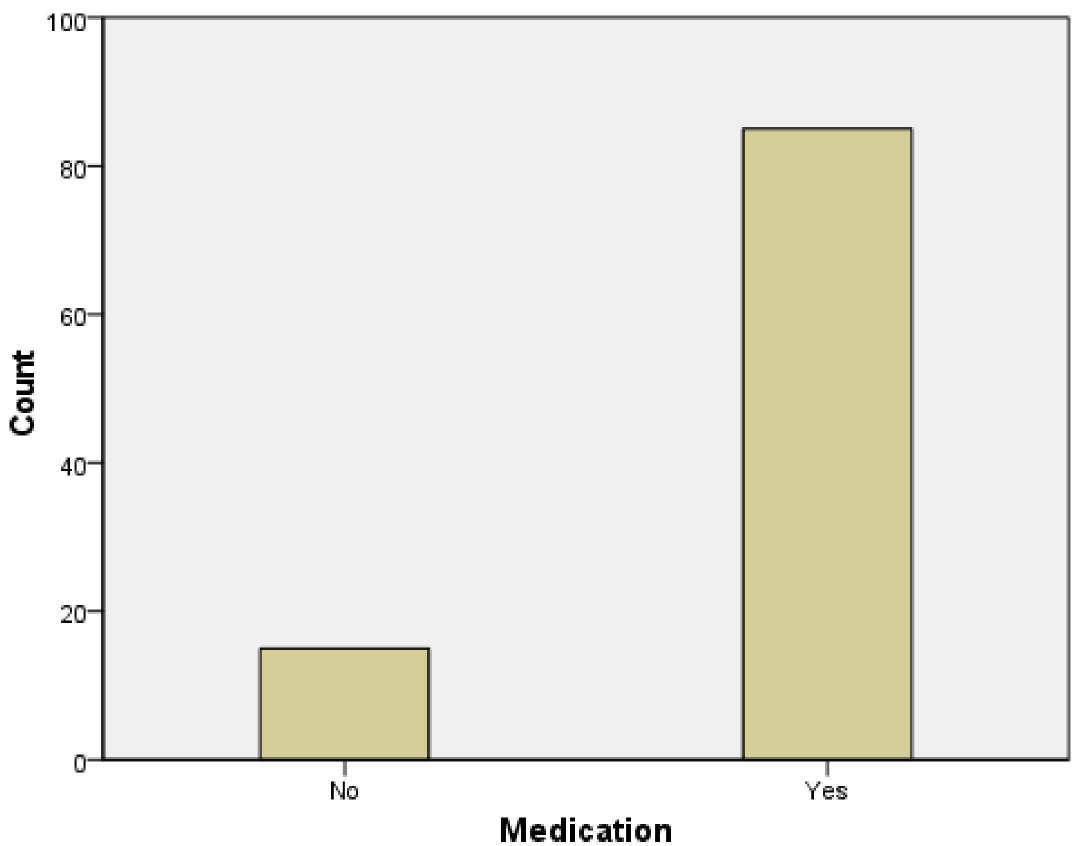


Figure 4.16. Medication and incidence of diabetes

4.1.16 Relationship among quantitative variables (mean value) and qualitative variables

Male with Age of 44 years having BMI more than 28 and blood pressure above 143/88 were prone towards diabetes. Patients with family history (genetic association) were more prone towards diabetes. Patients who were sedentary with BMI above 28, and Blood pressure above 143/89 were higher in number than group of moderately performing physical activity. Patients with low high sugar diet with BMI more than 28, blood pressure above 143/89 and more than 43 years of age were more likely. Individuals with smoking and alcohol consumption habits were more likely to experience diabetes. Individuals under stress, with sleep disorders, under the influence of environmental factors, hormonal imbalance, sleep disorder, and medication having age above 43 years, blood pressure more than 143/88 with BMI greater than 28 were more prone towards diabetes than other factors.

Table 4.18. Relation between the mean value of quantitative variables and all qualitative variables.

		Risk Score Mean	BMI Mean	Blood pressure Systolic Mean	Blood Pressure Diastolic Mean	Age Mean
Gender	Female	6.85	28.24	142.97	89.07	42.00
	Male	6.91	28.03	142.84	88.87	44.91
Family History	No	6.92	27.25	135.83	86.67	44.08
	Yes	6.86	28.30	143.90	89.33	42.77
Physical Activity	Active	5.50	27.17	142.17	86.33	38.17
	Moderate	7.23	27.85	138.15	88.08	41.15
	Sedentary	6.91	28.30	143.75	89.36	43.57
Diet	Balanced	6.63	27.13	134.38	88.13	43.63
	High Sug	6.88	28.28	143.65	89.10	42.69
	Low Fat	7.00	28.00	144.00	88.83	45.50
Smoking	No	7.18	27.64	142.14	88.77	44.14
	Yes	6.78	28.32	143.15	89.08	42.59
	High	6.79	27.89	142.69	89.07	42.46

Alcohol Consumption	Low	7.86	27.86	142.86	89.43	40.29
	Moderate	7.00	29.75	138.25	88.63	44.88
	No	6.00	28.83	149.17	90.17	44.17
	Occasional	7.29	29.00	145.43	87.43	47.14
Stress	High	6.95	28.24	142.49	89.14	43.46
	Low	5.43	29.00	146.43	87.86	38.43
	Moderate	7.20	27.00	144.10	88.70	41.70
Sleep Disorder	No	6.76	28.10	142.05	89.10	43.86
	Yes	6.90	28.19	143.16	88.99	42.68
Environmental Factors	No	6.65	28.75	144.75	89.90	41.15
	Yes	6.93	28.03	142.47	88.79	43.38
Hormonal Imbalance	No	6.63	28.05	142.40	88.26	42.91
	Yes	7.05	28.26	143.33	89.58	42.95
Medication	No	6.93	29.60	144.07	89.13	46.87
	Yes	6.86	27.92	142.73	88.99	42.24

Table 4.19. Correlations Analysis among quantitative factors

	Age	Blood pressure Systolic	Blood Pressure Diastolic	Risk Score	BMI
Age	1				
Blood pressure Systolic	-.049	1			
Blood Pressure Diastolic	.059	.628**	1		
Risk Score	.038	-.003	.062	1	
BMI	.213*	-.029	.001	-.093	1

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

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

The correlation analysis depicts the positive and strong association among blood pressure (diastolic), risk score, and BMI. While it was negative among age, systolic blood pressure, risk score, and BMI.

Table 4.20. Relation between qualitative variables of diabetic patients

		Gender		Family History		Smoking		Sleep Disorder		Environmental Factors	
		Female	Male	No	Yes	No	Yes	No	Yes	No	Yes
Physical Activity	Active	4	2	0	6	2	4	0	6	1	5
	Moderate	8	5	2	11	2	11	1	12	3	10
	Sedentary	56	25	10	71	18	63	20	61	16	65
Diet	Balanced	3	5	2	6	3	5	3	5	2	6
	High Sug	60	26	10	76	17	69	18	68	18	68
	Low Fat	5	1	0	6	2	4	0	6	0	6
Alcohol Consumption	High	46	26	11	61	17	55	15	57	12	60
	Low	6	1	1	6	1	6	1	6	4	3
	Moderate	6	2	0	8	2	6	2	6	1	7
	No	6	0	0	6	0	6	2	4	2	4
	Occasional	4	3	0	7	2	5	1	6	1	6
Hormonal Imbalance	No	14	29	6	37	13	30	6	37	6	37
	Yes	54	3	6	51	9	48	15	42	14	43
Medication	No	10	5	2	13	2	13	3	12	3	12
	Yes	58	27	10	75	20	65	18	67	17	68
Stress	High	56	27	11	72	18	65	20	63	15	68
	Low	7	0	0	7	0	7	0	7	2	5
	Moderate	5	5	1	9	4	6	1	9	3	7

4.2 Research Question Two

A total of 100 Alzheimer patients were engaged for evaluation of associated potential risk factors. During the current study fifteen risk factors were evaluated including age, gender, education, body mass index (BMI), physical exercise, cognitive activity, Smoking, family history, plasma Ca and vitamin level, cardiovascular illness, diabetes, stroke, brain injury, and alcohol consumption. The descriptive statistical analysis was performed for quantitative variables which shows mean value 61.05, 2.11 (25>30 group), 2.56hrs, 2.59hrs for age, BMI, physical activity, and cognitive activity respectively. The minimum and maximum value were calculated along with variance as shown in **Table 4.2.1**.

Table 4.2.1. Descriptive statistics of quantitative variables

Parameters	Age	BMI	Physical Activity (Hrs)	Cognitive Activity (Hrs)
Mean	61.0500	2.1100	2.5600	2.5900
Std. Error of Mean	1.30371	.07092	.14447	.19802
Median	60.0000	2.0000	2.0000	2.0000
Mode	58.00	2.00	2.00	1.00
Std. Deviation	13.03715	.70918	1.44474	1.98018
Variance	169.967	.503	2.087	3.921
Minimum	28.00	1.00	1.00	1.00
Maximum	88.00	3.00	6.00	12.00

4.2.1. Role of age in the occurrence of Alzheimer

Among the Alzheimer patients, the highest incidence of disease was prevalent in the individuals who were above 50 years of age as shown in the above **Table 4.2.2.** and **Figure 4.2.1**. Early aged people were less prone to Alzheimer as compared to middle aged population. The most infected individuals have an age above 75 years (77) while less infected have an age less than 65 years (62) with a maximum frequency for 58 years depicting the possibility of other factors involvement.

Table 4.2.2. Frequency of Alzheimer with age

Age (years)	Frequency	Percent	Valid Percent	Cumulative Percent
28.00	1	1.0	1.0	1.0
29.00	1	1.0	1.0	2.0
34.00	2	2.0	2.0	4.0
38.00	1	1.0	1.0	5.0
39.00	2	2.0	2.0	7.0
41.00	1	1.0	1.0	8.0
42.00	1	1.0	1.0	9.0
44.00	1	1.0	1.0	10.0
45.00	1	1.0	1.0	11.0
47.00	2	2.0	2.0	13.0
48.00	2	2.0	2.0	15.0
49.00	1	1.0	1.0	16.0
51.00	3	3.0	3.0	19.0
52.00	5	5.0	5.0	24.0
53.00	4	4.0	4.0	28.0
54.00	3	3.0	3.0	31.0
55.00	5	5.0	5.0	36.0
56.00	1	1.0	1.0	37.0
57.00	4	4.0	4.0	41.0
58.00	6	6.0	6.0	47.0
59.00	3	3.0	3.0	50.0
61.00	4	4.0	4.0	54.0
62.00	2	2.0	2.0	56.0
63.00	1	1.0	1.0	57.0
64.00	3	3.0	3.0	60.0
65.00	1	1.0	1.0	61.0
66.00	4	4.0	4.0	65.0
67.00	3	3.0	3.0	68.0
68.00	3	3.0	3.0	71.0
69.00	1	1.0	1.0	72.0
71.00	3	3.0	3.0	75.0
72.00	1	1.0	1.0	76.0
73.00	2	2.0	2.0	78.0
74.00	3	3.0	3.0	81.0
75.00	3	3.0	3.0	84.0

76.00	1	1.0	1.0	85.0
77.00	5	5.0	5.0	90.0
78.00	1	1.0	1.0	91.0
79.00	2	2.0	2.0	93.0
81.00	2	2.0	2.0	95.0
82.00	1	1.0	1.0	96.0
83.00	3	3.0	3.0	99.0
88.00	1	1.0	1.0	100.0
Total	100	100.0	100.0	

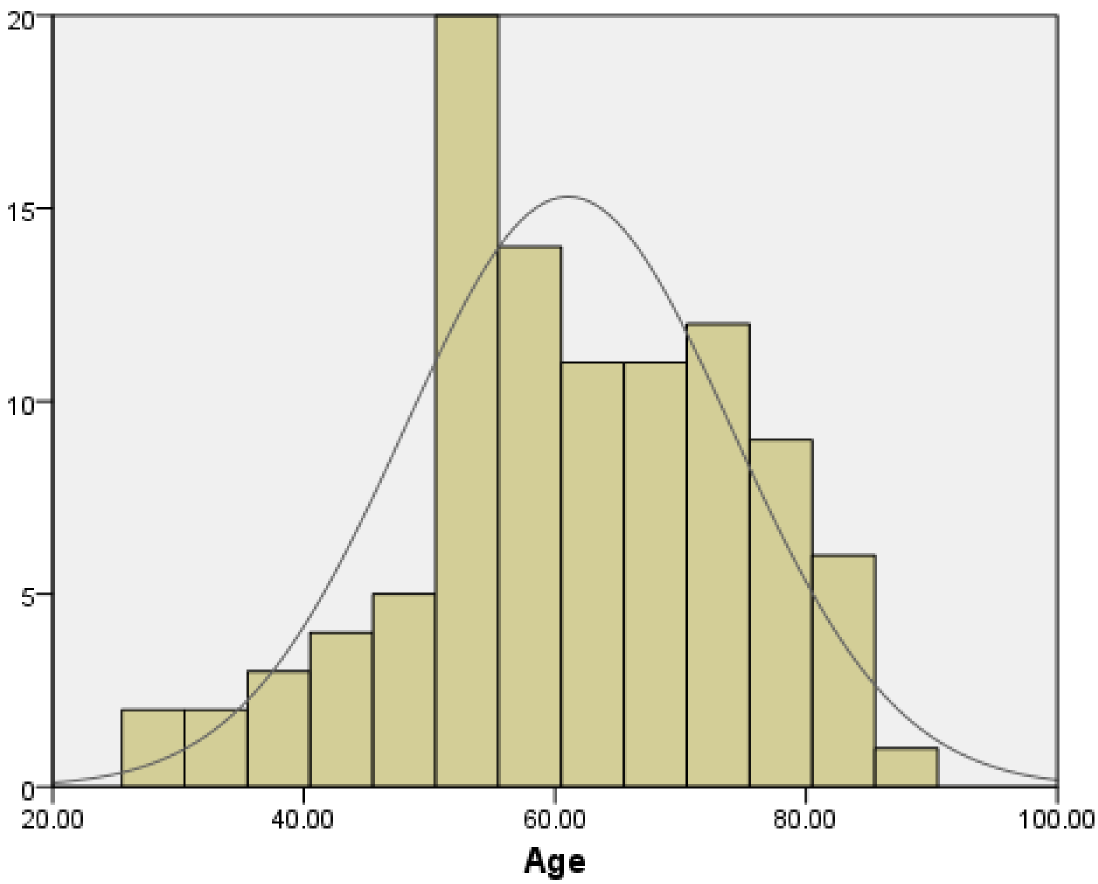


Figure 4.2.17. The age of study individuals and frequency of disease

4.2.2. Gender-based frequency of Alzheimer cases

The incidence of Alzheimer disease was recorded higher among females than males as shown in the **Table 4.2.3** and **Figure 4.2.2**. The frequency of Alzheimer was found associated with age of the individual.

Table 4.2.3. Gender based variability in the occurrence of Alzheimer.

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Female	62	62.0	62.0	62.0
Male	38	38.0	38.0	100.0
Total	100	100.0	100.0	

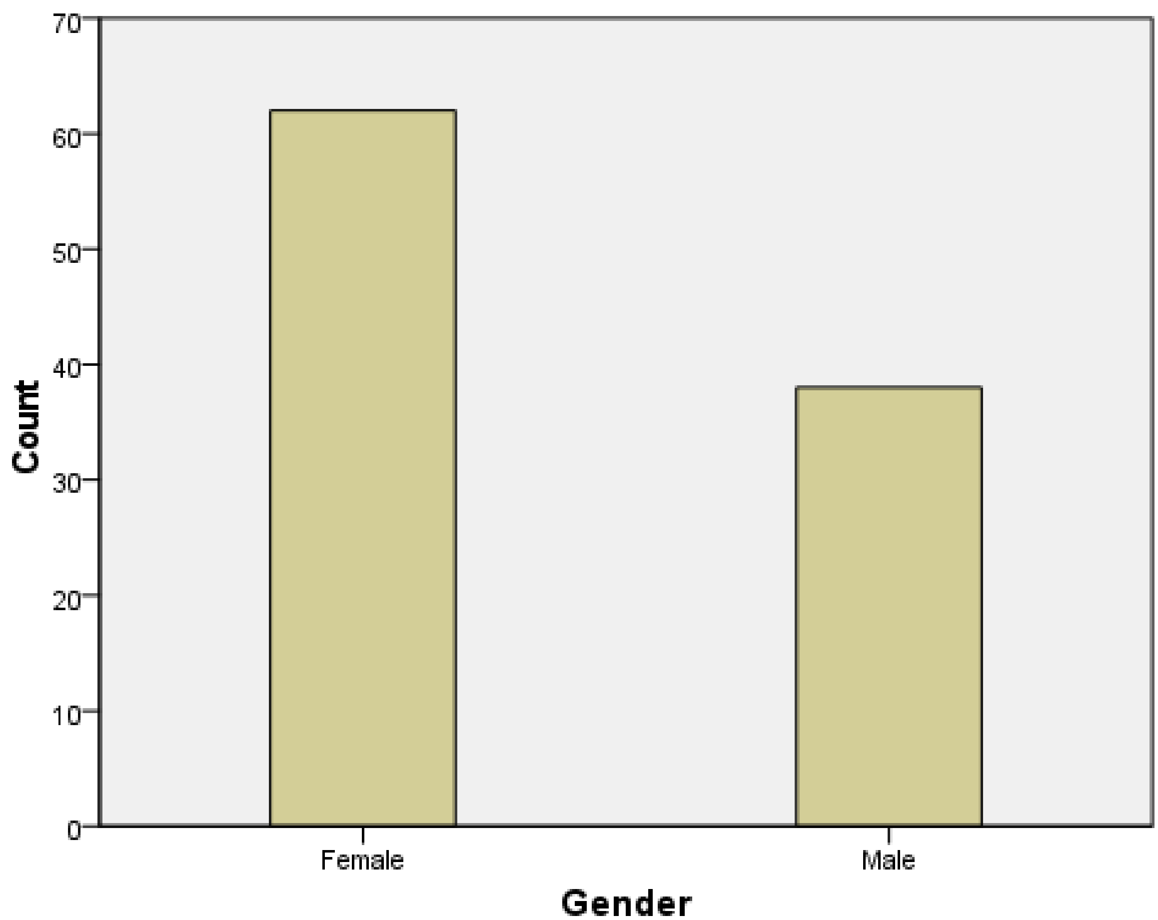


Figure 4.2.18. Frequency distribution of Alzheimer with gender of individual

4.2.3. Role of education in the abundance of disease

There is a relationship between the occurrence of Alzheimer and education. The trend of disease was observed highest in uneducated people (due to depression), after that the undergraduate students, then in the postgraduates and a little in graduate students as shown in **Table 4.2.4** and **Figure 4.2.3**.

Table 4.2.4. Education level and Alzheimer frequency

Education Level	Frequency	Percent	Valid Percent	Cumulative Percent
Graduate	14	14.0	14.0	14.0
Postgraduate	24	24.0	24.0	38.0
Undergraduate	28	28.0	28.0	66.0
Uneducated	34	34.0	34.0	100.0
Total	100	100.0	100.0	

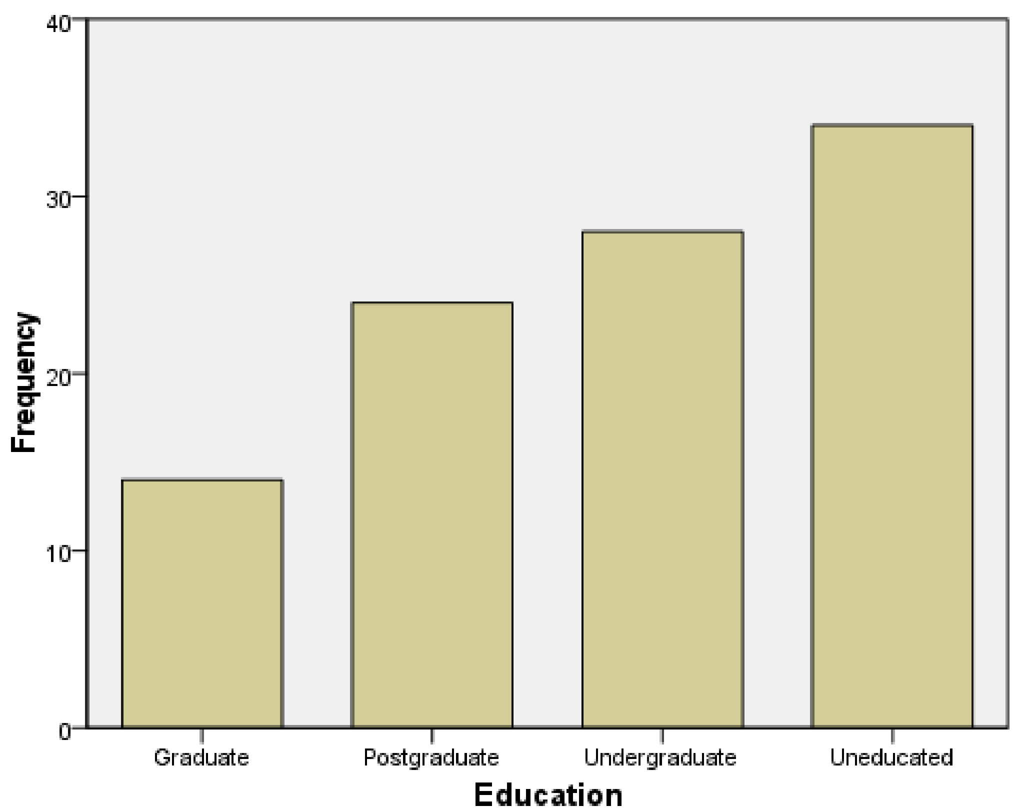


Figure 4.2.19. Education level-based frequency of Alzheimer's cases

4.2.4. BMI and occurrence of Alzheimer

The presence of Alzheimer was observed highest in the patients whose BMI was above 25 and below 30. The individuals having BMI below 25 were little prone to Alzheimer as shown in the **Table 4.2.5.** and **Figure 4.2.4**.

Table 4.2.5. Frequency of BMI and Alzheimer

BMI	Frequency	Percent	Valid Percent	Cumulative Percent
18<25	20	20.0	20.0	20.0
25<30	49	49.0	49.0	69.0
>30	31	31.0	31.0	100.0
Total	100	100.0	100.0	

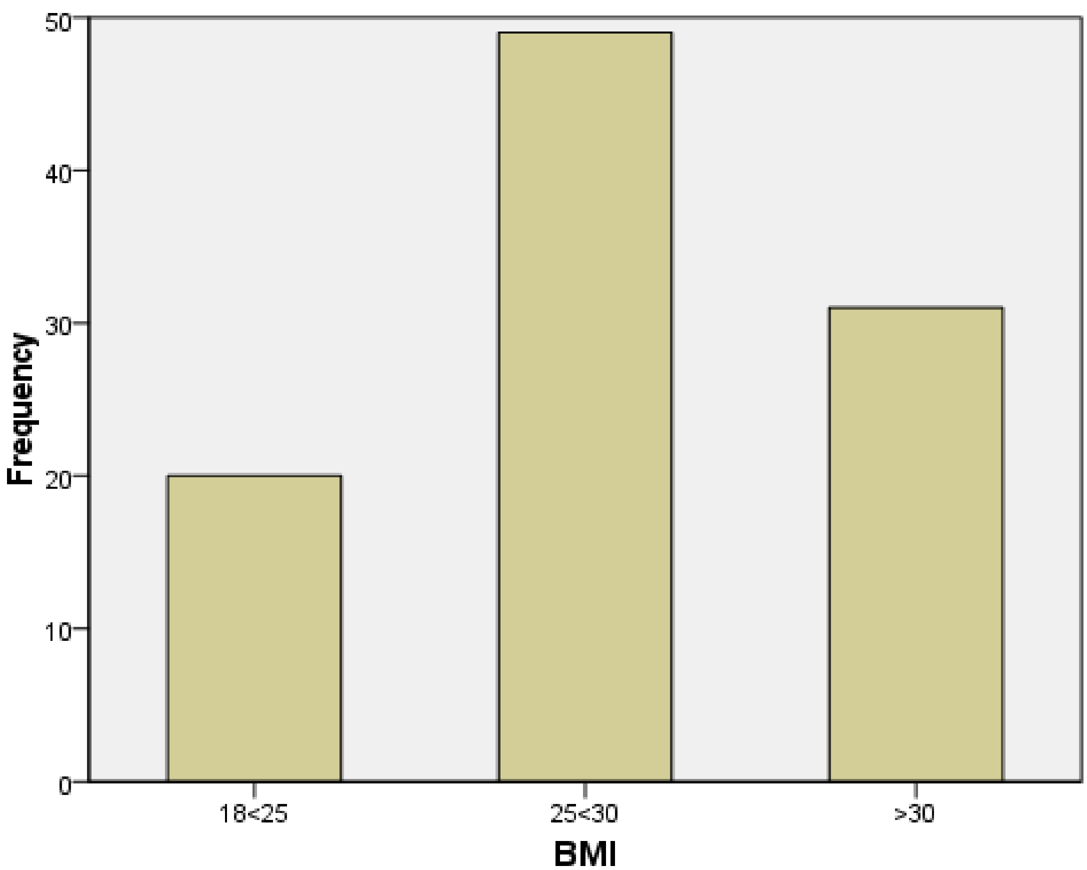


Figure 20.2.4. Frequency of Alzheimer's cases with respect to BMI of individual.

4.2.5. Physical Activity and Alzheimer's cases

The trend of Alzheimer was linked with physical activity of humans as shown in the **Table 4.2.6** and **Figure 4.2.5**. The individuals with less physical activity were more prone to Alzheimer as compared to those whose physical activity was more due to the proper brain functioning in more active people as shown in the above shared data.

Table 4.2.6. Physical activity and occurrence of Alzheimer

Physical Activity (Hrs)	Frequency	Percent	Valid Percent	Cumulative Percent
1.00	28	28.0	28.0	28.0
2.00	29	29.0	29.0	57.0
3.00	17	17.0	17.0	74.0
4.00	18	18.0	18.0	92.0
5.00	1	1.0	1.0	93.0
6.00	7	7.0	7.0	100.0
Total	100	100.0	100.0	

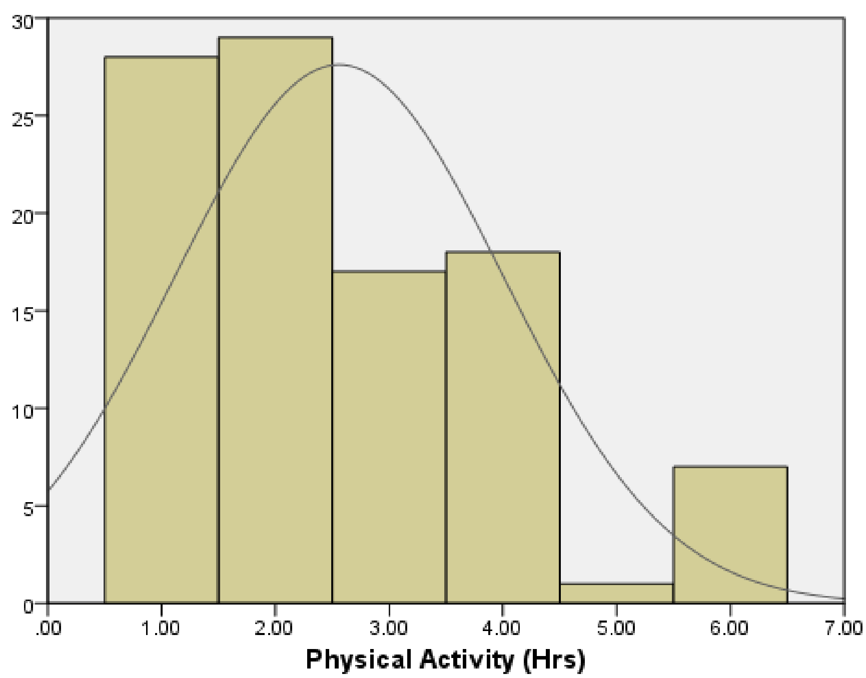


Figure 4.2.21. Frequency of Alzheimer's cases with respect to physical activity. Increase in the physical activity and decrease the chances of Alzheimer.

4.2.6. Role of cognitive activity in the Alzheimer's cases

Cognitive activity is also linked with the occurrence of Alzheimer as depicted from the data given in **Table 4.2.7** and **Figure 4.2.6**. The individuals with more cognitive hours were less prone to Alzheimer and the people with less cognitive hours were more prone to Alzheimer happening.

Table 4.2.7. Alzheimer's cases frequency and Cognitive activity

Cognitive Activity (Hrs)		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.00	36	36.0	36.0	36.0
	2.00	28	28.0	28.0	64.0
	3.00	11	11.0	11.0	75.0
	4.00	14	14.0	14.0	89.0
	6.00	7	7.0	7.0	96.0
	8.00	3	3.0	3.0	99.0
	12.00	1	1.0	1.0	100.0
	Total	100	100.0	100.0	

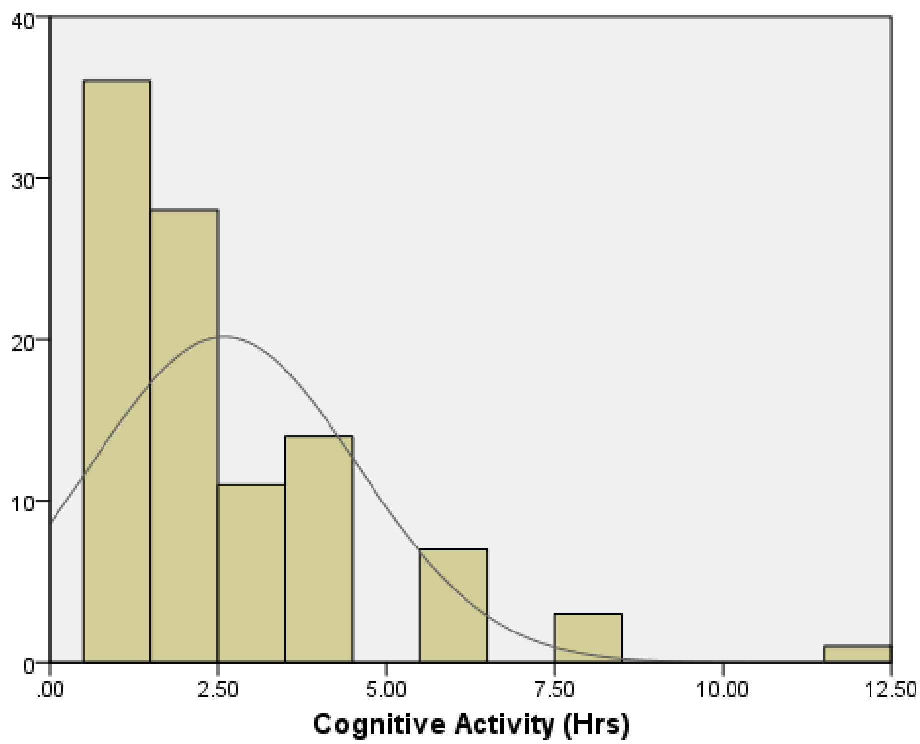


Figure 4.2.22. Cognitive activity and occurrence of Alzheimer's cases

4.2.7. Role of smoking in the occurrence of Alzheimer

Alzheimer disease was reported highest in the patients who were habitual to smoking as compared to the individuals which were not prone to smoking as shown in **Table 4.2.8** and **Figure 4.2.7**. With smoking habit risk of Alzheimer increase.

Table 4.2.8. Smoking status and Alzheimer's cases

Smoking		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	56	56.0	56.0	56.0
	No	44	44.0	44.0	100.0
	Total	100	100.0	100.0	

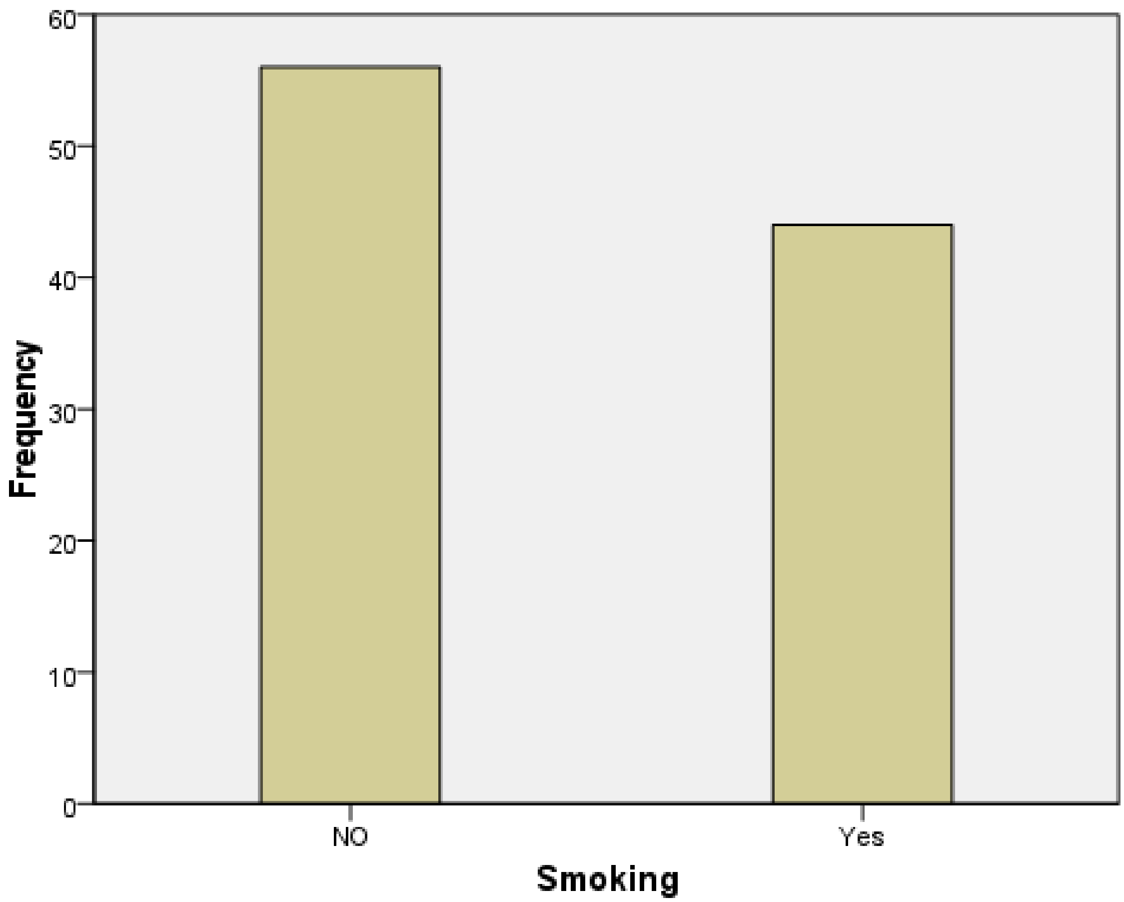


Figure 4.2.23. Alzheimer's frequency with Smoking habit

4.2.8. Family History and Alzheimer's cases

Family history was directly linked with the Alzheimer disease occurrence. The patients reported positive for Alzheimer having prior history of Alzheimer in their family as compared to the individuals reported no history for Alzheimer as shown in **Table 4.2.9** and **Figure 4.2.8**. The findings depicts that there is link of genetics with the occurrence of Alzheimer in individuals.

Table 4.2.9. Family history and Alzheimer’s cases

Family History		Frequency	Percent	Valid Percent	Cumulative Percent
	No	12	12.0	12.0	12.0
	Yes	88	88.0	88.0	100.0
	Total	100	100.0	100.0	

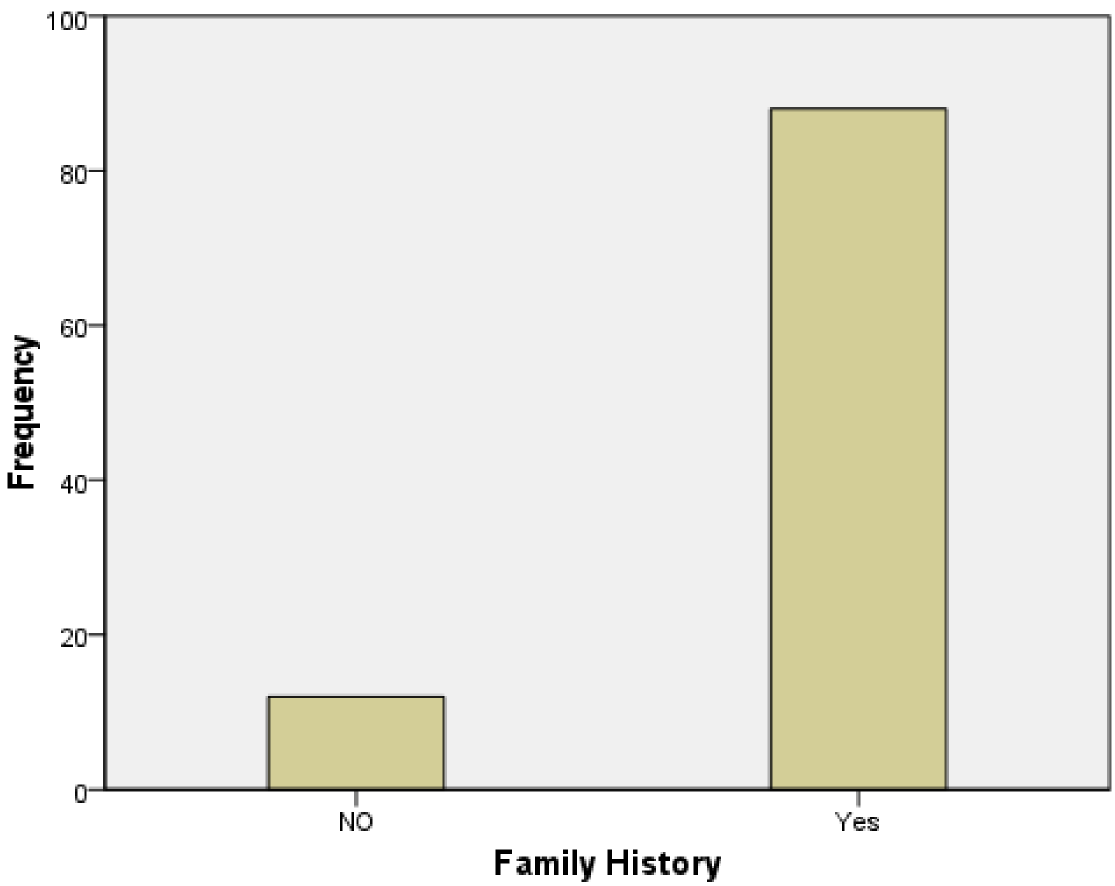


Figure 4.2.24. Family history and frequency of Alzheimer's cases

4.2.9. Role of plasma Ca-level with Alzheimer's cases

Plasma Calcium level also linked with Alzheimer incidence as shown in the tabular data where highest incidence of Alzheimer was reported in the patients having high plasma calcium level as compared to the patients with lower calcium level in their plasma as shown in **Table 4.2.10** and **Figure 4.2.9**.

Table 4.2.10. Plasma Ca-level and frequency of Alzheimer's cases

Plasma Calcium level	Frequency	Percent	Valid Percent	Cumulative Percent
Adequate	19	19.0	19.0	19.0
High	53	53.0	53.0	72.0
Low	28	28.0	28.0	100.0
Total	100	100.0	100.0	

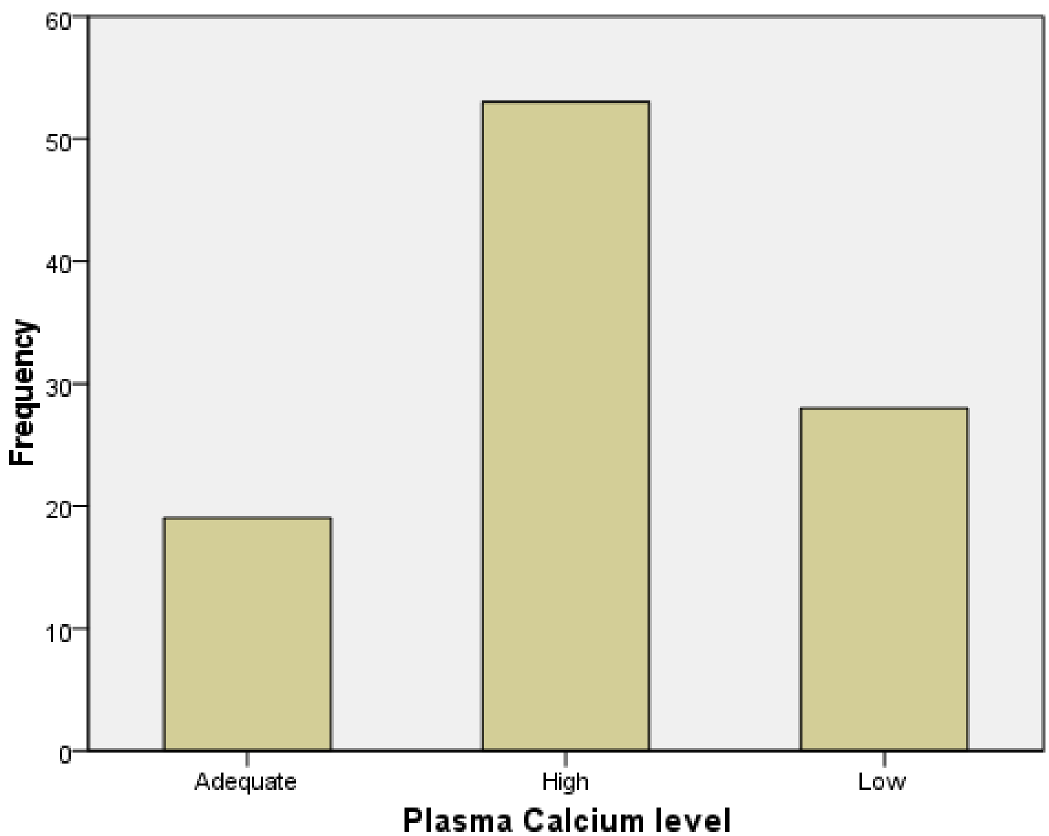


Figure 4.2.25. Frequency of Alzheimer increases with the increase and decrease in plasma-Ca level.

4.2.10. Role of plasma vitamin level in Alzheimer's cases

Plasma vitamin level also gave hint of Alzheimer as shown in the table and figure, where the patients with lower plasma vitamin level were more positive to Alzheimer as compared to the people with adequate level of plasma in them as shown in **Table 4.2.11** and **Figure 4.2.10**.

Table 4.2.11. Plasma Vitamin Level and frequency of Alzheimer

Plasma Vitamin Level	Frequency	Percent	Valid Percent	Cumulative Percent
Adequate	20	20.0	20.0	20.0
Low	80	80.0	80.0	100.0
Total	100	100.0	100.0	

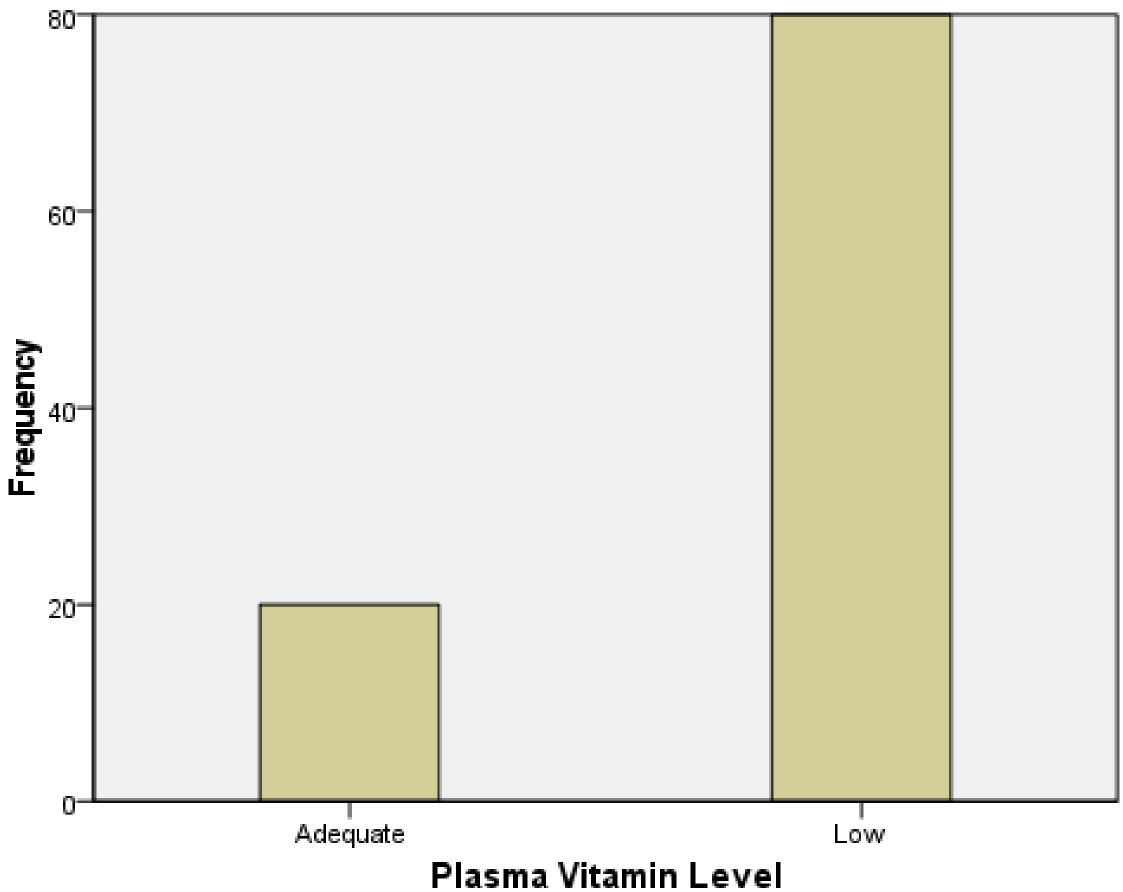


Figure 4.2.26. Plasma vitamin level and frequency of Alzheimer directly linked with the decrease in vitamin level number of cases increase.

4.2.11. Role of Cardiovascular Illnesses in Alzheimer's cases

Cardiovascular also plays a key role in the happening of Alzheimer disease. The patients with higher frequency of cardiovascular disease were more prone to Alzheimer disease as compared to the individuals with less heart pathologies as shown in **Table 4.2.12** and **Figure 4.2.11**.

Table 4.2.12. Frequency of Alzheimer's cases with cardiovascular illness

Cardiovascular Illness	Frequency	Percent	Valid Percent	Cumulative Percent
NO	25	25.0	25.0	25.0
Yes	75	75.0	75.0	100.0
Total	100	100.0	100.0	

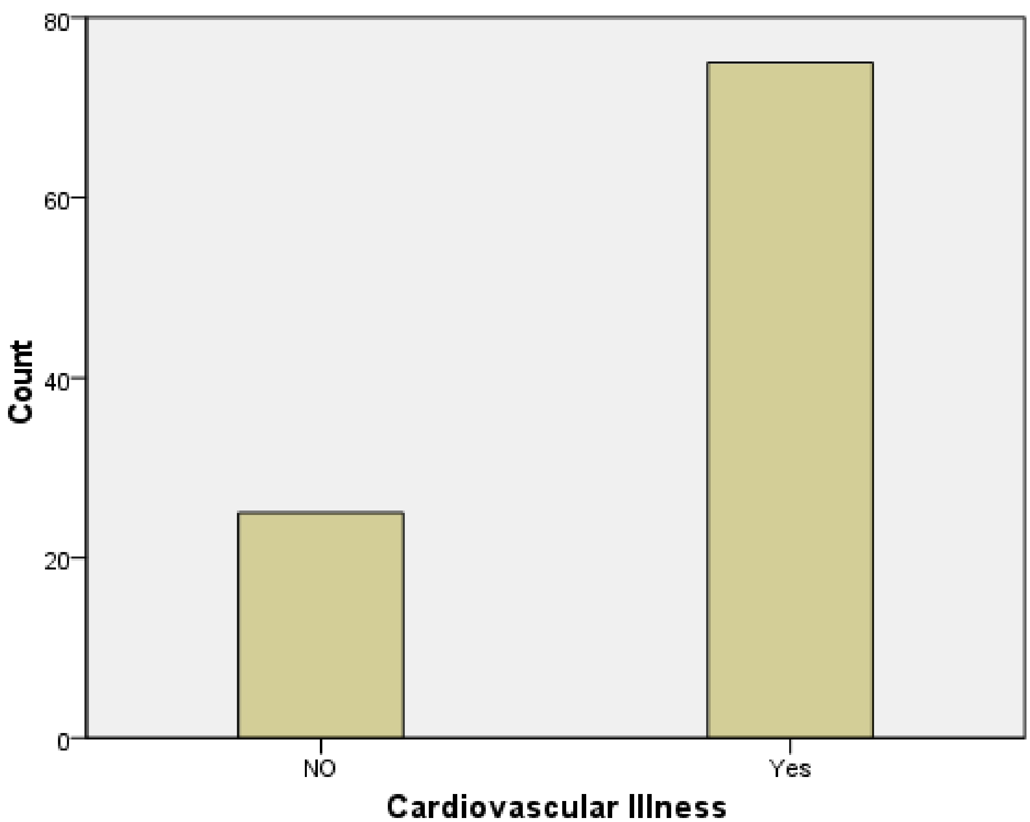


Figure 4.2.27. Cardiovascular Illnesses directly influence the frequency of Alzheimer's cases.

4.2.12. Role of Diabetes in Alzheimer's cases

Diabetes and Alzheimer are also linked together. The diabetic patients were more prone to Alzheimer disease as compared to the people who were not infected with diabetes as shown in Table **4.2.13** and **Figure 4.2.12**.

Table. 4.2.13. Frequency of Alzheimer's cases with diabetes status

Diabetes		Frequency	Percent	Valid Percent	Cumulative Percent
	Yes	82	82.0	82.0	82.0
	No	18	18.0	18.0	100.0
	Total	100	100.0	100.0	

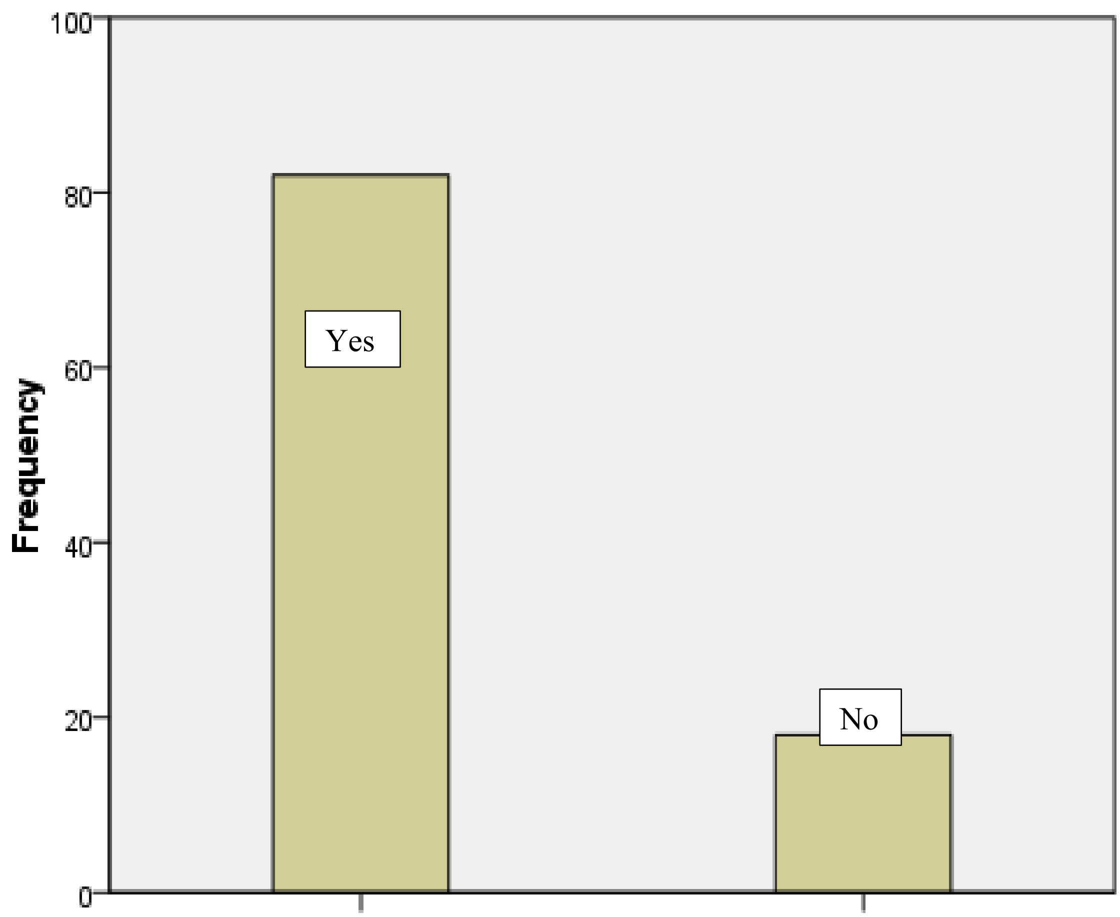


Figure 4.2.28. Direct association of Alzheimer's cases with diabetes

4.2.13. Influence of head stroke on Alzheimer's cases frequency

The incidence of Alzheimer disease was also linked with stroke. The patients with stroke were more positive for Alzheimer as compared to the individuals who were not positive for stroke and reported no stroke as well as shown in **Table 4.2.14** and **Figure 4.2.13**.

Table 4.2.14. Alzheimer's cases and Head stroke

Stroke	Frequency	Percent	Valid Percent	Cumulative Percent
Yes	82	82.0	82.0	82.0
No	18	18.0	18.0	100.0
Total	100	100.0	100.0	

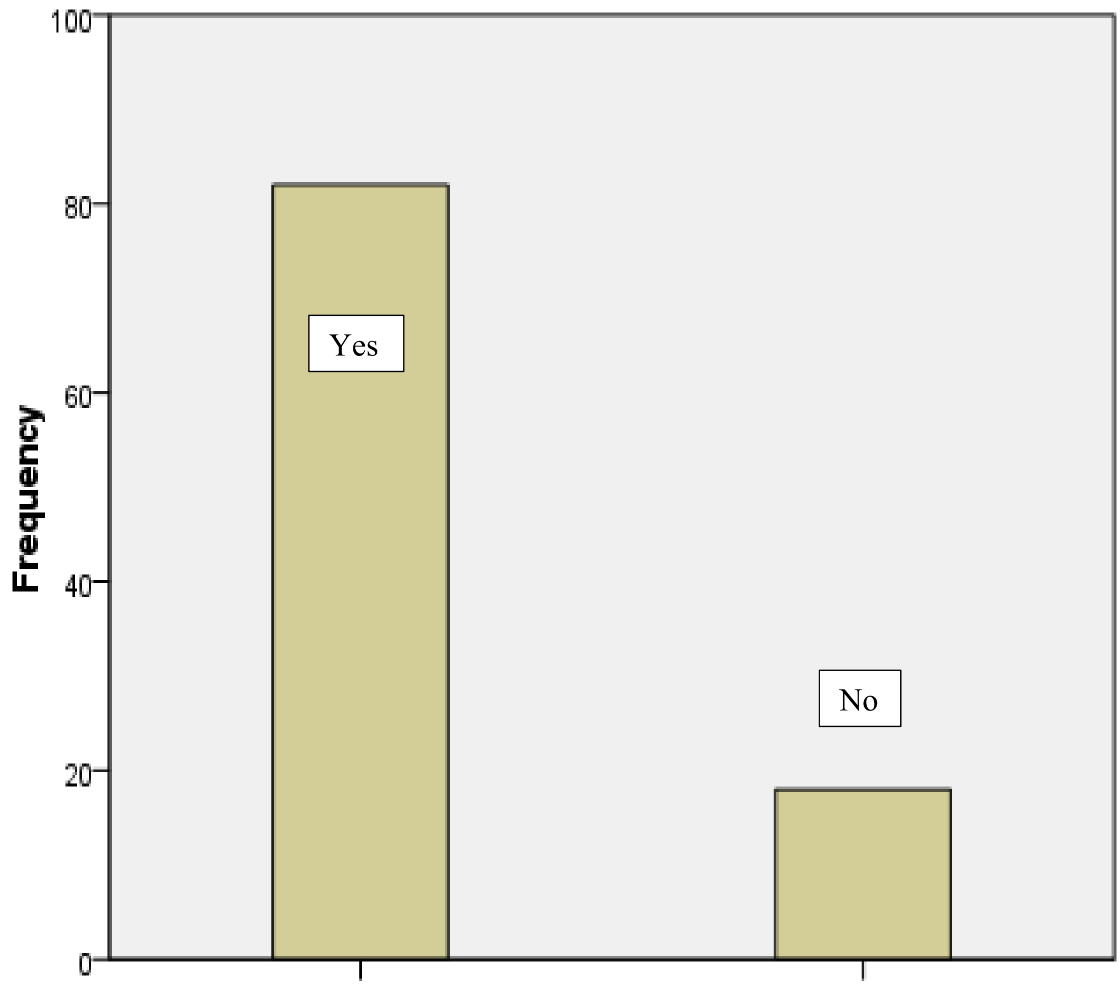


Figure 4.2.29. Head stroke has direct influence on the occurrence of Alzheimer.

4.2.14. Role of brain injury and frequency of Alzheimer

Brain pathologies and Alzheimer shared a close relationship. The individuals with brain injury were more prone to Alzheimer disease and reported positive results as compared to the individuals who did not have any brain injury as shown in **Table 4.2.15** and **Figure 4.2.14**.

Table 4.2.15. Brain injury and frequency of Alzheimer's cases

Brain Injury	Frequency	Percent	Valid Percent	Cumulative Percent
Yes	91	91.0	91.0	91.0
No	9	9.0	9.0	100.0
Total	100	100.0	100.0	

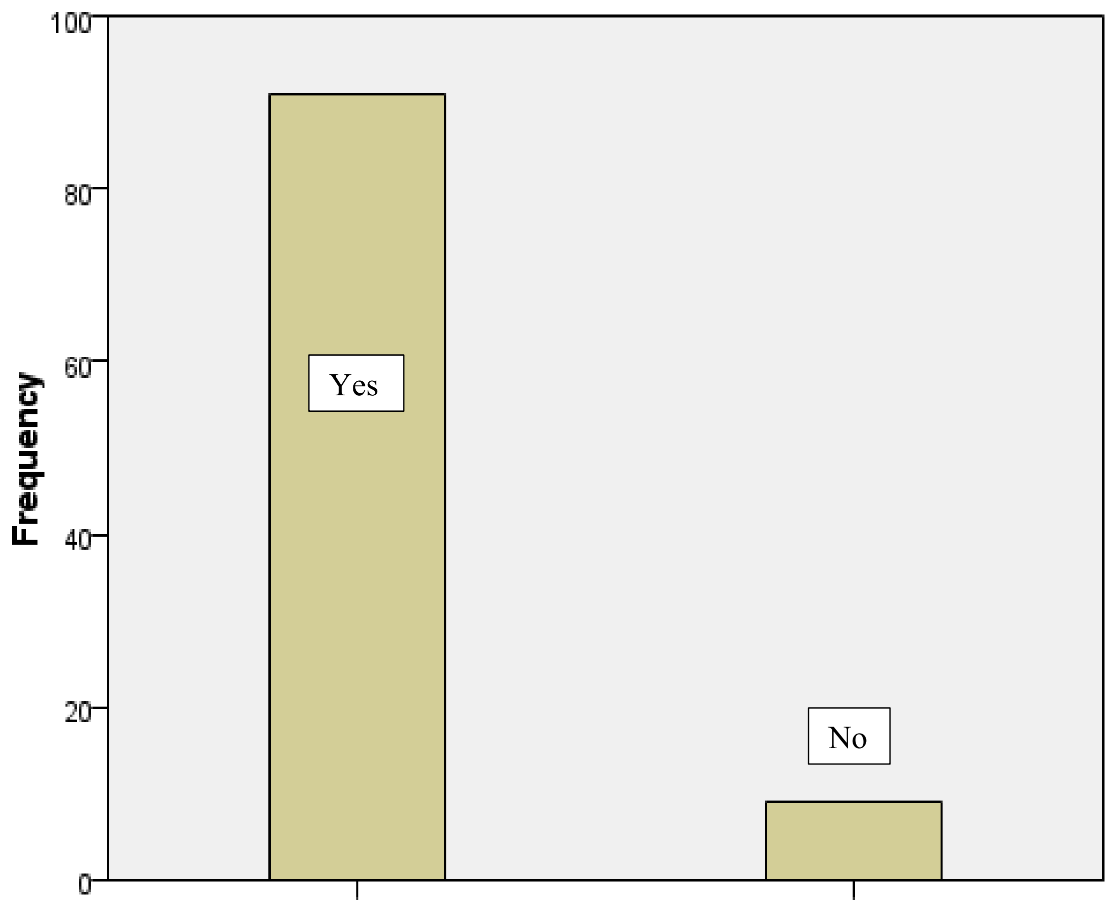


Figure 4.2.30. Frequency of Alzheimer's cases with brain injury

4.2.15. Alcohol consumption and frequency of Alzheimer's cases

Alcohol and incidence of Alzheimer are closely linked together. The patients who were alcoholic were positive for Alzheimer and the individuals who were not involved in alcohol consumption showed little incidence of Alzheimer as depicted in **Table 4.2.16** and **Figure 4.2.15**.

Table 4.2.16. Role of Alcohol in the Alzheimer's incidence

Alcohol Consumption	Frequency	Percent	Valid Percent	Cumulative Percent
Yes	83	83.0	83.0	83.0
No	17	17.0	17.0	100.0
Total	100	100.0	100.0	

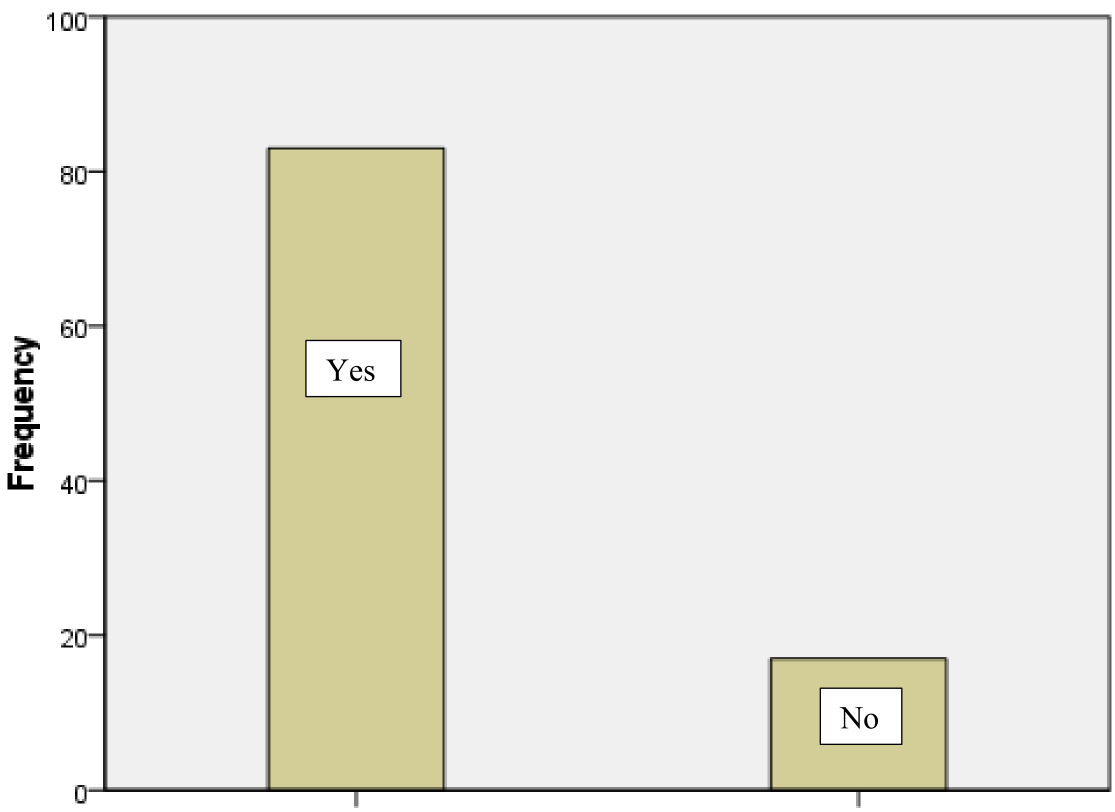


Figure 4.2.31. Frequency of Alzheimer's cases varies with alcohol consumption.

Table 4.2.17. The association of qualitative variables with quantitative variable mean values.

Factor	Level	Age	PA (Hrs)	CA (Hrs)	BMI		
		Mean	Mean	Mean	18<25	25<30	>30
Gender	Female	60.21	2.74	2.61	29	20	13
	Male	62.42	2.26	2.55	20	11	7
Education	Graduate	54.00	2.43	2.14	5	9	0
	PG	62.54	1.88	4.46	13	2	9
	UG	61.43	2.54	1.93	16	7	5
	U	62.59	3.12	2.00	15	13	6
Smoking	No	61.14	2.55	2.82	26	17	13
	Yes	60.93	2.57	2.30	23	14	7
Family History	No	60.75	2.42	4.50	6	3	3
	Yes	61.09	2.58	2.33	43	28	17
Plasma Calcium level	Adequate	67.32	2.68	2.84	10	6	3
	High	59.51	2.68	2.53	24	19	10
	Low	59.71	2.25	2.54	15	6	7
Plasma Vitamin Level	Adequate	60.75	3.10	3.15	7	10	3
	Low	61.13	2.43	2.45	42	21	17

Factor	Level	Age	PA (Hrs)	CA (Hrs)	BMI		
		Mean	Mean	Mean	18<25	25<30	>30
Cardiovascular Illness	No	60.08	2.60	1.96	13	7	5
	Yes	61.37	2.55	2.80	36	24	15
Diabetes	Yes	60.44	2.55	2.68	42	24	16
	No	63.83	2.61	2.17	7	7	4
Stroke	Yes	61.54	2.67	2.52	42	23	17
	No	58.83	2.06	2.89	7	8	3
Brain Injury	Yes	61.38	2.51	2.60	43	29	19
	No	57.67	3.11	2.44	6	2	1
Alcohol Consumption	Yes	61.28	2.57	2.60	41	25	17
	No	59.94	2.53	2.53	8	6	3

Here PA(Physical Activity), CA(Cognitive Activity), PG(Postgraduate), UG(undergraduate), U(uneducated)

Table 4.2.18. Association of qualitative variables with each other

Factor	Level	Gender			Education			BMI			Smoking		B I		AC	
		F	**M**	**G**	**PG**	**UG**	**U**	**L1**	**L2**	**L3**	**N**	**Y**	**Y**	**N**	**Y**	**N**
FH	**N**	8	4	0	6	2	4	3	6	3	7	5	9	3	11	1
	Y	54	34	14	18	26	30	17	43	28	49	39	82	6	72	16
PCL	**Ad**	10	9	2	5	6	6	3	10	6	10	9	18	1	15	4
	H	37	16	6	13	17	17	10	24	19	35	18	47	6	47	6
	L	15	13	6	6	5	11	7	15	6	11	17	26	2	21	7
PVL	**Ad**	15	5	2	6	3	9	3	7	10	12	8	18	2	17	3
	L	47	33	12	18	25	25	17	42	21	44	36	73	7	66	14
CI	**N**	16	9	4	7	8	6	5	13	7	12	13	21	4	24	1
	Y	46	29	10	17	20	28	15	36	24	44	31	70	5	59	16
Diabetes	**Y**	55	27	11	20	25	26	16	42	24	47	35	78	4	66	16

	N	7	11	3	4	3	8	4	7	7	9	9	13	5	17	1
Stroke	Y	52	30	6	18	26	32	17	42	23	48	34	75	7	70	12
	N	10	8	8	6	2	2	3	7	8	8	10	16	2	13	5

Here FH (family history), PCL (Plasma Calcium Level), PVL (Plasma Vitamin level), CI (Cardiovascular Illness), D(Diabetes), S(Stroke), N(No), Y(Yes), Ad(Adequate), L(Low), H(High), M(Male), F(Female), G (graduate), PG(Post graduate), UG(Undergraduate), U(uneducated), L1(18<25), L2(25<30), and L3(>30). AC (Alcohol Consumption) BI (Brain Injury)

Table 4.2.19. Correlation Analysis of quantitative variables

Factor	Age	BMI	Physical Activity (Hrs)	Cognitive Activity (Hrs)
Age	1			
BMI	-.450**	1		
Physical Activity (Hrs)	-.314**	.205*	1	
Cognitive Activity (Hrs)	-.053	-.140	-.177	1

Among Alzheimer patients' correlation analysis depicts the negative association of BMI and physical activity with age and cognitive activity. But BMI and physical activity have positive correlation with each. The cognitive activity has negative correlation (inverse relation) with all the factors as shown in **Table 4.2.19**.

4.2 Summary of Findings

A total of 100 diabetic patients presented to selected hospitals were subjected for evaluation of associated risk factors of diabetes. About thirteen risk factors were evaluated including age, gender, body mass index (BMI), diet plan, physical exercise, Blood pressure, Smoking, family history, alcohol consumption, sleep disorder, hormonal alterations, risk score, and hypertension. All the examined risk factors were found to be significantly associated with the occurrence of diabetes. For quantitative variables age, blood pressure, risk score, and body mass index mean value along with other parameters were calculated.

Similarly, a total of 100 Alzheimer patients were engaged for evaluation of associated potential risk factors. During the current study fifteen risk factors were evaluated including age, gender, education, body mass index (BMI), physical exercise, cognitive activity, Smoking, family history, plasma Ca and vitamin level, cardiovascular illness, diabetes, stroke, brain injury, and alcohol consumption. The descriptive statistical analysis was performed for quantitative variables which shows mean value 61.05, 2.11 (25>30 group), 2.56hrs, 2.59hrs for age, BMI, physical activity, and cognitive activity respectively.

4.2 Conclusion

It can be concluded that artificial intelligence is an important gizmo towards control of emerging diseases in decentralized health care unit. The status of disease and associated risk factors can be evaluated and validated through AI. In the the current study significantly risk factors of diabetes were age, gender, body mass index (BMI), diet plan, physical exercise, blood pressure, smoking, family history, alcohol consumption, sleep disorder, hormonal alterations, risk score, and hypertension while that of Alzheimer's were age, gender, education, body mass index (BMI), physical exercise, cognitive activity, smoking, family history, plasma Ca and vitamin level, cardiovascular illness, diabetes, stroke, brain injury, and alcohol consumption with only plasma Ca level and vitamin were non-significant towards Alzheimer's occurrence. Future control of these diseases by overcoming these risk factors can be possible and artificial intelligence is a helpful tool in this regard.

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

Within decentralised healthcare systems, artificial intelligence (AI) has great promise for managing and controlling diabetes and Alzheimer's disease. Artificial intelligence (AI) systems can detect people with prediabetes or those at risk of developing diabetes by analysing patient data, including electronic health records. Healthcare professionals can take preventive action and lifestyle modifications earlier by using predictive analytics. AI can customise diabetes treatment regimens based on genetics, lifestyle factors, and unique patient traits by analysing large datasets.AI-driven modifications to treatment regimens can be facilitated by real-time data obtained from wearables and sensors used for continuous monitoring. Mobile apps with AI capabilities can check medication adherence, remind users to take their prescriptions, and offer individualised learning materials to improve comprehension and compliance. Healthcare practitioners can remotely monitor their patients' blood sugar levels, physical activity, and other pertinent metrics by using wearables and Internet of Things (IoT) devices to gather and transfer data to a centralised artificial intelligence system. With the use of AI models, diabetes-related problems such retinopathy, nephropathy, and neuropathy can be predicted with greater accuracy, allowing for early intervention to avoid or lessen the effects of these diseases.

Artificial intelligence systems are able to detect people who are at risk of acquiring Alzheimer's disease by analysing genetic data, brain imaging, and cognitive tests.

Before clinical symptoms appear, machine learning models are able to identify tiny patterns suggestive of Alzheimer's disease in its early stages. Programmes for AI-based cognitive training can be created to target particular cognitive processes, assisting people with Alzheimer's in preserving their cognitive capacities for extended periods of time. Applications for virtual reality (VR) can be utilised to improve the quality of cognitive rehabilitation of Alzheimer's patients. Smart device continuous monitoring can give carers and medical professionals important insights into daily activities, sleep patterns, and behavioural changes, enabling them to track the evolution of a patient's illness. AI can speed up drug discovery efforts by analysing massive datasets to find promising medication candidates for the treatment of Alzheimer's disease. AI-driven algorithms can be used to create individualised treatment recommendations based on patient reactions to drugs and genetic profiles.Chatbots and virtual assistants driven by artificial intelligence (AI) can provide carers with resources and support, including knowledge, help with daily tasks, and emotional support.

5.2 Discussion of Research Question One

When a patch-like ECG with an AI-based arrhythmia detection algorithm was approved in 2012, the US Food and Drug Administration (FDA) cleared the first AI-based medical gadget, Body Guardian. Since then, several nations, including the USA, Europe, China, and Japan, have progressed with their laws governing programmed medical devices, including artificial intelligence. The number of approved AI-based medical devices has expanded substantially in the USA and Europe in the last few years, mainly due to the remarkable development of deep learning technology and advances in clinical applications (Muehlematter, Daniore and Vokinger, 2021).

Numerous AI- and machine learning-based medical devices have received FDA approval. The application of artificial intelligence in preventive and decentralized health care was helpful in diabetes prevention as an early step in disease prevention and management. Three AI-based medical devices are relevant to diabetes treatment despite most of these approvals being dedicated to radiology, cardiology, and cancer (Benjamens, Dhunnoo and Meskó, 2020). As of 2020, 12 AI-based medical devices were authorized in Japan. Nevertheless, none of these medical devices are approved for treating diabetes; instead, they are all for image processing related to radiology and diagnostic imaging.

The four main areas of focus for efforts aimed at using AI in clinical settings for diabetes diagnosis and treatment are (1) automated retinal screening, (2) clinical diagnosis support, (3) patient self-management tools, and (4) risk stratification (Ellahham, 2020). The first type of AI technology is automatic retinal screening, which uses fundus images to determine if diabetic retinopathy, a significant consequence of diabetes, is present or absent. The FDA approved Digital Diagnostics Inc.'s IDx-DR gadget in 2018 due to its diagnostic solid performance as determined by clinical trials, serving as an example of this technology (Abràmoff et al., 2018). Without the expert opinion of an ophthalmologist, individuals might be diagnosed with diabetic retinopathy or not with this AI technology. After that, primary care doctors have the option of having the patients' fundus photographs examined by an ophthalmologist or having the IDx-DR device reexamined after a year. This tool makes it easier to screen for and diagnose diabetic retinopathy, particularly in remote areas where patients may find it difficult to see an ophthalmologist. Support for clinical diagnosis falls under the second group. Rather than only providing support for diabetes diagnosis, artificial intelligence (AI) solutions that imitate the "hidden tips of treatments by a specialist"—such as adjusting insulin dosage—are now being explored. Advisor Pro, made by Dreamed Diabetes Ltd., is one product the FDA authorized in 2018. This system utilizes artificial intelligence (AI) to determine and recommend remotely whether insulin dose adjustments are necessary. It sends data from continuous glucose monitoring (CGM) and self-monitoring blood glucose (SMBG) to a cloud server. Doctors can then evaluate the suggestions and let patients know. We present one of the 2020 published clinical trials (Nimri et al., 2020) that assessed the effectiveness of this AI system. 108 type 1 diabetes patients were randomly assigned to one of two groups in this non-inferiority study: an AI-managed group that received insulin treatments via the AI system or a manually managed group that received insulin treatments from a diabetic specialist. According to the findings, the AI-guided group's targeted blood glucose concentration maintenance and hypoglycemia rates were comparable to those of the expert manual-managed group. In the future, AI-powered medical devices will take the position of diabetes specialists in more scenarios similar to this one regarding adjusting insulin administration. The instrument for patient self-management falls into the third category. Some diabetes patients are familiar with self-management tools because they have self-checked various biometric data, including actively measuring blood glucose levels using SMBG. With this technology, patients receive alerts for hypoglycemia based on their biometric data—which might sometimes be challenging to interpret. After that, the patient can take medication, such as glucose pills, to avoid hypoglycemia and its related consequences.

Similarly, in the current study, AI was used to prevent diabetes. In this regard, the patient and device were given specific IDs and records were analyzed for validation of significantly associated risk factors and their role in the occurrence of diabetes. The patients were subjected to evaluation of associated risk factors such as age, body mass index (BMI), physical exercise, diet plan, smoking, blood pressure, alcohol consumption, hormonal alterations, risk score, hypertension, and sleep disorder and all of them were found significantly associates with disease occurrence. Various studies have been conducted on the role of artificial intelligence in the evaluation and control of diabetes, viz; prediction of type 2 diabetes using electronic health records and machine learning (Hasan et al., 2020; Simanto et al., 2022), retinopathy screening of diabetes using deep learning (Gulshan et al., 2016; Islam et al., 2020), risk assessment of diabetes using predictive modelling (Dall et al., 2014; Kengne et al., 2014; Bhat et al., 2023), management of diabetes through machine learning (Gargeya and Leng, 2017; Sowah et al., 2020), prediction of diabetes onset using machine learning (Chou, Hsu and Chou, 2023), and personalized decision-making for diabetes management (Bottrighi et al., 2010; Ertuğrul et al., 2023). Among these studies, the detailed evaluation of risk factors with reference to diabetes management was lacking, and it was explored during the current study. The frequently observed risk factors among diabetes patients were age, gender, body mass index, diet plan, physical exercise, blood pressure, smoking, family history, alcohol consumption, sleep disorder, hormonal alterations, risk score, and hypertension. All the examined risk factors were found to be significantly associated with diabetes. Genetic makeup plays a significant role in the development of diabetes among patients (Meigs et al., 2008; Hubacek et al., 2023). Obesity is a considerable risk factor for diabetes (Colditz et al., 1995; Orsi et al., 2022); similar findings were observed in our findings. The observed body mass index has a 28.17 mean value, depicting the high obesity level in our observed diabetes patients. It can be predicted that individuals with high BMI are more prone towards diabetes, and among such patients, disease management is mainly associated with a diet plan to overcome obesity (Cowie et al., 2006).

The patient's age was one of the significant factors responsible for the existence of diabetes, and the average age was 43 years, with a frequently observed age of 33 years, depicting that elders are more prone towards diabetes than younger. Age-wise prevalence was explored by (Satman et al., 2023), and similar findings were reported with a high occurrence of disease in middle-aged and older individuals.

The targeted individual's gender was also associated with diabetes occurrence as females were more infected than males, which might be due to gestational influences (hormonal alterations), older females are more prone towards disease than older males, variability of lifestyle (physical activity), and health-seeking behaviour varies between male and female (Grant et al., 2009; Peek, 2011).

Dietary ingredients play a pivotal role in diabetes, particularly type-2 diabetes, which is linked to lifestyle-related factors, including diet. In our study, we also found a significant impact of diet on diabetes occurrence as people feeding on highly refined carbohydrates and sugar have more risk of insulin resistance (type 2 diabetes). Carbohydrates are a rich source of glucose, and taking ingredients boosts blood glucose levels. Individuals under a continuous state of hyperglycemia are prone towards insulin resistance. Similarly, high-quality fat (saturated fatty acids and trans fats) and protein, especially of animal origin in diet, can increase the diabetes risk. However, individuals taking a balanced diet or a fibre-rich diet (whole grains, vegetables, fruits, and legumes) have slow glucose absorption and help control blood sugar levels. Furthermore, meal timing also influences blood sugar levels as individuals with extensive, infrequent meals have more chances of diabetes than individuals with whole-day meals (Ojo, 2019; Liu et al., 2023).

Physical exercise is a significant factor that plays a pivotal role in managing and preventing diabetes, specifically type-2 diabetes. In our findings, most individuals (more than 80%) with diabetes were not performing any physical activity that depicts a significant role of physical activity. Because physical activities augment the insulin sensitivity that controls blood glucose levels, increases glucose uptake by muscles and improves muscle health, and burn calories to reduce weight by burning abdominal fat, the risk of cardiovascular diseases decreases, reduces stress, which has a positive impact on diabetes management, and lifestyle improve with improvement in physical and mental health (Colberg et al., 2016; Melmer, Kempf and Laimer, 2018; García-Hermoso et al., 2023).

Blood pressure and diabetes have a bidirectional relationship because they are at risk for each other, and in their co-existence, cardiovascular disorders are significantly increased. In current findings, all diabetic patients have high blood pressure, which depicts its significant role in disease occurrence. Our findings are in accordance with the previously reported findings of (Do et al., 2023; Fottrell et al., 2023), suggesting that high blood pressure leads to insulin resistance. By plunging the insulin sensitivity level, impairing the pancreatic beta cells function responsible for insulin production, activating the renin-angiotensin system, increasing vascular tension, developing obstructive sleep apnea, declining glucose metabolism due to endothelial dysfunction, developing metabolic syndrome that leads to obesity, and taking anti-hypertension medication.

Smoking is a risk factor for various ailments, including cardiovascular disorders, respiratory disease, diabetes (type-2), and carcinomas (Campagna et al., 2019). In the current study, similar findings were reported as most of the patients have smoking habits, depicting the positive role of smoking on diabetes occurrence. The development of type diabetes is influenced by smoking, which leads to insulin resistance, inflammation, which impairs glucose metabolism, and disruption of insulin-producing beta cells. Further, the interaction effect of smoking with other risk factors increases the diabetes occurrence risk multiple times (Jeong et al., 2023). The impact of alcohol on diabetes varies due to various risk factors, including the quantity and frequency of intake, health status, and lifestyle. Moderate alcohol consumption has a positive impact on preventing type-2 diabetes as it leads to increased insulin sensitivity. Similar findings are reported in the current studies. Excessive alcohol consumption leads to diabetes because of liver damage, as the liver is pivotal for glucose metabolism (Lai et al., 2019; Kim and Sull, 2023).

A significant impact of sleep disorder was found on diabetes management and development, and our findings are in accordance with the previous reports (Hashimoto et al., 2020; Hemati et al., 2022). Sleep disorder (more specifically chronic condition) increases insulin resistance, disrupts glucose metabolism, impairs glucose tolerance, affects hormones, i.e. leptin and ghrelin, which are involved in appetite and metabolism and leads to overeating and weight gain, increase fatigue, reduce physical activity, increase inflammatory responses, increase the risk of complications, and alters melatonin production that influence glucose metabolism (Schipper et al., 2021; Hemati et al., 2022).

Hormones directly impact diabetes as insulin, a hormone produced by the pancreas, plays a central role in regulating blood glucose levels. So, insufficient insulin production and increased insulin resistance are leading causes of diabetes. As in type 1 diabetes, insulin-producing beta cells of the pancreas are destroyed by autoimmune disorders, while in type 2 diabetes, the body is resistant to insulin, although its level is high. Stress hormone (cortisol) increases insulin resistance (Lundqvist et al., 2023), hormones of metabolism and appetite regulation (adiponectin and leptin) produced by fat cells increase obesity and diabetes risk (Al-Hussaniy, Alburghaif and Naji, 2021), sex hormones (estrogen and testosterone) influence insulin sensitivity (Andlib et al., 2023; Urhan et al., 2023), thyroid hormones (T3 and T4) impact glucose metabolism (Cui et al., 2023), and incretin hormone stimulate insulin release in response to feeding intake (Nauck and Müller, 2023). Disturbance in the level of any of these hormones influences diabetes development. Our findings also reported a significant impact of hormonal disturbance on diabetes, as reported earlier, for the aforementioned possible reasons. Individuals with high-risk scores based on various risk factors, viz. demographic information, medical history, lifestyle, and others, play a crucial role in the development of diabetes. Patients who exhibit high-risk scores depict the significant role of risk scores in diabetes management. A larger waist circumference (abdominal fat) and sedentary lifestyle increase insulin resistance. Risk score was calculated based on various possible risk factors viz; age, BMI, physical activity, waist circumference, ethnicity, blood pressure, dietary patterns, and sleep patterns. Most of these factors were elaborated exclusively similarly; their combined effect also depicts a significant role in diabetes development (Ferrat et al., 2020; Mendez et al., 2021).

Information about the disease, associated risk factors, therapeutic and managemental protocols, and preventive measures can be dispersed using AI in the decentralized healthcare units and the community to prevent disease outbreaks. There are growing advantages to using AI in patient care, but many obstacles remain. Establishing strategy and execution priorities for organizations may benefit significantly from understanding these new difficulties. AI has a lot of promise in addressing several significant healthcare issues. Once top universities have established the necessary infrastructure for AI-enabled businesses, imagining any other type of organization won't be easy. However, there are a few uncomfortable realities that healthcare executives will have to face as they investigate the idea of an AI-enabled organization. Two significant painful realities of AI in our healthcare system have been highlighted; many AI technologies are still in the early stages of development and lack the clinical value and sophistication necessary to be widely adopted in the medical field. Research and development are still ongoing for many of these AI tools. There is a significant chance of harm when AI techniques are used improperly or too soon. The gap between an algorithm's functionality and its capacity to provide clinical results, known as the "AI chasm," can arise even when an algorithm, for instance, performs well in testing but not in clinical settings.

Moreover, regulatory agencies continue to develop methods for handling newly developed algorithms. When applying AI in healthcare settings, many regulatory authorities rely heavily on critical healthcare judgment as a last resort. It will become increasingly difficult for people to stay updated with the rapidly evolving digital and AI landscape as AI technologies proliferate exponentially. Organizations will need to cultivate a workforce that possesses the competencies to provide care using these tools and can learn and adapt quickly to comply with new regulations.

5.2 Discussion of Research Question Two

Finding people with mild cognitive impairment who may eventually develop Alzheimer's disease (AD) is one of the ongoing issues in the study of AD. Artificial intelligence emerged as one of the more effective methods for automatically classifying various AD symptoms and extracting trustworthy predictors. The time has come to expedite the application of this information in therapeutic practice, primarily through the utilization of low-cost features derived from neuropsychological assessments. Various studies have been conducted on the use of AI tool in the Alzheimer's disease (Fabrizio et al., 2021), Alzheimer's classification based on multisite DTI database (Qu et al., 2021), early disease detection (Subasi, 2020), detection through DNA methylation and AI technology (Alfonso Perez & Caballero Villarraso, 2021), early diagnosis (V. O. K. Li et al., 2021; Verma et al., 2022), patient's monitoring (Corchado et al., 2008), mobile device-based record of taking AD medicine (Jones et al., 2022), personalized medicine record (Silva-Spínola et al., 2022), and Daily routine assistance (Nithya et al., 2023).

With the integration of AI-based prediction models a multidomain prevention approach can be assessed by enabling accurate assessment and monitoring of cognitive trajectories and dementia risk. Additionally, AI implements an ICT-based multidomain lifestyle intervention that can be tested in a validation trial among subjects who are at risk of dementia. This framework combines cutting edge and innovative technologies from three distinct technical domains: big data, artificial intelligence analytics, and visualization. Big data has emerged as a disruptive technology in recent years, permeating our daily lives and enabling personalized services based on behavioral predictions. A comparable objective for cognitive decline and dementia risk exists in AI: to provide individualized risk assessment and forecast cognitive changes based on previous and present behavior and health data to address the immediate and long-term requirements of those who are at risk. Modern technology's accessibility provides a lighthouse for the development of novel, hitherto unexplored approaches to risk assessment and prevention in at-risk stages in individuals who exhibit either negligible or no cognitive symptoms. This potential is further increased by combining data from widely used technology across all societal levels, such as wearables, smart sensors, mobile devices, inventive biomarkers, and intelligent Electronic Health Records (EHRs). Some of the initial difficulties have mostly been resolved as big data and analytics have seen significant technological advancements.

Scalability and adaptability to data growth; generating insights and information on the temporal evolution of cognitive decline in predementia stages; integrating heterogeneous sources of structured and unstructured data; obtaining high-quality data and validating and verifying it; and protecting health information while maintaining anonymity despite personalization are the primary challenges that need to be overcome. Some research that has used wearables, sensors, and/or mIoT have tackled many of these concerns in multiple ways thus far. A big data architecture for data analytics gathered from smart mIoT and wearable data was proposed by (Bashir & Gill, 2016). The usage of Firework, which offers virtual data views on physically scattered data and enables them to be handled as a single data source, was suggested by (Q. Zhang et al., 2016). Another strategy proposed by (Rathore et al., 2016) calls for the application of the MapReduce Hadoop ecosystem in a real-world setting, where data is gathered through the deployment of various IoT devices and smart sensors and then utilized for big data analytics.

There are several risk variables and biomarkers associated with dementia, AD, and cognitive impairment, but their clinical value is still restricted when it comes to dementia prediction models. Numerous risk prediction models have already been created. For example, the CAIDE dementia risk score (Kivipelto et al., 2006), created by the LETHE consortium, has been used as a screening tool to identify participants who are at-risk for the FINGER trial as well as an educational tool to spread knowledge about dementia risk factors. To date, nonetheless, there remains a great deal of work to be done before practical application of precise and trustworthy prediction systems for early risk diagnosis and dementia prevention can occur. AI expands on existing successes and the availability of additional research in the field of dementia risk assessment to establish the best guidelines for use cases involving dementia risk assessment and prediction, enhances them, or discovers new model and tools if needed. Large volumes of complex multimodal data, such as cognitive, clinical, blood, genetic, and environmental risk variables, as well as their temporal dynamics, must be handled by algorithms to accurately forecast dementia. These systems must also be able to handle novel digital biomarkers from sources like wearables. To assist doctors in making decisions, data mining should be transparent and trustworthy, providing not only with a dementia likelihood number but also with an all-encompassing and objective signature of risk and preventative potential (Hall et al., 2019; Pekkala et al., 2017). Members of the consortium have previously created these models through machine learning techniques, and a similar strategy can be constructed utilizing unique risk signature data gathered as part of the LETHE project.

In the current study 100 Alzheimer's patients were evaluated for associated potential risk factors including age, gender, education, body mass index (BMI), physical exercise, cognitive activity, smoking, family history, plasma Ca and vitamin level, cardiovascular illness, diabetes, stroke, brain injury, and alcohol consumption. Similar study on evaluation of risk factors was performed by (Armstrong, 2019; Borenstein et al., 2006).

In our findings, early age people were less prone to Alzheimer as compared to middle age population. The most infected individuals have an age above 75 years (77) while less infected have an age less than 65 years (62) with a maximum frequency for 58 years depicting the possibility of other factors involvement. Similar findings have been reported by (Saddiki et al., 2020). The association of age with Alzheimer's patients was significant may be due to age linked changes viz; genetic alterations, age linked structural and functional modifications in brain, deposition of beta-amyloid and tau tangles in brain, vascular changes associated with hypertension, and lifestyle factors (Frigerio et al., 2019; Masters, 2020). Further, during aging there are molecular and cellular changes in the whole body including the brain which may affect the functionality of brain and development of neurodegenerative disorders.

In the current study most of the Alzheimer’s patients were female 62% than male 38% depicting the significant impact of gender in the occurrence of Alzheimer it might be due to hormonal alterations (menopause declines the estrogen level which is neuroprotective), the genetic factor APOE-e4 has greater impact on female than male, the cognitive disorders are at high rate in women due to unknown factors, socioeconomic and lifestyle factors influence cognitive decline. Our findings are in accordance with the findings of (Ferretti et al., 2020; Rosende-Roca et al., 2021) as they reported significant role of gender in the occurrence of the disease.

Education plays a pivotal role in the maintenance of cognitive reserve which is the ability of the brain to sustain normal function despite pathological conditions. Higher education level and mental engagement in stimulating activities have positive impact on cognitive reserve. Therefore, highly educated individuals have delayed development of Alzheimer and associated cognitive symptoms. Education has a direct influence on the neural network complexity of the brain. The cognitive activities viz; problem solving, reading, and learning have stimulatory sway on brain and contribute to the rich network development, which may act as buffer against cognitive damage for occurrence of Alzheimer. Lifelong engagement in intellectual activities viz; learning new skills, pursuing hobbies, actively participating in cognitive and social activities, potentially reduce the risk. Individual with higher education experience delayed onset of Alzheimer's symptoms due to compensatory effects of brain (Rosselli et al., 2023). Further, education influence the early detection of cognitive changes also reduces the development of Alzheimer because of early seeking medical attention and adoption of control measures. In the current study, the highest number of cases were reported in uneducated people with decreasing trend with increase in education level. These findings are in accordance with the early report with possible reasoning of education and cognitive activities reduces the risk of Alzheimer’s symptoms (Gonneaud et al., 2020; Kim et al., 2020).

Obesity is directly associated with Alzheimer reported in our findings as individuals with BMI above 25 were more among screened Alzheimer's patients. Such findings are in parallel with the previous reports (Ma et al., 2020; Nianogo et al., 2022). Obesity at the early age has greater influence on the development of cardiovascular disorder and diabetes which are linked with Alzheimer. Impact of BMI on Alzheimer’s development is also linked with age as higher BMI on early age increase the risk while lower of BMI in late age also upsurge cognitive damage and Alzheimer's occurrence. Researchers are exploring the complicated connection between BMI and cognitive damage, including other factors genetic factors, age, inflammatory processes, and physical activities. The concept of obesity paradox explained the positive impact of increasing BMI in old age individuals due to decline in the dementia, Further obesity influence the morphological changes in brain, vascular health, and brain physiology which are the possible reason for increase in the Alzheimer's risk with BMI (Flores-Cordero et al., 2022; Karlsson et al., 2020; Ma et al., 2020).

Physical exercise exerts various positive changes in the body which decrease the risk of Alzheimer, which are improvement in brain health, enhancement in cognitive reserve, augmentation in cardiovascular health, reduction in amyloid plaques, enrichment in neuroprotection, and positive impacts on mood. Physical exercise promotes the release of chemicals which are essential for neurogenesis, synaptic plasticity, and learning processes. Reports suggest the reduction in the risk of developing Alzheimer's disease due to physical activities might be due to enhancement in the blood flow towards brain. Cognitive reserve augments with the increase in physical activity because of stimulatory impacts which potentially delay Alzheimer's onset. Exercise reduces the accumulation of tau tangles and beta-amyloid plaque which are Alzheimer's hallmarks. Deposition of these proteins significantly reduces with exercise (De la Rosa et al., 2020). Further, physical exercise enhances the release of neuroprotective factors viz; brain derived neurotrophic factor (BDNF) that support neuronal growth and protect against neurodegenerative disorders (Arrieta et al., 2020). Lon term stress and depression makes body sensitive towards Alzheimer, but exercise overcome stress and minimize the risk of disease. Similar findings are reported in the current study as many patients lack physical exercise. Depicting the significant role of physical exercise in declining the diseases.

Cognitive activities have inverse relation with the development to Alzheimer as found in the current study individuals with minimum hours or no cognitive activity were significantly high in number than individuals with cognitive activity of 3 to 4 hours. Our these findings are in line with findings of (Oveisgharan et al., 2020). The inverse relation of cognitive activity might be due to its positive impact on the enhancement of cognitive memory by mental stimulation. Cognitive activities have been linked to potential benefits in terms of lowering the risk of dementia, including Alzheimer's disease and other types. Although preventing Alzheimer's disease cannot be ensured by any activity or lifestyle modification, research indicates that cognitive engagement may assist develop cognitive reserve, which is thought to help the brain repair damage brought on by Alzheimer's pathology. Reading, figuring out problems, picking up new abilities, and other cognitive pursuits are believed to help build cognitive reserve. Higher educated people or those with a history of regular cognitive activity may have a delayed development of Alzheimer's symptoms. The brain's capacity to make up for the changes brought on by the illness is thought to be the cause of this delay. Playing an instrument, joining a social club, or engaging in hobbies are examples of mentally taxing activities that may offer protection. It is believed that lifelong learning—which includes both formal education and studying outside of formal settings—is good for cognitive health (Benussi et al., 2022). Acquiring new knowledge and abilities can improve cognitive reserve and aid in the preservation of brain connections. The brain's capacity to adapt and create new connections is known as neuroplasticity, and it can be enhanced by cognitive activity. This flexibility might be essential for the brain to offset the damage caused by Alzheimer's disease. Better cognitive performance is linked to regular engagement in cognitive activities over the lifespan. Enhancements in memory, focus, problem-solving, and other cognitive areas are included (Clemmensen et al., 2020; T. Li et al., 2021).

According to the current study, the role of smoking in Alzheimer’s occurrence was non-significant but a greater number of patients have smoking habits. It has been also reported by (Y. Liu et al., 2020; Otuyama et al., 2020). The nonsignificant association might be due to indirect relation of smoking with Alzheimer's and sometime people smoke to get relief from tension. It has been determined that smoking may increase the risk of developing dementia, including Alzheimer's disease. While the association between smoking and Alzheimer's is complex and not entirely understood. It is well recognized that smoking harms the cardiovascular system. It may result in blood vessel narrowing, decreased blood flow, and an elevated risk of atherosclerosis, or artery hardening. These vascular alterations raise the possibility of developing vascular dementia, a form of dementia brought on by reduced blood supply to the brain, as well as contributing to cognitive loss. There is a link between smoking and persistent inflammation all over the body. Numerous diseases, including neurological disorders like Alzheimer's, have been linked to inflammation. The development of tau tangles and beta-amyloid plaques, two hallmarks of Alzheimer's disease, may be facilitated by chronic inflammation. Smoking creates oxidative stress, which throws the body's balance between antioxidants and free radicals off (Y. Liu et al., 2020). Oxidative stress has been connected to neurological illnesses and is implicated in the ageing process. Due to the brain's heightened susceptibility to oxidative damage, Alzheimer's disease may develop as a result. According to certain research, smoking may interact with specific hereditary variables to raise the possibility of developing Alzheimer's disease. Certain genetic variations, particularly those associated with inflammation and the oxidative stress response, may make a person more vulnerable to the negative effects of smoking. Smoking has been linked to decreased cerebral blood flow, which may have detrimental effects on brain health. The brain needs enough blood flow to carry oxygen and nutrients, and disturbances in this process can lead to cognitive impairment (Deal et al., 2020).

Family history (genetics) has direct association with the occurrence of Alzheimer, have been reported in our findings and that of (Subramaniapillai et al., 2021). Although most occurrences of Alzheimer's are thought to be random and not inherited, there are genetic variables that can raise the risk. Certain gene mutations, including those in APP, PSEN1, and PSEN2, have been connected to the emergence of early-onset Alzheimer's disease in some families when a genetic component is evident. Late-onset Alzheimer's is the most prevalent type and usually develops after age 65. A family history of the disease can still raise the chance of late-onset Alzheimer's, although the overall risk is probably influenced by a combination of genes and environmental factors. One of the most well-known genetic risk factors for late-onset Alzheimer's disease is the APOE-e4 gene variant. If you inherit one copy of the APOE-e4 gene from a parent, your risk may be raised. The risk increases even more if you inherit two copies—one from each parent. There is a complicated link between genetics and Alzheimer's. Neither a family history nor lack thereof ensures protection against the disease. A family history does not ensure that you will get it. An individual's risk is also influenced by lifestyle decisions and environmental circumstances. Although a person's family history is one risk factor, medical professionals take several factors into account when determining a person's overall risk for Alzheimer's disease. Age, heredity, way of life, and the existence of specific medical disorders are other variables. Genetic counselling might be advised if Alzheimer's disease is known to run in the family and there is a known genetic mutation linked to the disease. Genetic counsellors can offer details regarding the gene's inheritance pattern, chance of being passed down to future generations, and possible interventions or preventive measures (Prokopenko et al., 2020).

Calcium is involved in various physiological functions. The body needs calcium for several physiological functions, including nerve transmission and function. The connection between hypocalcemia and Alzheimer's disease is not entirely known, however abnormalities in calcium levels can have an impact on the health of neurons. So, low level of calcium influences the cognitive functioning of brain that’s why individuals with low plasma calcium level are prone towards Alzheimer and cognitive memory loss (Cascella & Cecchi, 2021). Similarly, in our study a higher number of patients have lower plasma calcium level than normal level of calcium in plasma. Our findings are in line with the findings of (Ryan et al., 2020; Wang et al., 2020).

Vitamins like E, D, B complex, C, and A, and omega-3 fatty acid play pivotal roles in cognitive activities in our daily life. The low level of these vitamins in our blood increases the chances of loss in cognitive memory and makes our body prone towards Alzheimer. Similar findings have been reported in our study as higher number of patients were with low level of plasma vitamins which depicts the significant role of these vitamins in the occurrence of Alzheimer. These findings are supported by the findings of (Blasko et al., 2021; H. Liu et al., 2021) Researchers have investigated the possible links between several vitamins and Alzheimer's disease. These vitamins are thought to have roles in brain health. While some vitamins may be linked to cognitive health, it's crucial to remember that no one vitamin or supplement has been shown to be 100% effective in preventing or treating Alzheimer's disease. Antioxidant vitamin E aids in defending cells against harm from free radicals. Although the evidence is inconclusive, some studies have suggested that vitamin E may have a preventive impact against cognitive deterioration. Excessive consumption of vitamin E can have negative effects, therefore it's best to approach high levels of supplementation cautiously. In addition to being crucial for maintaining healthy bones, vitamin D may also have an impact on cognitive performance. Low vitamin D levels have been linked in several studies to an increased risk of dementia and cognitive decline. However, more investigation is required to clearly identify a relationship. The B vitamins, folic acid (B9), B6, and B12, are involved in the breakdown of homocysteine. An increased risk of cognitive deterioration has been linked to elevated homocysteine levels. The possible advantages of B vitamin supplementation in lowering homocysteine levels and delaying cognitive deterioration have been examined in a few trials. Antioxidants like vitamin C aid in shielding cells from oxidative damage. Although vitamin C is crucial for good health in general, there isn't much research connecting it especially to preventing Alzheimer's. Immune system and visual health depend on vitamin A. Although some research has hinted to a possible connection between vitamin A levels and cognitive performance, additional investigation is required to prove a firm correlation. Studies have been conducted on the possible cognitive benefits of omega-3 fatty acids, including EPA (eicosatetraenoic acid) and DHA (docosahexaenoic acid), which are contained in fish oil. A diet high in omega-3 fatty acids may be linked to a lower risk of cognitive impairment, according to some research (Alam, 2022).

Most of the Alzheimer’s patients were infected with cardiovascular disorders depicting the significant role of these ailments on developing Alzheimer. An increasing amount of research points to a connection between cardiovascular diseases and Alzheimer's. Although the precise nature of the association is nuanced and varied, a few cardiovascular health-related factors may impact the likelihood and course of Alzheimer's disease. The state of the brain and the circulatory system are intimately related. Blood vessel-related diseases like diabetes, atherosclerosis, and hypertension may be a factor in the brain's decreased blood supply (Soto-Rojas et al., 2021). Vascular variables may be involved in the onset of Alzheimer's disease as well as vascular dementia. Blood is pumped by the heart to the brain, where it delivers nutrients and oxygen. The oxygen and nutrients that reach the brain can be affected by cardiovascular illnesses that compromise blood vessel integrity or heart function. This raises the possibility of cognitive deterioration and may cause harm to brain cells. All over the body, including the brain, blood vessels can be harmed by persistently high blood pressure. It has been linked to a higher chance of Alzheimer's disease and cognitive impairment (Tini et al., 2020). Blood pressure control is thought to be crucial for maintaining general brain health. Plaque accumulates in the arteries and causes atherosclerosis, which limits blood flow. Cerebral blood vessel damage may result from this illness, which may exacerbate cognitive impairment. An increased risk of Alzheimer's disease has been linked to elevated cholesterol levels, especially those of low-density lipoprotein (LDL) cholesterol. Changing one's lifestyle or taking medicine to lower cholesterol may have positive effects on brain function. Alzheimer's disease and cardiovascular diseases both share chronic inflammation. The buildup of tau tangles and beta-amyloid plaques in the brain, which are indicative of Alzheimer's disease, can be attributed in part to inflammation (Saeed et al., 2023). Cardiovascular problems and Alzheimer's disease share multiple risk factors, such as age, heredity, and lifestyle choices. People who have experienced circulatory problems in the past may be more susceptible to Alzheimer's. Similar findings have been reported in the current study as more patients of Alzheimer also have cardiovascular abnormalities.

In the current study number of Alzheimer' patients simultaneously infected with diabetes was higher than no infected. Diabetes and Alzheimer's disease have a well-established connection, indicating that people with diabetes have a higher chance of getting Alzheimer's. The intricate connection between diabetes and Alzheimer's disease is being actively researched by researchers. Both disorders have certain similar risk factors and underlying mechanisms (Jash et al., 2020). Increased oxidative stress and inflammation are linked to elevated glucose levels and are thought to have a role in the etiology of Alzheimer's disease. Insulin is also used by the brain, and there is evidence that the brain's insulin resistance may affect cognitive performance (Sun et al., 2020). Neuroprotection, synaptic plasticity, and the control of beta-amyloid—a protein linked to Alzheimer's disease—are all impacted by insulin. Chronic inflammation is linked to Alzheimer's disease and diabetes. Alzheimer's disease can start and advance due in part to inflammation, and diabetes-related inflammation may be involved in this process. Diabetes has been linked to structural brain abnormalities, including modifications to the hippocampus, a part of the brain crucial for memory and learning. Cognitive decline may be exacerbated by these alterations. Numerous risk factors, such as age, genetics, and lifestyle choices including food and exercise, are shared by diabetes and Alzheimer's disease (Stanciu et al., 2020).

A significant number of patients have history of brain injury reported in the current study. According to numerous studies, those who have suffered from severe traumatic brain injuries (TBIs) may be more susceptible to Alzheimer's disease in later life. Instances of moderate to severe brain injuries seem to carry a heightened risk. A traumatic brain injury (TBI) can set off a series of biochemical reactions in the brain, such as inflammation, the build-up of aberrant proteins (like tau), and cellular destruction (Brett et al., 2022). These mechanisms have also been linked to Alzheimer's disease, and traumatic brain injury may hasten the pathophysiological progression of the illness. A neurodegenerative disorder called chronic traumatic encephalopathy (CTE) is linked to recurrent head trauma or traumatic brain injury. Despite several similarities to Alzheimer's disease, such as aberrant tau protein accumulation, CTE is a different illness. In athletes with a history of recurrent head trauma, veterans of the armed forces, and other TBI exposure, CTE has been noted (Johnson et al., 2023; Kempuraj et al., 2020).

Role of alcohol consumption was evaluated in the current study and most of the Alzheimer’s patients were found addictive of alcohol consumption (irrespective of their quantity or frequency of consumption). The volume and pattern of alcohol consumption, individual differences, and other lifestyle factors can all have an impact on the complex link between alcohol consumption and Alzheimer's disease. According to certain research, a moderate alcohol intake may be linked to a decreased risk of Alzheimer's. “moderate” drinking is defined as one drink for women and two for males per day. It is believed that alcohol's influence on cardiovascular health is connected to its possible beneficial benefits. Red wine has been linked to benefits for the cardiovascular system, including increased blood flow and a lower risk of heart disease, when consumed in moderation. There is a strong correlation between cardiovascular and brain health, and there may be beneficial impacts on the brain from elements that support a healthy heart. Resveratrol, a substance included in red wine, has been linked in certain studies to neuroprotective effects and a lower risk of cognitive decline (Reale et al., 2020). On the other hand, there is conflicting data on resveratrol's particular advantages for Alzheimer's. However, excessive alcohol use is linked to several detrimental health effects, such as a higher risk of dementia, cognitive decline, and other neurological conditions. Long-term excessive alcohol consumption can harm the brain and affect cognitive function (Kivimäki et al., 2020). Individual reactions to alcohol might differ, and the possible effects of alcohol on the brain can depend on several factors including age, heredity, general health, and other lifestyle choices.

Regulatory and Policy Implications of AI Adoption in Healthcare

The use of AI in the care sector provides exciting possibilities for improvement, and at the same time generates new questions about the applicable law. These issues include understanding health care laws and insurance policies, and handling issues to do with data management and protection. Healthcare organisations therefore need to ensure that their AI initiatives are compliant with regulation and are ethical before they can correctly implement them.

That is why the healthcare regulations are set down to deliver protection and guarantee that the AI technologies mean safety and reliability. The devices themselves can be seen as their own category of AI tools; companies that create medical devices which include AI tools, have to go through agencies similar to the FDA in the United States and Europe’s EMA, Health Canada, etc. However, the dynamicity of AI creates some issues; since, the models of machine learning change with time and may need to be supervised frequently for compliance standards. Moreover, the requirement of interpretability is in contrast with many ‘black-box’ models which are hard to explain. This variability is especially problematic for multinational healthcare organizations, as they need to meet the regulatory needs of multiple different regions and jurisdictions.

They found out that reimbursement policies greatly affect the ability of healthcare organizations to generate enough revenue for AI implementation. Today, insurance companies, as well as Medicare, Medicaid, and other insurance companies, are gradually beginning to see the effectiveness of technologies based on artificial intelligence. But, reimbursement structures continue to be uncertain especially for preventive and non-conventional care delivery systems. The fee-for-service payment models are ill-suited for AI because of the emphasis on the outcomes and cost reductions that are inherent in the value-based models. To bridge these gaps, it is predicted that the new payment models including subscription-based care model or using shared savings model could become popular for AI-based healthcare.

This means that data management and data privacy form the core of the business consequences of AI integration. AI particularly depends on a huge volume of patient data and, therefore, sound data management solutions are critical. For the data of healthcare organizations to be trusted and have clear ownership rights to be preserved from lawsuits, the data quality and security must be a priority. Others like General Data Protection Regulation (GDPR), in the European Union, and the Health Insurance

Portability and Accountability Act (HIPAA) in the United States present strict compliance measures. These are the following; getting patient consent, limiting use of the data, and either encrypting or anonymizing the data. Failure to compliance entails severe penalties, loss of reputation and business disruptions.

Bias and fairness of an AI system are also paramount to its ethical concern. This means that if self-learning AI models draw from biased datasets then current and future healthcare disparities may be prolonged, therefore training of AI models will require diverse datasets and periodic bias scans. Another ethical consideration; patients must understand that AI is involved in their treatment or operations. In addition, there should be legal obligations to prevent potential adverse consequents of AI's application and guarantee patients' trust.

However, there are regulatory and policy implications involved that make it challenging for healthcare organisations to accomplish this task. This involves hiring compliance departments, working with policy makers and defining roles of partnership with developers of artificial intelligence. The policies and standards of the contracts signed with AI vendors should state compliance requirements and responsibilities for when the liability is going to be split. Moreover, there is a need to regard continuous monitoring and auditing to check compliance with new or changed regulations and ethically relevant aspects throughout the lifecycle of the AI systems.

Understanding and solving those issues will let healthcare organizations run AI-assisted programs legally, safely, and ethically. This view also minimizes the risks while preparing organizations for success in the changing face of healthcare.

Market Dynamics of AI in Healthcare

The competition by market players in the application of AI in the healthcare industry is intensifying with new entrants, the traditional healthcare players, and the tech giants in the market. Leading IT giants like Google, IBM, and Microsoft are investing in the AI healthcare with their expertise, while new entrant firms concentrate on a particular product segment including diagnosis, telemedicine, and drug discover. AI is now being embraced in traditional health care providers and insurers as a way of increasing operational efficiency and ever enhancing patient experience. This competitive pressure for innovation is also a pressure for healthcare organizations to implement AI solutions to stay competitive. Many more healthcare providers enter partnerships with tech companies so that both of them will benefit from each other's expertise.

The use of AI in healthcare is of great business interest since it contributes to better decision making processes within organizations, makes the work of healthcare institutions more efficient and increases patients' satisfaction . AI applications can enhance the allocation of resources, detect patients' needs, and find problem areas, thereby, reducing costs and enhancing value. Also, intelligent diagnosis and individual approaches to treatment are new sources of revenue for organizations ready to implement extremely innovative solutions. Remote consultation, assisted by AI, has been rapidly growing, especially after the onset of COVID-19, and could serve as a basis for providing more access to healthcare services at lower costs. Such developments place AI as a feasible proposition especially for institutions that wish to offer quality care services at low cost.

However, there are difficulties in adopting AI in healthcare. The costs of implementing the main processes of samples can be very high and the required infrastructure is specialized and necessarily requires significant investments, which can discourage smaller organizations. In addition, the implementation of AI in organizations frequently means changes on a large scale, such as retraining and changes in working processes. Ethical issues, including the fairness of AI system and protection of data, also pose some challenges. That is, regulatory factors or lack of certainty about reimbursement policies may also hamper the process. To meet these challenges, healthcare organizations should work through a four-step process of implementing AI solutions, using incremental change, and embracing change at the cultural level.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

Recommendations for Healthcare Leaders on AI Implementation

Since many healthcare managers have not started employing AI technologies, they should follow specific guidelines when introducing these technologies into the organization to facilitate the receipt of various values by the organization and patients. The first recommendation is to develop a futuristically coherent vision and strategic outlook for AI and its application in the organization. This strategy should focus on determining where AI is going to be most beneficial; whether its application is going to have the greatest impact in regards to clinical decision making, workflow optimization, or patient satisfaction. Managers must consider how best to deploy AI to help the organization change and improve, and there are numerous ways this can be done, from using it to cut through paper work, forecast customer needs or use it to better manage resources, or to automate processes. Establishing goals and expected outcomes through a strategic plan will guide healthcare leaders on the most appropriate ways for applying AI for the maximum return on investment while remaining consistent with the healthcare organization's vision and mission to give patients quality care.

The third recommendation for healthcare leaders is to embrace ways of creating a culture that supports AI use across the organization. AI implementation is a multidimensional process, in which all employees and managers, clinicians, administrators, information technologists, and executives, must be committed and engaged. It is therefore important for healthcare organizations to understand that adoption of AI is not just a technology issue but also an organizational issue. Management should go out of the way to make staff participate in seminars that aim to inform them of the existence of artificial intelligence, its benefits and impacts on their work. Thus, the healthcare organizations should create demand for the training and professional development of the workforce to address the compounding questions of how to use AI effectively and responsibly. Third, healthcare leaders should also promote communication about AI and address issues like the effect that AI has on patients and jobs, as well as the ethical aspects of that by being as transparent as possible across the organization.

It is also important for the healthcare leaders to pay attention in choosing right AI tools and technology that will be more beneficial to the organization. The implemented AI tools should be relevant to the organization's requirements for the particular application whether it is in diagnosis or care delivery or even administrative work. Healthcare leaders should pay special attention to the issue of scalability, flexibility, and integration when choosing the AI tools. For instance, the technology which should be given high priority by healthcare providers is the AI solutions that are compatible with EHR systems and other existing technologies in the healthcare domain. If the leaders source the technology from the vendors and tech partners, then they are assured of getting technology that is easy to use, robust, and adaptable enough to accommodate the company's needs. Besides, AI solutions should be designed relative to the organizational strategic objectives for example, optimizing clinical outcomes, patient safety, or cost optimization.

It is also necessary to mention that implementing AI requires meeting the requirements about organizational change management in the course of the adoption. AI involves a great deal of alterations to the initial organizational processes, positions, and duties, which provoke barriers to staff members' resistance to incorporating new technologies into their work. Managers for healthcare care require to put in place strategic change management processes that would manage the change process. These strategies should center on how to garner staff support when implementing AI by selling the advantages of AI, by addressing the issues of concern on job loss, and by reassuring the employees that they will get support during this change. Another perspective is that more frequent communication support should be offered during the implementation process to ensure that employees are aware of the occurring changes, the reasons for them as well as the advantages of introducing AI into the organization in the future. An effective and organized plan should therefore be developed in order to reduce disruption and enhance the implementation of change to AI methods.

Secondly, there is organizational readiness of AI adoptions, which means that leaders in healthcare organizations need to determine whether their organizational environment can accommodate the new AI tools. Healthcare AI's fundamentals are created with robust data infrastructure, safe cloud environments, and data protection procedures. Due to many patients generating considerable data, the healthcare organizations must possess the capacity and relevant measures of implementing the same legally and securely. This means that the AI should be capable of integrating with current EHR technology and interchanging data with other info systems. Additionally, organizations should ensure better protection of data using encryption, access control, or adherence to the modified HIPAA or GDPR standards. Managers should evaluate and update the infrastructure for the organization with the needs for AI applications and constantly develop it further.

While it is equally crucial for the healthcare leaders to embrace AI, there is need to put in place an acceptable policy framework on how it should be adopted while at the same time putting into consideration ethical issues and risk factors. Concerning ethical implication of AI in healthcare; they include; Patient's privacy, balance, and accuracy of the algorithms used, and the ability of the end users of the AI to understand the AI and take responsibilities of the results produced. It is recommended that the healthcare organizations should ensure that there are proper frameworks which will determine the use of the AI technologies. It is recommended that policy makers adopt strategies that will be applicable in the ethical usage of AI in the following ways; ensuring that the algorithm used in AI is derived from a desirable distribution. Further, leaders should advocate for the transparency of the AI systems in order that the clinical staff and the patient understand the rationale for the suggested action or a decision. They have also defined a number of problems in this area and mentioned that forming an ethical board or an AI governance committee may help healthcare organizations to address such problems and promote the effective use of AI in accordance with the organization's ethical standards.

The second essential suggestion to healthcare leaders is the primary focus on the continuous assessment and improvement of the AI systems' performance as soon as they are implemented. AI tools must always be checked and audited to see how effective it is, how relevant today and whether it complies with the currently existing laws. The healthcare organizations should monitor the AI tools' effectiveness regularly and potential issues such as the decline of the accuracy or shifting of clinical outcomes. In addition, there is a requirement of feedback from the users of AI which includes the clinicians, the patients and the administrative staff in order to determine if the AI systems are fulfilling the intended purpose and enhancing the delivery of the care. Leaders should also be aware of issues such as the algorithmic drift where an AI model gradually deteriorates and should be trained again or the model should be changed. This continual evaluation process is useful to improve the application of AI while minimising risk and optimising the patient's experience in the long run.

Finally, the healthcare leaders have the challenge of the longevity of the AI implementation process. While there is capital expenditure that is needed for the implementation of AI, the processes, patients, and financial saving that AI can bring can be a strength of implementing it. Healthcare organizations should look at the long-term horizon in financial strategic planning for AI that will entail the allocation of adequate capital for the implementation process. Leaders should also consider other areas of joint expense such as in technology domains or joint participation in investment undertakings among them. When integrating the goals of AI with overall organizational goals in healthcare, leaders can ensure that AI is not only functional in the future of health care concerns, but also productive in the future of health care concerns.

Hence, healthcare executives continue as the key players in AI technology implementation in their health entities. In this paper, the guidelines, which may be useful to the leaders in the integration of AI in the healthcare systems are outlined as follows: development of the clear strategy, increase of the active culture of innovation, including the change management in the organizations, the state of the infrastructure, and the maintenance of the ethical standards. In addition, constant evaluation and an approach based on the future perspective will enable maintaining AI as the necessary tool that contributes to improving the results of the health care system. When these measures are put in place, healthcare leaders will be able to leverage AI in increasing the value of the quality of care and organizational productivity.

Conclusion

Adoption and use of AI in the healthcare management and administration has been described as a revolution in the industry. Across the board, from patient care to administrative tasks, AI provides healthcare leaders with tools that can help to reduce costs, increase productivity, and enhance decision-making. One of the major points of concern to come out of this discussion is the potential of AI in improving the efficiency of healthcare systems by providing the much needed analytics, especially on resource use, staff productivity and patients' conditions. AI technologies including machine learning algorithms, predictive analytics and natural language processing enables the delivery of quality patient care through timely anticipation of needs, effective work flow and minimized errors.

In addition, AI makes it possible to reduce clerical work that includes appointment setting, invoicing, record keeping, and others so that health care personnel can focus on value added work. AI can help healthcare organisations to reduce some of these time-consuming tasks, and therefore improve operational efficiency. This can result in a certain level of cost savings that can then be funnelled to other aspects of the business like research, training or patient care. AI's ability to cut cost while increasing the quality of services being delivered makes it an appealing solution that is as timely as it is relevant given that healthcare institutions are increasingly being tasked with the responsibility of delivering quality care at a cheaper price.

From the business standpoint, the application of AI in health care has a number of strategic implications. AI brings a new way to healthcare organizations to shift from the paradigm of episodic care to a proactive model based on data analysis. The fact that AI can predict the needs of patients and study their state to find issues before they turn into severe conditions allows moving from the treatment approach to the preventive one. This change is in step with the development of value-based care systems in which physicians are rewarded for the outcomes of their actions and specifically for minimizing the number of invasive procedures. AI thus has a significant responsibility of helping organizations to adapt new business models to meet emerging patient, insurer, and regulatory expectations.

In fact, the benefits of AI go beyond the benefits that patients and staffs will reap from the technology. Since AI allows healthcare organizations to make care more individual and enhance clinical results, patient satisfaction may improve resulting in improved patient loyalty and retention. When consumers are empowered as they become more involved in their care, they will want to get care from organizations that are likely to offer solutions that are more enhanced by artificial intelligence. Thus, the improved patient experience along with operating efficiency allows healthcare organisations to enhance their competitiveness in the context of the growing market saturation. The financial consequences are also phenomenal as AI can open up new revenue streams for an organization through products like telemedicine, remote monitoring, and customized health care services.

However, the integration of AI also presents some of the issues that need to be solved by healthcare organizations. Another crucial issue is to understand whether the organisation can support the integration of AI solutions into its infrastructure as a major priority. The IT structure of a healthcare organization must be adequate to store the tremendous amount of information that belongs to AI systems, and secure and compliant with the law such as HIPAA or GDPR. There are always issues of data governance and privacy that need to be paid attention to in order to avoid misuse, loss of patient data, and thus the patient trust. Leaders need to engage IT experts on how to incorporate AI with the current EHR systems and other technologies in the provision of healthcare.

Another critical issue is the issue of resistance to change. AI utilization is a paradigm change in the delivery of health services, and this change may be resisted by staff of the health institutions including clinician, administrators, and IT personnel. To achieve this, healthcare leaders need to share the value proposition of AI and engage staff in the process. This involves developing courses, which will help educate and empower the workforce to not only engage AI tools and technologies but to do so responsibly. It is important for managers to be honest in explaining how AI is going to help patients get better care and why employee's jobs are not at risk. When it comes to the integration of AI into healthcare organisations, the culture of innovation and continuous education will be beneficial.

AI also needs a good change management plan, which involves the management of technology and people as well. AI is not a mere process of procuring software or hardware and getting them installed; it is a process of change management. Managers need to assess readiness for change on the technological level and the organizational level of culture. Appointing an IT department, medical workers, lawyers, and mangers who are aware of business goals and requirements can contribute to creating the right vision of the use of AI. However, there is a need for constant assessment and follow up to check on the efficiency of AI tools with relevant feedback necessary to make improvements.

Ethical and regulatory issues are also core to the AI adoption process, and are often considered as being within the scope of AI governance. These aspects mean that today the leaders of healthcare organizations have to take a number of steps to guarantee the integration of AI technologies into the work of healthcare systems adheres to the current legislation and ethical norms. This comprises of AI awareness of how it integrates with the healthcare legal requirements, payment procedures, and patient confidentiality regulations. Policies on the use of data must be well articulated to maintain the privacy of patient data while at the same time making AI systems more open, safe, and neutral. When AI models are trained with big data, it becomes mandatory that the data should not be biased and should include all kinds of patients to avoid discriminating them. AI is not just a question of ethics, but it is about the patient, the doctor-patient relationship and about developing an AI that is going to be used properly in the right way for the patient.

When considering the future of healthcare organisations, the issues of strategy in connection with the implementation of artificial intelligence are vast. Healthcare is on the verge of a revolution with AI as a technology that can revolutionize the practice of care delivery, processes and organizational structures. AI technology if deployed efficiently can help healthcare organisations become more efficient and deliver better patient experience and value at lower cost. The business processes linked to AI, including market opportunities, new services development and enhancing patients' experience, ensure AI becomes the cornerstone of competitiveness. But four issues namely infrastructure, change management, and ethics should be well managed to ensure that AI is implemented effectively and sustainably.

In conclusion, it is apparent that the integration of AI in healthcare poses great opportunities for increasing the quality of care delivery, increasing organizational effectiveness, and fostering new thinking about business model innovation. The issues that are important for healthcare leaders are the integration of AI for organizational objectives, workforce preparedness, and infrastructure and governance considerations. Thus, when healthcare organizations embark on an AI journey, they can embrace the opportunities AI offers while tackling the ethical, regulatory, and cultural issues that will follow it. Therefore, AI is on its way to becoming the transformative driver of healthcare management and delivery, with potential for the sustainable changes to the business and clinical sides of healthcare organizations.

APPENDIX A

SURVEY COVER LETTER

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APPENDIX B

INFORMED CONSENT

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APPENDIX C

INTERVIEW GUIDE

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<Follow APA or Harvard citation format and guidelines. Indicate materials referenced in the dissertation and from sources you have used.>

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{Author, A. A., Author, B. B., & Author, C. C. (Year). Title of article. *Title of Periodical, volume number*(issue number), pages. http://dx.doi.org/xx.xxx/yyyyy}

APPENDIX A:

FIRST APPENDIX TITLE [USE “CHAPTER TITLE” STYLE]

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