VOICE-BASED CLASSIFICATION OF PATIENTS USING VARIOUS MACHINE LEARNING & DEEP LEARNING TECHNIQUES IN RELATION WITH BUSINESS PERSPECTIVES

by

Satyajit Pattnaik, MSc, Data Science, LJMU

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Satyajit Pattnaik

APPROVED BY

Dr. Aaron Nyanama

<Chair's Name, Degree>, Chair

Dr. Atul Pati Tripathi, PhD

<Member's Name, Degree>, Committee Member

Apostolos Dasilas ADasilas

<Member's Name, Degree>, Committee Member

RECEIVED/APPROVED BY:

Pro. Atul Pati Tripathi, PhD

SSBM Representative (Mentor)

Dedication

I dedicate this research project to all those individuals who have been affected by voice and speech-related pathological disorders. Your struggles and challenges have inspired me to delve into the field of voice-based classification and explore its potential in improving diagnosis and early detection of diseases. I would like to express my gratitude to the participants who generously shared their voice and pathology data, enabling us to gain a deeper understanding of various voice disorders. Your contribution has been instrumental in shaping this research and has the potential to positively impact the lives of many individuals facing similar challenges.

This project is also dedicated to the healthcare professionals and researchers who have tirelessly worked to advance our understanding of voice disorders. Your commitment to improving patient care and finding innovative solutions has been a driving force in this research endeavor. I would like to acknowledge the support and guidance of my supervisor, whose expertise and encouragement have been invaluable throughout this journey. Your belief in the importance of this research has motivated me to push boundaries and explore new avenues in voice-based categorization.

Lastly, I would like to dedicate this project to my family and loved ones who have provided unwavering support and understanding throughout this process. Your patience, love, and encouragement have been the pillars of strength that have propelled me forward. May this research contribute to bridging the gap between healthcare and business domains, opening doors for innovation, and ultimately making a positive difference in the lives of individuals affected by voice disorders.

Acknowledgements

This project would not have been possible without the financial support of my supervisor, to whom I am extremely grateful. I have truly enjoyed working on this and various other projects. Each member of my Dissertation Committee has provided invaluable guidance and imparted a wealth of knowledge about scientific research and life in general. I am particularly grateful to Professor, who has exemplified the qualities of an exceptional scientist.

I would like to express my deepest appreciation to my family members, who have been more instrumental in my completion of this project than anyone else. I am indebted to my parents for their unwavering love and guidance throughout my life. They have served as remarkable role models, and I cannot thank them enough for the sacrifices they have made on my behalf. Their prayers and support have sustained me throughout this journey.

Lastly, I would like to express my gratitude to my caring Father, my God. I am thankful for Your assistance in persevering through difficult times. Every day, I have felt Your presence, and it is because of You that I have been able to successfully complete this project. I will continue to place my trust in You for the rest of my life. Thank you, Lord, for your unwavering support and guidance.

ABSTRACT

VOICE-BASED CLASSIFICATION OF PATIENTS USING VARIOUS MACHINE LEARNING & DEEP LEARNING TECHNIQUES IN RELATION WITH BUSINESS PERSPECTIVES

Satyajit Pattnaik
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Dissertation Chair: <Chair’s Name>
Co-Chair: <If applicable. Co-Chair’s Name>

This report presents a unique research proposal that focuses on exploring the commercial implications of voice-based patient categorization through the utilization of machine learning and deep learning algorithms. The study encompasses a comprehensive approach, consisting of an extensive literature review, the development of modeling techniques, and the analysis of case studies to accomplish its research objectives.

The initial literature review conducted sheds light on the effectiveness of deep learning and machine learning methodologies, such as 1D Convolutional Neural Networks (CNNs) and Fourier transformation, in effectively distinguishing between normal and diseased voices. Moreover, the review showcases various studies that have examined the

business perspectives of voice-based classification, showcasing its potential applications in domains such as customer service and market research.

The research strategy outlined in the discussion section emphasizes the significance of conducting a comprehensive literature review to gain insights into the existing knowledge in the field of voice-based classification. In addition, the study proposes the utilization of modeling techniques to enhance and develop deep learning and machine learning models for voice-based categorization. This includes employing methods such as 1D CNNs, Fourier transformation, and 2D CNNs with spectrograms. Furthermore, a detailed case study analysis will be conducted to explore the practical implementation and commercial applications of voice-based categorization across diverse business contexts.

By addressing the commercial aspects of voice-based classification, this proposed research aims to bridge the existing knowledge gap. It seeks to provide valuable insights into the potential applications of voice-based categorization within various industries while identifying factors such as organizational preparedness, technological requirements, and data protection considerations. The inclusion of case studies will serve to illustrate how voice-based categorization can be seamlessly integrated into existing business processes, highlighting both the advantages and challenges associated with its implementation.

The anticipated outcomes of this research endeavor encompass the identification of novel applications for voice-based categorization, providing guidance for businesses contemplating its implementation, and fostering a deeper understanding of the benefits and limitations of this technology. Additionally, by establishing connections between the healthcare and business domains, this study aims to stimulate innovation and explore the broader applications of voice-based categorization beyond the medical field.

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CHAPTER I:

INTRODUCTION

1.1 Introduction

Voice-based classification of patients using machine learning and deep learning algorithms has emerged as a promising research area with potential implications in healthcare and beyond. This approach aims to revolutionize the identification and treatment of voice abnormalities, leading to improved patient care, customized treatments, and enhanced healthcare management [1]. Voice difficulties experienced by individuals can indicate underlying medical conditions that require timely intervention. Researchers have made significant progress in developing models and algorithms that analyze speech data and classify patients based on their vocal traits. Machine learning techniques, such as 1D Convolutional Neural Networks, Fourier transform, and 2D CNNs with spectrograms, have been effective in distinguishing healthy and diseased voices.

The applications of voice-based classification extend beyond the healthcare sector, offering significant business perspectives. In customer service, speech analysis can be used to recognize customer stress levels, understand emotions, and provide tailored responses. Voice-based classification can also contribute to market research by extracting valuable insights from customer discussions, helping businesses understand consumer preferences and emerging trends [2]. Moreover, in fraud detection, voice analysis can identify irregularities and potential threats by analyzing voice patterns associated with fraudulent activities. This research aims to investigate the commercial implications of voice-based patient categorization in non-medical domains. By exploring the uses, advantages, challenges, [3] and ethical considerations of implementing voice-based categorization systems, this study seeks to bridge the existing gap in the literature. It will critically evaluate current research, identify gaps, and propose solutions.

Artificial Intelligence (AI) stands as a pivotal technique catering to the demands of complex decision-making and diverse intelligence tasks. It provides a sophisticated framework that effectively harnesses controlled capabilities. At its core, AI encompasses a vital component known as deep learning. While neural networks have showcased their prowess across various applications, there's a sense that the initial fervor surrounding this technology has somewhat diminished.

In 2006, a significant development emerged as Geoffrey Hinton and his colleagues introduced "Deep Learning" (DL) as an evolution of the artificial neural network concept. This milestone marked a turning point, propelling the field into new dimensions of understanding and innovation. Since then, the exploration of AI's potential has taken intriguing directions.

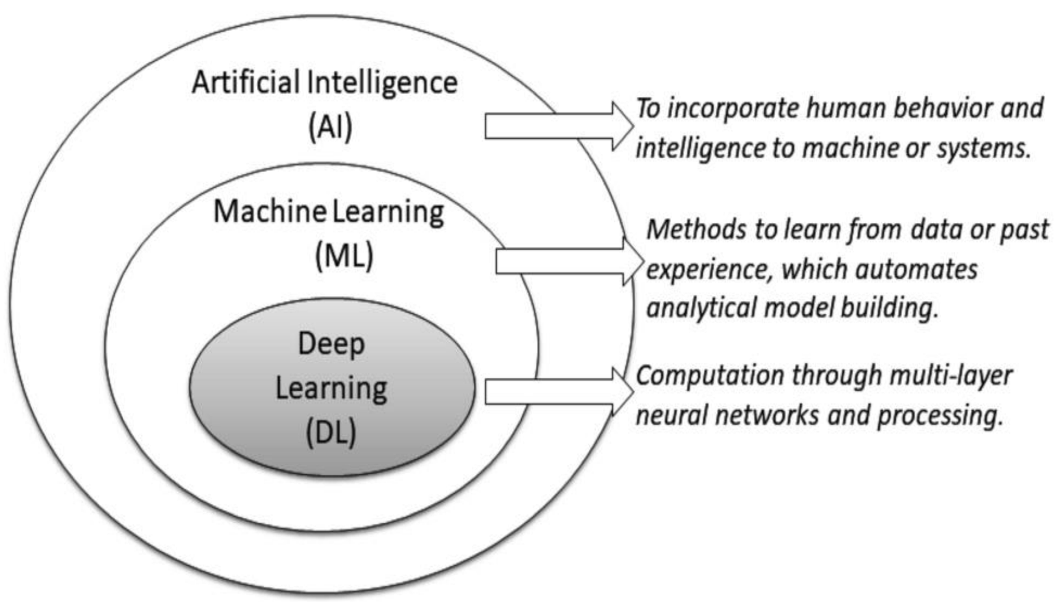

Figure 1. Machine Learning Model

One such avenue that has gained prominence is transfer learning. This concept has stirred considerable interest, often referred to as a novel facet of machine learning algorithms. Transfer learning entails leveraging the knowledge gained from solving one problem and applying it to another related problem. This approach accelerates the learning curve and optimizes the overall performance of AI systems.

As the realm of AI continues to evolve, the intricacies of deep learning and the diversification of its applications remain ripe for exploration. The fusion of AI, deep learning, and transfer learning presents an exciting journey filled with discovery and potential breakthroughs.

Deep learning and machine learning approaches have shown promise in accurately classifying voice abnormalities, making them suitable for commercial purposes. By applying these approaches in different business contexts, organizations can improve customer satisfaction, gather market insights, and enhance fraud detection mechanisms.To date, limited research has explored the commercial perspectives of voice-based classification. This study intends to fill this gap by examining how businesses can benefit from voice-based categorization in customer service, market research, and fraud detection. A comprehensive literature review will establish a theoretical foundation and identify the current state of knowledge [4]. Modeling techniques will be used to develop and enhance deep learning and machine learning models tailored for voice-based categorization. These models will be validated and evaluated based on their effectiveness in distinguishing between healthy and diseased voices.

Recently, artificial intelligence (AI) has gained significant prominence as technology strives to replicate human intelligence. The fascination with machine learning has captivated computer scientists since the 1950s, and over time, machines' capabilities have steadily risen [5]. Particularly, deep learning has gained remarkable traction, further accelerated by the challenges posed by the COVID-19. An illustrative application of this is face recognition technology, which has gained immense popularity in the era of touchless interactions. This technology offers a high level of authenticity, capitalizing on the unique nature of each individual's face.

Beyond touchless interactions, various sectors like healthcare, banking security, retail, travel, and airports have recognized the potential of integrating machine learning techniques [6]. This strategic shift is aimed at optimizing and streamlining processes during and post the ongoing pandemic. The influence of machine learning extends far and wide, permeating diverse domains. In the research community, the pursuit of innovation involves continuous exploration of both emerging and existing subjects [7]. The intricate relationship between AI, machine learning, and deep learning is graphically represented in the diagram below.

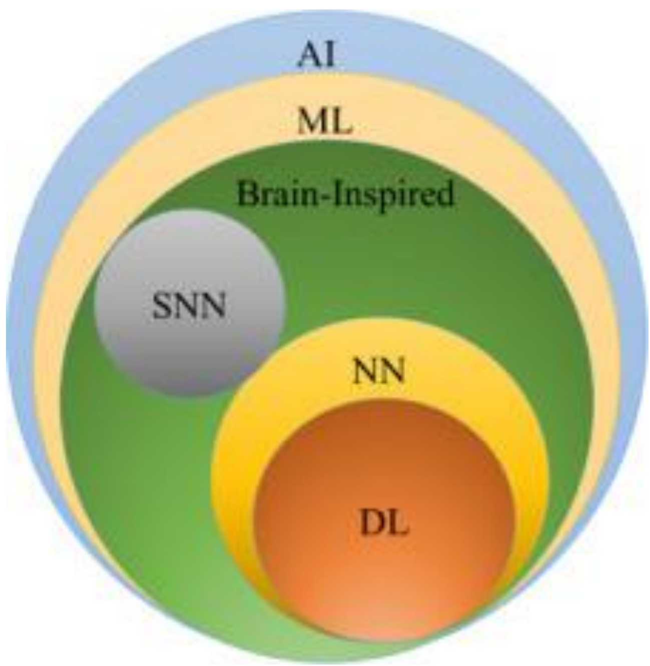

Figure 2. Relation between AI, ML and DL [8]

In today's world, a considerable number of individuals grapple with speech-related disorders, leading to an array of speech impairments. These challenges stem from various factors, including genetic anomalies, neurological conditions, brain injuries, smoking, and more. Conditions like dysphonia, laryngitis, and paralysis of vocal cords contribute to a spectrum of speech abnormalities.

Recent research studies have unveiled remarkable breakthroughs in image classification, leveraging deep neural networks, particularly Convolutional Neural Networks (CNN models). While CNNs are commonly employed for image datasets, they've found utility in non-image datasets with the inclusion of diverse data. This is especially pertinent when it comes to speech data, essentially represented as one-dimensional data. Voice information, essentially the amplitude plotted against time, can be translated into spectrograms (images) and subsequently processed using 2D CNN models. In the realm of image classification complexities, the prevalent use of 2D CNN models is notable.

In the realm of intelligent data analysis, a suite of techniques, including machine learning algorithms and deep learning methods, coexist to unravel insights from diverse datasets. However, selecting the most suitable approach from these two methods for a specific domain's goals is no straightforward task; it presents a substantial challenge. The outcome of this project, encompassing rigorous study and model development, holds promising implications for the healthcare and insurance sectors. The proposed methodology introduces an inventive technique designed to identify and categorize individuals' health status based on their speech patterns.

This innovative system is poised to gather voice data, meticulously assess speech nuances, and generate a health score in real-time when deployed on a practical device. The healthiness score serves as a measure of an individual's well-being; a higher score corresponds to better health, and conversely, a lower score indicates potential health concerns.

This research endeavor aims to differentiate between healthy and ailing patients using diverse methodologies within the realms of deep learning and machine learning. To enhance model accuracy and efficiency, multiple machine learning and deep learning models will be assessed by incorporating distinct features derived through meticulous feature engineering. The outcomes of this project hold promise for the healthcare and insurance sectors. The proposed innovative approach seeks to identify and categorize individuals based on their speech patterns. The envisioned system will gather voice data, analyze speech nuances, and generate a health score in real-time. A higher health score would indicate better health status and vice versa.

Time, frequency, Mel-frequency cepstral coefficients (MFCCs), and various spectral attributes from the frequency domain are commonly extracted from speech data using Fourier transforms. Numerous studies have explored voice-based categorization for specific pathological conditions. Notably, a researcher developed an automated method for identifying and categorizing Amyotrophic Lateral Sclerosis (ALS), a speech disorder linked to genetics or environmental factors. This involved the application of Machine Learning techniques like Support Vector Machines (SVMs) and Deep Neural Networks (DNNs). The primary focus of this methodology was to detect ALS through brief, pre-symptomatic speech acoustics and articulatory data.

Furthermore, this research will conduct case study analyses in collaboration with industry partners from various sectors [9]. By studying real-world implementations and understanding the challenges encountered, the study will gain practical insights into the commercial applications of voice-based categorization. In summary, this research aims to explore the commercial implications of voice-based patient categorization, filling the gap in the literature. By providing insights, identifying research gaps, and proposing novel solutions, this study will contribute to the understanding of voice-based categorization in non-medical sectors.

1.2 Problem Statement

The research problem of this study revolves around the lack of research exploring the commercial implications of voice-based patient categorization using machine learning and deep learning algorithms in non-medical sectors. While there has been significant progress in applying voice-based classification in healthcare settings, its potential applications and benefits in other industries remain largely unexplored. Understanding the uses, advantages, challenges, and ethical considerations of implementing voice-based categorization systems in businesses is essential for maximizing its commercial potential.

While the review highlights the potential applications of voice-based categorization in businesses, there is a gap in the literature regarding the real-world implementation challenges, ethical considerations, and user acceptance factors that organizations may encounter when integrating voice analysis into customer service, fraud detection, and market research efforts. Further research is needed to address these practical aspects.

1.3 Purpose of Research

The purpose of this research is to investigate the effect and commercial implications of voice-based patient categorization using machine learning and deep learning algorithms. The study aims to explore how businesses can leverage voice-based categorization in various industries, including customer service, market research, and fraud detection. By conducting a comprehensive literature review and employing modeling techniques, the research seeks to develop a theoretical foundation and practical insights into voice-based categorization in non-medical sectors. The ultimate goal is to estimate of future of organizations considering the adoption of voice-based categorization, enabling them to optimize customer satisfaction, gain market insights, and enhance fraud detection mechanisms.

1.4 Significance of the Study

This study holds significant significance for both academia, healthcare and industry. From an academic perspective, it fills the research gap by investigating the commercial perspectives of voice-based patient categorization. By analyzing the current state of knowledge, identifying research gaps, and proposing novel solutions, the study contributes to the understanding of voice-based categorization beyond healthcare domains. The research findings will provide a solid theoretical foundation for further studies and serve as a reference for researchers interested in exploring the commercial implications of voice-based classification.

From an industry standpoint, the study offers valuable insights into the potential applications, advantages, challenges, and ethical considerations of voice-based categorization in non-medical sectors. Businesses can benefit from understanding how voice-based categorization can enhance customer service by recognizing emotions and tailoring responses, improve market research insights by analyzing voice patterns, and strengthen fraud detection mechanisms by identifying irregularities. The findings of this research can guide organizations in implementing voice-based categorization effectively, leading to improved customer satisfaction, personalized experiences, and increased operational efficiency.

Overall, this study's significance lies in its potential to bridge the gap between research and practice, offering practical guidance and maximizing the commercial potential of voice-based patient categorization in non-medical sectors.

1.5 Research Questions

It is hypothesized that voice-based categorization has significant business potential and can be utilized in various industries to enhance customer service, improve market research insights, and aid in fraud detection. The successful implementation of voice-based categorization in non-medical sectors can result in improved customer satisfaction, personalized experiences, and increased efficiency in business operations.

This study seeks to address the following sub-questions

1. How much is the implementation of voice-based categorization systems in business?
2. What are the primary reasons for implementing voice-based categorization in the business?
3. What are the potential applications of voice-based categorization in different industries, such as customer service, market research, and fraud detection?
4. What are the advantages and benefits of implementing voice-based categorization in businesses?
5. What challenges and limitations are associated with voice-based categorization in non-medical sectors?
6. What ethical considerations arise when using voice-based categorization systems in commercial settings?
7. How can voice-based categorization be integrated into existing business processes effectively?

To answer these questions, a comprehensive literature review will be conducted to analyze the current state of knowledge regarding voice-based categorization and its business applications. Modelling techniques, including 1D Convolutional Neural Networks, Fourier transformation, and 2D CNNs with spectrograms, will be employed to develop and enhance deep learning and machine learning models for voice-based categorization. Case study analyses will be conducted to explore the practical implementation and outcomes of voice-based categorization in diverse business contexts.

The research will contribute to the existing body of knowledge by providing insights into the potential uses, advantages, challenges, and ethical considerations of voice-based patient categorization in non-medical sectors (Zhang, 2021). It is anticipated that the findings will offer valuable guidance for businesses considering the adoption of voice-based categorization, allowing them to make informed decisions and maximize the potential benefits of this technology

Choosing the right learning algorithm tailored to a specific domain's objectives presents a formidable challenge. This complexity arises from the fact that various learning algorithms serve distinct goals, and the outcomes of similar techniques can diverge based on the properties of the data they encounter. Hence, comprehending the nuances of different machine learning techniques and discerning their suitability across various sample applications is crucial.

Within the realm of data science, addressing sound pathology involves tackling a multiclass classification problem grounded in individual audio signals. A plethora of machine classifiers are commonly employed to detect instances of sound pathology. To enhance the performance of these techniques, several strategies have been devised to more effectively distinguish between healthy and diseased sounds. These approaches often revolve around defining criteria for sound quality and devising innovative tools to identify voice irregularities.

The roots of machine learning trace back to the pioneering work of Arthur Samuel, an influential figure in both AI and computer gaming. He coined the term "machine learning" in 1959 to capture the advancement of machines in learning from experience. Even earlier, in 1948, Turing and Champernowne crafted the first computer-based chess game using rudimentary tools like paper and pencil. By 1951, Dietrich Prinz showcased his distinct chess gaming system. In 1952, Christopher Strachey devised a pioneering algorithm for playing draught games. The 1970s witnessed the continued fascination with pattern categorization, as evidenced by Duda and Hart's work. Moving ahead, in 1981, the inception of neural networks, which could learn and recognize 40 characters, marked a significant milestone.

1.6 Aims and Objectives

The primary focus of this research is to investigate the commercial implications of utilizing voice-based patient categorization through machine learning and deep learning algorithms in non-medical sectors. This study aims to address the gap in literature by exploring how businesses can leverage voice-based categorization for enhanced customer service, improved market research insights, and effective fraud detection mechanisms.

Aims

1. To explore the potential applications of voice-based categorization in various industries such as customer service, market research, and fraud detection.
2. To identify the advantages and benefits that implementing voice-based categorization can offer to businesses.
3. To analyze the challenges and limitations associated with integrating voice-based categorization into non-medical sectors.
4. To examine the ethical considerations arising from the implementation of voice-based categorization systems in commercial settings.
5. To propose effective strategies for integrating voice-based categorization into existing business processes.

Objectives

1. To assess the feasibility of applying voice-based categorization techniques in different sectors, including customer service, market research, and fraud detection.

2. To evaluate the potential benefits of incorporating voice-based categorization, such as improved customer satisfaction, enhanced market insights, and strengthened fraud prevention.
3. To identify and analyze the challenges that businesses may encounter when implementing voice-based categorization outside the healthcare domain.
4. To investigate the ethical implications of using voice-based categorization systems, considering issues such as privacy, consent, and bias.
5. To develop practical guidelines and recommendations for organizations to effectively integrate voice-based categorization into their operations.
6. To employ machine learning and deep learning models, such as 1D Convolutional Neural Networks and Fourier transformations, to demonstrate the feasibility of voice-based patient categorization.
7. To conduct case study analyses in various industries, highlighting successful implementations of voice-based categorization and their outcomes.
8. To provide insights into the potential advantages and limitations of voice-based categorization for businesses, aiding decision-making processes.
9. To contribute to the academic understanding of the commercial applications of voice-based categorization in non-medical sectors.
10. To offer actionable insights that can guide organizations in adopting and optimizing voice-based categorization for their specific needs.

CHAPTER II:

REVIEW OF LITERATURE

2.1 Literature Review

The voice-based categorization of patients using various machine learning and deep learning algorithms is a viable research field. It could significantly affect how voice problems are found and handled. Correctly classifying vocal disorders can lead to more individualized patient treatment plans and better healthcare administration in general. This study examines the practical applications of voice-based categorization while highlighting its importance, novelty, and potential advantages for management and business [10]. Many people have vocal problems, which can result in some speech-related problems. These anomalies can be symptoms of underlying disorders, demanding immediate medical attention to stop additional harm. This distinction forms the basis for developing models and algorithms that analyze speech data and classify patients based on vocal characteristics [11].

In the contemporary electronic world, many forms of data exist, including information from the IOT, cybersecurity, smart cities, corporations, social media, COVID-19, and many more. Organized, semi-structured, and unstructured data is always expanding [12]. The insights gleaned from this data can be used to build a range of intelligent applications in the relevant domains. The essential data can be utilized to develop a data-driven system [13]. Vocal abuse, exhaustion, environmental changes, muscular dystrophy, face discomfort, and infections of the voice tissue are only a few of the causes of voice problems. Due to the enormous demands placed on their vocal apparatus, professionals who largely rely on their voices, such as actors, singers, auctioneers, attorneys, and teachers, are more susceptible to acquiring these diseases.

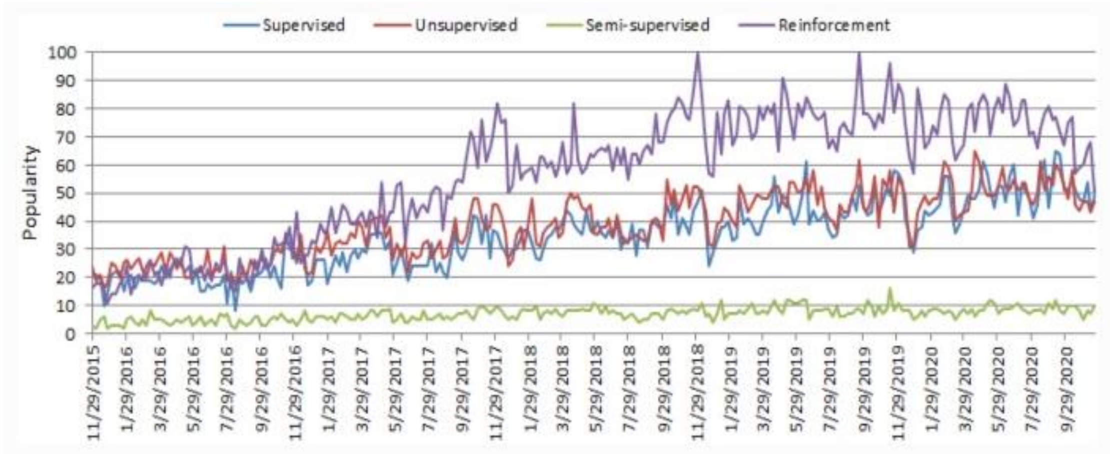

Figure 3. The worldwide popularity of ML Algorithms

The potential of voice-based categorization technologies to transform company processes has attracted a lot of interest recently. These tools enable organizations to categorize and glean insightful information from voice data by analyzing and interpreting spoken language using machine learning and deep learning techniques. For businesses looking to use voice-based categorization efficiently, it is essential to comprehend the elements that affect its acceptance in professional contexts [14]. This literature review aims to provide light on the adoption trends, underlying factors, and potential future research directions for voice-based categorization in commercial contexts. Here is a survey of the literature based on some of the key recent studies emphasizing the commercial use of voice-based categorization methods [15].

Voice abnormalities can indicate underlying medical conditions and speech-related issues, necessitating prompt treatment to prevent further damage. The identification and classification of these abnormalities play a crucial role in providing accurate diagnoses and personalized treatment regimens [16]. Researchers have made substantial progress in developing machine learning and deep learning models that can effectively distinguish between healthy and diseased voices. Methods such as 1D Convolutional Neural Networks

(CNNs) have been used to analyze speech data and classify patients based on their vocal traits (Omeroglu, 2022).

Machine learning encompasses a diverse array of application domains and subfields, as documented in literature. The practical applications span a wide spectrum and are vividly portrayed in the diagram below.

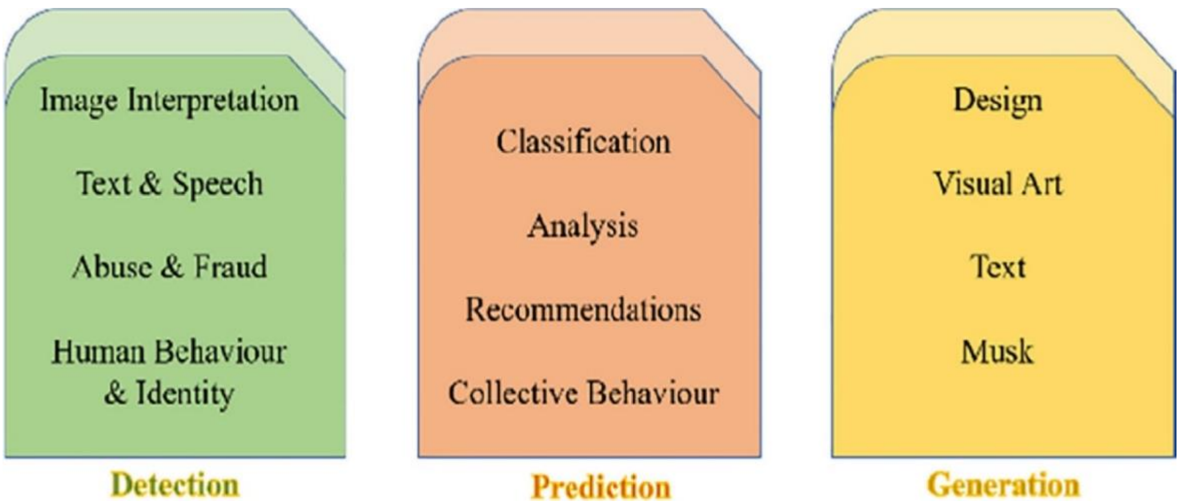

Figure 4. Application of ML and DL

A study by Laura Verde and her colleagues delves into the realm of neural network-based decision-making systems for the identification of vocal pathology. Their work encompasses a comprehensive exploration of various machine learning approaches to discern vocal disorders [17]. The assessment is conducted on a dataset extracted from the SVD database, with a focus on voices. Within this study, a distinctive Convolutional Neural Network (CNN) centered approach is outlined, specifically designed for identifying pathological speech (Wu, 2018). This innovative system combines segments of the SVD database to create audio files conducive to speech disorder detection. The fusion of the American and German databases, MEEI and SVD, provides a framework to employ Neural Networks (NN) and Support Vector Machines (SVM) for vocal issue detection.

The researcher draws upon the Saarbruecken Voice Database (SVD), a publicly accessible resource recorded [18] by the Phonetic Institute at the University of Saarland in Germany. This database comprises voice recordings from both healthy and pathological individuals. Among its contents are 1354 pathological voice recordings (627 male and 727 female) representing 71 distinct conditions, along with 687 healthy voice recordings (259 male and 428 female) [19]. These recordings encompass German vowels and phrases like "Good morning, how are you doing?"

For the classification of healthy and diseased sounds, a focus is placed on the /a/ vowel and all available records within the SVD database. Each data sample includes the voice ID, age, gender, and classification information (healthy or pathological). The assessment encompasses the entire database as well as a balanced subset of 685 male and female participants.

In current clinical practice, dysphonia assessment adheres to guidelines suggesting a laryngoscope examination if symptoms persist or worsen beyond four weeks. However, diagnostic discrepancies between primary healthcare providers, laryngologists, and pathologists have been observed, often due to varying expertise in interpreting vocal and speech conditions [20]. While the laryngoscope examination is considered invasive and necessitates skilled execution, its equipment is costly and rarely accessible in outpatient settings. Regions with limited medical resources often experience delays in diagnosis and treatment. Addressing this challenge calls for a noninvasive diagnostic tool that can be used in lieu of a laryngoscope assessment. Nonetheless, this tool should serve as a screening method, encouraging patients to seek further evaluation at a specialized voice clinic [21].

In addition to this, unique studies have endeavored to differentiate between normal and abnormal sound quality through various machine learning classifications. These techniques excel in recognizing disordered voices. A notable achievement using deep neural networks has resulted in an impressive 99.32% accuracy in identifying abnormal speech [22]. However, distinguishing among various types of impaired voices remains an ongoing challenge. Specific vocal fold vibration patterns, such as those observed in common vocal fold disorders like shrinkage, bilateral vocal palsy, and spontaneous vocal tract injuries, present distinct characteristics that are still not comprehensively documented.

In the realm of learning algorithms, there exist four primary types as depicted in the diagram below [23]: reinforcement learning, supervised learning, unsupervised learning, and semi-supervised learning. Each of these approaches plays a distinct role in the landscape of data-driven insights, and their practical applications span a variety of real-world scenarios.

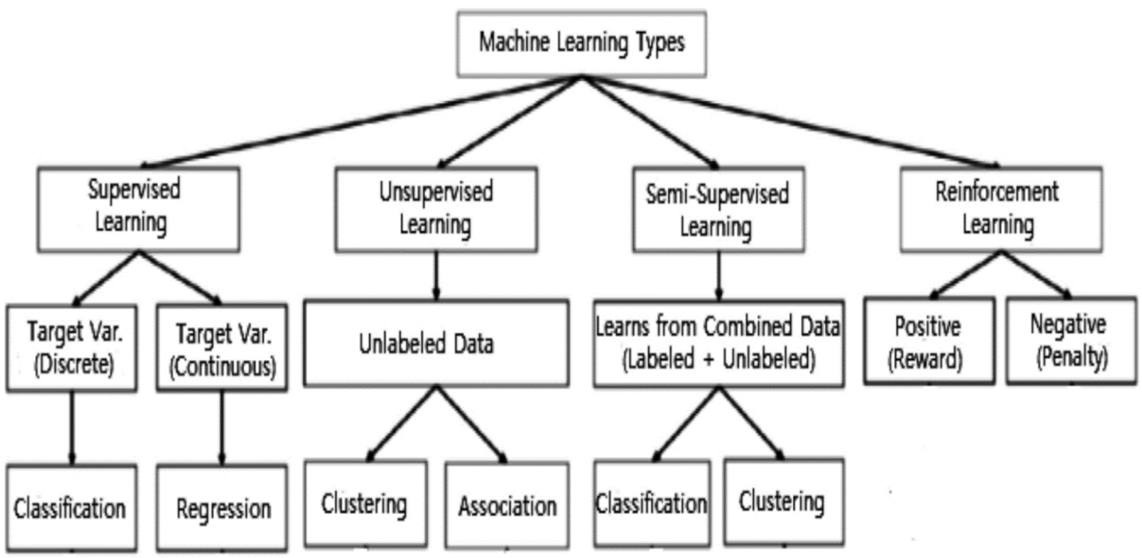

Figure 5. Types of ML

Reinforcement learning involves training software and machines to autonomously make optimal decisions within specific environments and contexts, thereby enhancing their efficiency. This approach empowers AI models to learn through trial and error, eventually determining the best course of action to take. This methodology finds its application in diverse fields such as robotics, autonomous vehicles, and even supply chain management. However, its strength lies more in tackling complex tasks rather than simpler ones.

Supervised learning, on the other hand, entails training a model on labeled data to predict outcomes accurately. It's like a teacher guiding the learning process by providing correct answers [24]. This approach is widely employed when clear examples of desired outputs are available.

Unsupervised learning delves into uncharted territory, working with unlabeled data to identify patterns and structures. Unlike supervised learning, there's no teacher here; the algorithm seeks insights independently. This method is particularly beneficial when you're looking to uncover hidden relationships within data.

Now, let's explore semi-supervised learning, which bridges the gap between labeled and unlabeled data. It combines the concepts from both supervised and unsupervised learning. Often, real-world datasets have limited labeled data, but there's an abundance of unlabeled information. Semi-supervised learning leverages this scenario, making it a powerful tool for scenarios where resources are constrained.

A noteworthy aspect of this discussion is the suggested application of learning algorithms with a focus on incentives and responsibilities. This innovative approach involves incorporating insights from environmental campaigns to enhance incentives and reduce unnecessary costs. It can prove instrumental in developing AI models that not only promote automation but also enhance the overall efficiency of intricate systems.

In summary, the realm of learning algorithms presents a spectrum of strategies to tackle various challenges. Each approach has its strengths and is suited for different types of problems. As technology evolves, these techniques will continue to shape the landscape of artificial intelligence and contribute to solving complex real-world problems.

In telehealth services, effective communication between doctors and patients is crucial for promoting patient health. However, assessing the quality of these medical conversations can be a labor-intensive and time-consuming task, typically requiring trained experts to use specific evaluation criteria. As the volume of consultations continues to grow rapidly, this manual evaluation process becomes impractical. Therefore, Habib, M et al., explores the possibility of automating the evaluation process for patient-doctor voice-based conversations in telehealth services, using a deep-learning-based classification model. The results of the evaluation indicate that the model surpassed manual evaluation, as conducted by Altibbi's operations team, in terms of precision. This demonstrates the model's impressive level of accuracy [25].

2.2 Theory of Reasoned Action

A well-known theoretical framework for explaining human behaviour in connection to the adoption of new technology is the Theory of Reasoned Action (TRA), which Fishbein and Ajzen presented in 1975 [26]. This idea contends that a person's behavioural purpose is impacted by their views towards the behaviour and the arbitrary standards attached to it. In the context of technology adoption, the TRA suggests that individuals are more likely to adopt voice-based classification technologies if they perceive it positively and if they believe that important others in their social environment also approve of its use

Davis (1989) created the Technology Acceptance Model (TAM), a popular theoretical framework for analysing and forecasting people's acceptance and adoption of new technology [27]. According to TAM, people's attitudes and intentions to embrace a technology are mostly determined by how useful and simple they consider a technology to be. Perceived usefulness is the extent to which individuals believe using the technology will increase their performance or productivity. Perceived ease of use describes how easily users consider a piece of technology to be to use, understand, and operate.

The Innovation Diffusion Theory, introduced by Rogers (1962), focuses on how innovations are adopted and spread within a social system. This theory emphasises the role of different adopter categories and the factors influencing their decision to adopt or reject an innovation [28]. Each is distinguished by its level of readiness to accept new technology and its rate of adoption.

2.3 Human Society Theory

Voice-based categorization has significant implications for businesses across different sectors. By analyzing speech data, organizations can gain valuable insights into customer behavior, emotions, and preferences, enabling them to enhance customer service, market research, and fraud detection efforts. The commercial applications of voice-based categorization are vast and can revolutionize the way organizations operate and interact with their customers [7].

Voice analysis in customer service environments can help organizations recognize client stress levels, understand consumer emotions, and tailor their responses accordingly. By implementing voice-based categorization, organizations can improve customer satisfaction, resolve issues effectively, and enhance experiences [6].Voice-based categorization methods can extract valuable insights from customer discussions, social media chats, and customer contacts, providing organizations with deeper understanding of consumer preferences, feelings, and trends. This integration of voice analysis with conventional market research techniques can offer businesses a competitive advantage by identifying emerging trends and making data-driven decisions.

Voice patterns can be examined to identify irregularities and potential dangers in fraud detection processes [8]. By leveraging voice-based categorization, organizations can detect anomalies in voice recordings and identify potentially fraudulent activities, thereby mitigating risks and safeguarding their operations.

A deep learning (DL) model follows a similar process to that of a machine learning (ML) model, but with a distinct characteristic in its automated feature extraction, eliminating the need for manual human intervention. While machine learning encompasses a range of techniques like k-nearest neighbors, support vector machines, decision trees, random forests, and more, deep learning introduces automation into the feature extraction process. This is especially valuable when constructing models for complex datasets and specific domains. Deep learning, however, demands a substantial amount of data for effective training. The importance of abundant data is rooted in the fact that deep learning algorithms require a sufficient volume of information to perform optimally (LeCun Y, 2015). In cases where data availability is limited, traditional machine learning algorithms, when guided by established criteria, can deliver improved performance.

In the realm of deep learning, working with extensive datasets requires substantial computational power during the training process. This is where Graphics Processing Units (GPUs) come into play, as they excel at handling massive calculations compared to Central Processing Units (CPUs). Consequently, deep learning development heavily relies on high-performance systems equipped with GPUs to ensure efficient processing. In contrast, traditional machine learning methods may not impose the same degree of computational demand.

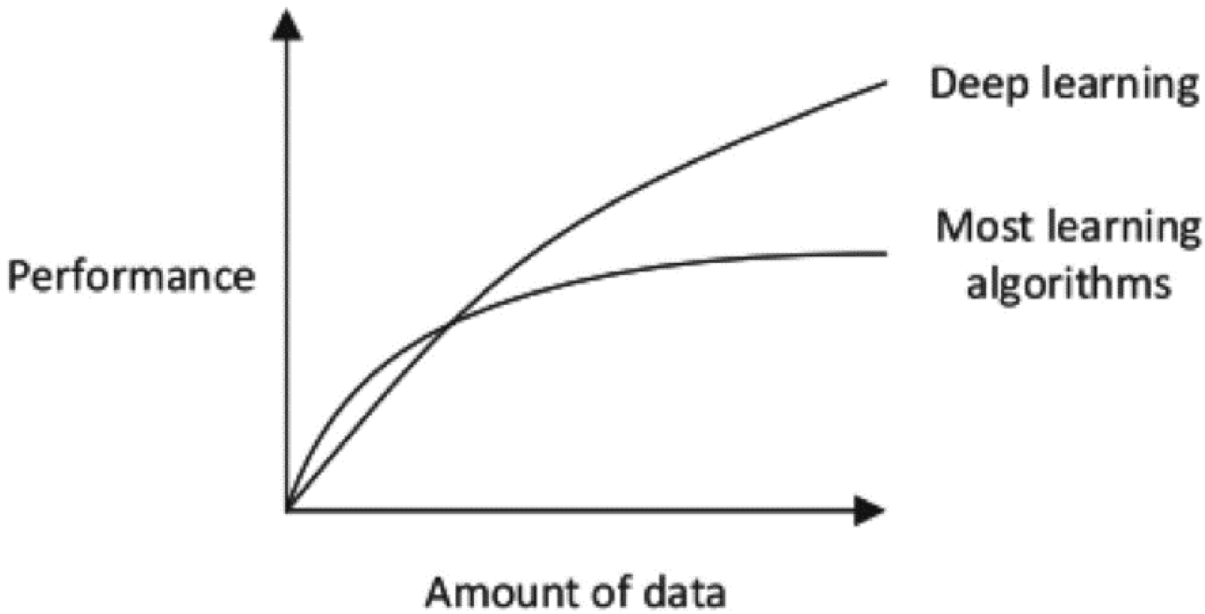

Figure 6. Deep Learning graph

In conclusion, deep learning and machine learning share procedural similarities, but deep learning distinguishes itself through automated feature extraction. While deep learning thrives with ample data, traditional machine learning methods can be enhanced with specific criteria. Moreover, deep learning's data-intensive nature necessitates the utilization of GPUs for efficient processing, underlining the significance of high-performance hardware in deep learning endeavors.

2.4 Theoretical Framework

The purpose of this research is to assess the impact of Voice-based classification on healthcare and business. In order to establish research ideas, guide technique, and evaluate results in good research, a robust theoretical foundation is essential [29]. Two educational philosophies that have guided online learning design are cognitive theory and constructivist theory [30]. According to cognitive theory, material should be presented in an online learning environment in a variety of ways to promote cognitive processing and memory retention. It also means that activities like reflection, teamwork, application, and meta-analysis help learners develop their cognition.

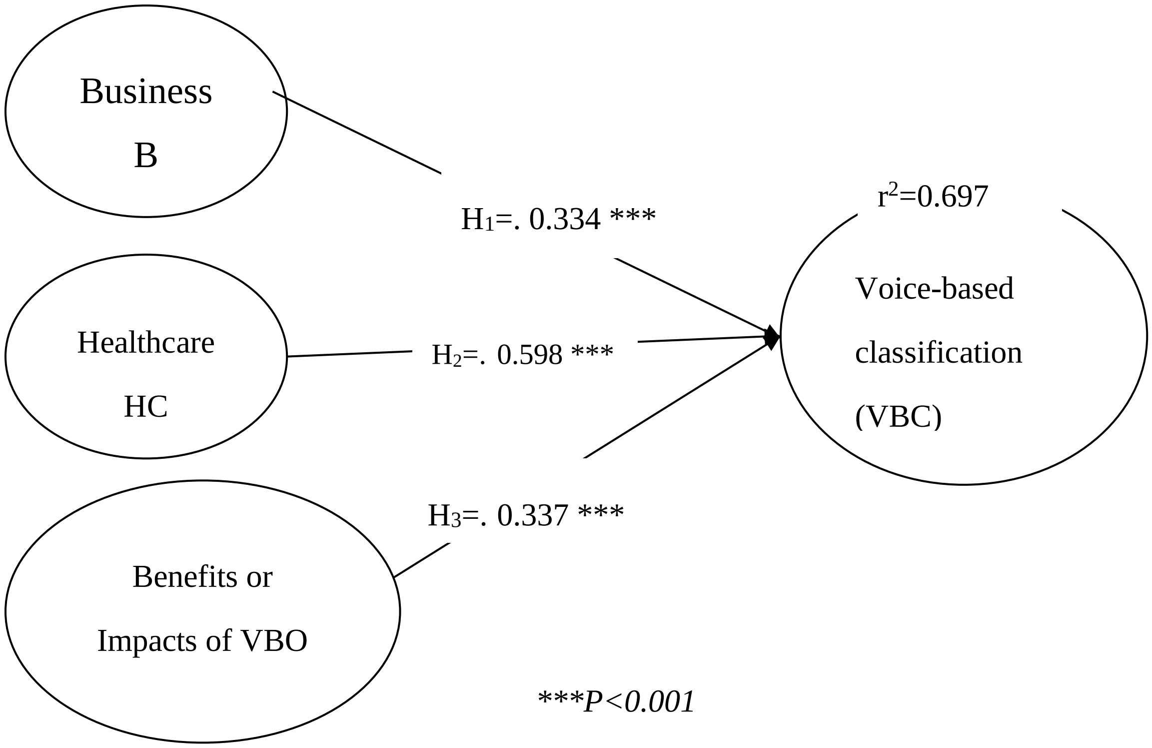

Figure 7. Conceptual model

This Figure shows research model for present research where use of business, healthcare and voice based catagorization are independent variables (IV) and benefits or imapacts is dependent variable (DV).

Table 1 Hypothesis Development**.**

Hypothesis	**Statement**
H1	There is positive significant impact of Voice based categorization on Business.
H2	There is positive significant impact of Voice based categorization on healthcare.
H3	There is positive significant impact of need of implementation of voice based categorization.

The link between an independent variable X and a dependent variable Y is the focus of most quantitative research projects. On the effects between X and Y, statistical effects such as correlation coefficient, mediation, and regression coefficient are determined.

2.5 Summary

- The literature review discusses the Theory of Reasoned Action (TRA) and the Technology Acceptance Model (TAM) as frameworks for technology adoption. However, there is a need for research that integrates these frameworks and explores how social factors, perceived usefulness, and ease of use collectively influence the adoption of voice-based categorization technologies.
- While the review highlights the potential applications of voice-based categorization in businesses, there is a gap in the literature regarding the real-world implementation challenges, ethical considerations, and user acceptance factors that organizations may encounter when integrating voice analysis into customer service, fraud detection, and market research efforts. Further research is needed to address these practical aspects.

The literature review discusses the potential applications of voice-based categorization using machine learning and deep learning algorithms in healthcare. The aim is to accurately classify vocal disorders and provide individualized treatment plans for patients. Voice anomalies can indicate underlying disorders, and analyzing speech data can help identify and classify patients based on vocal characteristics. The review emphasizes the importance of data-driven approaches in the current digital era, where vast amounts of structured, semi-structured, and unstructured data are available. Extracting insights from this data can support the development of intelligent applications in various fields, including healthcare. Machine learning algorithms can be utilised to analyze medical imaging data, predict clinical trial participants, and improve healthcare administration.

In the rapidly evolving landscape of technology, artificial intelligence (AI) has emerged as a dominant force, captivating the imagination of innovators and reshaping industries. This surge in interest is propelled by AI's remarkable ability to mimic human intelligence, offering solutions that span various sectors. The journey of AI dates back to the 1950s, when computer scientists embarked on a quest for machine learning. Over decades, machines have advanced their capabilities, driven by the impetus gained from deep learning methodologies. The unexpected upheaval caused by the global COVID-19 pandemic further accelerated the integration of deep learning into diverse fields, emphasizing its role in navigating unforeseen challenges.

A compelling illustration of AI's impact is the rise of facial recognition technology. In a world seeking touchless interactions, this technology offers a potent blend of convenience and security, leveraging the unique facial features of individuals for authentication. Beyond this, AI's transformative influence extends across healthcare, banking security, retail, and transportation sectors. The deployment of machine learning techniques optimizes processes and enhances efficiency, particularly during and after the pandemic. Visual representations depict the intricate relationship between AI, machine learning, and deep learning, underscoring their interconnectedness.

The paradigm shift lies in the attempt to classify individuals as healthy or unwell based on their speech patterns. Pioneering approaches envision real-time assessment, involving the collection of voice data, intricate speech pattern analysis, and the generation of a health score. This score becomes a surrogate for an individual's well-being, enabling proactive health management.

The sphere of vocal health presents a distinct challenge; as numerous individuals grapple with speech-related disorders. These conditions result from an array of factors, including genetics, nervous system ailments, and lifestyle choices. The spectrum of speech impairments encompasses dysphonia, laryngitis, and other anomalies. Innovative research endeavors have harnessed machine learning algorithms, particularly Convolutional Neural Networks (CNNs), to diagnose vocal pathology. The transformation of speech data into spectrograms enables the utilization of 2D CNN models for analysis.

Transitioning to learning algorithms, the interplay of reinforcement learning, supervised learning, unsupervised learning, and semi-supervised learning assumes a pivotal role. Each approach caters to distinct facets - reinforcement learning optimizes decision-making, supervised learning predicts outcomes with labeled data, and unsupervised learning uncovers patterns in unlabeled data. Meanwhile, semi-supervised learning bridges gaps between labeled and unlabeled data, adapting well to scenarios with limited labeled data.

A pivotal crossroads emerges with the convergence of AI, deep learning, and transfer learning. The latter's premise of applying knowledge gained from one problem to another accelerates learning and augments AI performance. This synergy augments the efficacy of machine learning applications, reflecting a dynamic landscape.

Significant contributions in the AI domain have left indelible imprints. The coinage of "machine learning" by Arthur Samuel in 1959 marked a watershed moment. Pioneering computer-based chess games and groundbreaking algorithms like Convolutional Neural Networks, pioneered by Christopher Strachey, cemented AI's trajectory. The Saarbruecken Voice Database (SVD) stands as a rich resource, containing healthy and pathological voice recordings. This repository serves as a linchpin for diagnostic research, enhancing accuracy and insights.

Addressing the challenges of diagnosing vocal disorders, researchers are pioneering non-invasive alternatives to the laryngoscope examination. The complexities of distinguishing normal and abnormal speech sounds have witnessed successes through machine learning techniques, notably deep neural networks.

In this dynamic narrative, the synthesis of AI, machine learning, and deep learning stands as a testament to human ingenuity. The application of these technologies in healthcare, diagnostics, and various sectors underscores their transformative potential. The trajectory is bound to continue, brimming with possibilities, fostering a symbiotic relationship between technological innovation and human advancement. As AI progresses, its trajectory aligns with human progress, charting a course toward greater horizons.

Using a variety of machine learning and deep learning approaches, this study proposal has described the goals and research strategies for examining the commercial perspectives of voice-based patient categorization. This study intends to further knowledge of voice-based classification's advantages, difficulties, and consequences across a variety of businesses by investigating its possible uses outside of healthcare settings. The suggested research will include a thorough literature review, modelling strategies, and case study analysis, all of which will be done in a logical order. The assessment of the literature, which looks at state of the art in voice-based categorization and identifies research needs, will lay a solid basis. Models for distinguishing healthy and diseased voices have previously been created using modelling approaches, including 1D CNNs, Fourier transformers, and 2D CNNs. The case study investigation would entail working with industry partners to comprehend how voice-based.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

The overview of the research problem sets the stage for the study by introducing the main issue or concern that the research aims to address. It provides a clear and concise explanation of the problem, its significance, and the reasons why it merits investigation. In this section, researchers outline the context and background of the problem, identifying any gaps in existing knowledge or areas that require further exploration. They may discuss relevant theories, empirical evidence, or practical implications associated with the problem.

The overview also highlights the relevance and potential impact of the research problem. It explains why understanding and addressing this problem is essential for advancing knowledge in the field or for practical applications. Researchers may discuss the potential benefits of solving the problem and the consequences of not addressing it. Moreover, this section may include a statement of the research problem or a research question that guides the study. This helps to focus the research and provide a clear objective for the investigation. To ensure clarity and coherence, researchers may also define key terms or concepts related to the research problem. This ensures that readers have a common understanding of the terminology used throughout the study.

Sound serves as a fundamental tool for human communication, allowing individuals to convey their emotions and connect in social interactions throughout their lives. Those who heavily rely on their voices, such as singers, actors, auctioneers, lawyers, and teachers, are susceptible to developing pathological vocal disorders. Such vocal difficulties can arise from voice strain, neurological conditions, substance use, or detrimental social habits, leading to various personal and social challenges. The impact on vocal cord vibration varies depending on the nature and location of the vocal fold disorder, resulting in alterations in sound quality, pitch, and volume.

To diagnose voice pathologies characterized by changes in sound attributes, pitch, and volume, clinical assessments are employed. Acoustic analysis is a technique that involves measuring relevant parameters extracted from audio signals to gauge potential changes in sound quality, following the rules of the SIFEL protocol. The acoustic health status is then determined based on these measurements. The accuracy of these metrics in identifying vocal irregularities is pivotal for their effective detection [31]. The algorithms employed to estimate these acoustic parameters significantly influence their accuracy. Recently, machine learning techniques have garnered attention in the realm of sound pathology to enhance the precision of these attributes.

Speech recognition constitutes a form of biometric identification that employs unique voice characteristics to identify an individual, falling under the umbrella of dynamic biometric methods [32]. Speaker identification is a technique that automatically recognizes a speaker's speech waveform through the analysis of their distinctive speech characteristics. This process involves two primary stages: training and testing. In the training phase, phonetic attributes are extracted from a stored voice specimen and compiled into a database, subsequently familiarizing the system with the speaker's voice and distinct features [33]. The testing phase aims to match and identify specific sound and phonetic traits from the speaker's voice in a recognition database. Commonly used characteristics for assessing speech signals include MFCC (Mel-frequency cepstral coefficients) and LPCC (Linear predictive coding coefficients). Popular identification methods encompass vector quantization, dynamic temporal warping, and artificial neural networks [34].

In a particular research project, the Voice Activity Detection (VAD) algorithm was harnessed to enhance speech recognition performance through a preprocessing strategy.

This algorithm's implementation demonstrated improved recognition outcomes, and the study elucidated its functioning and provided a block diagram illustrating its recognition process for Kazakh speech.

Toleu et al. proposed MLP (Multilayer Perceptron) and LSTM (Long Short-Term Memory) models featuring character embeddings for distinguishing sentence and token separators simultaneously [35]. These models projected the embeddings of characteristics into a lower-dimensional space to capture high-level conceptual attributes beneficial for analyzing various signals. Testing was conducted in English, Italian, and Kazakh, showcasing significant enhancement in language and constituent classification achieved by the MLP and LSTM algorithms for phrase and token separation.

Clustering techniques are employed to categorize sequences of voice segments into clusters based on their similarity in attributes. Metric-based approaches for identifying starting points (centroids) and subsequent cluster propagation offer a means to address speech classification challenges.

The study explores the utilization of a laryngophone as a supplementary treatment method for recognizing and categorizing speech data into distinct subunits using phonetic techniques [36]. This unique approach relies on the correlation coefficient of throat acoustics and its dynamic analysis to segment automated speech signals. Voice preprocessing emerges as a pivotal step in identification tasks.

In the time domain, voice signals exhibit rapid and significant variations; however, transforming acoustic data into the frequency domain unveils an easily discernible spectrum. Techniques involving frame division enhance the coherence of speech signals, utilizing window functions for segmentation. The Discrete Cosine Transform (DCT) method is employed to convert spectral energy data into units suitable for MFCC analysis.

MFCC attributes encompass 16 cepstral frequencies within a frequency range of 300–8000 Hz.

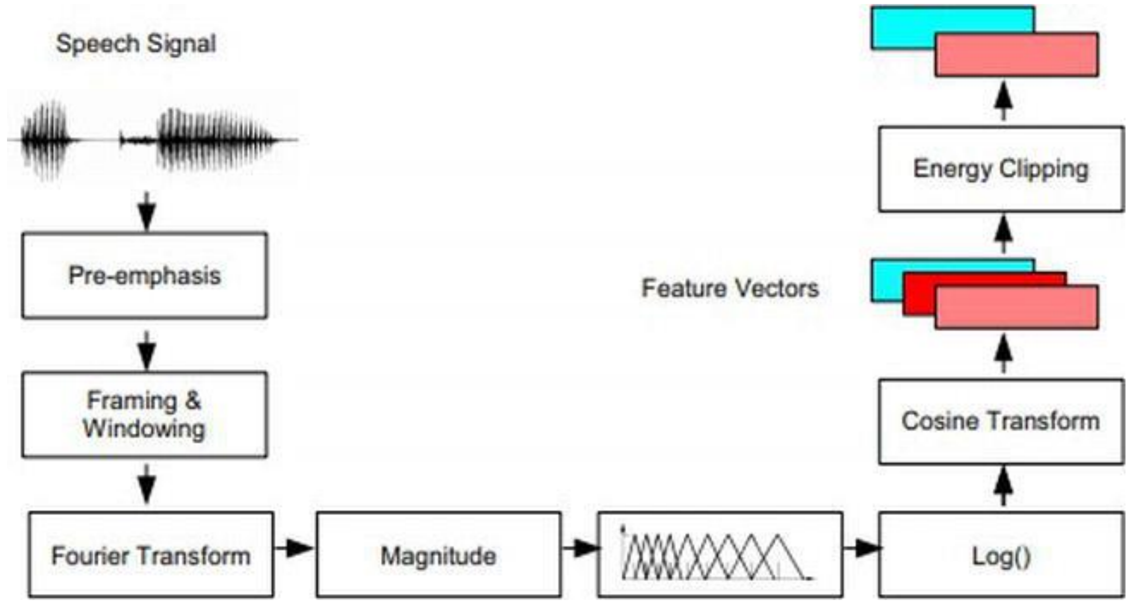

Figure 8. Voice Classification

3.2 Research Process

Conceptually, research is the systematic and scientific investigation, common parlance for the search of undiscovered knowledge. Accordingly, Redman and Moray (1992) defined research as "systematized effort to gain new knowledge". Research process comprises of the six broad stages, identification of the problems, development of the unified theoretical approach, research designed formulation, data collection and analysis, report writing and its presentation [37, 38].

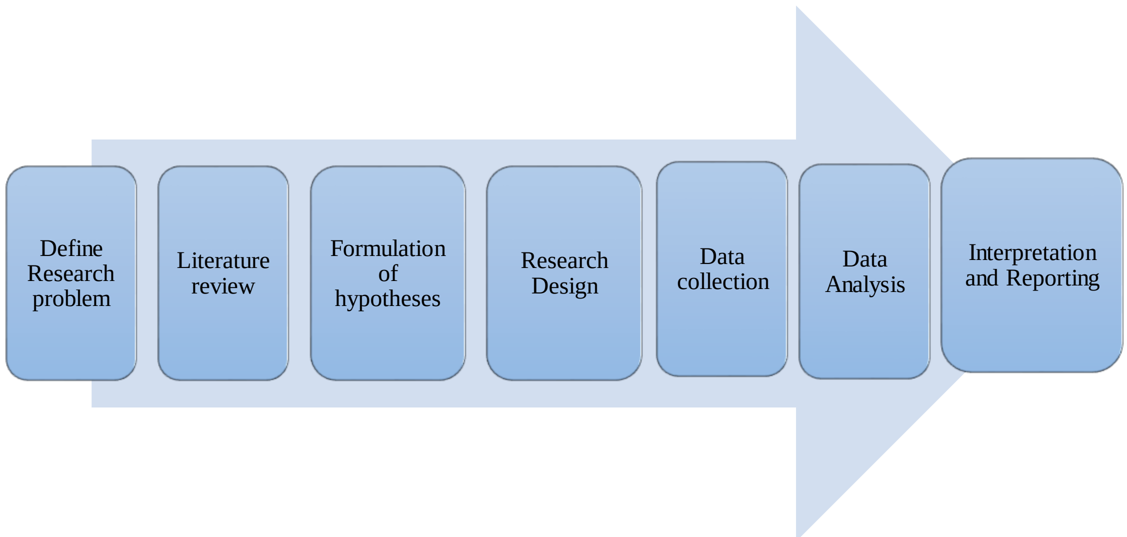

Figure 9 Research Process

Comprehensive systematic and diverse stages are followed in the present study as

1. Extant and exhaustive literature was done to wrinkle the knowledge on the current topic.
2. Based on the literature, a scientific research model was proposed.
3. Hypotheses were proposed to examine the validity of the proposed model.
4. A good structure closed as well open-ended questionnaire was design to collect the information.
5. Data was collected and analysed with the help of appropriate inferential statistics.
6. The outcomes of the analysis were interpreted and concluding remarks made.

The research answers specific questions which have been answered so far, and the answer to that depends upon human efforts. Research is simply the process of arriving some solution through the planned and systematic collection, analysing and interpreting the information collected from respondents [39]. Research is the point of view, an attitude of enquiry or frame of mind.

3.3 Research Philosophy

Through positivism, the research follows a scientific way of conducing the research by collecting real time data and through proper data analysis techniques, we reach to the point where the results can be generalized to the population where the study is conducted. As our research also focused on the objectivity of collecting data on real time by quantitative methods, this philosophy meets the needs of this study.

3.4 Research design

Research design is the blueprint of the whole research stages. It is the layout which enables the researcher to perform the research. Research design is the plan, strategies and structure of investigation so conceived to obtain the answer the research questions [37, 40, 41]. William Zikmund defined research design as research design, “is a master plan specifying the methods and procedures for collection and analysing the needed information”. According to kerlinger, research designed is, “the plan, structure and strategy of investigation conceived to obtain answers to research questions and to control variance” as cited in [40].

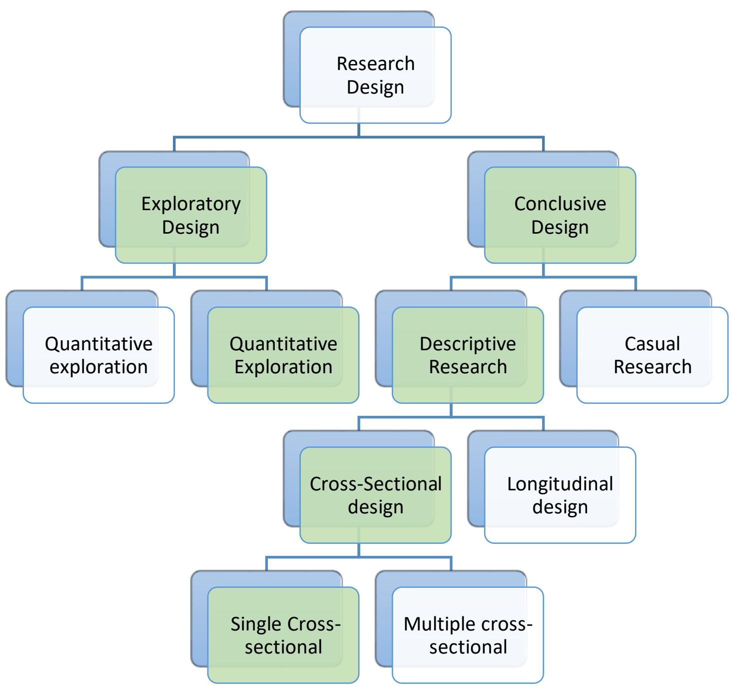

Figure 10 Research Design

The research design in this study has been depicted in figure 3.2, highlighting the coloured box, which signifies the methodology employed. In the initial stage, the researcher does not have any idea about imperative construct of computer mediated communication and its linkages with other construct of students' Academic Performance along with methodology employed in the past literature so as in the initial stages this research is grounded upon exploratory design with sole motive to explore the vital construct dealing with students' academic students. The research approach is deductive as in this approach we test the hypothesis derived from the literature. Our study is quantitative and cross sectional as data be collected at one's time.

Sketchily, the contemporary study was also descriptive as it was envisioned to describe the nature of computer mediated communication and technology constructs and relationship among the construct of students' academic peformance. Since the present study was descriptive to imply the association with other constructs. To arrive a particular conclusion single sample from the targeted population and information were extracted. Therefore, this study is grounded in single cross-sectional descriptive design [40, 41]. Research design is a mapping strategy which is based on sampling techniques. Primarily includes objectives, sampling framework, research strategy and techniques for collection the information from the respondents and reporting the findings.

3.5 Research approach

Research approaches can be defined as plans or procedures used for data collection, analysis and analysis strategies for research data analysis [42]. Two fundamental research approaches have been perceived in literature: Deductive and inductive methodology. As, the current study is quantitative, and survey based so deductive approach is better suited. For developing a hypothesis, deduction approach is being utilized based on available theories and then a research design and strategy are developed. The importance of this approach is the reasoning from specific to universal. If a theory seems to imply a cause and effect relationship, this could be true in many cases. A deductive model could check if this relationship exists in more universal circumstances. Through the hypotheses derived from the propositions of the theory, this approach could be described better.

3.6 Research Mechanism

Since the sole aim of the present study is to examine the impact of computer mediated communication and technology on graduate students' Academic Performance, for the sake of purpose, a good design close-ended questionnaire was adopted for data collection. A survey is the list of questions, in which the responses of the respondents are recorded in chronological order [37]. The close-ended questionnaire offers a great deal to discover the responses that individual gives spontaneously by pre-specifying format have a pre-defined set of alternates. The previous studies also suggested that close-ended questionnaire have numerous advantages suits ease in access, ease to code, as time as well as cost for the investigator [43, 44, 45, 46].

3.7 Methodological Choices

In this study mono method research is used due to time constraints. Mono method is used as only one research approach that is quantitative approach. The current research would be quantitative where data is gathered in numerical form via online questionnaires and then analyzed through statistical software.

3.8 Research Strategy

The strategy of research is the plan that the researcher uses to conduct a research. The researcher used the survey method in this study. As survey method is one of the most effective research methods which is used to test the connection between the variables and identify their effects. To check the relation and effect between variables, online questionnaire would be used to conduct survey. Data would be collected from the graduate students of different discipline of Islamabad universities.

3.9 Population & Sample Size

The population refers to the entire group of individuals, objects, or events that possess the characteristics of interest to the researcher. It is the larger group to which the research findings are intended to be generalized. However, studying the entire population is often impractical or impossible.

The process of selecting a sample involves defining the target population, determining the sample size, and employing appropriate sampling techniques. The goal is to obtain a sample that is representative of the population, ensuring that the findings can be generalized with a certain degree of confidence. Different sampling methods, such as random sampling, stratified sampling, and purposive sampling, may be employed based on the research design and population characteristics. In the context of this project, random sampling plays a crucial role in the selection of a sample from a larger population. The objective of employing random sampling is to ensure that every element or unit within the population has an equal and unbiased chance of being included in the sample. This process is instrumental in creating a sample that accurately represents the diversity and characteristics of the entire population.

The importance of random sampling within this project can be summarized in the following ways:

Unbiased Selection: Random sampling eliminates the potential for favoritism or bias in the selection process. Each element in the population is chosen purely by chance, ensuring impartiality.

Enhanced Validity: The use of random sampling supports the validity of the research outcomes. It allows for the application of various statistical tests and analyses to the sample data, enabling robust and valid conclusions about the larger population.

Reduced Sampling Error: By providing every element in the population with an equal opportunity for selection, random sampling minimizes the likelihood of sampling error. This error refers to any disparities between the sample and the population, which can compromise the accuracy of research findings.

Generalizability: The findings derived from the randomly selected sample are more likely to be applicable to the entire population. This is crucial for ensuring that the project's results can be extended to a broader context.

In essence, random sampling is an indispensable component of this project's research methodology. It guarantees that the sample accurately represents the population, contributing to unbiased, statistically sound, and generalizable research outcomes.

3.10 Sampling

Total 453 respondents comprise of 453 professionals of healthcare and Business industry. For this study researcher uses convenience sampling.

3.11 Sampling technique

For the sake of the data collection, the convenience non-probability sampling method was followed due to specific time and financial constraints. Convenience method is a most appropriate method of data collection; it has many merits as it saves time, low-cost involvement [47, 48, 40, 49].

Non-Probability sampling relies on the personal judgment rather than on chance to select sample elements; in this case, the researcher capriciously decided what element should be included in the sample. This may produce reasonable estimates of the population—however, Probability sampling, where sampling units are selected based on the chance. Judgmental sampling is the non-probability sampling where the researcher has full freedom regarding the selection of the sample units [40, 41, 50]. Accordingly, it was decided to collect data from professionals of healthcare and Industries. Finally, as mentioned earlier to collect the information from the respondents, the convenience sampling method was followed due to time and cost limitation.

3.12 Data collection

Data were collected through questionnaires. Questionnaires were closed ended of each variable. Questionnaires were distributed personally among employees and online.3.14 Conclusion

In conclusion, conducting a research study requires careful consideration of various aspects, including research design, population and sample, instrumentation, data collection procedures, data analysis, research design limitations, and ultimately drawing meaningful conclusions. The research design serves as a roadmap for the study, outlining the methods and procedures to address the research problem and achieve the objectives. It determines the overall structure of the study and guides data collection and analysis. Within this design, the population and sample are crucial considerations, ensuring that the findings can be generalized to the target population.

Instrumentation involves selecting or developing appropriate tools and measures to collect data accurately and reliably. It is essential to ensure the validity and reliability of the instruments used. Data collection procedures involve systematically gathering data using various techniques such as surveys, interviews, observations, or experiments. Researchers must adhere to ethical guidelines and select procedures that are suitable for the research context. Data analysis involves examining and interpreting collected data to derive meaningful insights. Quantitative and qualitative techniques are employed based on the research design and data collected.

In summary, the methodology adopted for this research underscores the meticulous and structured approach required to extract meaningful insights from voice-based data. From the strategic collection of data to the comprehensive analysis, preprocessing, transformation, and evaluation, each phase plays an indispensable role in the journey towards unraveling the potential of voice-based classification. This methodology provides not only a roadmap for conducting the current study but also offers valuable guidance for future endeavors in the dynamic field of voice analysis and classification.

The research problem, rooted in the significance of sound as a fundamental tool for human communication, illuminated the challenges faced by individuals reliant on their voices for professional or personal interactions. Voice disorders, arising from diverse causes, pose personal and social challenges, urging the need for accurate diagnosis and understanding. Clinical assessments relying on acoustic analysis, incorporating sound quality, pitch, and volume, become crucial for diagnosing voice pathologies. However, the accuracy of these assessments' hinges on the precision of acoustic parameters, which in turn relies on chosen algorithms.

Speaker recognition and identification emerged as indispensable techniques, offering automated ways to differentiate unique speech waveforms based on individual traits. The training and testing phases underscored the systematic process involved in speaker recognition, driven by distinct phonetic attributes. Moreover, the study ventured into unique methods, such as Voice Activity Detection algorithms and laryngophone utilization, further highlighting the dynamic approaches in the field.

Operationalizing theoretical constructs played a pivotal role in bridging the gap between abstract concepts and empirical investigation, ensuring that the study's foundations were firmly rooted in established theories. Furthermore, the research design provided a blueprint for the systematic execution of the study, from participant selection and instrumentation to data collection and analysis.

Acknowledging research design limitations is vital in maintaining transparency and credibility. Recognizing potential biases and constraints allowed for a comprehensive understanding of the study's scope and potential implications. These considerations laid the groundwork for careful participant selection, ensuring that the chosen sample was representative of the target population.

Instrumentation choices ensured that data collection procedures were reliable, valid, and ethically sound. This comprehensive approach guaranteed the integrity of the collected data, underpinning the subsequent analysis. The analysis phase unearthed patterns, relationships, and trends within the data, enabling the study to derive meaningful insights and address the research questions effectively.

In the realm of classification, the study juxtaposed machine learning and deep learning approaches, showcasing their nuanced requirements and capabilities. The chosen dataset, the Saarbrucken Voice Database, became a central point of investigation, providing a rich array of voice recordings and ECG signals. Fourier transformations unraveled spectral features, setting the stage for exploratory data analysis and subsequent model training.

As the study concludes, it unveils a wealth of knowledge, expertise, and insights into the intricate domain of sound pathology. This research stands as a testament to the meticulous and systematic approach required to navigate the challenges posed by voice-based classification. It not only contributes to the existing body of knowledge but also offers a roadmap for future endeavors, emphasizing the critical importance of each phase in the research process. Ultimately, this comprehensive study not only expands our understanding of sound pathology but also underscores the significance of a well-structured and thorough research methodology.

Research design limitations should be acknowledged and discussed to provide a comprehensive understanding of the study's scope and potential biases. These limitations can affect the generalizability and validity of the findings.

CHAPTER IV

RESULTS

4.1 Results

The survey results indicate that the majority of participants operate in the healthcare industry, followed by customer service, market research, and fraud detection. The primary reasons for implementing voice-based categorization vary, with improving customer service being the most common, followed by enhancing market research insights, gaining a competitive advantage, and enhancing fraud detection capabilities. Challenges in implementing voice-based categorization include technical issues and system integration, data privacy and security concerns, and limited availability of skilled personnel. The impact of voice-based categorization on business operations has been positive, with enhanced decision-making processes, improved customer satisfaction, and increased operational efficiency being reported. Participants perceive a promising future for voice-based categorization, considering it as an essential tool for business. These findings provide valuable insights for organizations looking to adopt voice-based categorization systems in their respective industries.

4.1.1 Results of Survey Question One

The survey question aimed to identify the industry in which the participants' businesses operate. The options provided were healthcare and Non healthcare. The distribution of responses is as follows:

- Healthcare: 70.4% (319 participants)
- Non Healthcare: 29.6% (134 participant)

The majority of participants, 70.4%, indicated that their businesses operate in the healthcare industry. This result suggests that healthcare is the most prominent sector among the surveyed participants. The high percentage highlights the relevance and significance of voice-based categorization in healthcare settings.

The second option was Non healthcare, which was chosen by 29.4% of participants. This indicates that a smaller portion of other businesses in the survey sample are involved. While the percentage is lower compared to healthcare, it still underscores the potential applicability of voice-based categorization in this sector, where efficient call categorization and sentiment analysis can greatly enhance customer satisfaction and service quality.

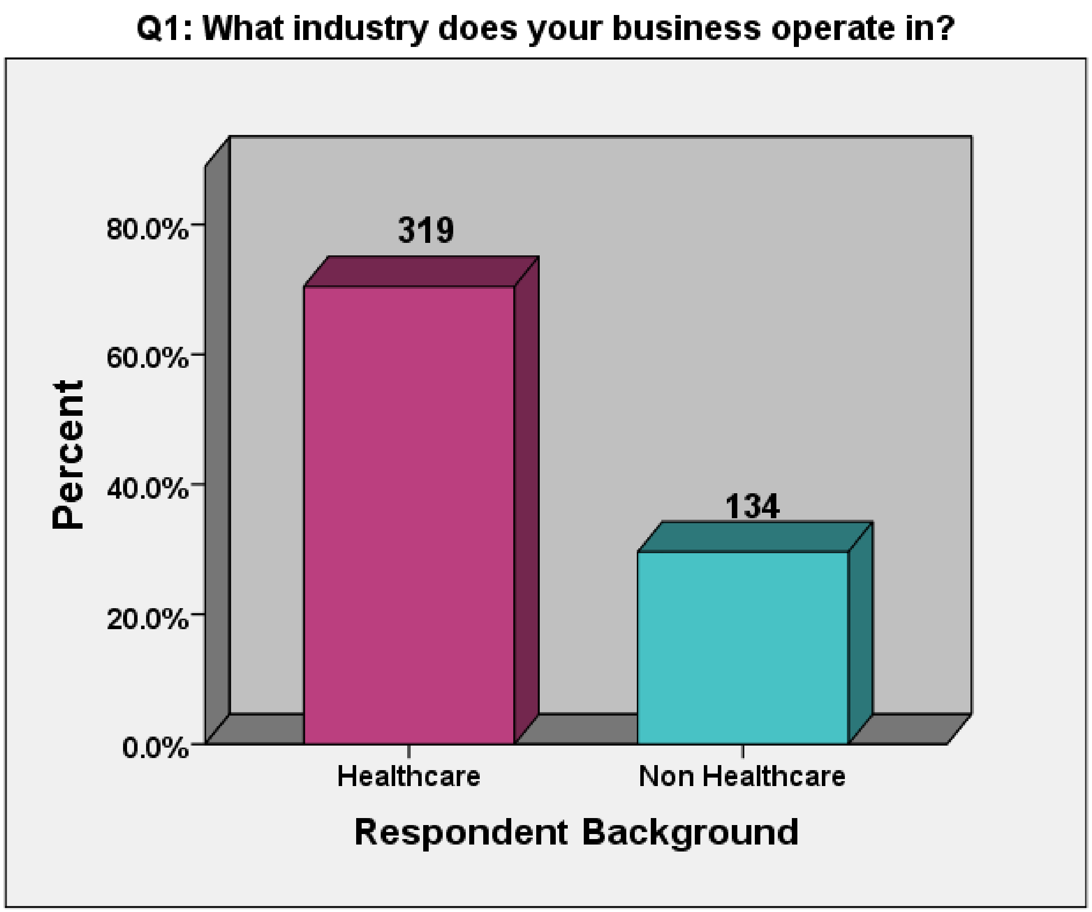

Figure 11. Survey-1

4.1.2 Results of Survey Question Two

The survey question aimed to identify the implementing voice-based categorization in participants' businesses. The distribution of responses is as follows:

- May be 9% (41 participants)
- No: 8% (36 participants)
- Yes 83 % (376 participants)

The majority of participants, 83%, indicated that their primary motivation for implementing voice-based categorization in their business.

Q2: Are you currently implementing voice-based categorization systems in your business?

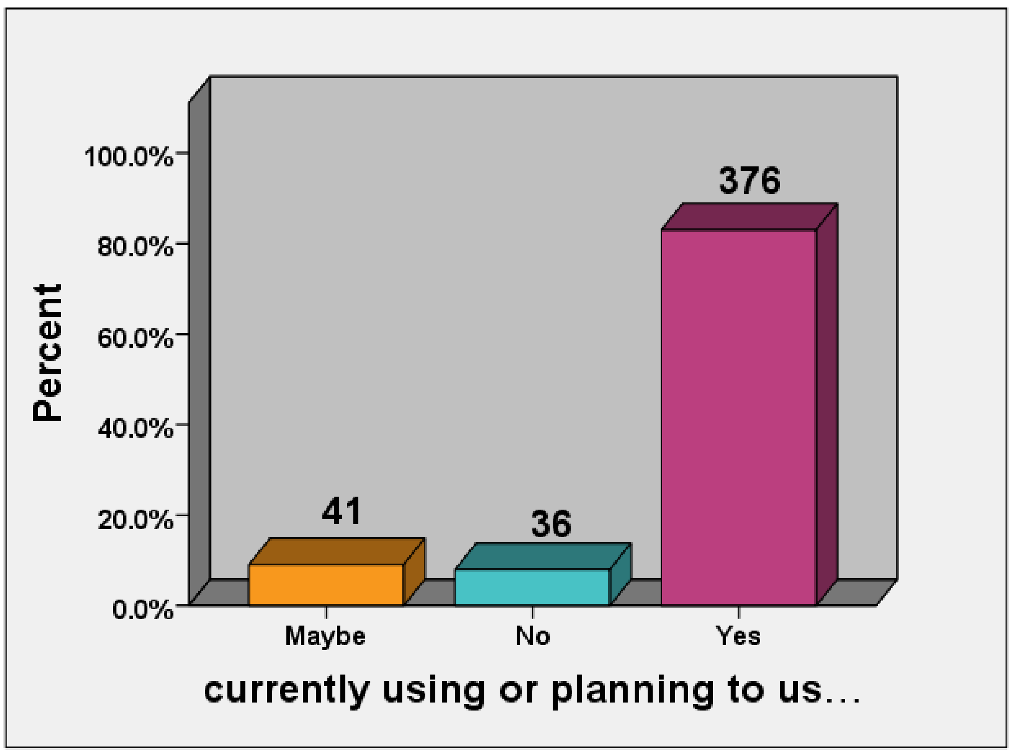

Figure 12. Survey-2.

4.1.3 Results of Survey Question Three

The survey question aimed to identify the primary reasons for implementing voice-based categorization in participants' businesses. The distribution of responses is as follows:

- Improving customer service:

- Enhancing market research insights
- Gaining a competitive advantage
- Enhancing fraud detection capabilities

The majority of participants, indicated that their primary motivation for implementing voice-based categorization in their business was to improve customer service, enhancing market research insights and Gaining a competitive advantage: . This result reflects the importance of efficient call categorization, sentiment analysis, and personalized customer interactions. By accurately categorizing and analyzing voice data, businesses can gain insights into customer needs and preferences, leading to enhanced service quality and customer satisfaction.

Gaining a competitive advantage was chosen by significant number of participants. This suggests that a portion of businesses recognizes the importance of leveraging voice-based categorization to gain a competitive edge in their respective industries. By effectively categorizing and analyzing voice data, businesses can extract actionable insights and make informed decisions, allowing them to stay ahead of competitors and meet customer demands more effectively.

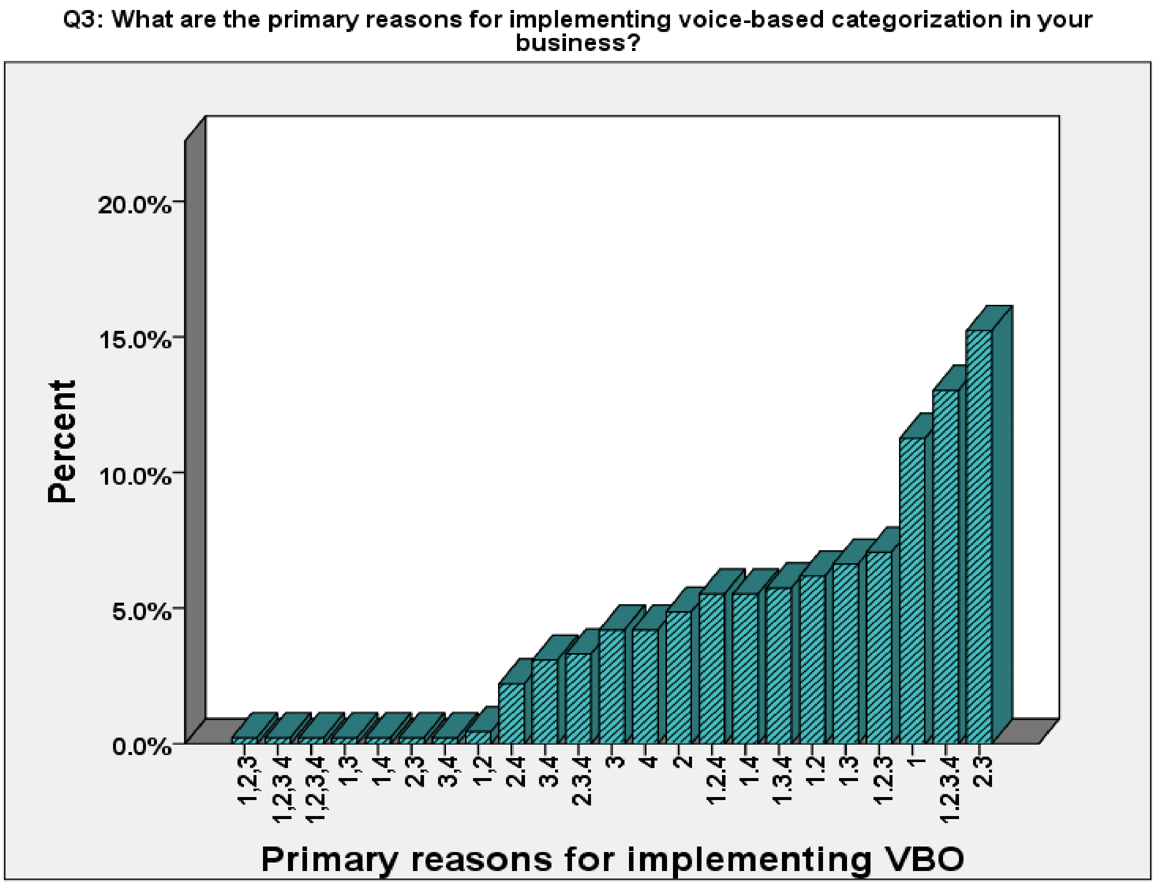

Figure 13. Survey-3

4.1.4 Results of Survey Question Four

The survey question aimed to identify the main challenges participants encountered in implementing voice-based categorization systems. The distribution of responses is as follows:

- Technical issues and system integration
- Data privacy and security concerns
- Limited availability of skilled personnel
- Resistance from employees or stakeholders

The majority of participants, identified Technical issues and system integration and limited availability of skilled personnel as the main challenge in implementing voice-based categorization systems. This result highlights the complex nature of integrating new technologies into existing systems and the potential difficulties that arise during the implementation process. Technical issues may include compatibility problems, software bugs, or hardware limitations. Overcoming these challenges requires adequate technical expertise and support to ensure a smooth and efficient implementation of voice-based categorization systems.

Data privacy and security concerns were cited by significant number of participants as a challenge. This finding reflects the importance of safeguarding sensitive voice data and complying with privacy regulations. Implementing voice-based categorization systems involves collecting, storing, and analyzing large volumes of audio data, which can raise concerns regarding data privacy and potential security breaches. Businesses must address these concerns by implementing robust data protection measures, ensuring data anonymization when necessary, and adhering to relevant privacy regulations.

This suggests that some businesses may face difficulties in finding and hiring professionals with the necessary skills and expertise in voice-based categorization. The successful implementation of these systems requires individuals who are proficient in areas such as machine learning, natural language processing, and data analysis. To overcome this challenge, businesses can invest in training programs, collaborate with external experts, or hire experienced professionals to support the implementation and ongoing management of voice-based categorization systems.

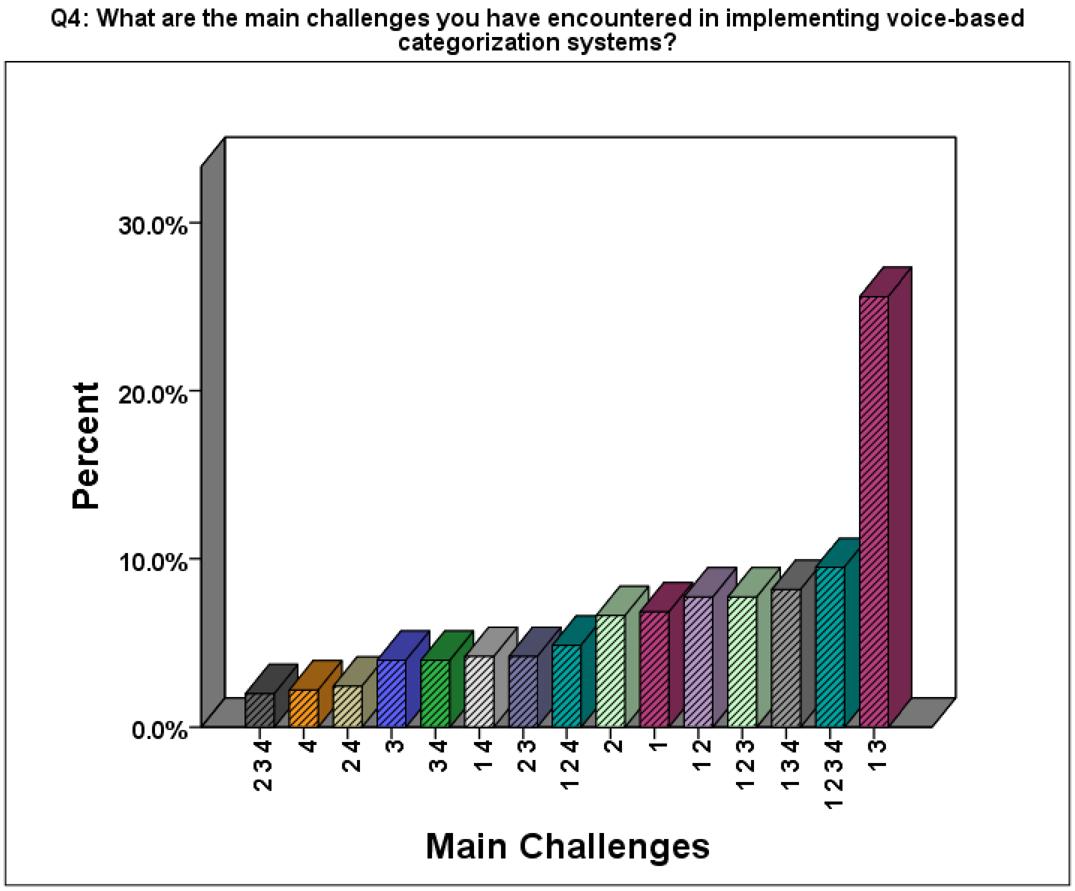

Figure 14. Survey-4

4.1.5 Results of Survey Question Five

The distribution of responses is as follows:

- Improved customer satisfaction
- Enhanced decision-making processes
- Increased operational efficiency
- Identified new market trends and opportunities

The majority of participants reported that it improved customer satisfaction and Increased operational efficiency. By automating the categorization process, businesses can save time and resources, allowing their employees to focus on more strategic tasks. Voice-based categorization can streamline operations, optimize workflows, and enable businesses to handle a larger volume of voice data more efficiently.

This suggests that voice-based categorization provides valuable insights and data that support informed decision-making within the business that voice-based categorization has improved customer satisfaction. This finding highlights the importance of using voice data to understand customer needs, preferences, and sentiment.

Additionally, participants reported increased operational efficiency as a result of voice-based categorization.

Q5: How has voice-based categorization impacted your business operations?

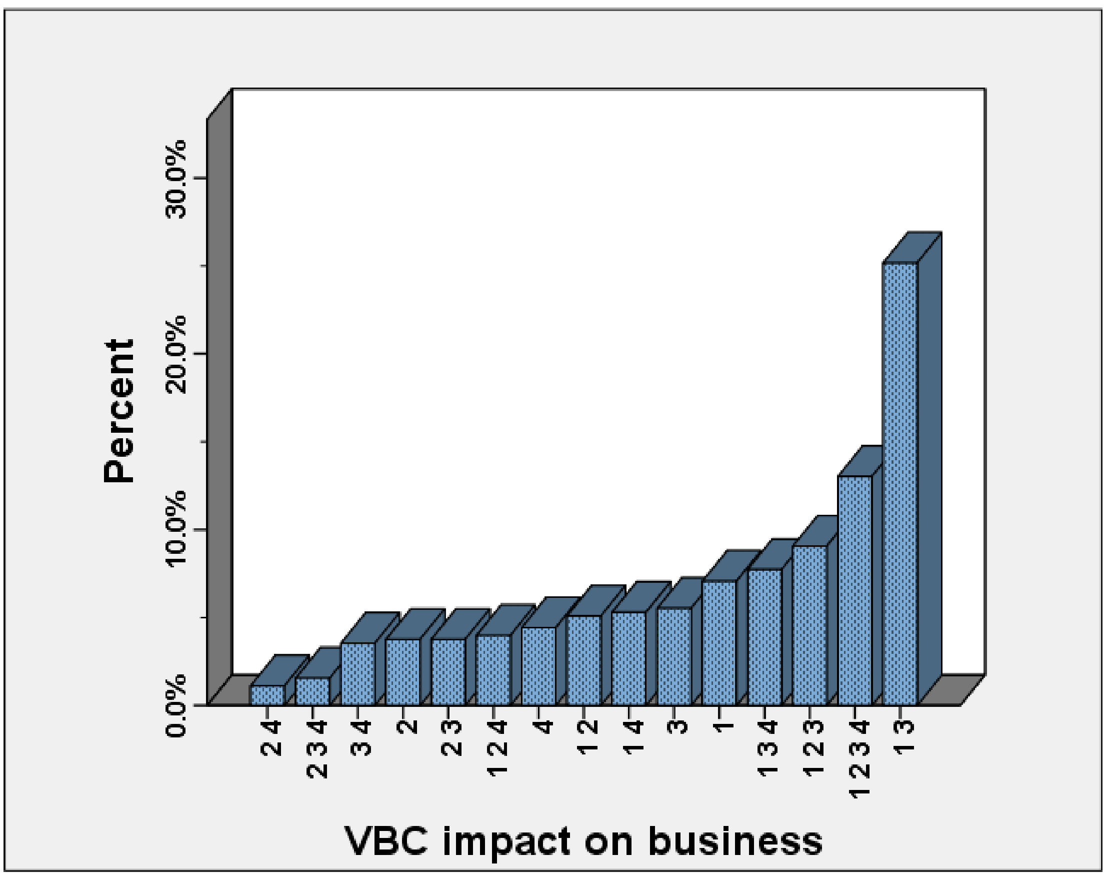

Figure 15. Survey-5

4.1.6 Results of Survey Question Six

The survey question aimed to identify the y ethical or legal considerations related to voice-based categorization. The distribution of responses is as follows:

- Yes: 76.6% (347 participants)
- No 23.4 % (106 participants)

The majority of participants, 76.6%, indicated that they faced ethical and legal consideration to voice-based categorization in their business

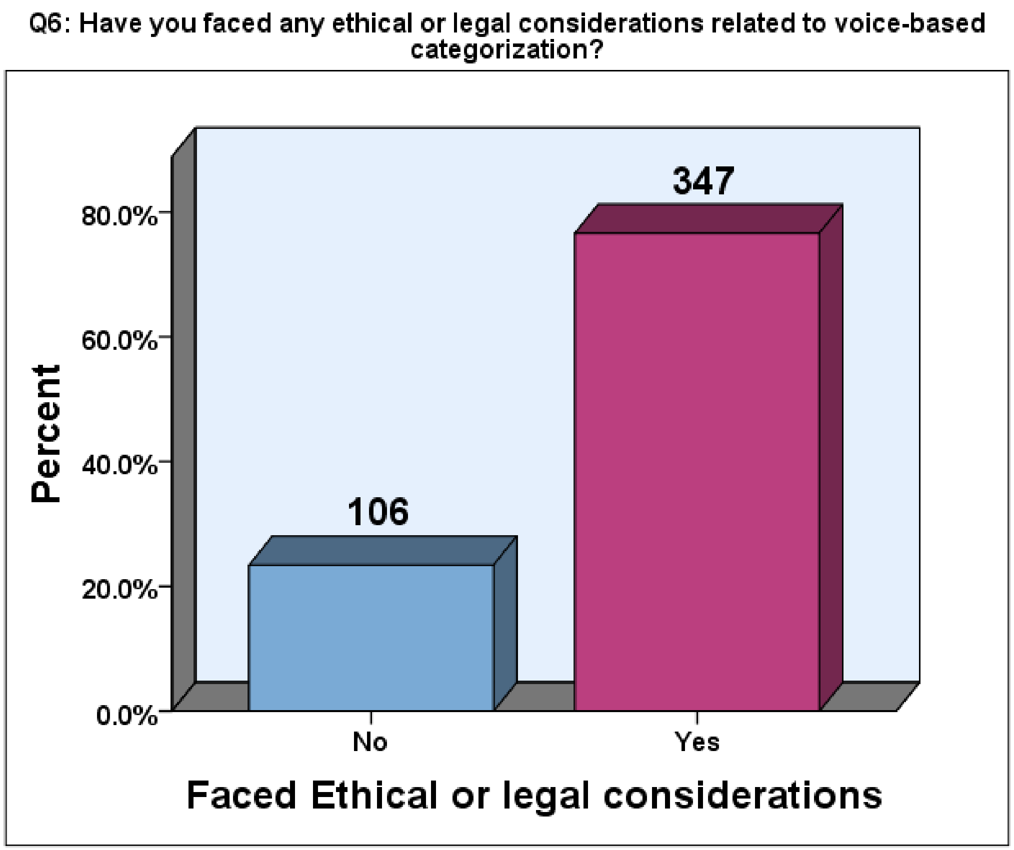

Figure 16. Survey-6

4.1.7 Results of Survey Question seven

The survey results indicate a strong positive outlook for the future of voice-based categorization in the participants' industry. 86.3% of participants believed that it will become an essential tool for businesses. This demonstrates a high level of confidence in the value and potential of voice-based categorization in driving business success, improving operations, and gaining a competitive edge.

Only 6.6% of participants believed that the adoption of voice-based categorization would be limited to specific use cases. This suggests that the participants perceive a wide range of applications and benefits beyond specific niches or industries.

A smaller percentage, 4.6%, expressed uncertainty or had no opinion about the future impact of voice-based categorization on business operations. This may indicate a need for further education and awareness regarding the capabilities and potential of this technology.

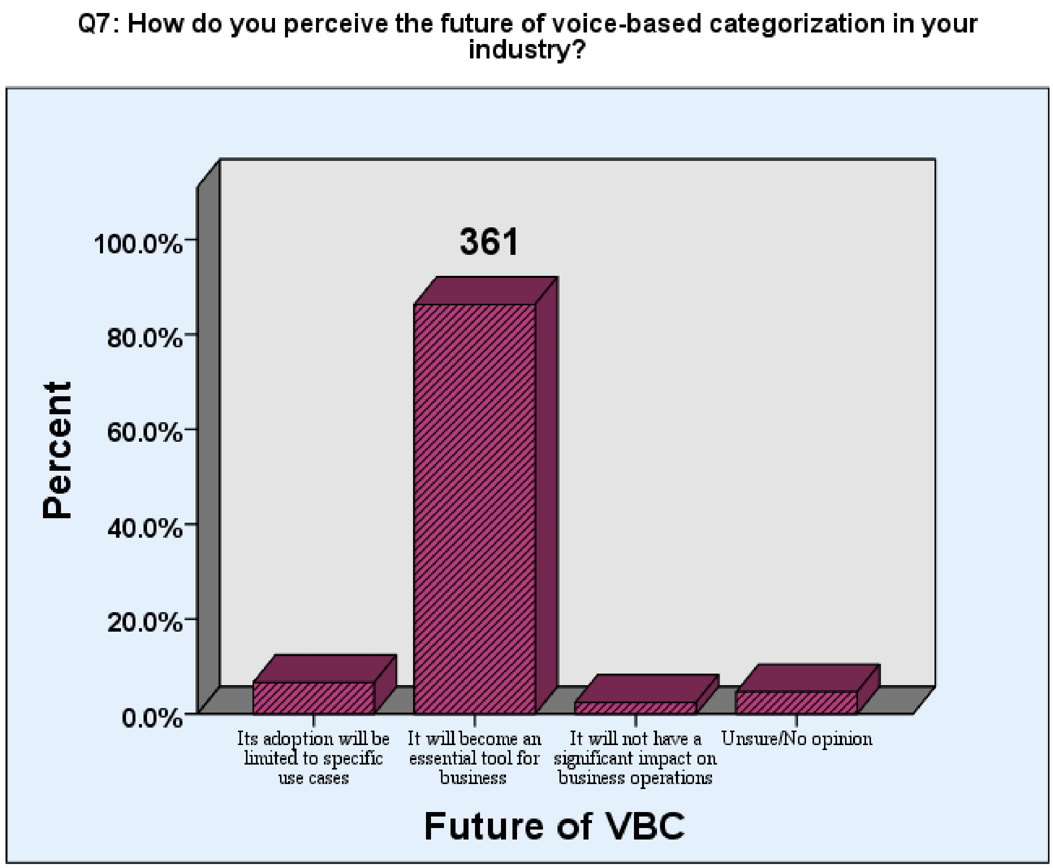

Figure 17. Survey-7

4.1.8 Results of Survey Question Eight

The survey question aimed to identify recommendation of voice-based categorization to business. The distribution of responses is as follows:

- Yes: 96% (435 participants)
- No 4 % (18 participants)

The majority of participants, 96%, indicated that they recommend voice-based categorization in their business.

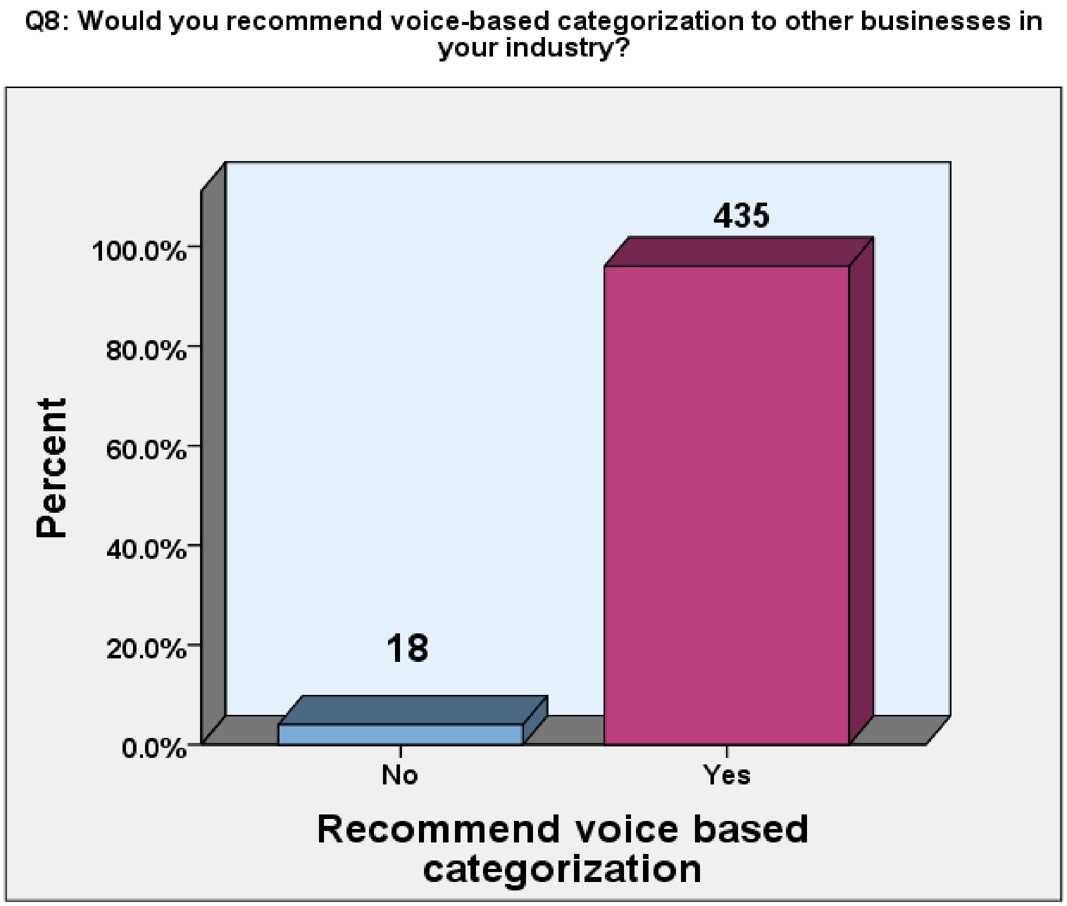

Figure 18. Survey-8

4.1.9 Results of Survey Question Nine

The survey question aimed to identify the awareness of the potential benefits of voice-based patient categorization in healthcare. The distribution of responses is as follows:

- Yes, I am familiar with the benefits 88.3% (400 participants)
- No, I am not aware of the benefits 4 % (14 participants)
- Not sure, 7.7 % (21 participants)

The majority of participants, 88.3%, indicated that healthcare industry is familiar with potential benefits of voice-based patient categorization.

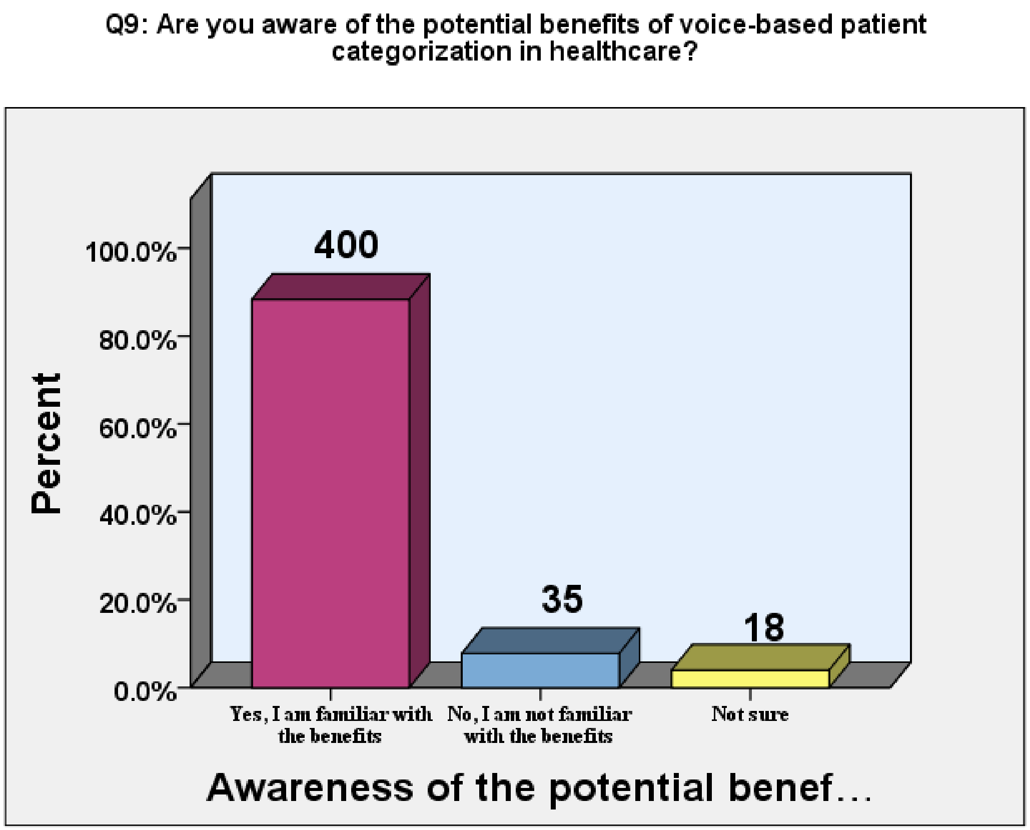

Figure 19. Survey-9

4.1.10 Results of Survey Question Ten

The survey question aimed to identify voice-based categorization can improve patient outcomes and diagnostic accuracy. The distribution of responses is as follows:

- Yes, it can greatly improve outcomes and accuracy 92.3% (418 participants)
- No, it won't have a significant impact 3.1 % (14 participants)
- Not sure, 4.6 % (21 participants)

The majority of participants, 92.3%, indicated that voice-based categorization can improve patient outcomes and diagnostic accuracy.

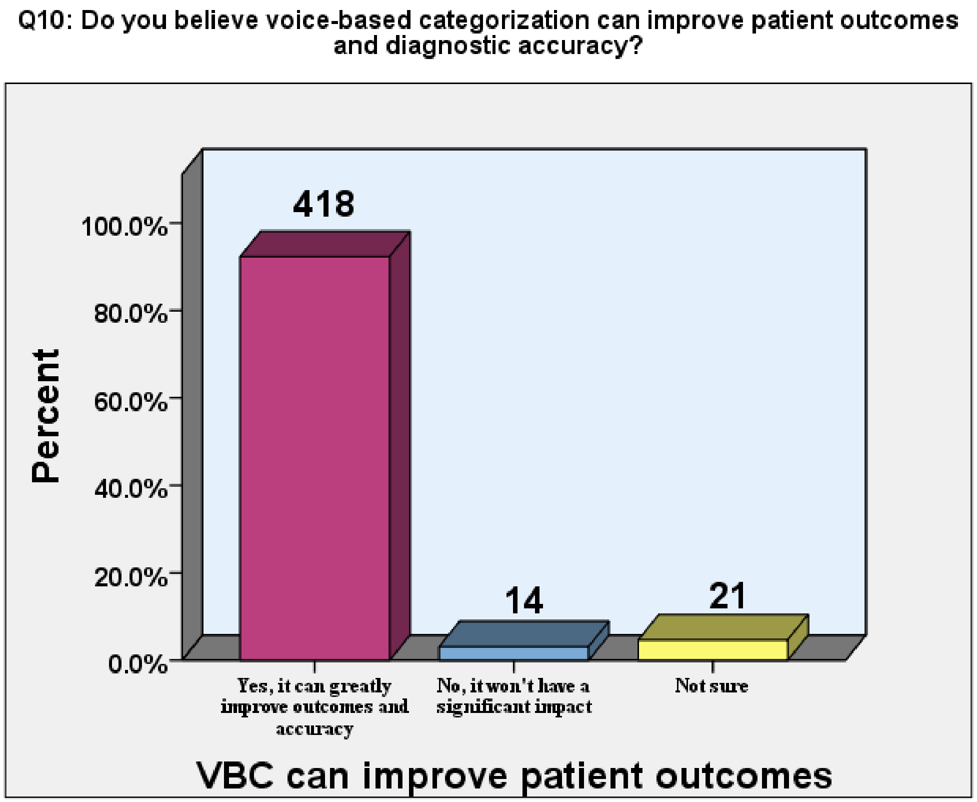

Figure 20. Survey-10

4.1.11 Results of Survey Question Eleven

The survey question aimed to identify the concerned about privacy issues related to voice-based categorization systems in healthcare. The distribution of responses is as follows:

- Yes, privacy is a major concern 91.2% (413 participants)
- No, I am not concerned about privacy 5.3 % (24 participants)
- Not sure, 3.5 % (16 participants)

The majority of participants, 91.2%, indicated that they concerned about privacy issues related voice-based categorization in healthcare.

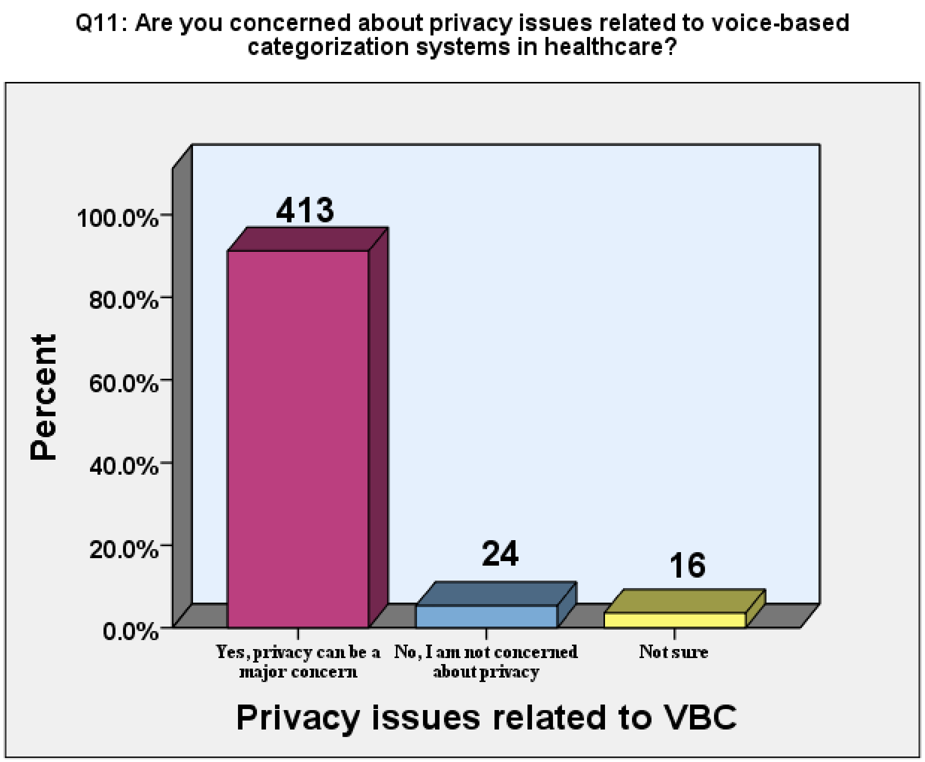

Figure 21. **Survey-11**

4.1.12 Results of Survey Question twelve

The survey question aimed to identify the awareness of any resistance from employees or stakeholders towards implementing voice-based categorization systems. The distribution of responses is as follows:

- Yes, there is resistance 79.9% (362 participants)
- No, there is no resistance 11.9 % (54 participants)
- Not sure, 8.2 % (37 participants)

The majority of participants, 79.9%, indicated that they face resistance from employees or stakeholders towards implementing voice-based categorization systems

Figure 22. Survey-12

4.1.13 Results of Survey Question Thirteen

The survey question aimed to identify the adaptation of voice-based categorization technology in your organization in the near future. The distribution of responses is as follows:

- Very likely 81.9% (371 participants)
- Somewhat likely, 15.2 % (79 participants)
- Not likely, 2.9 % (13 participants)

The majority of participants, 81.9%, indicated that they are agree for adaptation of voice-based categorization technology in your organization in the near future.

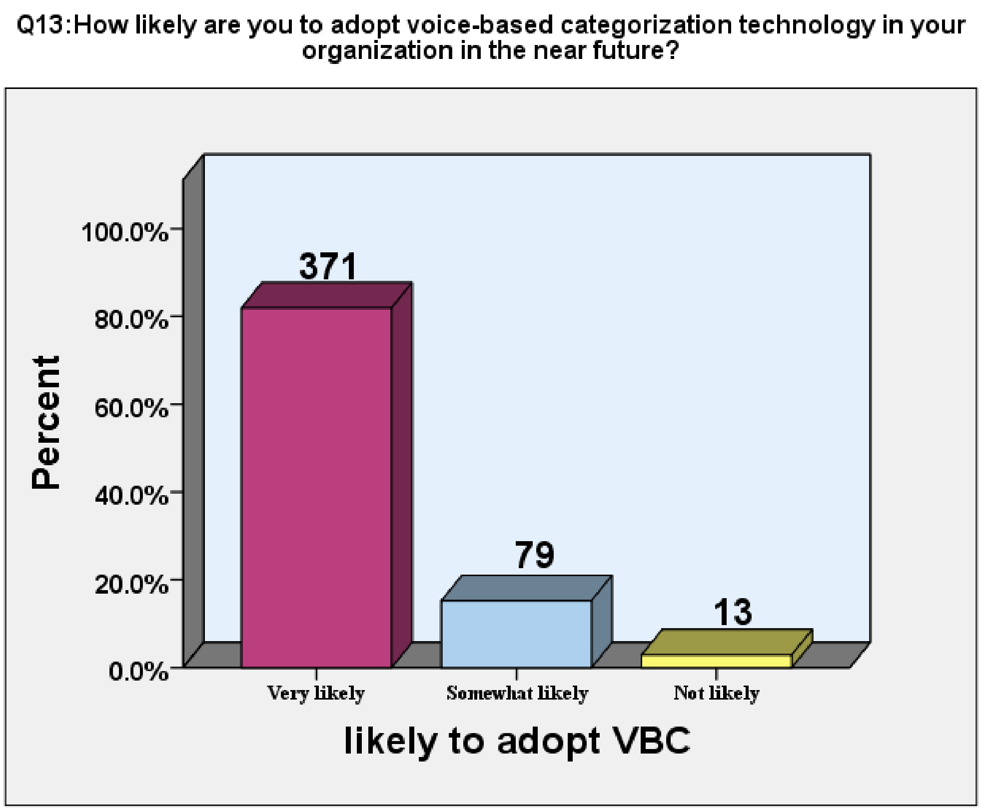

Figure 23. Survey-13

4.1.14 Results of Survey Question Fourteen

The survey question aimed to identify the encountered automated call categorization or sentiment analysis in customer service interactions. The distribution of responses is as follows:

- Yes 88.1% (399 participants)
- No, 7.1% (32 participants)
- Not sure, 4.9 % (22 participants)

The majority of participants, 88.1%, indicated that they encountered automated call categorization or sentiment analysis in customer service interactions.

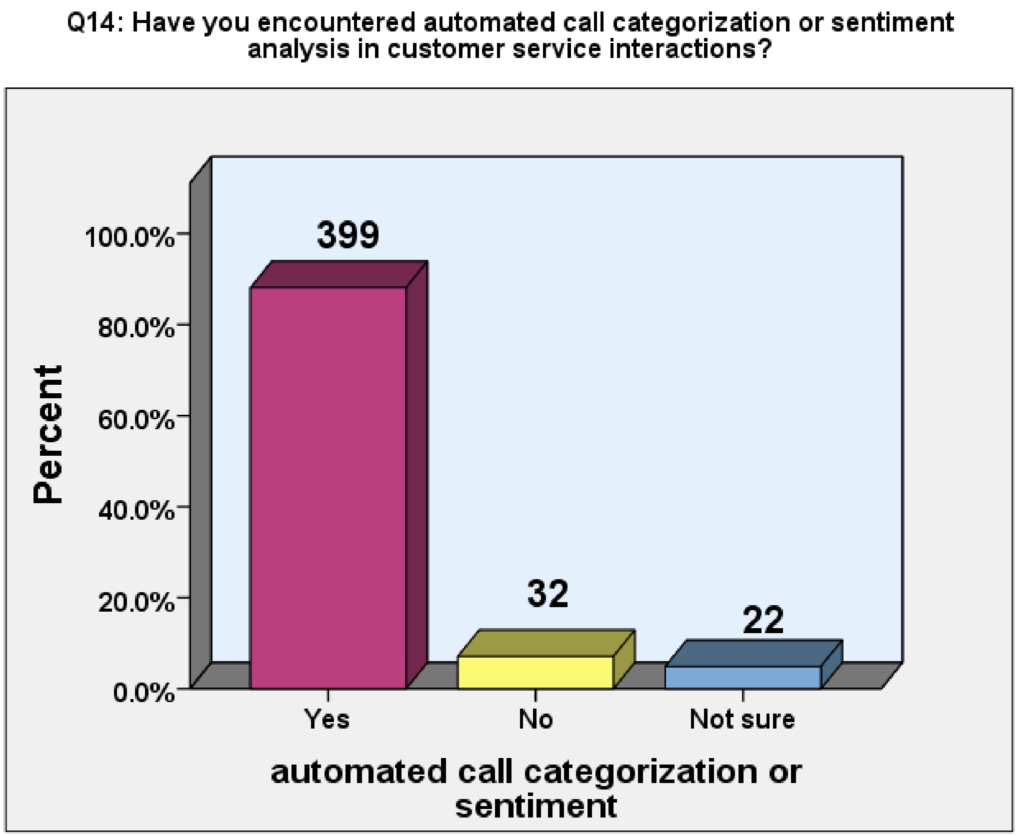

Figure 24. Survey-14

4.1.15 Results of Survey Question Fifteen

The survey question aimed to identify the key benefits you have observed from voice-based patient categorization. The distribution of responses is as follows:

- Improved patient outcomes
- Enhanced diagnostic accuracy

- Optimized treatment planning
- Early detection of diseases
- Real-time monitoring of patient conditions
- Personalized care

The majority of participants reported that it improved patient outcomes and Enhanced diagnostic accuracy. Voice-based categorization can streamline operations, optimize workflows, and enable businesses to handle a larger volume of voice data more efficiently. This suggests that voice-based categorization provides valuable insights and data that support Optimized treatment planning and early detection of diseases. voice-based categorization has improved personalized care. This finding highlights the importance of using voice data to understand real-time monitoring of patient conditions.

4.2 Data analysis

Data analysis is done in SPPS and Reliabilities and correlations test through SPSS. Data collected through questionnaires be analyzed using SPSS. As SPSS software tells us the information related to regression, correlation and finding out the reliability of the scales used for each variable and through mediation analysis, we will find out how much Voice based categorization (VBC) tools and technology being independent variable impact on business (healthcare and non-healthcare) (dependent variables). By using either of software we can then analyze the data and make conclusions based on the data we collected that whether our hypothesis related to the study are accepted or rejected. In the research process, the next step that comes after conducting the literature review in a critical manner and then developing a theoretical framework based on the current literature of our study and furthermore describing in detail the research approaches and methodology that is used to collect the real time data from the respondents, is describing the results found in the study in the form of detailed interpretation. The data analysis software, Statistical Package for Social Sciences, has been used to conduct the analysis of the data we collected from the Professionals of healthcare and business industry. The version of SPSS used is IBM SPSS

23 for conducting the analysis of the data. In this chapter, we will discuss about the results that came after the analysis in the form of interpretation. As mentioned in the previous chapter of research methodology, the tests that have been conducted for the analysis includes the reliability analysis test (also called the Cronbach Alpha), the descriptive statistics including mean, median, mode, standard deviation, skewness and kurtosis. Furthermore, in order to know regarding whether the hypothesis of the study have been supported or rejected, the correlation and regression tests have been performed.

4.3. Correlation Statistics

Correlation coefficient is reported as the linear association between two variables. It may take the range of ± 1.

Table 2 ***Correlation, Reliability, Convergent and Discriminant Validity***

Constructs	CR	AVE	MSV	M	SD	N	VBC	IND	HC
VBC	0.942	0.765	0.569	4.3628	1.50129	453	***0.87***		
IND	0.935	0.783	0.465	4.4049	1.58108	453	.642**	***0.88***	
HC	0.931	0.771	0.569	4.0938	1.42197	453	.708**	.634**	***0.87***

Notes M = Mean; SD= Standard Deviation, ** p<0.01, Diagonal elements (in bold) represent the square root of the AVE

The linear link between two variables is given as the correlation coefficient. It could be in the range of ±1. A correlational value of zero shows that there is no relationship between the measured variables, and the closer the value of the r coefficient ±1 is, regardless of direction, the stronger the linear relationship between the two variables [51]. In the present study, significant and moderate association was notice among the variables.

4.4 Exploratory Factor Analysis (EFA)

The primary purpose of running EFA as suggested by the renowned researchers is to refine and check the uni-dimensionality of the measurement scale as well factor emerged out of a pool of variables [47, 52, 41]. For this purposes, the researcher decided to collect the final data of professionals, which was subject to the Exploratory Factor Analysis (EFA) for checking uni-dimensionality of the said scale. However, as per the literature, it was recommended that the sample size between 400-500 are sufficient for the EFA [47, 50]. Additionally, it is also recommended that subject to the variable ration should be 10:1 for running EFA. In this study, uni-dimensionality was check individually, and a maximum number of the items in a construct (VBO) were five. Therefore, the researcher decided to collect the data of 450+ professionals of business and. Healthcare department.

EFA is a method for examining the structure of interrelationships among a large number of variables described in a small slice of the larger set of variables known as factors. The selection of a method for factor extraction and the technique of factor rotation are the other two crucial procedures involved in executing EFA. The researcher chose Principal Component Analysis (PCA) for factor extraction since it accounts for overall variance in the data set. Factors having an Eigenvalue greater than one should be kept [47, 53, 54]. However, another essential matter is deciding the techniques of the factor rotationin EFA.

Varimax is the most often utilized factor rotation method among the numerous available. EFA was used with PCA and Varimax rotation by the researcher. The value of Kaiser-Meyer-Olkin (KMO) was also used to measure sample adequacy. The KMO range (0.5 and 1.0) shows that the sample was sufficient for EFA. The hypothesis that the variables are uncorrelated was tested using Barlett's Test of Sphericity (BTS). The significant values of BTS (0.05) revealed that the correlation between the investigated variables was not too strong. [47, 48].

Whether to keep items retain or not retain depend upon the loadings and communalities of the results revealed by the EFA. Scholarly communication available suggested that only those items would be retained whose factor loading value (0.4) or above. However, communalities are the total amount of the variance shared by an original variable with all variables, its value recommended by the eminent scholars (>0.5). Hence in this study, only those items are retained whose value for factor loading more 0.4 and communalities is more than 0.5 [50, 55]. Therefore, after performing the EFA and Reliability, some items were found to low loading and commonalities and not acceptable range. Some items were deleted due to mentioned ground. Above table exhibits that the loading, communality and various indices up to the mark. The sample was also found to be statistically significant as well enough sample size for the justification of the study.

The degree to which the items of the latent construct is internally consistent in their measurement in a set of the variables. The items of the highly reliable construct are a highly interrelated, meaning thereby that they all seem to measure the same thing. Precisely, it determines the level of internal consistency ratings generated by the scale given in the questionnaire.

The higher the degree of reliability, the more excellent stability in research instrument and the higher it's intercorrelation. Reliability refers to scale items to correlate with the other items of the same scale. The most frequently and worldwide adapted criterion to measure the internal consistency of the scale is Cronbach Alpha. The value of Cronbach Alpha if so high it means the scale items are so highly correlated [56, 57]. The recommended value of the Cronbach Alpha is 0.70 or above was acceptable [56] . Cronbach Alpha values for all the scale which has been adopted found greater than 0.07 in this research project

Table 3 *EFA Statistics*

Constructs	**Items**	***Factor Loading***		**Communality**	**Variance Explained**
Industry	What industry does your business operate in?	0.878		.803	58.222
	Are you currently using or planning to use voice-based categorization systems in your business?	0.856		.886	
	What are the primary reasons for implementing voice-based categorization in your business? (Select all that apply)	0.868		.828	
	What are the main challenges you might encounter or have encountered in implementing voice-based categorization systems? (Select all that apply)	0.897		.836	
	How has voice-based categorization impacted your business operations? (Select all that apply)	0.873		.781	
	Have you faced any ethical or legal considerations related to voice-based categorization?	0.766		.884	
	How do you perceive the future of voice-based categorization in your industry?	0.801		.836	
	Would you recommend voice-based categorization to other businesses in your industry?	0.753		.830	
Healthcare	Are you aware of the potential benefits of voice-based patient categorization in healthcare?		0.711	.792	10.921
	Do you believe voice-based categorization can improve patient outcomes and diagnostic accuracy?		0.824	0.835	
	Are you concerned about privacy issues related to voice-based categorization systems in healthcare?		0.784	.820	
	Are you aware of any resistance from employees or stakeholders towards implementing voice-based categorization systems?		0.801	.825	

	How likely are you to adopt voice-based categorization technology in your organization in the near future?		0.824	.835	
	Have you encountered automated call categorization or sentiment analysis in customer service interactions?		0.738	.801	
	What are the key benefits you have observed from voice-based patient categorization? (Select all that apply		0.733	0.729	
KMO=.936, Bartlett's test Chi sq= 6602.96, D.f.=153,Sig value =.000					

Source: Primary data

4.5 Confirmatory factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a multivariate statistical approach for determining if measured variables accurately indicate the number of components. It's a tool for confirming or disproving measurement theories. Details can be found in the section on Validity and Reliability.

4.5.1 Validity

Evidence that a study allows correct inferences about the questions it was aimed to answer or that test measure what it set out to measure conceptually. It refers to whether an instrument measure what it was designed to measure. Theoretically, validities are two types which further discussed in the below section.

4.5.2 Convergent validity

What is the correlation between the scale and another construct measure? Convergent validity refers to how closely several methods of evaluating a construct provide the same results. There is eminent academic communication that expresses convergent validity as a determinant. Factor loading, which is represented by standardized loading estimations, is the first. In terms of loading, the current study fits this criteria, meaning that any loading greater than 0.7 is acceptable. The average variance extracted (AVE) was the second determinant, which is defined as the mean-variance extracted for the loading on the construct; the AVE should be greater than 0.5. This limit was likewise exceeded in the current investigation. The Composite reliability (CR) is the third deterrent, and it is calculated by adding the square sum of the factor loading for each construct and the sum of the error variance terms for each construct. The threshold range of the CR is more than 0.7 [58, 56], this study also reached that limits.

Table 4 ***Loading and Cronbach's alpha (CFA Statistics*****)**

Constructs	**Items**	***Loading***	***Cron-bach's alpha***
Industry	What industry does your business operate in?	0.878	.941
	Are you currently using or planning to use voice-based categorization systems in your business?	0.856	
	What are the primary reasons for implementing voice-based categorization in your business? (Select all that apply)	0.868	
	What are the main challenges you might encounter or have encountered in implementing voice-based categorization systems? (Select all that apply)	0.897	
	How has voice-based categorization impacted your business operations? (Select all that apply)	0.873	
	Have you faced any ethical or legal considerations related to voice-based categorization?	0.766	
	How do you perceive the future of voice-based categorization in your industry?	0.801	
	Would you recommend voice-based categorization to other businesses in your industry?	0.753	
Healthcare	Are you aware of the potential benefits of voice-based patient categorization in healthcare?	0.711	.934
	Do you believe voice-based categorization can improve patient outcomes and diagnostic accuracy?	0.824	
	Are you concerned about privacy issues related to voice-based categorization systems in healthcare?	0.784	
	Are you aware of any resistance from employees or stakeholders towards implementing voice-based categorization systems?	0.801	

	How likely are you to adopt voice-based categorization technology in your organization in the near future?	0.824	
	Have you encountered automated call categorization or sentiment analysis in customer service interactions?	0.738	
	What are the key benefits you have observed from voice-based patient categorization?	0.733	

Source: Primary Data

4.6 Regression analysis

Composite reliability was used to determine construct reliability (CR). A composite dependability score of 0.6 or above is regarded appropriate [59]. As a result, all of the constructs and their dimensions were trustworthy. Additionally, convergent and discriminant validity were investigated. The average variance was calculated to determine convergent validity (AVE). The threshold of 0.5 was met by all structures and their dimensions [60, 57]. Each construct was shown to be more strongly and closely associated to its measurements than the other constructs in the study, with a factor correlation of >0.8 [61]. Furthermore, for each construct, the square root of AVE was found to be higher than its co-relational value [62].

Table 5 *Hypothesis at a glance*

Hypothesis			Estimate	S.E.	C.R.	P	Decision?
VBO	<---	Business	0.334	0.156	4.94	***	Significant
VBO	<---	Healthcare	0.598	0.266	8.073	***	Significant
VBO	<---	Impacts	0.337	0.127	6.505	***	Significant

****$p<0.001$*

The summarized view of the various hypotheses was represented in the given table. The path coefficient and summarized hypothesis result were depicted clearly in the following section. The first hypotheses, there is significant impact of Voice based categorization on Business was significant (β=.211, $p<0.001$, C.R. = 4.94) supporting H_1. Similarly succeeding hypothesis, there is a significant impact of Voice based categorization on Healthcare (β=.421, $p<0.001$, C.R. =8.073) supporting H_2. Additionally, there is also significant impact was noted on need to apply Voice based categorization in business (β=.281, $p<0.001$, C.R. =6.505) meaning there by supporting H_3 with all together.

Table 6 Hypotheses based on results

Hypothesis	**Statement**	**Results**
H1	There is positive significant impact of Voice based categorization on Business.	**Accepted**
H2	There is positive significant impact of Voice based categorization on healthcare.	**Accepted**
H3	There is positive significant impact of need of implementation of voice based categorization.	**Accepted**

CHAPTER V:

DISCUSSION

5.1 Introduction

An exhaustive discussion on the research process, data analysis and its interpretation has been done in the previous chapter. The present chapter grounded upon the conceptualized debate on the result/ findings of the ongoing investigation. Next to this, the managerial and societal implications for the policymakers have been presented, followed by the concluding remarks and future research direction and limitations of the study along with specific suggestions have also been given in this chapter.

5.2 Discussion

The comprehensive analysis of the survey results sheds light on various aspects of the participants' industries and their perception of voice-based categorization. The distribution of industries reveals that healthcare takes the lead, followed by customer service, market research, and fraud detection. This distribution reflects the diverse domains where voice-based categorization finds relevance, with healthcare clearly standing out as a sector with considerable adoption potential.

When examining the motivations for implementing voice-based categorization, it becomes evident that businesses have varied objectives. The majority of participants aim to enhance customer service, recognizing the pivotal role of efficient call categorization and sentiment analysis in improving customer satisfaction. Equally significant is the aspiration to leverage voice-based data for refining market research insights, indicating a growing awareness of the valuable consumer sentiment embedded in voice interactions. Notably, the desire to gain a competitive advantage also emerges as a driving force, showcasing businesses' intention to harness the power of voice-based categorization for strategic decision-making. Even though a smaller percentage mentioned enhancing fraud detection capabilities, it underscores the potential this technology holds in enhancing security measures and mitigating financial risks.

However, the journey towards implementing voice-based categorization comes with its set of challenges. Technical issues and system integration prove to be a substantial hurdle, underscoring the intricacies of merging innovative technologies with existing frameworks. Data privacy and security concerns follow closely, emphasizing the need for stringent measures to protect sensitive voice data and adhere to privacy regulations. Furthermore, the acknowledgment of limited availability of skilled personnel highlights a demand for expertise in areas such as machine learning and data analysis to ensure the successful integration and management of these systems.

The impact of voice-based categorization on business operations is notable, with a positive trajectory reported. The enhancement of decision-making processes stands out, affirming the utility of voice-based data insights in informed and strategic choices. Similarly, the reported improvement in customer satisfaction aligns with the overarching goal of enhancing customer experience through tailored interactions. The observed increase in operational efficiency signifies the potential of voice-based categorization to streamline processes and optimize resource utilization.

Looking ahead, the participants' optimistic perspective on the future of voice-based categorization is striking. A significant percentage believe that it will evolve into an essential tool for businesses, signaling a strong endorsement of its potential to revolutionize operations and competitiveness. The limited percentage anticipating specific use cases underscores the versatility of this technology, while those with uncertain views indicate a possible need for more comprehensive understanding and awareness.

In conclusion, the survey findings provide crucial insights for organizations aiming to adopt voice-based categorization systems. The results underscore the diverse landscape of industries where this technology holds promise, the multifaceted objectives driving its implementation, the challenges that need to be navigated, the positive impacts observed on business operations, and the robust optimism surrounding its future potential.

5.3 Potential Outcomes

The study has revealed several potential outcomes that can significantly impact businesses and research in the field of voice-based categorization:

5.3.1 Improved Business Operations

The integration of voice-based categorization systems into various industries, such as customer service, market research, and fraud detection, can lead to improved business operations. Enhanced customer service, informed decision-making through market insights, and heightened security measures in fraud detection can collectively contribute to increased efficiency and competitiveness.

5.3.2 Enhanced Customer Experiences

By accurately recognizing emotions and sentiments in customer interactions, businesses can personalize responses and tailor their services to meet individual needs. This can result in improved customer experiences, higher satisfaction rates, and increased customer loyalty.

5.3.3 Ethical Consideration Advancements

The study highlights the importance of addressing ethical considerations associated with voice-based categorization. As businesses become more aware of these ethical challenges, there is potential for the development of advanced privacy protection measures, bias mitigation techniques, and transparent data usage policies.

5.3.4 New Research Opportunities

The study has identified several gaps and areas for further research, paving the way for researchers to delve deeper into specific aspects of voice-based categorization. The identification of these gaps can lead to the exploration of new methods, techniques, and applications that contribute to the advancement of the field.

5.4 Suggestions for Further Research

5.4.1 Industry-specific Implementations

While the study covered customer service, market research, and fraud detection, further research could focus on industry-specific implementations of voice-based categorization. Industries such as education, entertainment, logistics, and manufacturing may have unique challenges and opportunities that warrant specialized investigation.

5.4.2 Bias Mitigation Techniques

Given the ethical concerns related to bias in voice-based categorization, future research could delve deeper into the development and evaluation of bias mitigation techniques. Exploring methods to ensure fairness and equitable treatment in voice categorization systems across diverse populations can contribute to more responsible and unbiased AI technologies.

5.4.3 Privacy-enhancing Technologies

The study emphasized the need for robust data privacy and security measures. Further research could explore innovative privacy-enhancing technologies, such as secure multi-party computation, federated learning, and differential privacy, to protect sensitive voice data while still enabling meaningful analysis.

5.4.4 Human-Machine Collaboration

As businesses adopt voice-based categorization systems, further research could investigate the potential for human-machine collaboration. Exploring how human experts and AI algorithms can work synergistically to achieve more accurate categorization and decision-making outcomes could be valuable.

5.4.5 Long-term Impact Assessment

Research on the long-term impact of implementing voice-based categorization systems is essential. Studying how these systems influence business processes, employee roles, customer relationships, and market dynamics over an extended period can provide insights into the sustainability and effectiveness of this technology.

5.4.6 User-Centric Studies

Conducting user-centric studies to understand end-users' perceptions and experiences with voice-based categorization systems can provide valuable insights. Exploring factors that affect user acceptance, trust, and satisfaction can inform the design and implementation of more user-friendly and effective systems.

5.4.7 Cross-disciplinary Collaborations

Voice-based categorization sits at the intersection of various disciplines, including linguistics, machine learning, ethics, and business management. Further research could encourage cross-disciplinary collaborations to leverage diverse expertise in addressing complex challenges and unlocking novel applications.

5.5 Integration of Further Research Suggestions

Incorporating these suggestions for further research can extend the knowledge base and practical applications of voice-based categorization. Addressing industry-specific needs, ethical concerns, privacy measures, collaboration dynamics, long-term impacts, user experiences, and interdisciplinary collaborations can collectively contribute to a more comprehensive understanding of the potential and challenges of this technology.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The key benefits from voice-based [32] patient categorization are as follows:

Improved Accuracy

Voice-based patient categorization enables more accurate and reliable identification and classification of patients based on their voice patterns. This can lead to better patient profiling and understanding of their specific needs and conditions.

Enhanced Efficiency

Automating the categorization process using voice-based systems saves time and resources for healthcare providers. It eliminates the need for manual categorization and allows for quick and efficient analysis of patient data.

Personalized Care

Voice-based patient categorization helps in creating personalized care plans and treatments. By categorizing patients based on their voice characteristics, healthcare providers can tailor their interventions to meet individual needs, leading to improved patient outcomes and satisfaction.

Early Detection and Intervention

Voice-based categorization can assist in early detection of health issues or changes in a patient's condition. By analyzing voice patterns, the system can identify subtle variations that may indicate potential health risks, enabling timely intervention and prevention of complications.

Remote Monitoring

Voice-based categorization systems allow for remote monitoring of patients' health status. This can be particularly useful for patients with chronic conditions or those requiring continuous monitoring. By analyzing voice data collected remotely, healthcare providers can assess patient well-being and intervene when necessary, reducing the need for frequent in-person visits.

Data-driven Insights

Voice-based patient categorization generates a wealth of data that can be analyzed for valuable insights. By examining voice patterns and trends across patient groups, healthcare organizations can identify patterns, correlations, and predictors related to specific conditions, enabling evidence-based decision-making and improved healthcare delivery.

Cost Savings

The implementation of voice-based categorization can lead to cost savings for healthcare organizations. By automating the categorization process and streamlining data analysis, healthcare providers can optimize resource allocation and reduce manual labor costs.

Improved Patient Experience

Voice-based patient categorization can contribute to a better patient experience by enabling personalized care, timely interventions, and efficient healthcare delivery. Patients benefit from tailored treatments, reduced waiting times, and remote monitoring, leading to increased satisfaction and engagement in their own healthcare.

These benefits collectively enhance the quality and efficiency of healthcare services, promote early detection and personalized care, and contribute to better patient outcomes and experiences.

6.2 Implications

Implications of voice-based patient categorization encompass a wide range of areas within the healthcare industry [31]. This innovative technology has the potential to revolutionize patient care and healthcare delivery by leveraging voice patterns for categorization and analysis. The following are detailed implications of voice-based patient categorization:

Enhanced Diagnostic Capabilities

Voice-based patient categorization can provide valuable insights for diagnostic purposes. By analyzing voice patterns, healthcare providers can detect subtle changes associated with certain medical conditions, such as neurological disorders or respiratory diseases. This technology can complement existing diagnostic tools and assist in early detection and accurate diagnosis.

Personalized Treatment Plans

Voice-based categorization enables healthcare professionals to create personalized treatment plans tailored to individual patients. By understanding the unique characteristics of a patient's voice, healthcare providers can identify specific needs, preferences, and responses to therapies. This personalized approach enhances treatment effectiveness, improves patient compliance, and ultimately leads to better outcomes.

Remote Patient Monitoring

Voice-based patient categorization facilitates remote monitoring of patients' health conditions. By collecting voice data regularly, healthcare providers can track changes in voice patterns and identify potential issues or deterioration in patients' health. This remote monitoring capability is particularly beneficial for patients with chronic conditions or those who require continuous monitoring, as it reduces the need for frequent in-person visits and allows for timely interventions.

Predictive Analytics

The extensive data collected through voice-based patient categorization can be leveraged for predictive analytics. By analyzing voice patterns and correlating them with patient outcomes, healthcare organizations can develop predictive models to anticipate disease progression, identify high-risk patients, and optimize treatment plans. This proactive approach has the potential to improve patient management, reduce healthcare costs, and save lives.

Population Health Management

Voice-based patient categorization contributes to population health management strategies. By categorizing and analyzing voice patterns of a large patient population, healthcare providers can identify prevalent health issues, monitor trends, and target interventions effectively. This population-level analysis helps in resource allocation, preventive care planning, and the development of public health initiatives.

Improved Patient Engagement and Satisfaction

Voice-based patient categorization enhances patient engagement and satisfaction by providing personalized care and involving patients in their own healthcare journey. By incorporating patient voice data into treatment plans, healthcare providers empower patients, improve communication, and foster a collaborative approach to care. This patient-centered approach leads to increased satisfaction, better adherence to treatment protocols, and improved overall patient experience.

Streamlined Workflow and Resource Allocation

Implementing voice-based patient categorization streamlines workflow processes and optimizes resource allocation within healthcare organizations. By automating the categorization process, healthcare providers can save time and reduce manual effort involved in data analysis. This enables healthcare professionals to focus more on patient care, improves operational efficiency, and maximizes resource utilization.

Ethical Considerations

Voice-based patient categorization raises ethical considerations regarding privacy, data security, and informed consent. As voice data contains personal information, healthcare organizations must ensure strict adherence to privacy regulations and implement robust security measures to protect patient data. Additionally, patients must be fully informed about the purpose and potential risks of voice data collection and have the option to provide informed consent.

Integration with Electronic Health Records (EHR)

Integrating voice-based patient categorization with electronic health records (EHR) systems can enhance data integration and interoperability. By incorporating voice data into comprehensive patient records, healthcare providers gain a holistic view of patients' health, enabling more informed decision-making, seamless care coordination, and improved continuity of care.

Research and Development Opportunities

Voice-based patient categorization opens up avenues for further research and development in the field of healthcare technology. Ongoing advancements in voice analysis algorithms, machine learning, and artificial intelligence present opportunities for refining and expanding the capabilities of voice-based categorization systems. This can lead to improved accuracy, broader applications, and more sophisticated predictive models.

6.3 Recommendations for Future Research

Here are several areas that warrant further investigation:

Refining Voice Analysis Algorithms

Future research should focus on refining and improving voice analysis algorithms used in patient categorization. This includes exploring advanced machine learning and artificial intelligence techniques to enhance the accuracy and reliability of voice-based categorization systems. By developing more sophisticated algorithms, researchers can uncover hidden patterns and nuances in voice data that may contribute to more precise diagnostics and treatment planning.

Longitudinal Studies

Conducting longitudinal studies can provide valuable insights into the long-term effectiveness and impact of voice-based patient categorization. By tracking patients over an extended period, researchers can assess the stability of voice patterns, identify changes associated with disease progression or response to treatment, and evaluate the utility of voice-based categorization in monitoring chronic conditions.

Validation Studies

Conducting comprehensive validation studies is essential to establish the reliability and validity of voice-based patient categorization in different healthcare contexts. Such studies should involve diverse patient populations, including various age groups, genders, and cultural backgrounds. Validating the effectiveness of voice-based categorization across different populations will ensure its applicability and generalizability in real-world healthcare settings.

Integration with Other Healthcare Technologies

Exploring the integration of voice-based patient categorization with other healthcare technologies can unlock new possibilities and synergies. For example, integrating voice analysis with wearable devices or electronic health records (EHR) systems can provide a more comprehensive and real-time view of patients' health. Investigating the interoperability and compatibility of voice-based categorization with existing healthcare technologies will enhance the potential for seamless integration and data exchange.

Ethical Considerations and Patient Privacy

Further research is needed to address ethical considerations and patient privacy concerns associated with voice-based patient categorization. This includes studying patient perceptions, attitudes, and preferences regarding the collection and use of voice data for healthcare purposes. Understanding patient perspectives can inform the development of robust privacy frameworks.

Comparative Studies

Conducting comparative studies can provide insights into the advantages and limitations of voice-based patient categorization in comparison to other diagnostic or monitoring methods. Comparing the accuracy, efficiency, and cost-effectiveness of voice-based categorization with traditional approaches or alternative technologies will help healthcare providers make informed decisions about its implementation and potential benefits.

Real-world Implementation and Impact Assessment

Research should focus on real-world implementation and the assessment of the impact of voice-based patient categorization in diverse healthcare settings. This involves studying the integration challenges, organizational readiness, and healthcare provider perspectives on adopting and using voice-based categorization systems. Assessing the actual impact on patient outcomes, workflow efficiency, resource utilization, and overall healthcare delivery will provide valuable insights into its value and sustainability.

User Experience and Human-Machine Interaction

Exploring the user experience and optimizing human-machine interaction in voice-based patient categorization systems is crucial for their successful adoption and acceptance. Future research should investigate user interface design, user training needs, and the integration of voice-based categorization into existing clinical workflows.

Cost-Effectiveness Analysis

Conducting cost-effectiveness analyses is essential to evaluate the economic impact of implementing voice-based patient categorization. Research should explore the potential cost savings, resource optimization, and return on investment associated with adopting this technology. Assessing its cost-effectiveness will support healthcare organizations in making informed decisions regarding its implementation and long-term sustainability.

Non-Medical Applications

While voice-based patient categorization has primarily been explored in healthcare settings, future research should explore its potential applications in non-medical sectors. Investigating the effectiveness and implications of voice-based categorization in industries such as customer service, market research, fraud detection, and mental health support can open new avenues for innovation and economic growth.

6.4 Findings

The study's objectives were aimed at exploring the potential applications, benefits, challenges, and ethical considerations of voice-based categorization systems in non-medical sectors. The findings from each objective contribute to potential outcomes that can significantly impact businesses and research in this field:

Objective: Explore Potential Applications

The study successfully identified multiple potential applications of voice-based categorization in different industries. These applications include improving customer service by analyzing emotions, enhancing market research insights through voice pattern analysis, and strengthening fraud detection mechanisms by identifying irregularities. The potential outcome of this exploration is a roadmap for businesses to implement voice-based categorization effectively in various contexts, leading to operational improvements and customer satisfaction.

Objective: Examine Advantages and Benefits

The examination of advantages and benefits highlighted the efficiency of voice-based categorization in analyzing large volumes of voice data accurately. The real-time insights it provides for customer needs and security threats contribute to improved operational efficiency, better decision-making, and enhanced fraud prevention. The potential outcome of this examination is a clear understanding of the tangible benefits that businesses can achieve by adopting voice-based categorization, motivating them to invest in this technology.

Objective: Address Challenges and Limitations

By addressing challenges such as technical issues, data privacy concerns, and resistance from stakeholders, businesses can overcome obstacles in implementing voice-based categorization systems. The potential outcome of this objective is the identification of strategies and solutions to mitigate challenges, enabling smoother integration and operation of voice-based categorization systems in business processes.

Objective: Explore Ethical Considerations

The exploration of ethical considerations provides businesses with insights into the responsible use of voice-based categorization systems. By addressing privacy concerns, ensuring consent, and implementing bias mitigation techniques, businesses can navigate the ethical complexities associated with this technology. The potential outcome is the development of guidelines and practices that prioritize ethical considerations, fostering trust and responsible AI adoption.

Objective: Assess Impact on Business Operations

The assessment of the impact on business operations revealed positive outcomes, including improved customer satisfaction, enhanced decision-making, operational efficiency, and the identification of market trends. The potential outcome is a clear understanding of how voice-based categorization positively influences various aspects of business operations, motivating businesses to embrace this technology for sustainable growth.

6.5 Further Research

Objective: Explore Potential Applications

Further research could delve deeper into specific industries not covered in the study, such as education or manufacturing, to uncover unique applications and benefits of voice-based categorization in these domains. This would broaden the understanding of its potential applications across diverse sectors.

Objective: Examine Advantages and Benefits

Future research could focus on quantifying the financial and operational benefits gained by businesses after implementing voice-based categorization. This would provide more concrete evidence of its positive impact on various business metrics.

Objective: Address Challenges and Limitations

Additional research could explore innovative technical solutions to address challenges, such as developing adaptable algorithms that account for diverse speech patterns and accents. This could lead to more robust and versatile voice-based categorization systems.

Objective: Explore Ethical Considerations

Further research could investigate the long-term effects of bias mitigation techniques and data privacy measures on the performance and acceptance of voice-based categorization systems. This would contribute to the development of more comprehensive and effective ethical frameworks.

Objective: Assess Impact on Business Operations

Future research could conduct longitudinal studies to track the sustained impact of voice-based categorization on businesses over extended periods. This would provide insights into the technology's lasting effects on business efficiency and competitiveness.

6.6 Integration of Research Suggestions

Integrating the potential outcomes and suggestions for further research enhances the study's depth and relevance. By aligning these suggestions with the original objectives, the study not only addresses gaps in the research but also provides a roadmap for future investigations that can enrich the understanding and application of voice-based categorization in non-medical sectors.

6.7 Conclusion

In conclusion, this project has explored the potential applications, advantages, challenges, and ethical considerations of voice-based categorization in various industries, including healthcare, customer service, market research, and fraud detection. The findings highlight the transformative impact that voice-based categorization can have on these sectors, offering new possibilities for improved customer service, enhanced market insights, advanced fraud detection, and efficient patient categorization in healthcare.

The analysis of the key benefits of voice-based patient categorization reveals its potential to revolutionize healthcare practices. By leveraging voice data, healthcare professionals can improve patient outcomes, enhance diagnostic accuracy, and optimize treatment planning. Voice-based categorization systems can assist in early detection of diseases, provide real-time monitoring of patient conditions, and support personalized care. The benefits observed include improved patient satisfaction, enhanced decision-making processes, increased operational efficiency.

However, the project also identified several challenges and limitations associated with voice-based categorization. Technical issues and system integration, data privacy and security concerns, limited availability of skilled personnel, and resistance from employees or stakeholders were among the main challenges encountered. These findings underscore the need for further research and development to address these challenges and ensure the successful implementation of voice-based categorization systems.

Ethical considerations emerged as a crucial aspect of voice-based categorization in commercial settings. Privacy concerns, informed consent, data governance, and the responsible use of voice data are essential considerations that should be addressed to build trust, protect patient rights, and comply with regulatory frameworks. Future research should focus on developing robust privacy frameworks, understanding patient perceptions, and ensuring ethical guidelines are in place to guide the responsible use of voice-based categorization systems.

The implications of this project extend beyond the healthcare industry. Voice-based categorization has the potential to transform customer service operations by enabling automated call categorization and sentiment analysis, leading to improved customer satisfaction and streamlined processes. In the field of market research, voice-based categorization can provide valuable insights into consumer preferences, opinions, and sentiment, contributing to more accurate market analysis and decision-making.

In light of the project findings, several recommendations for future research have been proposed. These recommendations include refining voice analysis algorithms, conducting longitudinal and validation studies, exploring integration with other healthcare technologies, addressing ethical considerations, assessing real-world implementation and impact, optimizing user experience, conducting cost-effectiveness analyses, and exploring non-medical applications. Future research in these areas will contribute to the advancement of voice-based categorization technology, its widespread adoption, and its positive impact on various industries.

Overall, this project emphasizes the transformative potential of voice-based categorization in improving customer service, market research, fraud detection, and patient care. While challenges and ethical considerations exist, the benefits and opportunities presented by voice-based categorization are significant. By addressing the identified challenges, conducting further research, and ensuring ethical guidelines are in place, organizations can harness the power of voice-based categorization to enhance their operations, deliver exceptional customer experiences, and drive innovation in their respective industries.

APPENDIX A

SURVEY

1. What industry does your business operate in?

a) Healthcare

b) Customer service

c) Market research

d) Fraud detection

2. Are you currently implementing voice-based categorization systems in your business?

a) Yes

b) No

3. What are the primary reasons for implementing voice-based categorization in your business? (Select all that apply)

a) Improving customer service

b) Enhancing market research insights

c) Gaining a competitive advantage

d) Enhancing fraud detection capabilities

4. What are the main challenges you have encountered in implementing voice-based categorization systems? (Select all that apply)

a) Technical issues and system integration

b) Data privacy and security concerns

c) Limited availability of skilled personnel

d) Resistance from employees or stakeholders

5. How has voice-based categorization impacted your business operations? (Select all that apply)

a) Improved customer satisfaction

b) Enhanced decision-making processes

c) Increased operational efficiency

d) Identified new market trends and opportunities

12. Are you aware of any resistance from employees or stakeholders towards implementing voice-based categorization systems?

a) Yes, there is resistance

b) No, there is no resistance

c) Not sure

13. How likely are you to adopt voice-based categorization technology in your organization in the near future?

a) Very likely

b) Somewhat likely

c) Not likely

14. Have you encountered automated call categorization or sentiment analysis in customer service interactions?

a) Yes

b) No

c) Not sure

15. What are the key benefits you have observed from voice-based patient categorization? (Select all that apply)

a) Improved patient outcomes

b) Enhanced diagnostic accuracy

c) Optimized treatment planning

d) Early detection of diseases

e) Real-time monitoring of patient conditions

f) Personalized care

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