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AI in Healthcare: Era of Healthcare Innovation, Role, Current Issues, Challenges, Recommendations and Future Directions

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Keywords— ***Artificial Intelligence (AI), challenges, clinical trials, Drug discovery, Health Care, Machine Learning (ML), medicine, patients care.***

Abstract— *The use of artificial intelligence (AI) in healthcare has revolutionized the field. The rapid progress in AI has resulted in the development of diagnostic, therapeutic, and intervention-based applications in the medical industry. Currently, there is a significant gap between AI-based research publications and their use in clinical anesthesia, which requires attention and resolution. AI technologies have made significant progress in recent years and are now widely used in several aspects of our everyday existence. Various endeavors are now underway in the healthcare sector to incorporate AI technology into practical medicinal interventions. Due to the rapid advancements in machine learning (ML) algorithms and enhancements in hardware capabilities, AI technology is anticipated to have a significant impact on efficiently processing and using vast quantities of health and medical data. Nevertheless, AI technology has distinct attributes that set it apart from current healthcare technologies. There are many aspects in the existing health care system that need to be improved in order to enhance the use of AI in health care. Furthermore, there is a limited acceptance of AI in the healthcare field among both medical professionals and the general public. Additionally, there are several worries around the safety and dependability of AI technology deployments. Hence, the purpose of this study is to provide the present state of research and implementation of AI technology in the field of healthcare and analyze the unresolved challenges. This research is conducted via a comprehensive literature review that explores the function of AI in the field of healthcare. This research offers valuable insights into the primary uses of AI in addressing particular difficulties in the construction industry. It also outlines the steps necessary to achieve the clear benefits associated with AI in healthcare.*

I. INTRODUCTION

Artificial intelligence (AI) refers to the expansive notion of computers that are specifically engineered to comprehend and execute tasks independently in an intelligent way. Initial endeavors in medical automation depended on manually designed algorithms that were based on inflexible principles, resulting in their inability to handle intricate clinical scenarios. The current healthcare industry is facing a significant shortage of human resources, which presents an opportune situation for using technology to address this issue. This may begin with the implementation of telemedicine and digital health platforms, and eventually advance to the integration of artificial intelligence [1].

The healthcare sector is now undergoing a significant change. The revolution is caused by the increasing overall expense of healthcare and the growing shortage of healthcare professionals. Consequently, the healthcare sector is seeking to adopt novel information technology-driven solutions and procedures that may reduce expenses and address these increasing challenges. Healthcare systems globally have significant challenges, such as limited accessibility, exorbitant expenses, inefficiency, and an aging population. Pandemics such as the coronavirus (COVID-19) place a burden on healthcare systems, leading to shortages of protective equipment, inadequate or inaccurate diagnostic tests, overwhelmed doctors, and limited information sharing, among other consequences [2-3]. Significantly, a healthcare disaster such as COVID-19 or the emergence of the human immunodeficiency virus (HIV) in the 1980s reveals the harsh truth about the deficiencies in our healthcare systems. As the healthcare crises worsen existing challenges, we have the opportunity to transform and implement systems of care and backoffice health systems to address issues such as: unequal access to healthcare, insufficient availability of on-demand healthcare services, exorbitant charges, and a lack of transparency in pricing [4]. The adoption of technological innovations is occurring at a gradual pace. Burnout among healthcare practitioners is caused by doctors' inability to stay updated with the newest advancements in medicine owing to the overwhelming volume of material that has to be absorbed [53].

The ongoing advancements in AI technology are anticipated to revolutionize the future of healthcare. Machine learning (ML) is a branch of AI that focuses on the development of computer algorithms capable of improving themselves via experience using mathematical methods [6-11]. Deep learning (DL) is a kind of machine learning that involves using artificial neural networks to interpret input data, simulating the neurons in the human brain [12]. The rapid proliferation of digital data, coupled with advancements in computing power driven by innovations in hardware technologies like graphics processing units, and the swift progress in ML algorithms, particularly those based on deep learning, are profoundly impacting the healthcare industry. Many medical publications have published a large number of papers that analyze extensive health data using ML technologies to diagnose and treat patients [13-14]. Moreover, several research have shown that the use of artificial intelligence in the field of healthcare yields superior outcomes in comparison to the current technology. Several studies involve utilizing AI technology to analyze medical images, distinguishing between images and utilizing them for treatments. Additionally, these studies aim to forecast the progression of diseases using diverse medical and healthcare data, create medical devices that aid in treatment decision-making and diagnosis, and secure medical data through encryption [15-21].

Moreover, several endeavors have been undertaken to create and market medical gadgets that use AI. Not only are major medical device manufacturers like General Electric, Siemens, and Phillips involved in the field, but also prominent global information technology companies such as Samsung, Google, Apple, Microsoft, and Amazon, as well as several competitive startups, have made notable research advancements in utilizing AI in healthcare. Building upon these scientific accomplishments, the firms are striving to build tangible commercial successes. In addition, the industry and medical field's endeavors are playing a significant role in the effective authorization of AI-based medical devices by regulatory organizations. In 2017, the Food and Drug Administration (FDA) in the United States granted approval for the use of medical devices based on AI. Similarly, in Korea, the Ministry of Food and Drug Safety has been granting approval for the usage of AI-based medical devices since 2018.

Nevertheless, there are lingering apprehensions surrounding AI-driven medical technology due to the stark differences between AI-based healthcare technologies and conventional healthcare technologies. Consequently, the use of AI in real clinical treatments remains restricted, as seen by low adoption rates [22-23]. In order to successfully adopt and use AI technology in real medical settings and provide valuable results to healthcare stakeholders, such as physicians and patients, it is crucial to tackle a range of problems. This paper explores the present state of domestic and international AI technology in health care and addresses the unresolved challenges that must be overcome for the successful use of AI in the health care sector [24].

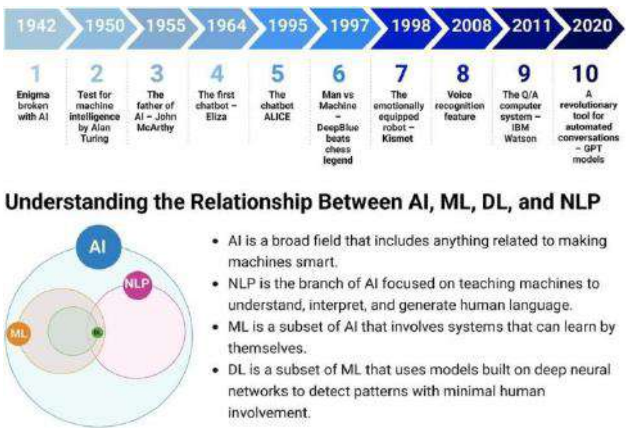

Fig.1. Historical journey of AI

Despite advancements in AI and ML technology, there are still barriers hindering their full integration into healthcare systems. These challenges include issues related to the lack of openness in algorithms, concerns about data privacy, and the presence of biases in AI models. The integration of AI technologies into the existing medical infrastructure is a significant hurdle for the healthcare industry, impeding widespread adoption. The absence of adequate regulation to ensure ethical and unbiased artificially intelligent applications poses a threat to patient safety and equitable healthcare delivery. In order to properly use the transformative capabilities of these procedures, it is crucial to concentrate on strengthening overall healthcare results via the customization of treatment programs and the improvement of diagnostic accuracy. To address these intricate anxieties, it is imperative to conduct a thorough examination of the current applications of AI in healthcare. This examination should include an analysis of the challenges and ethical considerations associated with these applications. Such an analysis is crucial in order to establish a clear path for future research and development endeavors that aim to overcome these issues [25].

The primary objective of this systematic literature review is to comprehensively assess the current state of AI applications in cutting-edge healthcare. This will be achieved by emphasizing the most significant advancements, evaluating their practical benefits and limitations, and examining the ethical and legal challenges associated with the implementation of these technologies. To provide readers a comprehensive understanding of how artificial intelligence and machine learning are used in healthcare, they are employed across several sectors such as diagnostics, tailored medication, predictive data analytics, and administrative operations. This study contradicts the growing body of evidence from diverse studies. These evaluations discuss the legal and ethical frameworks around AI systems, emphasizing the need of ensuring that these systems are fair, unbiased, and easily accessible. The objective is to provide practical insights and suggestions for healthcare professionals, authorities, and scholars to promote the appropriate integration of AI technologies, improving patient outcomes and promoting the overall quality of healthcare facilities.

II. THE ERA OF HEALTHCARE INNOVATION

The influence of big data and machine learning is pervasive in several domains of contemporary society, including entertainment, commerce, and healthcare. Netflix has knowledge of individuals' preferred films and series, Amazon possesses knowledge of individuals' preferred things for purchase, including the time and location of such purchases, and Google possesses knowledge of the symptoms and medical issues individuals are looking for. The abundance of data may be used for intricate personal profiling, offering valuable insights into behavior and enabling precise targeting [26]. Additionally, it has the potential to forecast healthcare trends. There is a strong belief that the use of AI may lead to significant advancements in all aspects of healthcare, ranging from diagnosis to treatment. There is already substantial evidence indicating that AI algorithms are achieving comparable or superior performance to humans in different tasks, such as analyzing medical images or correlating symptoms and biomarkers from electronic medical records (EMRs) to determine the nature and prognosis of diseases [27]. There is a growing demand for healthcare services worldwide, and many nations are facing a lack of healthcare practitioners, particularly doctors.

Healthcare facilities are grappling with the challenge of keeping pace with the rapid advancements in technology and meeting the heightened expectations of patients. These expectations are influenced by the high standards set by consumer goods such as those offered by Amazon and Apple [28]. The progress in wireless technology and smartphones has created possibilities for on-demand healthcare services via health monitoring applications and search platforms. It has also facilitated a novel method of healthcare delivery, allowing remote interactions that are accessible at any location and time. These services are beneficial for locations with limited access to healthcare and a shortage of experts. They assist to save expenses and minimize the risk of unwanted exposure to infectious diseases at the clinic. Telehealth technology is applicable in emerging nations with increasing healthcare systems and the ability to create healthcare infrastructure to match current demands [29]. Although the principle is understandable, these solutions still need significant independent validation to demonstrate patient safety and effectiveness.

The healthcare industry is becoming aware of the significance of AI-driven technologies in the advancement of healthcare technology. AI is thought to have the potential to enhance all aspects of healthcare operations and delivery. For example, the financial benefits that AI may provide to the healthcare system are a significant motivator for adopting AI applications. AI applications are projected to reduce yearly US healthcare expenses by USD 150 billion in 2026. A significant portion of these cost savings arise from shifting the healthcare paradigm from a responsive to a proactive strategy, emphasizing health maintenance rather than illness treatment. This is anticipated to lead to a reduction in hospitalizations, a decrease in medical visits, and a decrease in treatments. AI technology will play a crucial role in assisting individuals in maintaining good health via ongoing monitoring and guidance. It will also facilitate earlier detection of medical conditions, personalized treatment plans, and more effective post-treatment monitoring. [30].

Significant technical advancements have occurred in the area of AI and data science during the last decade. While research in AI has been conducted for many years across several fields, the present surge of AI excitement distinguishes itself from prior instances. The rapid development of AI tools and technologies in healthcare has been made possible by the right mix of faster computer processing speed, extensive data gathering libraries, and a plentiful supply of AI expertise [31]. This will result in a significant change in the degree of AI technology and its acceptance and influence on society.

III. AI: KEY PRINCIPLES, COMPONENTS, ETHICS, TYPES AND SUBFIELDS

3.1 Key principles of AI

The key principles collectively enable AI to mimic aspects of human intelligence and perform complex tasks. The key principles of AI include:

Learning: AI systems learn from data through algorithms. ML (a subset of AI) allows models to improve over time by identifying patterns in data [7-11].

Reasoning: AI systems use logical reasoning to make decisions and solve problems, often simulating human cognitive processes. This can involve rule-based or probabilistic approaches.

Perception: AI systems interpret inputs from the environment, such as images, sounds, or text, through sensors or data, enabling the machine to understand and interact with the world.

Planning: AI systems can plan actions or sequences of decisions to achieve specific goals. This often involves optimization and predicting outcomes based on certain variables.

Natural Language Processing (NLP): AI can understand, interpret, and generate human language, allowing for communication between humans and machines.

Autonomy: AI systems can perform tasks without human intervention, making decisions based on data and learned behavior.

3.2 Components of AI

The components work together to enable AI systems to perform a wide variety of tasks that require human-like intelligence [42]. The various components of AI are:

ML: A subset of AI, ML involves training models to recognize patterns and make decisions or predictions based on data. Techniques like supervised, unsupervised, and reinforcement learning fall under this category.

DL: A specialized type of ML that uses neural networks with multiple layers (deep neural networks) to model complex patterns in large datasets. It's particularly effective for tasks like image recognition, speech processing, and natural language understanding.

NLP: NLP enables AI to understand, interpret, and generate human language. It's used in applications like chatbots, language translation, and text analysis.

Computer Vision: AI systems use computer vision to analyze and interpret visual data (images or videos), allowing for object detection, image classification, facial recognition, and more.

Robotics: AI in robotics involves creating machines that can interact with their physical environment, perform tasks autonomously, and improve through learning. This includes navigation, object manipulation, and interaction with humans.

Expert Systems: These are AI programs that mimic human decision-making by using a predefined set of rules to analyze data and make recommendations. They're used in areas like medical diagnosis and troubleshooting.

Speech Recognition: AI systems convert spoken language into text and vice versa, allowing machines to understand and generate human speech, enabling applications like virtual assistants and voice control.

Knowledge Representation: AI models the world and stores information in a way that machines can understand, allowing for reasoning and decision-making. This is crucial for AI systems to interpret complex relationships and draw inferences.

3.3 Types of AI

The types of AI represent different stages and capabilities of AI, ranging from task-specific systems (Narrow AI) to potentially self-conscious systems (Self-aware AI) in the future [43]. The various types of AI can be broadly categorized into the following:

Narrow AI (Weak AI): Narrow AI is designed to perform a specific task or a set of tasks. It operates under predefined rules or is trained on specific datasets to excel in that domain. Virtual assistants (e.g., Siri, Alexa), recommendation systems, and image recognition software. It cannot perform tasks outside its domain or learn beyond its initial scope.

General AI (Strong AI): General AI refers to systems that possess the ability to understand, learn, and apply intelligence across various domains, just like human cognition. This level of AI is theoretical and hasn't been achieved yet. It would be capable of performing any intellectual task that a human can, from creative thinking to problem-solving.

Superintelligent AI: It surpasses human intelligence in all aspects, including creativity, problem-solving, and emotional intelligence. Currently speculative and not yet realized. It could outperform humans in all cognitive tasks, potentially making decisions beyond human comprehension.

Reactive AI: This type of AI operates purely on present inputs and doesn't store any past information to improve over time. It reacts to specific stimuli. Chess-playing AI (like Deep Blue) that only considers the current board configuration. Lacks memory and cannot learn from past experiences.

Limited Memory AI: Limited memory AI can make decisions based on past experiences by storing and using data for a short period. Self-driving cars that monitor road conditions and adapt based on recent data. It can improve performance by learning from historical data but has a limited capacity to store long-term knowledge.

Theory of Mind AI: This is an advanced type of AI that could understand emotions, beliefs, intentions, and thoughts, simulating human-like interactions and empathy. Hypothetical and under development in advanced research areas. It would interact with humans in a social and emotionally intelligent way.

Self-aware AI: The most advanced form of AI, where machines possess self-consciousness, awareness, and intelligence similar to humans. Currently non-existent and largely hypothetical. It would have its own identity and the ability to make decisions based on self-awareness.

3.4 Subfields of AI

Each of these subfields contributes unique methods and applications to AI, driving the development of intelligent systems across various industries [44]. The various subfields of AI are given in Table 1.

Table 1. Subfields of AI

Fields	Definition	Applications	Techniques
ML	ML focuses on creating algorithms that enable systems to learn from data and improve performance over time without explicit programming .	Spam filtering, recommendation engines, fraud detection.	Supervised learning, unsupervised learning, and reinforcement learning
Computer Vision	This subfield focuses on enabling machines to interpret and make sense of visual information from the world, such as images or videos.	Facial recognition, object detection, medical image analysis.	Image processing, feature extraction, neural networks.
Robotics	Robotics involves the design and development of robots capable of performing tasks autonomously or semi-autonomously.	Manufacturing automation, healthcare robots, drones.	Motion planning, manipulation, sensor fusion, and control systems.
NLP	NLP enables machines to understand, interpret, and generate human language.	Chatbots, language translation, sentiment analysis.	Speech recognition, text generation, language translation.
Expert Systems	Expert systems are AI programs that mimic human decision-making in specific domains by applying predefined rules and knowledge bases.	Medical diagnosis, technical support, troubleshooting systems.	Knowledge base, inference engine, and user interface.
Reinforcement Learning	A type of machine learning where agents learn by interacting with their environment to	Game playing (e.g., AlphaGo), autonomous	Exploration, exploitation, rewards, and penalties.

	maximize cumulative rewards.	vehicles, robotics.	
Fuzzy Logic	Fuzzy logic deals with reasoning that allows for approximate rather than fixed, binary answers, useful in decision-making processes.	Climate control systems, image processing, decision support systems.	Handling uncertainty and imprecision in data.
Neural Networks	Neural networks are inspired by the structure of the human brain, consisting of interconnected nodes (neurons) that process information in layers.	Image and speech recognition, language modeling, deep learning.	Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs).
Genetic Algorithms	A type of optimization algorithm inspired by the process of natural selection, used to solve problems by evolving solutions over time.	Optimization problems, automated design, scheduling.	Selection, mutation, crossover, and evolution.
Knowledge Representation and Reasoning (KR&R)	KR&R focuses on how AI systems store and apply knowledge to reason and solve complex problems.	Semantic web, expert systems, intelligent agents.	Ontologies, logic programming, frames, and semantic networks.
Speech and Audio Processing	This subfield deals with the recognition, processing, and generation of speech and audio signals.	Voice assistants, speech-to-text systems, audio classification.	Speech synthesis, speech recognition, sound event detection

3.5 Ethics of AI

The ethics of AI focus on addressing the potential risks, challenges, and moral considerations associated with the development and deployment of AI technologies. Some of the key ethical principles in AI are stated in Table 2. These ethical principles are essential for guiding the responsible and beneficial development of AI, ensuring that it serves society while minimizing risks and harm [45].

Table 2. Key Ethical Principles in AI

Parameter	Definition	Challenges	Goal
Fairness and Non-Discrimination	AI systems should treat all individuals and groups fairly, without bias or discrimination based on factors like race, gender, or socio-economic status.	Bias in training data can result in unfair outcomes, such as biased hiring algorithms or discriminatory predictive policing.	Ensure equitable treatment and outcomes for all individuals by addressing biases in AI models and decision-making processes.
Transparency and Explainability	AI systems should be transparent in how decisions are made, and the reasoning behind those decisions should be explainable to users and stakeholders.	Complex models like deep learning can be difficult to interpret, making it hard to understand how decisions are reached.	Provide clear, understandable explanations for AI decisions to increase trust and accountability.
Accountability	Developers and users of AI should be held accountable for the outcomes of AI systems, particularly in cases where decisions have significant consequences.	Identifying responsibility when an AI system causes harm or makes incorrect decisions can be difficult, especially in autonomous systems.	Establish clear guidelines for responsibility, liability, and oversight of AI systems.
Privacy and Data Protection	AI systems should respect individuals' privacy and protect sensitive personal data from	AI often relies on large datasets that can include personal information, raising	Implement strong data protection measures and ensure that data collection

	misuse or unauthorized access.	concerns about data security and surveillance.	and use comply with privacy laws and regulations (e.g., GDPR).
Safety and Security	AI systems should be designed to operate safely, minimizing risks to humans and other systems, and protecting against malicious attacks.	Autonomous systems, like self-driving cars or drones, could malfunction or be exploited by bad actors, causing harm or disruption.	Ensure robust testing, safety mechanisms, and security protocols to prevent accidents and malicious misuse of AI technologies.
Human Control and Autonomy	AI should enhance human decision-making and respect human autonomy rather than replacing or undermining it.	The increasing autonomy of AI systems, especially in areas like warfare (autonomous weapons) or healthcare, raises concerns about loss of human control.	Keep humans "in the loop" for critical decisions and ensure AI complements rather than diminishes human judgment.
Beneficence and Non-Maleficence	AI should be used for the benefit of humanity and should avoid causing harm or exploitation to individuals, communities, or the environment.	AI has the potential to be used in harmful ways, such as mass surveillance, misinformation, or reinforcing harmful societal structures.	Ensure that AI is developed and used with the intention of improving societal well-being and minimizing harm.
Environmental Impact	The development and deployment of AI systems should take into account their environmental footprint, including energy consumption and resource use.	Large AI models and data centers consume significant amounts of energy, contributing to environmental degradation and carbon emissions.	Promote sustainable AI practices by optimizing energy efficiency and minimizing resource consumption.
Inclusivity and Accessibility	AI technologies should be designed to be accessible to all, including marginalized or underserved populations, ensuring that the benefits of AI are shared broadly.	Some AI technologies may be inaccessible to certain groups due to high costs, technical barriers, or lack of inclusivity in design.	Make AI systems more inclusive and accessible by considering diverse user needs and ensuring equal access.
Long-Term Societal Impact	Consideration of the long-term consequences of AI on society, including its potential impact on employment, the economy, and societal structures.	AI could lead to job displacement, exacerbate inequalities, or disrupt social and economic systems.	Plan for responsible AI development that balances innovation with societal stability and ensures that technological progress benefits all sectors of society.

IV. ROLE OF AI IN HEALTHCARE

AI plays a transformative role in healthcare by enhancing the efficiency, accuracy, and personalization of medical services. AI is revolutionizing healthcare by improving diagnostic accuracy, personalizing treatments, and enhancing the efficiency of healthcare delivery systems, ultimately improving patient care and outcomes [46].

Medical Diagnosis: AI helps in analyzing medical images (e.g., X-rays, MRIs, CT scans) for early detection of diseases such as cancer, cardiovascular issues, and neurological conditions. AI-driven diagnostic tools can detect patterns that might be missed by human doctors, leading to earlier and more accurate diagnoses.

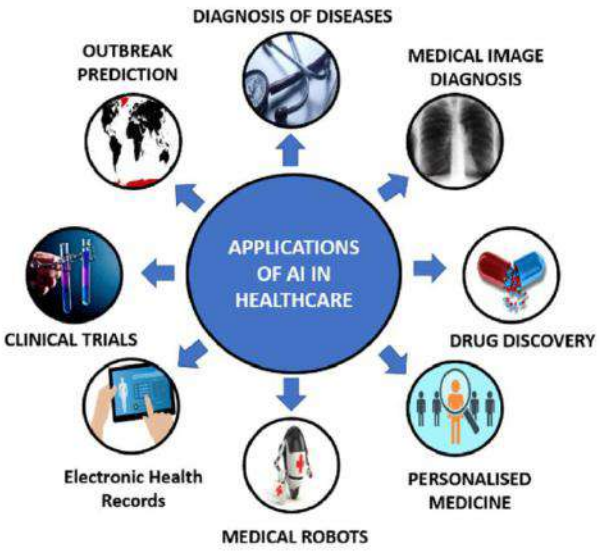

Fig.2. Applications of AI in healthcare

Predictive Analytics: AI algorithms can predict patient outcomes, disease progression, and potential health risks by analyzing historical data. Predictive analytics help in proactive healthcare, enabling doctors to intervene early and improve patient outcomes.

*Personalized Treatment:*AI supports personalized medicine by analyzing genetic data, patient history, and real-time health data to recommend tailored treatment plans. AI systems can suggest the most effective treatments based on a patient's unique genetic makeup and health profile.

Drug Discovery and Development: AI accelerates drug discovery by analyzing large datasets to identify potential drug candidates, reducing the time and cost of drug development. It can simulate how new drugs will interact with biological systems, speeding up preclinical testing.

Virtual Health Assistants: AI-powered chatbots and virtual health assistants can provide basic healthcare advice, schedule appointments, and answer patient questions. These tools enhance patient engagement and reduce the workload of healthcare professionals.

Robotic Surgery: AI enables robotic-assisted surgeries that are more precise and less invasive, reducing recovery times and improving patient outcomes. AI-driven robots can assist surgeons in complex procedures, enhancing accuracy and reducing human error.

Administrative Automation: AI automates administrative tasks such as medical record management, billing, and appointment scheduling, improving operational efficiency in healthcare institutions. This allows healthcare providers to focus more on patient care and less on paperwork.

Telemedicine: AI enhances telemedicine by enabling remote diagnostics, real-time monitoring, and virtual consultations. AI-powered tools can analyze patient data from wearables and other devices, enabling continuous care from a distance.

4.1 AI in Medical Diagnosis

AI is playing a pivotal role in transforming medical diagnosis by enhancing speed, accuracy, and the ability to process vast amounts of medical data. AI is becoming a valuable tool in medical diagnosis by enhancing accuracy, speed, and accessibility, ultimately improving patient care and health outcomes across various medical fields [47].

4.1.1. Medical Imaging and Radiology:

AI is widely used in analyzing medical images like X-rays, MRIs, CT scans, and ultrasounds to detect abnormalities and diseases such as cancer, fractures, and organ damage. It helps radiologists in:

Disease Detection: AI algorithms can detect early signs of diseases like cancer (e.g., breast cancer or lung cancer) by identifying patterns and abnormalities that may be difficult to detect with the naked eye.

Image Segmentation: AI can precisely segment images, isolating areas of concern, such as tumors, lesions, or tissues, enabling detailed analysis and diagnosis.

Reduced Human Error: By assisting radiologists, AI reduces the chances of misdiagnosis and improves diagnostic accuracy.

Example: Google's DeepMind developed an AI system that can detect over 50 types of eye diseases by analyzing 3D retinal scans.

4.1.2. Pathology and Histology:

AI is revolutionizing pathology by analyzing tissue samples, blood smears, and other biological samples under microscopes, detecting diseases at the cellular level. Key areas include:

Cancer Diagnosis: AI can analyze biopsy results and identify cancerous cells, providing faster and more accurate diagnoses for conditions like skin cancer, breast cancer, and prostate cancer.

Digital Pathology: AI-powered digital pathology platforms scan and analyze slides, helping pathologists review results more quickly and accurately.

Example: AI algorithms have been developed that analyze digitized pathology slides for identifying breast cancer metastases with high precision.

4.1.3. Cardiology:

AI is applied in cardiology to assess heart health and detect cardiovascular diseases early:

ECG Interpretation: AI systems can interpret electrocardiograms (ECGs) to identify irregular heart rhythms, arrhythmias, and other cardiac conditions more quickly than traditional methods.

Heart Disease Prediction: AI-based tools use patient data (e.g., blood pressure, cholesterol levels, and family history) to predict the likelihood of heart attacks, strokes, and other cardiovascular events.

Cardiac Imaging: AI enhances the analysis of echocardiograms and other heart imaging techniques, providing detailed assessments of heart function.

Example: An AI-based system developed by Stanford researchers can diagnose arrhythmias more accurately than experienced cardiologists by analyzing ECG readings.

4.1.4. Dermatology:

AI is used in dermatology to diagnose skin conditions by analyzing images of the skin, helping in the detection of:

Skin Cancer: AI algorithms can analyze skin lesions and moles to identify melanoma and other types of skin cancer.

Skin Conditions: AI helps dermatologists diagnose other skin conditions like eczema, psoriasis, and acne based on patient images and data.

Example: The SkinVision app uses AI to assess the risk of skin cancer by analyzing images of moles or skin lesions captured by the user's smartphone.

4.1.5. Genomics and Precision Medicine:

AI aids in diagnosing genetic disorders by analyzing genetic sequences and mutations:

Genome Sequencing: AI algorithms can process large amounts of genomic data to identify mutations or genetic markers associated with hereditary diseases.

Precision Medicine: AI helps in identifying the right treatments based on a patient's genetic profile, leading to more personalized and effective medical interventions.

Example: AI-driven platforms like IBM Watson for Genomics analyze patient genetic data to recommend targeted therapies for cancer treatment based on specific genetic mutations.

4.1.6. Neurology and Mental Health:

AI is assisting in the diagnosis of neurological and mental health conditions through advanced data analysis:

Brain Imaging Analysis: AI systems can analyze MRI and CT scans to detect early signs of neurological diseases like Alzheimer's, Parkinson's, or multiple sclerosis.

Mental Health Screening: AI tools can analyze speech patterns, facial expressions, and patient-reported data to screen for conditions such as depression, anxiety, and schizophrenia.

Example: AI models trained on brain scans can predict the onset of Alzheimer's disease years before symptoms appear, enabling early interventions.

4.1.7. Lab Testing and Diagnostics:

AI can be used to assist in lab testing and clinical diagnostics by analyzing blood samples, urine tests, and other laboratory results to detect diseases:

Blood Test Analysis: AI tools can quickly analyze blood samples for abnormalities like infections, anemia, or metabolic disorders.

Diagnostic Automation: AI systems automate the analysis of common lab tests, providing faster results and reducing the workload of lab technicians.

Example: AI has been integrated into laboratory information systems (LIS) to flag abnormal test results for conditions such as diabetes or infections, speeding up diagnosis and treatment.

4.1.8. AI in Electronic Health Records (EHR):

AI can analyze patient data from EHRs to aid in diagnostics:

Pattern Recognition: AI can recognize patterns in medical records that might indicate undiagnosed conditions or complications.

Predictive Analytics: AI can predict the likelihood of future health events (e.g., disease progression or hospital readmission) based on historical patient data.

Example: AI systems integrated into EHRs can alert doctors to potential diagnoses or missed conditions by analyzing patient histories and symptoms.

4.1.9. Infectious Disease Diagnosis:

AI plays a role in diagnosing infectious diseases by analyzing symptoms, medical data, and epidemiological information:

Pandemic Detection: AI can track and predict the spread of infectious diseases, such as COVID-19, by analyzing global health data.

Diagnostic Tools: AI-driven diagnostic platforms use symptoms and other patient data to rapidly identify infections like malaria, tuberculosis, or flu.

Example: AI tools like BlueDot use machine learning to track and predict outbreaks of infectious diseases by analyzing global datasets, helping healthcare systems respond more quickly.

4.1.10 Benefits of AI in Medical Diagnosis

Speed and Efficiency: AI can analyze medical data much faster than humans, allowing for quicker diagnoses and treatments.

Accuracy: AI reduces human errors and can detect subtle patterns in data that might be missed by clinicians.

Scalability: AI systems can process large amounts of data, making it easier to handle an increasing volume of diagnostic information, especially in overburdened healthcare systems.

Early Detection: AI's ability to identify diseases in early stages leads to better prognosis and outcomes for patients.

4.1.11 Challenges and Considerations

Data Privacy: Protecting patient data is crucial, as AI relies on large datasets that contain sensitive medical information.

Bias: AI models may inherit biases from the data they are trained on, which can lead to inaccurate diagnoses for underrepresented groups.

Interpretability: Many AI models, especially deep learning models, are "black boxes," meaning their decision-making process can be difficult to interpret, making it harder for doctors to trust AI-generated diagnoses.

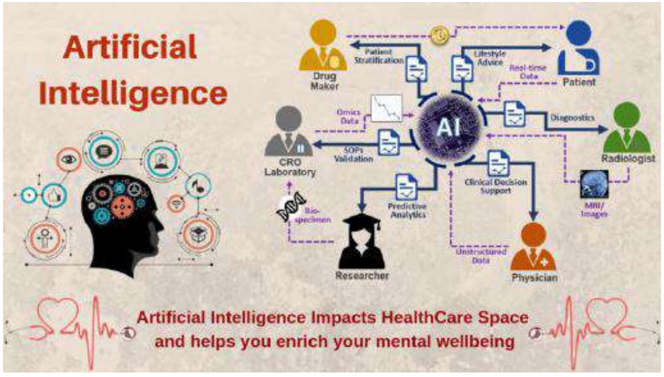

Fig.2. AI in Medical Diagnosis

4.2 AI in Drug Discovery and Development

AI is revolutionizing drug discovery and development by accelerating processes, improving accuracy, and reducing costs. AI transforms drug discovery by streamlining research, enhancing design, and optimizing clinical trials, making the development of safer, more effective drugs faster and more affordable.

4.2.1. Target Identification

AI can analyze vast biological data to identify potential drug targets (proteins, genes) involved in diseases. Techniques like ML and DL help in pattern recognition from genomic, proteomic, and clinical data, identifying novel targets for drug development.

4.2.2. Drug Design

Molecular modeling: AI predicts the structure and behavior of molecules, enabling the design of new compounds. Algorithms like GANs and RNNs can generate novel drug molecules with desired properties.

Virtual screening: AI tools rapidly screen millions of chemical compounds to find those that are most likely to interact with specific targets, reducing the need for costly lab experiments.

4.2.3. Drug Repurposing

AI examines existing drugs for new therapeutic uses by analyzing biomedical literature, patient records, and databases to find drugs that may be effective for conditions other than their original purpose. This can speed up drug development by bypassing early-stage research.

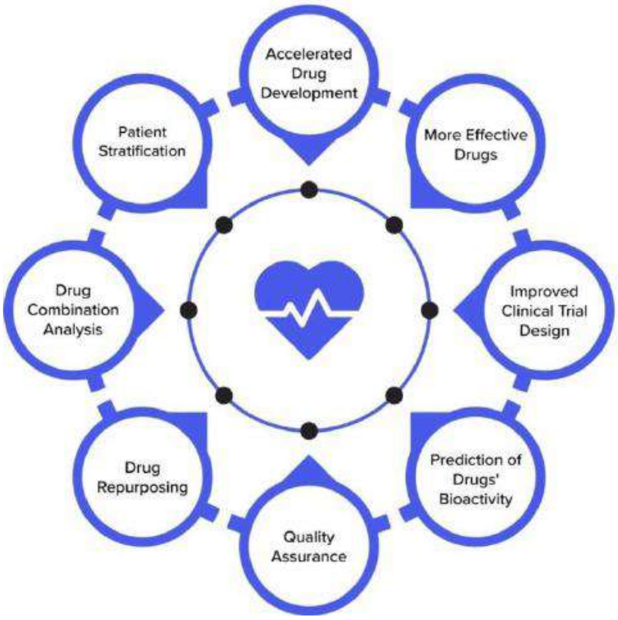

Fig.3. Ways in which AI transforms Drug discovery

4.2.4. Clinical Trials

AI optimizes clinical trial design by analyzing patient data to identify optimal participants, improving patient stratification, and predicting outcomes. AI can also monitor patient responses and adapt trials in real-time, enhancing efficacy and reducing costs.

4.2.5. Predicting Drug Toxicity and Side Effects

By leveraging large datasets, AI models predict potential side effects and toxicity of drug candidates before clinical trials. Machine learning algorithms analyze biological and chemical data to anticipate how a drug might interact with the body, improving safety and success rates.

4.2.6. Precision Medicine

AI aids in personalizing drug therapies by analyzing genetic, lifestyle, and environmental data. By predicting which treatments will work best for individual patients, AI enables more effective, tailored treatments, improving patient outcomes.

4.2.7 Benefits

Speed: AI accelerates drug discovery timelines by automating laborious processes.

Cost Reduction: AI decreases the need for physical experimentation, reducing R&D expenses.

Improved Success Rates: AI-driven insights increase the likelihood of finding effective drugs by optimizing decision-making and reducing human error.

4.3 AI in Clinical Trails

AI is increasingly being used to enhance the efficiency, accuracy, and success of clinical trials, which are critical in the drug development process. AI is transforming clinical trials by improving patient selection, real-time monitoring, adaptive trial designs, and data analysis, leading to faster, safer, and more successful trials.

4.3.1 Patient Recruitment and Selection

AI-powered algorithms analyze EHRs, genetic data, and patient history to identify individuals who meet the specific inclusion and exclusion criteria for a clinical trial. This reduces the time spent on recruitment and ensures more suitable participants are selected, which improves trial outcomes. AI can also predict patient eligibility based on historical trial data, helping match patients to the right trials faster, even across different geographic locations.

4.3.2. Patient Stratification and Personalization

AI can stratify patients based on genetic, clinical, or behavioral data to ensure that trials have more homogenous participant groups. This enhances the accuracy of trial results and can even personalize treatment within the trial, leading to more precise and targeted therapies.

4.3.3. Designing Adaptive Trials

Adaptive clinical trials modify the course of the trial based on interim results (e.g., patient responses or biomarker data). AI models can monitor ongoing results and make adjustments in real-time, such as changing dosages or the number of participants, to increase the likelihood of success. This reduces costs and time, while improving safety, by ensuring the trial remains relevant and effective as new data emerges.

4.3.4. Monitoring Patient Data in Real-Time

AI tools continuously analyze patient data during the trial, monitoring vital signs, biomarkers, and other health metrics. Machine learning algorithms detect patterns that may indicate adverse events or deviations from the expected outcomes. This allows for early detection of potential issues, such as drug toxicity, and can lead to timely intervention, which increases patient safety and trial success.

4.3.5. Predicting Clinical Trial Outcomes

AI models can predict the success of a clinical trial by analyzing historical data from past trials, including patient demographics, drug interactions, and trial methodologies. By simulating possible outcomes, AI helps optimize trial design and decision-making, potentially reducing trial failures.

4.3.6. NLP for Trial Data Management

NLP, a subset of AI, is used to process and analyze unstructured data (e.g., physician notes, patient surveys). This helps extract meaningful insights from a large amount of textual data generated during trials, leading to more comprehensive and accurate reporting of outcomes.

4.3.7. Automating Data Management

Clinical trials generate massive amounts of data from various sources (lab reports, patient devices, surveys). AI automates data cleaning, aggregation, and validation, ensuring that the information is accurate and ready for analysis. This accelerates the time to insights and ensures better decision-making.

4.3.8. Optimizing Clinical Trial Design

AI helps design trials by determining the most effective sample sizes, identifying the best control and test groups, and selecting optimal endpoints. It also predicts the most suitable trial locations based on population demographics and historical performance data, which can reduce logistical challenges.

4.3.9. Post-Trial Analysis

After a trial concludes, AI is used to analyze the outcomes more deeply. By comparing trial results to preclinical data and patient responses, AI can find patterns or new insights that may not have been evident during the trial, potentially leading to new applications for the drug or further research directions.

4.3.10 Benefits of AI in Clinical Trials

Speed: AI accelerates the time to complete trials by optimizing processes like recruitment and data management.

Cost-Reduction: By improving patient matching, reducing trial failures, and managing data efficiently, AI reduces overall trial costs.

Increased Accuracy: AI provides better data analysis, reducing human error, and ensuring that trial designs and outcomes are more accurate.

Safety: Real-time monitoring through AI enables quicker identification of adverse events, ensuring higher patient safety.

Enhanced Success Rates: By predicting trial outcomes and continuously adapting trial parameters, AI helps in increasing the chances of trial success.

4.4 AI in Patient Care

AI is revolutionizing patient care by improving diagnostics, personalizing treatments, streamlining operations, and enhancing patient outcomes. AI in patient care enhances diagnostic accuracy, enables personalized treatments, supports chronic disease management, and improves operational efficiency, ultimately leading to better patient outcomes and reduced healthcare costs.

4.4.1. Diagnosis and Early Detection

Medical Imaging: AI-driven tools analyze medical images like X-rays, MRIs, and CT scans with high accuracy. ML algorithms detect abnormalities such as tumors, fractures, and infections earlier and more precisely than traditional methods.

Predictive Analytics: AI can predict disease onset by analyzing patient data such as EHRs, lab results, and genetic information. This helps detect conditions like cancer, heart disease, or diabetes at an early stage, allowing for timely intervention.

NLP: AI-powered NLP systems analyze physician notes, lab reports, and medical literature to assist in making faster, data-driven diagnoses.

4.4.2. Personalized Treatment Plans

AI tailors treatments to individual patients by analyzing genetic data, lifestyle factors, and clinical history. This is crucial in fields like precision medicine, where AI helps determine the most effective treatments for conditions like cancer or autoimmune diseases.

Pharmacogenomics: AI uses genetic data to predict how a patient will respond to specific medications, helping in selecting drugs and dosages that will work best with minimal side effects. AI-based decision support systems assist healthcare providers in determining the optimal treatment course based on real-time analysis of clinical data and past cases.

4.4.3. Virtual Health Assistants and Chatbots

AI-powered virtual assistants and chatbots interact with patients through mobile apps or websites, providing real-time answers to medical queries, scheduling appointments, or offering medication reminders. These tools help patients manage chronic conditions (e.g., diabetes, hypertension) by guiding them on treatment adherence and lifestyle modifications, thus reducing the burden on healthcare systems. AI assistants also help triage patients by asking preliminary questions, determining the urgency of care, and routing patients to the appropriate healthcare resources.

4.4.4. Remote Monitoring and Telemedicine

AI enables remote patient monitoring through wearable devices and sensors, which continuously track vital signs like heart rate, blood pressure, or glucose levels. These devices send real-time data to healthcare providers, enabling timely interventions without the patient needing to visit a clinic. Telemedicine platforms use AI to assist in remote consultations, providing healthcare providers with real-time data and diagnostic support, enabling faster and more accurate treatment from a distance.

4.4.5. Clinical Decision Support

AI helps healthcare professionals make informed decisions by analyzing real-time patient data, medical histories, and treatment guidelines. ML algorithms recommend treatment options, suggest diagnostic tests, and even predict patient outcomes. These systems reduce cognitive overload for clinicians and improve decision-making, leading to better patient outcomes and fewer medical errors.

4.4.6. Predicting Patient Deterioration

AI-powered systems in hospitals monitor patients and alert healthcare teams when signs of deterioration are detected. For instance, AI can predict critical conditions like sepsis, heart failure, or respiratory decline by analyzing vital signs and lab results, allowing for rapid interventions.

4.4.7. Optimizing Hospital Operations

AI helps hospitals manage patient flow, reduce wait times, and allocate resources efficiently. By analyzing patient records and hospital data, AI can predict which departments will face high patient volumes and adjust staffing and resources accordingly. AI also supports inventory management by predicting the need for medical supplies based on patient admissions and treatment trends.

4.4.8. Mental Health Support

AI tools are being used in mental health care through apps that provide emotional support, monitor mental health conditions, and track mood changes. AI-powered chatbots offer 24/7 mental health support, guiding patients through cognitive behavioral therapy (CBT) exercises or mindfulness practices. AI can also analyze speech and behavior patterns to detect early signs of conditions like depression, anxiety, or schizophrenia.

4.4.9. Chronic Disease Management

AI supports patients with chronic conditions like diabetes, asthma, or hypertension by offering personalized care plans, tracking patient progress, and predicting potential complications. AI-powered apps and devices help patients manage their condition at home by reminding them to take medications, suggesting lifestyle changes, and tracking vital signs.

4.4.10 Benefits of AI in Patient Care

Improved Accuracy: AI-driven diagnostics and predictive tools reduce human errors, leading to more accurate diagnoses and personalized treatments.

Increased Efficiency: AI automates routine tasks such as data entry, appointment scheduling, and patient monitoring, freeing up healthcare professionals to focus on more complex tasks.

Better Outcomes: AI enables early detection, timely intervention, and personalized care, which improves overall patient outcomes and quality of life.

Cost Reduction: AI reduces healthcare costs by streamlining operations, minimizing hospital readmissions, and optimizing resource use.

4.5 AI in Robot Surgery

AI plays a crucial role in robotic surgery by enhancing precision, improving outcomes, and assisting surgeons in complex procedures. AI in robotic surgery improves precision, assists in real-time decision-making, automates routine tasks, enhances surgical planning, and provides surgeons with detailed visual guidance. It reduces the invasiveness of surgeries, improves patient outcomes, and helps train surgeons more effectively, making surgery safer and more efficient.

4.5.1. Enhanced Surgical Precision

AI-powered robotic systems provide high precision and control during surgery. These systems assist surgeons by filtering out hand tremors and enabling precise movements, especially in delicate procedures like neurosurgery, cardiac surgery, and orthopedic operations. AI algorithms help guide robotic arms with extreme accuracy, reducing the risk of damage to surrounding tissues and organs. This level of precision is crucial in minimally invasive procedures, where small incisions and narrow working spaces are required.

4.5.2. Real-Time Data Analysis and Decision Support

AI can process and analyze real-time data from cameras, sensors, and other surgical tools to assist surgeons during operations. Machine learning algorithms help identify anatomical structures, spot abnormalities, and provide recommendations to the surgeon during the procedure. For example, in laparoscopic surgery, AI systems can analyze the visual data from the camera and highlight critical areas like blood vessels or tumors, reducing the risk of accidental damage. AI also supports augmented reality (AR) in surgery by overlaying 3D models of patient anatomy onto real-time images, helping surgeons better visualize internal structures during the operation.

4.5.3. Preoperative Planning

AI assists in preoperative planning by analyzing patient data such as MRI, CT scans, or X-rays to create detailed, personalized surgical plans. Machine learning models can simulate different surgical approaches and predict potential complications, helping surgeons choose the best strategy for each patient. AI systems can also generate 3D models of the patient's anatomy, allowing surgeons to practice and plan for the surgery in advance, improving precision and reducing surgery time.

4.5.4. Automation of Routine Tasks

In robotic surgery, certain repetitive or routine tasks can be automated with AI. For example, stitching, suturing, and cutting tissues can be handled by AI-guided robotic systems with high accuracy. This reduces the surgeon's workload and improves the efficiency of the procedure.

AI-driven automation also helps maintain consistency and reduces human error, particularly in complex or lengthy surgeries.

4.5.5. Minimally Invasive Surgery

AI enhances the capabilities of minimally invasive surgery by improving control over robotic instruments that operate through small incisions. AI-powered robots can manipulate tiny surgical instruments with great precision, reducing the need for large incisions, minimizing tissue damage, and leading to faster patient recovery. Da Vinci Surgical System, a widely known robotic surgery platform, uses AI to enhance surgeon control over surgical instruments, enabling minimally invasive procedures with fewer complications.

4.5.6. Machine Learning for Surgical Training

AI-powered surgical robots can be used to train surgeons by simulating real-life surgical scenarios. AI systems track the performance of trainees, analyze their movements, and provide feedback to improve skills and techniques. AI-based training systems can also offer personalized learning experiences, adapting to the needs and progress of each surgeon, and helping them improve faster.

4.5.7. Intraoperative Guidance and Adaptation

During surgery, AI systems continuously monitor the progress of the operation and provide real-time guidance to surgeons. If the procedure deviates from the preoperative plan, AI can suggest adjustments or provide warnings. AI also helps in identifying and correcting any surgical errors or complications that arise during the procedure, improving patient safety.

4.5.8. Robotic-Assisted Microsurgeries

AI-powered robotic systems excel in microsurgeries, which require extreme precision and steadiness. For instance, in ophthalmic surgeries or vascular surgeries, AI can guide robotic arms to make precise incisions or sutures that are too delicate for human hands alone. These systems can work at sub-millimeter precision, significantly improving outcomes in surgeries that demand accuracy on a microscopic level.

4.5.9. Post-Surgical Data Analysis and Feedback

After surgery, AI analyzes the procedure's outcome by examining postoperative data, patient recovery, and any complications that arise. This data is used to continuously refine and improve future surgical procedures, creating a feedback loop that enhances the robot's capabilities over time. AI can also predict patient recovery times and potential complications, allowing healthcare providers to plan post-operative care more effectively.

4.5.10 Benefits of AI in Robotic Surgery

Improved Precision: AI-driven robots enable surgeons to perform highly precise movements, reducing errors and improving outcomes.

Minimally Invasive: Smaller incisions, less tissue damage, and faster recovery times are achieved through AI-assisted minimally invasive techniques.

Faster Recovery: With minimal incisions and reduced trauma, patients often experience faster recovery and fewer postoperative complications.

Better Training: AI systems improve surgeon training by simulating surgical environments and providing real-time feedback on technique.

Reduced Surgeon Fatigue: AI automation of routine tasks reduces the strain on surgeons, allowing them to focus on complex aspects of the surgery.

4.6 AI in Cancer Detection and Treatment

AI plays a transformative role in cancer detection and treatment by enabling early diagnosis, personalized therapies, and optimizing treatment outcomes. AI enhances cancer detection by improving early diagnosis, assists in personalized treatment planning, supports real-time decision-making during surgery and therapy, and enables continuous patient monitoring, ultimately improving the effectiveness and efficiency of cancer care.

4.6.1. Early Detection and Diagnosis

Medical Imaging Analysis: AI algorithms, especially deep learning, are used to analyze medical images such as mammograms, CT scans, MRIs, and histopathology slides. These algorithms can detect tumors, lesions, and other abnormalities at early stages, sometimes more accurately than human experts. For instance, AI can differentiate between benign and malignant growths based on image patterns.

Screening for Multiple Cancer Types: AI tools can be trained to recognize signs of different cancers, such as breast, lung, prostate, and skin cancers. For example, AI-based skin cancer detection systems analyze moles and skin lesions, while algorithms for lung cancer analyze chest X-rays and CT scans for nodules or other markers.

Biomarker Identification: AI helps identify molecular biomarkers (proteins, genes, etc.) linked to cancer in patient samples, which are critical for early detection. Machine learning algorithms analyze genetic data and help identify patients at risk of cancer based on inherited mutations (e.g., BRCA1/BRCA2 for breast cancer).

4.6.2. Personalized Treatment

Precision Medicine: AI tailors cancer treatments based on the patient's genetic makeup, tumor characteristics, and clinical data. By analyzing genomic data (DNA sequencing), AI identifies mutations driving cancer and recommends personalized therapies, such as targeted drugs or immunotherapies that specifically address those mutations.

Predicting Treatment Response: AI models predict how a patient's tumor will respond to different treatments (chemotherapy, radiation, immunotherapy) by analyzing clinical and molecular data. This ensures that patients receive treatments with the highest chance of success, reducing the trial-and-error approach to cancer therapy.

Pharmacogenomics: AI analyzes how a patient's genetic makeup will affect their response to certain cancer drugs, ensuring that they receive the most effective medication while minimizing side effects.

4.6.3. Cancer Prognosis and Outcome Prediction

AI helps predict the progression of cancer by analyzing clinical data, tumor markers, and patient history. Machine learning models assess factors such as tumor size, stage, and molecular markers to predict survival rates, recurrence risks, and treatment outcomes. AI systems assist in identifying high-risk patients who may require more aggressive treatments or additional monitoring, improving patient management.

4.6.4. Automated Pathology

Histopathology Analysis: AI tools are used to automate the analysis of biopsy samples, identifying cancerous cells with high precision. These algorithms examine thousands of tissue samples, learning to recognize cancerous patterns that might be overlooked by human pathologists.

AI-assisted Grading: For cancers like prostate or breast cancer, AI helps grade the severity of cancer by analyzing tissue samples and assigning Gleason or TNM scores, which guide treatment decisions.

4.6.5. Optimizing Radiotherapy and Surgery

Radiation Treatment Planning: AI improves radiotherapy by analyzing patient images to create precise radiation treatment plans that target cancer cells while sparing healthy tissues. AI algorithms calculate optimal dose distributions and reduce side effects.

AI in Surgical Guidance: During cancer surgeries, AI helps guide surgeons by analyzing real-time imaging data and providing information on tumor margins, ensuring complete removal of cancerous tissues while minimizing harm to healthy tissues.

4.6.6. Drug Discovery and Development

AI in Cancer Drug Discovery: AI accelerates the discovery of new cancer drugs by analyzing molecular data, predicting how different compounds will interact with cancer cells, and simulating their effectiveness. AI models can also identify existing drugs that could be repurposed for cancer treatment (drug repurposing).

Clinical Trial Optimization: AI optimizes the design and execution of clinical trials for cancer treatments. It helps match patients to the most suitable trials based on genetic profiles and clinical histories, increasing the success rate of trials.

4.6.7. AI for Immunotherapy

Predicting Response to Immunotherapy: AI analyzes a patient's tumor genetics and immune profile to predict the likelihood of response to immunotherapies such as checkpoint inhibitors or *CAR-T therapies*. AI helps identify biomarkers that indicate whether a patient will benefit from these treatments.

Optimizing Treatment: AI models continuously monitor a patient's response to immunotherapy, suggesting adjustments in the treatment course based on real-time data, ensuring maximum effectiveness with minimal side effects.

4.6.8. Patient Monitoring and Follow-up Care

AI in Remote Monitoring: AI-driven apps and wearable devices help monitor cancer patients during treatment and recovery, tracking vital signs, symptoms, and side effects. These systems alert healthcare providers to any changes that might require intervention.

Predicting Relapse: AI tools can predict the likelihood of cancer recurrence by analyzing data from follow-up exams, scans, and blood tests. This enables early intervention and close monitoring for high-risk patients.

4.6.9 Benefits of AI in Cancer Detection and Treatment

Increased Accuracy: AI improves the accuracy of cancer detection and diagnosis, reducing false positives and false negatives.

Early Detection: By identifying cancers at an earlier stage, AI improves survival rates and outcomes.

Personalized Treatments: AI ensures that patients receive the most effective and least toxic therapies tailored to their specific cancer.

Cost and Time Efficiency: AI accelerates drug discovery, treatment planning, and diagnostics, reducing costs and time for both patients and healthcare systems.

Better Patient Outcomes: AI-driven insights enable more effective treatments, leading to better patient outcomes, longer survival, and improved quality of life.

V. CURRENT ISSUES OF AI IN HEALTHCARE

AI has significant potential in healthcare, but there are several current challenges and issues that need to be addressed for it to be fully effective and widely adopted. Addressing the issues requires collaboration between technologists, healthcare professionals, regulatory bodies, and policymakers to create AI systems that are safe, reliable, ethical, and effective in improving patient care [41]. These issues can be categorized into several key areas are given in Table 3.

Table 3. Current Challenges and Issues of AI Healthcare

Issues	Problem	Explanation
Data Quality and Availability	AI models, particularly those based on machine learning, require large	AI systems can only be as good as the data they are trained on. Inconsistent or low-quality data

	amounts of high-quality data to be effective. However, healthcare data is often fragmented, incomplete, and siloed in different systems (e.g., electronic health records, wearable devices, imaging systems). Furthermore, data may be noisy, inaccurate, or subject to bias.	may lead to incorrect predictions or diagnoses, harming patient outcomes. Integrating data from different sources while maintaining privacy and quality is a significant challenge.
Bias in AI Models	AI systems may inherit biases from the data they are trained on, resulting in unequal healthcare outcomes. For example, if training data lacks diversity, AI algorithms may not perform well for underrepresented populations, leading to biased diagnosis and treatment recommendations.	Biases in AI can manifest in many forms, such as racial, gender, or socioeconomic disparities in healthcare. These biases may result from the historical inequities in data collection or care delivery. This can reinforce health disparities rather than alleviate them.
Ethical and Privacy Concerns	AI systems in healthcare often handle sensitive patient information. Ensuring patient privacy while using AI effectively is a major challenge, particularly given the potential for data breaches or unauthorized access.	AI models require access to personal health information (PHI) for training and operation. This raises concerns about how patient data is stored, processed, and shared. Misuse or mishandling of such data can lead to loss of patient trust, as well as legal and regulatory consequences.
Regulatory and Legal Challenges	Regulatory frameworks have not fully caught up with the rapid advancements in AI, leaving uncertainty about how AI should be governed in healthcare settings. Clear guidelines on accountability, transparency, and safety are still evolving.	Healthcare is a highly regulated industry, but many AI-driven healthcare solutions are still unregulated or only partially regulated. This uncertainty affects the pace of AI adoption, as companies are cautious about potential liability. Moreover, there is often a lack of clarity on how to certify AI tools for clinical use.
Integration with Existing Clinical Workflows	Many AI tools are developed in isolation from healthcare professionals, which can make them difficult to integrate into existing clinical workflows. This can lead to resistance from clinicians or reduced effectiveness of AI in practice.	AI systems should augment, not disrupt, the work of healthcare providers. However, poor integration can increase the workload for clinicians, causing frustration and reducing the utility of the AI system. Additionally, training healthcare professionals to use AI tools effectively is another barrier to integration.
Trust and Adoption by Healthcare Professionals	Healthcare professionals may be skeptical or mistrustful of AI due to its "black box" nature, where decision-making processes are not fully transparent or understandable.	For AI to be trusted, healthcare providers need to understand how the AI system reaches its conclusions, especially in critical applications like diagnosis or treatment planning. Explainable AI (XAI) is a growing area of research aimed at making AI systems more transparent, but it's not yet widely implemented in healthcare.
Cost and Infrastructure	Implementing AI systems requires significant investment in infrastructure, including hardware, software, and training for personnel.	Advanced AI models require significant computational resources and infrastructure, which can be costly to maintain. Additionally, hospitals and clinics may need to overhaul

	Smaller healthcare providers, especially in low-resource settings, may find it difficult to afford and implement AI solutions.	existing systems to integrate AI effectively, further increasing costs. The financial burden is especially challenging for rural or underfunded healthcare systems.
Generalization and Scalability	AI models that work well in one healthcare setting or with a specific patient population may not perform as effectively when deployed in different environments.	AI models can struggle to generalize beyond the specific dataset they were trained on, leading to poor performance in new regions, hospitals, or patient demographics. Ensuring that AI tools are scalable and adaptable across different healthcare settings is a major technical challenge.
Patient Acceptance and Understanding	Patients may have concerns about AI-driven healthcare, particularly when it comes to automated decision-making in diagnosis, treatment, or even surgeries. They may fear reduced personal interaction with healthcare professionals.	Patient trust in AI is crucial for its successful implementation in healthcare. If patients do not feel comfortable with AI-based recommendations, they may refuse treatment or demand more traditional care, even if AI could potentially provide better outcomes. AI must be framed as a tool to support clinicians, not replace them.
Validation and Clinical Trials	Many AI models are still in the experimental phase and lack large-scale clinical trials that validate their safety and efficacy in real-world healthcare settings.	Regulatory bodies and healthcare providers require rigorous validation of AI systems before they can be deployed in clinical environments. However, conducting clinical trials for AI systems can be complex, expensive, and time-consuming. There is also a lack of standardized benchmarks to measure AI performance in healthcare.

VI. RECOMMENDATIONS AND FUTURE DIRECTIONS FOR AI IN HEALTHCARE

AI in healthcare holds tremendous promise, but for it to reach its full potential, several recommendations and future directions must be considered. These recommendations and future directions aim to ensure AI's safe, ethical, and effective integration into healthcare, ultimately benefiting both patients and healthcare providers [50-52].

6.1 Key Recommendations for AI in Healthcare

The key recommendations for AI in healthcare are explained below. By following these recommendations, AI can be safely and effectively integrated into healthcare to enhance patient care, reduce errors, and improve outcomes [48].

6.1.1. Ensure Data Quality and Standardization

Improve data collection processes and standardize healthcare data formats to ensure that AI models are trained on accurate, high-quality, and consistent data across different sources. AI's effectiveness relies on large, high-quality datasets. Standardization helps avoid biases and errors in AI predictions and enhances interoperability between systems.

6.1.2. Focus on Explainability and Transparency

Develop AI systems that are explainable and transparent, allowing healthcare professionals and patients to understand how AI reaches its conclusions. Clear understanding of AI's decision-making process builds trust, ensures accountability, and supports better clinical decision-making.

6.1.3. Prioritize Patient Privacy and Data Security

Implement strict privacy measures and security protocols to protect sensitive patient data when using AI. Ensuring data security and compliance with regulations (e.g., HIPAA, GDPR) is essential to maintain patient trust and avoid potential data breaches.

6.1.4. Mitigate Algorithmic Bias

Actively work to identify and mitigate bias in AI models by using diverse, representative datasets and testing models for fairness. Reducing bias ensures that AI systems provide equitable healthcare across all demographic groups, preventing disparities in treatment outcomes.

6.1.5. Enhance Interdisciplinary Collaboration

Encourage collaboration between AI developers, healthcare professionals, ethicists, and policymakers to ensure AI addresses real clinical needs and adheres to ethical guidelines. Collaborative efforts help align AI development with healthcare goals, improving its adoption and impact in clinical practice.

6.1.6. Strengthen Regulatory Frameworks

Develop clear regulatory guidelines for the development, validation, and deployment of AI in healthcare, ensuring patient safety and model reliability. Strong regulations help ensure the safety and efficacy of AI applications while fostering innovation in a structured manner.

6.1.7. Promote Education and Training

Provide ongoing education and training for healthcare professionals on how to use AI tools effectively and responsibly. Equipping clinicians with AI knowledge ensures they can use these tools in their practice, improving adoption and enhancing patient care.

6.1.8. Encourage Real-World Validation

Conduct large-scale clinical trials and real-world validations to ensure that AI tools work effectively across diverse healthcare settings. Real-world validation ensures that AI models perform well outside of controlled environments, supporting their widespread clinical use.

6.2 Future Directions for AI in Healthcare

The future directions for AI in healthcare focus on enhancing the technology's impact and ensuring its safe and ethical integration into clinical practice. These future directions promise to revolutionize healthcare by making it more personalized, efficient, and accessible, ultimately leading to better patient care and outcomes [49].

6.2.1. Personalized and Precision Medicine

AI will increasingly enable personalized treatment plans based on individual patient data (genomics, lifestyle, medical history) and predictive analytics. This approach will improve treatment effectiveness and patient outcomes by tailoring interventions to each person's unique characteristics.

6.2.2. Predictive and Preventive Healthcare

AI will shift healthcare from reactive treatment to proactive, preventive care by predicting disease onset and complications before they occur. This will help in early detection and intervention, reducing the burden of chronic diseases and lowering healthcare costs.

6.2.3. Improved Diagnostics and Decision Support

AI tools will become more accurate in diagnosing diseases, assisting clinicians in real-time with decision support systems that suggest optimal treatments. Enhanced diagnostic accuracy and faster decision-making will lead to better patient outcomes and reduced diagnostic errors.

6.2.4. AI-Driven Drug Discovery and Development

AI will expedite drug discovery by analyzing large datasets to identify potential drug candidates and optimize clinical trials. This could dramatically reduce the time and cost of bringing new treatments to market, accelerating the development of life-saving drugs.

6.2.5. Integration with Wearables and IoT

AI will integrate with wearable devices and the Internet of Things [32-40] to monitor patient health in real time and provide continuous feedback. Continuous monitoring will allow for more personalized, real-time care, enabling early detection of health issues and improved chronic disease management.

6.2.6. Ethical and Explainable AI (XAI)

The development of explainable and ethical AI models that ensure transparency in decision-making processes and minimize bias. Increased trust among healthcare providers and patients, as well as improved compliance with ethical and regulatory standards.

6.2.7. AI-Assisted Surgery and Robotics

The use of AI in robotic surgery will expand, offering more precision and accuracy in complex procedures. AI-powered surgical robots will help minimize surgical risks, reduce recovery times, and improve overall patient outcomes.

6.2.8. Enhanced Interoperability and Data Sharing

AI will drive improvements in healthcare data sharing and interoperability across systems, enabling more comprehensive and coordinated care. Seamless data exchange will improve care coordination, patient outcomes, and the ability of AI systems to make informed decisions.

VII. CONCLUSION

It is important to emphasize the significant potential for collaboration between AI and healthcare professionals. AI is increasingly being used to the field of healthcare, as it becomes more widespread in contemporary business and daily life. Artificial intelligence has the capacity to assist healthcare personnel in several ways, including patient treatment and administrative duties. While the healthcare business benefits greatly from AI and healthcare breakthroughs, the approaches they support might vary significantly. AI technologies are anticipated to revolutionize current medical technology and shape the future of healthcare. AI-based health care solutions now demonstrate exceptional efficacy in precisely identifying and categorizing patient illnesses, as well as forecasting disease progression via the use of acquired medical data. These technologies are anticipated to aid medical professionals in therapeutic decision-making and enhance treatment outcomes. Nevertheless, AI-driven healthcare solutions presently encounter many concerns pertaining to privacy, dependability, security, and accountability. In order to increase the widespread use of AI technologies in healthcare, it will be necessary to enhance public knowledge of AI, set uniform standards, and implement systematic improvements, in addition to advancing the technology itself. AI has the capability to identify ailments, provide customized treatment strategies, and aid healthcare professionals in making informed decisions. AI focuses on the development of technology that may improve patient care in various healthcare environments, rather than only automating chores. Nevertheless, the appropriate and successful use of AI in healthcare necessitates the resolution of issues pertaining to data privacy, bias, and the need for human knowledge.

CONFLICT OF INTEREST

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Recommendation System Based on Semantic Analysis and Network Models

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***Keywords*— recommendation systems, semantic analysis, network analysis, machine learning**

***Abstract*— In this work, we implement a hybrid recommendation system for news articles that combines two primary approaches: semantic analysis via TF–IDF vectorization of headlines and Nearest Neighbors search, and network analysis using an article-similarity graph constructed from shared tags. To improve recommendation quality, rare tags were filtered out, and the number of articles per tag was capped to balance the dataset. A weighted combination of semantic and graph-based scores was also employed with parameter tuning. Precision was adopted as the evaluation metric, measuring the proportion of correctly predicted tags in the recommended articles against the ground-truth tags in the test set. Experimental results show that the hybrid model effectively leverages both semantic headline features and network connections between articles. When increasing the per-tag article cap from 1,000 to 3,000, precision rose from 0.168 to 0.187—an 11% improvement—while training time increased from 31.8 s to 506 s. This trade-off confirms the value of expanding the data scope and demonstrates the strength of the hybrid approach. The achieved precision on the test set indicates that integrating semantic and network analyses yields more accurate and well-grounded recommendations tailored to user interests.*

I. INTRODUCTION

The volume of scientific and popular publications is growing exponentially: tens of thousands of new research articles and millions of news items appear each year. At this pace of information accumulation, filtering truly important and relevant content becomes increasingly difficult. Standard search engines return long result lists, whose relevance does not always correlate with content depth or expert assessment. As a result, researchers, journalists, and curious readers spend hours navigating information streams and risk missing key discoveries or valuable insights [1].

Recommendation systems have emerged as an effective tool against information overload. They perform contextual filtering: instead of presenting thousands of irrelevant links, they provide a few personalized suggestions. To do so, these systems analyze document attributes (topics, keywords, semantic vectors) and study user behavior (clicks, reading time, ratings). By combining statistical models with machine learning techniques, modern recommenders can not only reproduce past interests but also propose related topics, thereby broadening users' horizons [2].

The application of recommendation systems has long since extended beyond e-commerce. Scientific databases help researchers quickly locate articles in their specialization, automatically notifying them of newly published reviews or experimental results. News portals use recommendations to keep readers engaged by suggesting reports and analyses similar to those already read. Educational platforms select learning modules and assessments according to a student's proficiency level and progress, making education more flexible and effective [3, 4].

A key objective of such systems is to predict the materials most likely to interest users. This entails generating a ranked list of articles or items with the highest probability of being rated "useful" or "interesting."

The goal of this research is to develop a recommendation system based on semantic analysis and network models.

II. MATERIALS AND METHODS

The research was conducted at the Department of Artificial Intelligence, Financial University under the Government of the Russian Federation. We used the Lenta.ru news dataset (1990–present) [5], and implemented the system in Python with the following libraries: pandas [6], matplotlib [7], collections, random, scikit-learn [8], networkx [9], itertools [10], and numpy [11].

III. RESULTS OF THE RESEARCH

In the initial phase of our research, we analyzed traditional approaches to recommendation system design. This investigation revealed several inherent limitations of such systems.

In particular, the content-based approach relies on analyzing individual document features—identifying keywords, calculating TF–IDF scores, or constructing vector embeddings. While recommendations are generated based on similarity between new and previously viewed content, the resulting articles often exhibit narrow thematic overlap and rarely expand beyond the user's established interests. The system is prone to "self-reinforcement," repeating familiar interest patterns without offering surprising or novel discoveries, which decreases overall diversity. Additionally, it fails to incorporate broader trends and community-wide preferences.

The second approach, collaborative filtering, focuses on collective user behavior—ratings, views, clicks, and other forms of interaction. This method identifies similar user profiles and recommends items that appealed to those with comparable preferences. However, it has significant limitations: during "cold-start" scenarios (involving new users or new items), data sparsity leads to poor recommendation accuracy; high-interaction items tend to dominate the output, crowding out niche or specialized content; and the sparsity of the interaction matrix makes it difficult to detect meaningful correlations. Furthermore, the algorithm cannot anticipate interest in entirely new topics that lack prior ratings.

Neither content-based nor collaborative filtering approaches integrates deep semantic analysis or captures the network structure between articles. Each functions within its own "dimension"—content features or behavioral patterns. Both approaches neglect nuanced semantic relationships, such as overlapping subtopics; they do not employ tag-based network models that reflect community clustering; and they omit social and contextual factors such as authorship, citation impact, or expert evaluations. As a result, their architectures lack flexibility in adapting to shifting interests and emerging themes.

In contrast, the hybrid system proposed in this study combines the strengths of both content-based and collaborative filtering techniques while enhancing them with semantic similarity analysis and a tag-based network model. Semantic analysis of article headlines enables identification of deep thematic relationships between articles, while the graph model encodes linkages via shared tags and social context. This design alleviates cold-start problems by relying on semantic structure—even for new articles; it mitigates popularity bias by prioritizing meaning-based connections; and it improves recommendation diversity and accuracy by blending both textual features and network structure.

Overall, the hybrid architecture significantly enhances article selection and contributes to higher user satisfaction. In the next section, we examine the proposed model in greater detail.

For the semantic component, we used the TfidfVectorizer to transform article headlines into TF–IDF vectors. For each article, the TF–IDF values are calculated per word (Fig. 1), creating a matrix where rows correspond to documents and columns represent terms with their respective TF–IDF scores.

$$TF(t,d) = \frac{number\ of\ times\ t\ appears\ in\ d}{total\ number\ of\ terms\ in\ d}$$

$$IDF(t) = log\frac{N}{1+df}$$

$$TF-IDF(t,d) = TF(t,d) * IDF(t)$$

Fig. 1: TF-IDF calculation: t - term; d - document (Karen Spärck Jones, 1972)

Based on the computed semantic representations, a Nearest Neighbors model was constructed to support article-to-article recommendations. Cosine distance was selected as the similarity metric, enabling precise measurement of angular proximity between TF–IDF vectors. Upon querying the system with a target headline, the algorithm returns the top kk articles that exhibit the smallest cosine distance to the query vector, representing the most semantically similar articles.

To build the hybrid recommender system in Python, a comprehensive preprocessing stage was conducted. The dataset consists of news articles collected from the Lenta.ru news portal, spanning content published since 1990. Each entry includes a tag, a headline, the full article text, and a topic classification.

During implementation, several preprocessing steps were applied. A range of libraries was used (Table 1) alongside custom Python code (Table 2) to remove non-informative tags and discard those appearing infrequently (fewer than 20 times across the dataset). As a result, a more balanced and representative tag distribution was achieved (see Fig. 2).

Table. 1: Python libraries used for data loading and preprocessing

n/n	Python libraries
1	import pandas as pd from collections import Counter

Table. 2: developed code for reading and preprocessing data

n/n	code

1	df = pd.read_csv('lenta-ru-news.csv')
	df = df[['title', 'tags']]
	df['tag_list'] = df['tags'].apply(lambda x: [tag.strip() for tag in x.split(',')] if isinstance(x, str) else [])
	all_tags = [tag for tags in df['tag_list'] for tag in tags]
	tag_counts = Counter(all_tags)
	df = df[df['tags'].str.strip() != 'Все']
	
	def remove_all_tag(tags):
	if pd.isna(tags):
	return ''
	tag_list = [tag.strip() for tag in tags.split(',')]
	tag_list = [tag for tag in tag_list if tag != 'Все']
	return ', '.join(tag_list)
	
	df['tags'] = df['tags'].apply(remove_all_tag)
	all_tags = [tag for tags in df['tag_list'] for tag in tags]
	tag_counts = Counter(all_tags)
	tag_min = 20
	popular_tags = {tag for tag, count in tag_counts.items() if count >= tag_min}
	
	def is_news_popular(row):
	tags_ok = any(tag in popular_tags for tag in row['tag_list'])
	return tags_ok
	
	df = df[df.apply(is_news_popular, axis=1)].drop(columns=['tag_list'])

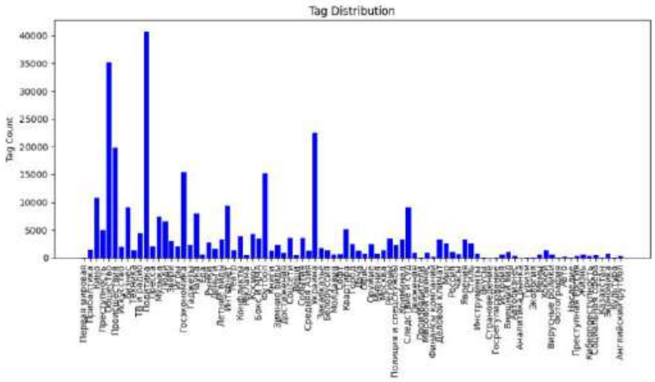

Fig. 2: distribution of tags after preprocessing

The semantic part of the hybrid recommender system was implemented using the Python programming language. To accomplish this, we utilized functions from the scikit-learn library (Table 3), as well as custom code developed during the course of this study (Table 4).

Table. 3: Libraries used in the implementation of the semantic component

n/n	Python libraries
1	from sklearn.feature_extraction.text import TfidfVectorizer from sklearn.neighbors import NearestNeighbors from sklearn.model_selection import train_test_split

Table. 4: Custom Python code for the semantic module

n/n	Custom code
1	df_train, df_test = train_test_split(df1, test_size=0.2, random_state=42) tfidf = TfidfVectorizer(max_features=2500) tfidf_matrix_train = tfidf.fit_transform(df_train['title']) nn_model = NearestNeighbors(n_neighbors=20, metric='cosine') nn_model.fit(tfidf_matrix_train)

In developing the tag-based network model, we relied on constructing an undirected weighted graph based on the tags present in the articles. Each vertex in this graph represents a single article, and an edge connects two articles if their tag sets intersect. The intensity of the thematic connection between articles i and j is quantitatively expressed by the edge weight, which equals the number of common tags:

$$w_{ij} = T_i \cap T_j$$

where T_i and T_j are the tag sets of articles i and j, respectively.

The resulting graph reflects not only the existence but also the strength of thematic overlaps: the more tags two articles share, the denser and more pronounced their connection in the network structure. This model allows identification of clusters of thematically related articles and accounts for the collective distribution of topics via labels assigned by authors or editors.

Subsequently, recommendations can be generated based on this structural component by selecting, for a given article, the nodes most strongly connected to it - i.e., the articles with the highest edge weights. By accounting for network connections, the model complements content analysis and provides a more diverse and well-founded selection of materials.

The network part of the hybrid recommendation system was then implemented in Python. For this purpose, we used a number of libraries (Table 5) and our custom code (Table 6).

Table. 5: libraries used for implementing the network component

n/n	Python libraries
1	from collections import defaultdict import networkx as nx from itertools import combinations

Table. 6: custom code for the network component

n/n	Custom code

1	tag_to_articles = defaultdict(set)
	for idx, row in df_train.iterrows():
	    for tag in row['tags'].split(','):
	        tag_to_articles[tag.strip()].add(idx)
	
	G1 = nx.Graph()
	for tag, articles in tag_to_articles.items():
	    for a1, a2 in combinations(articles, 2):
	        if G1.has_edge(a1, a2):
	            G1[a1][a2]['weight'] += 1
	        else:
	            G1.add_edge(a1, a2, weight=1)

This code builds a model that captures connections between articles based on their shared tags. Each article becomes a node in the graph, and an edge is created between two articles if they share at least one tag. The edge weight indicates how many tags they have in common—the higher the weight, the stronger the thematic similarity between the articles. Such a graph enables analysis of the content structure, identification of clusters of similar publications, and can be used for tasks like recommendation or content clustering.

During the development of the hybrid recommender system, we first limited the maximum number of news articles per tag to 1 000 items (Fig. 3). To further improve model quality, we then increased this cap to 3 000 items (Fig. 4).

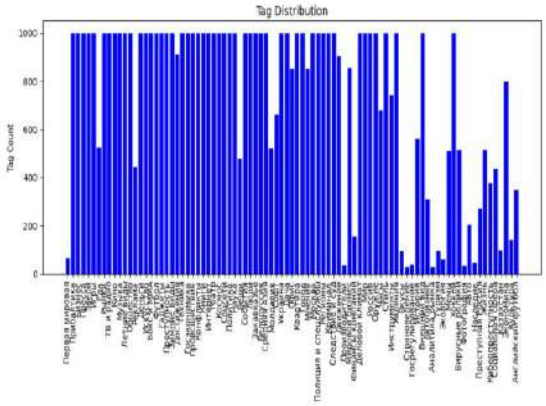

Fig. 3 – Tag distribution after capping the maximum amount of news per tag at 1 000 items

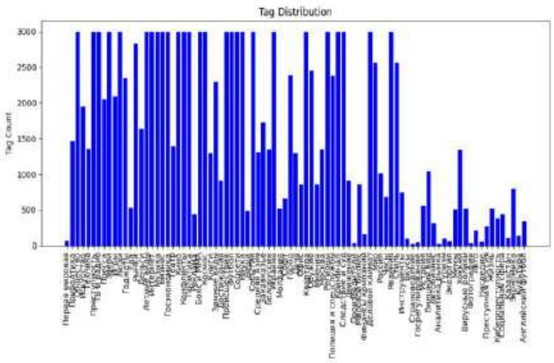

Fig. 4 – Tag distribution after capping the maximum amount of news per tag at 3 000 items

Precision was used as the evaluation metric, measuring the accuracy of predicted tags from recommended articles against the ground-truth tags in the test set. After raising the cap on the number of articles per tag, we observed an increase in precision, although training time also grew (Table 7).

Table. 7:Metrics for the model on different data volumes

Max. news per tag	Training time (s)	Precision
1000	31.8	0.168
3000	506.0	0.187

IV. CONCLUSION

During this work, a hybrid recommendation system for news articles was implemented, employing two key approaches: semantic analysis via headline vectorization (TF–IDF), a Nearest Neighbors search, and network analysis using an article-similarity graph constructed from shared tags. To improve quality, rare tags were filtered out and the number of articles per tag was capped to balance the sample. A combination of semantic and graph-based weights with parameter tuning was also employed.

The conducted experiments demonstrate that the proposed hybrid model effectively utilizes additional information on network connections between articles and semantic features of headlines. When increasing the number of news articles per tag from 1,000 to 3,000, a significant improvement in recommendation accuracy was observed: precision rose from 0.168 to 0.187. This 11% increase, while maintaining reasonable training time (increasing from 31.8 s to 506 s), confirms the high payoff of data expansion and the strength of the hybrid approach.

Thus, the hybrid architecture exhibits a steady increase in recommendation quality with the growth of the input data volume, and the additional training time is compensated by a noticeable gain in accuracy—the trade-off between speed and quality remains justified. The ability to accumulate additional connections in the graph component enhances its capacity to identify thematically relevant articles and reduces the effect of "noisy" matches.

Overall, the achieved precision on the test set confirms that integrating semantic headline analysis and a tag-based network model enables the hybrid system to provide more accurate and well-founded recommendations tailored to user interests.

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Teachers' Perceptions of Self-Efficacy and Awareness Levels in Occupational Health and Safety: A Local Study

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***Keywords*— Occupational health and safety, awareness level, self-efficacy, teacher training.**

***Abstract*— This study was conducted to determine the awareness levels of teachers working at Iğdır Vocational and Technical Anatolian High School regarding occupational health and safety (OHS) and to develop policy recommendations based on the findings. The study was designed using a quantitative research method and a descriptive survey model, with the population consisting of all teachers working at the school during the 2024–2025 academic year. The findings revealed that teachers' OSH awareness levels were generally high, but there were significant knowledge gaps in areas such as technical infrastructure, legal regulations, and disaster preparedness. While no significant differences were found in terms of gender, educational background, and length of service, the age variable had a significant effect on awareness levels. Additionally, the status of receiving firefighting training showed a significant relationship with gender. It was determined that the vast majority of participants (87.5%) had previously received OSH training; however, the low rates of firefighting (45%) and search-and-rescue (32.5%) training were notable. While the use of personal protective equipment and occupational risk awareness was above 80%, knowledge levels regarding structural safety elements (fire detection systems, water tank maintenance, lightning rods, etc.) remained irregular and insufficient. While teachers have a high level of individual safety awareness, it has been determined that this awareness is not integrated with the school's technical infrastructure and administrative processes. The study recommends strengthening regulatory training, increasing information about technical infrastructure, regularizing disaster drills, integrating OSH information into the curriculum, reinforcing PPE usage habits, and improving management-teacher communication.*

I. INTRODUCTION

Occupational health and safety (OHS) is a multidisciplinary field that aims to protect workers from all hazards they may encounter in the workplace. Today, OHS practices are of critical importance not only in the industrial sector but also in service sectors such as educational institutions. It is essential to be aware of the potential exposure of both teachers and students to physical, chemical, biological, and ergonomic risks in institutions where educational activities are conducted [1]. In this context, Vocational and Technical Anatolian High Schools, due to their workshops, laboratories, and practical course content, contain a higher level of risk factors compared to other types of schools [2]. In educational institutions, OSH must be addressed holistically, not only in terms of physical safety but also in terms of institutional culture, teachers' awareness levels, and managerial planning processes [3]. Awareness analyses conducted within this framework contribute significantly to controlling existing risks by determining teachers' knowledge levels. Measuring the awareness levels of teachers working in Vocational and Technical Anatolian High Schools regarding OSH is of critical importance both for evaluating the current safety culture and for shaping future education policies [4]. The occupational health and safety regulations published by the Ministry of National Education in Turkey define the duties and responsibilities of teachers and administrators in detail. However, the effective implementation of these regulations largely depends on teachers' knowledge, attitudes, and behavioral tendencies in the field of occupational health and safety [5]. In Iğdır, which is among the environmentally and socioeconomically disadvantaged regions, identifying teachers' competence in this area could provide valuable contributions to awareness-raising efforts at the national level. In addition, OSH awareness not only serves to protect teachers' own health and safety but also contributes to the sustainability of a safe learning environment for students [6]. Therefore, it is necessary to reveal the levels of awareness in question through local-scale scientific research.

A large portion of academic studies in the field of occupational health and safety (OHS) focus on the industrial sector, and the relative neglect of risks encountered in educational institutions presents a significant gap. However, a significant portion of workplace accidents in schools are preventable, and these accidents are often caused by teachers' lack of knowledge or inadequate risk perception [7]. Reports examining workplace accidents reveal that falls, collisions, and ergonomic issues faced by teachers are among the serious risk factors (SGK, 2022). This situation highlights the necessity of including OSH in teacher training programs. Indeed, providing pre-service teacher candidates with education on occupational health and safety issues can enable them to adopt a more conscious and preventive approach when they begin their careers [8]. Determining the awareness levels of current teachers is important for increasing the scope and effectiveness of in-service training programs [9].

The focus of the study is the Vocational and Technical Anatolian High School in Iğdır, which is located on Turkey's eastern border and has a unique demographic structure. Vocational and Technical Anatolian High Schools in the city constitute an important component of regional education in terms of both student and teacher numbers; however, physical infrastructure deficiencies and the absence of an established OSH culture increase the potential risk level [10]. In particular, the lack of maintenance of equipment used in workshops and deficiencies in fire prevention systems necessitate that teachers act consciously and cautiously in terms of OSH. In this context, determining the level of OSH awareness among teachers at the local level will provide a scientific basis for planning at the provincial level; it will also create a reference dataset for similar studies to be conducted in other provinces.

The main objective of this study is to determine the awareness levels of teachers working at Iğdır Vocational and Technical Anatolian High Schools regarding occupational health and safety (OHS) and to develop policy recommendations based on the findings. The questionnaire prepared for this purpose focuses on measuring teachers' knowledge, attitudes, behaviors, and perceptions regarding OHS and current practices. It is anticipated that the data obtained from the research will be of a quality that can be used in teacher training processes and contribute to school administrations' planning in the field of OSH [11]. Additionally, the data will enable the identification of areas where teachers demonstrate deficiencies, serving as an important reference source for the development of in-service training program content.

Although the study was conducted at the local level, it has the potential to provide generalizable findings for educational institutions throughout Turkey. In this respect, it contributes to the literature and develops solution-oriented recommendations in the field of application. The level of OSH awareness is directly related to teachers' capacity to manage the risks they may encounter in educational settings. The knowledge, attitudes, and behaviors of teachers working in Vocational and Technical Anatolian High Schools in this area contribute to the establishment of a safe educational environment at both the individual and institutional levels [12].

Measuring this level of awareness using scientific methods will contribute to the development of more effective and targeted education policies. This study, conducted in the province of Iğdır, will provide a framework that can contribute not only to the identification of local issues but also to the development of national OSH strategies. The policy recommendations to be developed as a result of the research require a multi-stakeholder approach that includes not only teachers but also school administrators and policymakers; this holistic perspective constitutes an important step in the process of creating safe school environments.

II. MATERIAL AND METHOD

Research Model

This study is a quantitative research-based study conducted to determine the awareness levels of teachers working at Iğdır Vocational and Technical Anatolian High School regarding occupational health and safety (OHS). The descriptive survey model was used in the study to present the current situation without any intervention [13]. This model is considered an appropriate method for assessing awareness levels because it allows data to be collected from large groups of participants and analyzed systematically [14].

Population and Sample

The population of the study consists of all teachers working at Iğdır Vocational and Technical Anatolian High School as of the 2024-2025 academic year. Sixty-eight teachers were identified using purposive sampling, but valid survey responses were obtained from 40 teachers. Purposive sampling ensures that data suitable for the purpose of the research is obtained by selecting individuals with specific criteria. The criteria for inclusion in the sample are as follows: teaching directly in technical and vocational fields, having at least one year of professional experience, and having a basic level of knowledge about OSH. Additionally, demographic variables such as gender, age group, educational level, and years of service were considered in the analysis process to identify potential relationships between individual characteristics and OSH perceptions.

Data Collection Tool

As the data collection tool, the Occupational Health and Safety Self-Efficacy Scale, developed and reliability-tested by Taşdemir and Gür, [15] was used. The questionnaire consisted of two sections. The first section included nine questions aimed at obtaining the demographic information of the participants, while the second section comprised 30 statements designed to measure teachers' self-efficacy perceptions regarding occupational health and safety (OHS). The items in the second section were prepared in a 5-point Likert scale format (1 = Strongly Disagree, 5 = Strongly Agree). The content of the questions was developed by taking into account scales available in the OHS literature and the national legislation.

The survey was administered online via Google Forms and completed following a data collection process that lasted approximately two weeks. To ensure content validity, the opinions of three academics who are experts in educational administration and occupational health and safety (OHS) were consulted. After conducting a pilot study to test language clarity and technical functionality, necessary revisions were made, and the final version of the questionnaire was prepared.

Data Analysis

The statistical analysis of the data obtained within the scope of the study was carried out using the SPSS software package. During the analysis process, data integrity, missing values, and outliers were first checked. As part of the descriptive statistics, the demographic characteristics of the participants were summarized through frequency and percentage distributions, and the responses to the scale items were evaluated using arithmetic means and standard deviation values. For comparisons between groups, the independent samples t-test was used for variables with two categories, while one-way analysis of variance (ANOVA) was applied for variables with more than two categories. In cases where ANOVA results were found to be significant, post-hoc multiple comparison tests were conducted to determine between which groups the differences occurred.

The reliability of the Occupational Health and Safety Self-Efficacy Scale used in the study was tested by calculating Cronbach's α internal consistency coefficient. In all statistical analyses, a significance level of 0.05 was adopted, and a p-value less than 0.05 was considered statistically significant. This methodological approach supported both the reliability of the data and the scientific validity of the results obtained.

Ethical Principles

Full compliance with ethical guidelines was ensured throughout the research process. The study was conducted with the approval of the Iğdır University Scientific Research and Publication Ethics Committee, granted under decision number 2025/12 dated April 25, 2025. At the beginning of the questionnaire, participants were informed about the purpose of the study and the principles of confidentiality, and participation was based on voluntary consent. No personal data were collected; only the information necessary for scientific analysis was used. The study was carried out based on a project proposal developed under the supervision of an academic advisor and submitted for academic review. The secure collection, evaluation, and reporting of the data strengthened the validity and reliability of the research.

III. FINDINGS

The internal consistency reliability of the scale used in the study was assessed using Cronbach's α coefficient. The Cronbach's α value for the overall scale was found to be 0.942, indicating a very high level of internal consistency and demonstrating that the items consistently measure the same construct. In addition, changes in the α coefficient were examined in the event that any item was removed from the scale. According to the results obtained from the sample, no significant decrease or increase in the α coefficient was observed when the specified items were removed (all ≈ 0.941). This finding suggests that these items contribute positively to the overall reliability of the scale.

The statistical analyses conducted on the collected data enabled the examination of teachers' occupational health and safety (OHS) awareness levels in relation to various demographic and educational variables.

In the comparison based on the gender variable (Independent Samples t-Tests), no statistically significant difference was found between the mean score of male teachers ($\bar{x}$ = 3.675) and that of female teachers ($\bar{x}$ = 3.566) (t = 0.540, p = 0.593). This indicates that OHS awareness levels do not vary according to gender. Similarly, no significant difference was identified for the variable "Have you previously received OHS training?" (Yes: $\bar{x}$ = 3.650; No: $\bar{x}$ = 3.523; t = 0.437, p = 0.679). For the variable "Have you received fire safety training before?", although the mean score of those who had received training ($\bar{x}$ = 3.735) was higher than those who had not ($\bar{x}$ = 3.551), this difference was not statistically significant (t = 0.906, p = 0.372).

Likewise, no significant difference was found for the variable "Have you received search and rescue training before?" (Yes: $\bar{x}$ = 3.615; No: $\bar{x}$ = 3.643; t = -0.110, p = 0.914). Similarly, in the case of the variable "Have you received first aid training before?", no statistically significant difference was observed between the group that had received training ($\bar{x}$ = 3.602) and the group that had not ($\bar{x}$ = 3.783) (t = -0.656, p = 0.530).

The comparison between age groups (One-Way Analysis of Variance – ANOVA) revealed a statistically significant difference in OHS awareness levels (p = 0.007). This finding suggests that age may be a determining factor in OHS awareness. In contrast, no significant differences were found for the variables of educational attainment (p = 0.175), years of service (p = 0.260), or employment status (p = 0.074).

The relationship between gender and participation in various OHS training programs was examined using Chi-Square Independence Tests. A significant difference was identified for the variable "Have you received fire safety training before?" (χ^2 = 7.785, df = 1, p = 0.005), indicating that participation in fire safety training may vary depending on gender. For the other variables—OHS training, search and rescue training, and first aid training—no significant relationships were detected between gender and training participation (all p > 0.05).

The research findings indicate that teachers working at Iğdır Vocational and Technical Anatolian High School exhibit a strong profile in certain aspects of occupational health and safety awareness, while demonstrating weaknesses in others. Demographic analysis shows that the majority of participants are male (62.5%) and in the middle age group (37.5% aged 32–38, 35% aged 39–45). In terms of years of service, half of the participants are within the first five years of their professional careers. This reflects a participant group that possesses both professional experience and an openness to new approaches.

In terms of educational background, nearly half of the participants are graduates of faculties of education, suggesting that they possess fundamental knowledge related to teacher training. Additionally, the 23.1% rate of postgraduate degree holders indicates that the teachers have a certain level of competence in terms of academic development. This diversity enables the examination of OHS awareness in relation to both professional training and academic advancement.

The data obtained show that the vast majority of participants (87.5%) have previously received OHS training; however, the rates of training in fire safety (45%) and search and rescue (32.5%) remain notably low. This deficiency in disaster preparedness training can be considered a significant gap, especially for educators working in regions with disaster risk. This finding highlights the need to expand the scope and increase participation rates in training programs to be organized in cooperation between the Disaster and Emergency Management Authority (AFAD) and the Ministry of National Education.

The relatively high rate of first aid training participation (82.5%) indicates that teachers possess a certain level of awareness regarding emergency medical intervention. However, the fact that this rate has not reached full participation suggests the possibility of knowledge gaps in situations requiring urgent intervention.

The findings reveal variability in awareness of structural safety components. For instance, while the awareness of the locations of emergency exits (82.5%) and assembly points (80%) is high, the level of knowledge regarding technical infrastructure elements—such as fire detection systems, water tank maintenance, periodic inspection of elevators, and lightning rod maintenance—is irregular and insufficient. In particular, the 50% rate of "undecided" responses concerning water tank maintenance points to a significant knowledge gap in this area. This situation suggests that informational and visibility efforts carried out by school administrations may be inadequate.

The high awareness rates (over 80%) regarding the use of personal protective equipment (PPE) and occupational risks are considered a positive finding. This result suggests that teachers demonstrate greater sensitivity toward issues that directly concern their own health. Similarly, the level of knowledge related to employee rights and accident reporting procedures was generally found to be high. However, the fact that nearly 30% of participants responded with "undecided" or "disagree" in these areas indicates that there may still be knowledge gaps in the exercise of these rights.

Awareness levels concerning physical safety measures—such as securing cabinets, restricting window openings to prevent falls, and ensuring stair rail safety—present a more fragmented picture. The high proportion of "undecided" responses in these areas suggests that teachers may lack sufficient information about the school's physical safety infrastructure or that these measures are not visibly implemented.

Overall, these findings indicate that teachers have a high level of awareness regarding issues that directly affect their personal health and safety; however, their awareness is more limited in system-oriented areas such as technical infrastructure, maintenance, and disaster management. This suggests that in-school OHS practices tend to focus informational activities primarily on personal safety and legal rights, while technical and structural safety components are not sufficiently emphasized.

Therefore, the results of the study highlight the need for more comprehensive in-service training programs for teachers in the areas of disaster preparedness, fire safety, and technical maintenance processes. In addition, it is recommended that school administrations develop practices to make existing safety measures more visible, such as informational boards and regular drills, in order to raise awareness. This approach would contribute to ensuring that both teachers and students can carry out educational activities in a safe school environment.

IV. DISCUSSION

The research findings reveal that teachers working at Iğdır Vocational and Technical Anatolian High School possess a general level of awareness regarding occupational health and safety (OHS), yet exhibit knowledge gaps particularly in areas such as legislation, technical infrastructure, and equipment maintenance. Although the majority of participants have previously received OHS training—which has had a positive impact on their overall knowledge level—uncertainties remain concerning the content of this training and its practical application. Indeed, the fact that only one-third of teachers reported being familiar with OHS legislation supports the "knowledge–behavior gap" problem frequently emphasized in the literature [1].

A comparison with existing literature shows that the findings of this study are consistent with previous research. Studies by Karapınar and Özen (2020) [16] and Ersoy and Akpınar (2020) [17] similarly reported that while teachers generally possess basic OHS knowledge, they are insufficient in technical details and infrastructure-related matters. In the present study, the low level of awareness regarding the presence or functionality of structural elements such as fire detection systems, water tank maintenance, and electrical installations further suggests that information sharing between school administrations and teachers is inadequate.

On a positive note, the fact that a large proportion of teachers (92.5%) share OHS knowledge with their students presents significant potential for promoting a safety culture within the school environment. However, it remains unclear whether this dissemination of information is systematic, integrated into the curriculum, or supported by assessment and evaluation processes. The literature indicates that OHS instruction based solely on individual initiative tends to have low retention, whereas approaches integrated with institutional support yield more effective results [18].

The finding that awareness of personal protective equipment (PPE) use and occupational risks exceeds 80% suggests that teachers working in technical education environments have internalized safety consciousness. Nevertheless, for this awareness to translate into actual behavior, there is a need to increase the use of practical training, case study analyses, and drills. Without such reinforcement, improvements in knowledge levels may not directly contribute to the prevention of accidents [19].

The low level of awareness regarding physical safety measures (such as stairwell safety, securing cabinets, window safety, and slippery floor warnings) suggests that safety inspections are either not sufficiently visible or are not effectively communicated to teachers. Similarly, the limited knowledge about infrastructural components such as lightning rods and fire detection systems indicates not only technical shortcomings but also gaps in communication and administrative practices.

Overall, while teachers possess a significant level of OHS awareness at the individual level, this awareness does not appear to be sufficiently integrated into the school's structural and administrative processes. Therefore, it is necessary to move beyond individual-focused approaches and promote system-based, participatory, and continuous training-oriented OHS practices. The sustainability of an

OHS culture depends not only on the enforcement of regulations but also on incorporating teachers' experiences and observations into institutional policies.

V. CONCLUSION AND RECOMMENDATIONS

The findings indicate that teachers' OHS awareness levels are largely similar across gender, educational background, and length of professional experience; however, age appears to have a significant effect on awareness. Additionally, the variation in fire safety training participation by gender points to the need for a more balanced training plan in this area. Based on the study results, the following recommendations can be made:

Strengthening Legislative Training: Incorporating comprehensive content on legislation and rights into OHS training programs.

Technical Infrastructure Briefings: Conducting regular information sessions for teachers on infrastructural elements such as fire systems, lightning rods, water tanks, and electrical installations.

Disaster and Emergency Drills: Organizing regular and practical fire, earthquake, and search-and-rescue drills.

Systematic OHS Knowledge Sharing: Integrating the OHS information shared by teachers with students into the curriculum and supporting it through assessment and evaluation processes.

Transforming PPE Use into Behavior: Reinforcing teachers' PPE usage habits through practical training, case studies, and scenario-based drills.

Enhancing Management–Teacher Communication: Ensuring that school administrations regularly share safety inspection results with teachers.

Local and National Collaboration: Developing specialized OHS programs for vocational high schools in cooperation with the Ministry of National Education, AFAD, and OHS experts.

These recommendations aim not only to increase teachers' individual awareness but also to foster an institutional safety culture at the school level. In doing so, OHS practices can go beyond mere regulatory compliance to establish a sustainable structure in which all school stakeholders actively participate.

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Comparative Analysis of Perceived Learning Effectiveness Between Online and Face-to-Face Internships of BS Medical Technology Students

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Abstract— *The study aimed to compare the perceived learning effectiveness of online and face-to-face internships among BS Medical Technology students at the World Citi College A quantitative-comparative research design was employed, with a total of 210 respondents from two distinct internship batches: 60 students from the Academic Year 2020–2021 who underwent online internships, and 150 students from the Academic Year 2023–2024 who completed face-to-face internships. Data were collected using a structured survey questionnaire measuring knowledge acquisition, skills development, problem-solving, critical thinking, communication, and professional preparedness. Descriptive statistics were used to present demographic profiles and perceived effectiveness, while independent samples t-tests determined significant differences between the two groups. Results revealed that face-to-face internship students consistently reported higher mean scores across all indicators of learning effectiveness compared to online interns. Statistically significant differences were observed in knowledge acquisition, skills development, problem-solving, critical thinking, communication, and professional preparedness, indicating that traditional internships provide more comprehensive experiential learning. While online internships ensured continuity of training during pandemic-related restrictions, they were limited in offering hands-on practice and direct mentorship. These findings highlight the importance of maintaining face-to-face internships as a core component of medical technology education while considering online modalities as supplemental tools to support theoretical learning. The study suggests that hybrid internship models may optimize both accessibility and practical skill development for future healthcare professionals.*

I. INTRODUCTION

The internship is an essential component of medical education, serving as the bridge between theoretical knowledge and practical application. It allows students to acquire clinical competencies, interpersonal skills, and professional experiences that cannot be fully gained in classroom settings. Traditional internships are typically characterized by direct patient interactions, hands-on training, and face-to-face mentorship, which are considered vital in shaping clinical judgment and preparedness for professional practice [1]. However, the COVID-19 pandemic disrupted conventional training models and accelerated the transition toward online platforms, raising questions about the overall effectiveness of digital learning in medical training [2][3].

Previous studies have highlighted the importance of adapting internship programs to ensure continuity in medical education during periods of disruption. Webinars and virtual simulations, for instance, were rapidly adopted to substitute clinical exposure, and these methods have been recognized as feasible and effective alternatives for maintaining academic engagement [2][3]. Digital platforms such as WeChat have further demonstrated the potential of integrating problem-based and case-based learning with interactive review methods, thereby enhancing student participation and learning outcomes in online internships [4]. Despite these innovations, it is also necessary to consider cultural and contextual factors, as they influence students' attitudes and professional development during their internship experiences [1].

The purpose of this study is to conduct a quantitative analysis of the perceived learning effectiveness between online and traditional internships among medical technology students. By comparing these two modalities, the paper aims to provide evidence on which approach offers more comprehensive learning opportunities. Furthermore, this study contributes to the growing body of research on medical education by addressing how online and face-to-face internship formats impact skill acquisition, critical thinking, and overall preparedness for professional practice in the post-pandemic educational landscape.

1.1 Traditional Internship and Clinical Competence

Traditional internships are regarded as a cornerstone of medical and allied health education, as they provide students with structured opportunities to integrate theoretical knowledge into real-world clinical practice. Almadani et al. [5] emphasized that nurse interns perceive clinical preparation and readiness as essential factors that directly influence their confidence and competence in clinical settings. This suggests that early and comprehensive preparation before entering internships enhances students' ability to adapt to the professional environment and handle patient care responsibilities effectively. Moreover, the traditional learning approach, when coupled with interactive learning activities, has been shown to positively impact both the personal and professional growth of interns. AlKhaibary et al. [6] highlighted that conventional clinical exposure plays a significant role in improving problem-solving abilities, communication, and teamwork, which are critical in ensuring successful transitions into professional nursing practice. These findings reinforce the value of hands-on experiences, where students not only refine technical skills but also cultivate professional behaviors that classroom instruction alone cannot achieve.

In addition, the role of clinical teaching faculty is vital in ensuring the effectiveness of traditional internships. Song et al. [7] established a framework of qualities for clinical teaching faculty, underscoring the importance of mentorship, guidance, and structured supervision in undergraduate medical internships. Their findings indicate that the presence of competent faculty enhances learning outcomes by fostering clinical reasoning, skill acquisition, and reflective practice among students. Collectively, these studies affirm that traditional internships, supported by strong preparation, interactive activities, and effective teaching faculty, remain indispensable in developing clinical competence among healthcare students.

1.2 Effectiveness of Online and Virtual Internships

The COVID-19 pandemic accelerated the adoption of online and virtual internship models in medical and health-related education. Hao et al. [8], through a systematic review, found that digital education offered an effective alternative to conventional training, ensuring that undergraduate nursing and medical interns continued their academic progression despite restricted clinical exposure. The study emphasized that virtual platforms enhanced knowledge acquisition, improved flexibility, and supported the development of essential competencies, although challenges such as limited hands-on practice remained. Similarly, Alsaywid et al. [9] reported that institutional preparedness played a significant role in the success of online medical training during the pandemic. Their study in Saudi Arabia highlighted that e-learning methods, when effectively designed and implemented, were perceived as both effective and adaptable for residents' medical training. However, the authors also noted that digital fatigue, reduced clinical engagement, and disparities in technological access posed significant barriers to maximizing the benefits of online internships.

Beyond the pandemic context, Feldman [10] argued that virtual internships may serve as a sustainable complement to traditional internship models. By providing opportunities for remote collaboration, professional networking, and exposure to global learning environments, virtual internships expand the scope of experiential learning. Nevertheless, the study cautioned that online training should not entirely replace hands-on clinical practice, but rather be integrated as a hybrid model to maximize both accessibility and skill development. Together, these findings suggest that online and virtual internships, while not without limitations, are effective alternatives that ensure continuity of medical education in times of disruption.

1.3 Cultural and Contextual Influences on Internship Learning

For medical technology students, cultural and contextual factors shape not only their motivation but also their preparedness for professional practice. Veselova et al. [11] demonstrated that cultural exposure during internships enhances student engagement and fosters motivation, which can be paralleled in medical technology programs. Exposure to diverse patient populations, healthcare practices, and professional values during internships can enrich med tech students' perspectives, motivating them to integrate both technical expertise and cultural sensitivity into their clinical training. The COVID-19 pandemic further highlighted the influence of contextual factors on health-related internship experiences. Duprez et al. [12] reported that nursing students' commitment to their education was affected by how their internships were structured during the pandemic. For medical technology students, similar challenges emerged: limited access to laboratory facilities, reduced patient interactions, and decreased opportunities for hands-on practice likely impacted both skill acquisition and professional identity formation. These contextual barriers underscore the need to create supportive learning environments that sustain students' motivation and ensure continuity of competence development, even in times of disruption.

Cultural competence also plays a critical role in preparing medical technology students for professional practice. Arruzza and Chau [13] emphasized that cultural competence education improves knowledge acquisition, performance, and student satisfaction in health sciences. Applied to med tech internships, fostering awareness of cultural diversity in laboratory and clinical settings ensures that students are not only technically skilled but also able to work effectively in multidisciplinary teams and serve diverse patient populations. Hence, cultural and contextual influences remain essential components of internship design, ensuring that medical technology students develop both professional competence and adaptability in a rapidly changing healthcare landscape.

II. METHODOLOGY

2.1 Research Design

This study employed a quantitative-comparative research design to determine the perceived learning effectiveness between online and traditional internships of BS Medical Technology students. This design was chosen because it allows the comparison of two distinct groups—students who underwent face-to-face internships and those who experienced online internships—using measurable indicators of academic and professional effectiveness.

2.2 Research Locale and Respondents

The study was conducted at the World Citi College The respondents were BS Medical Technology interns from two distinct batches. The Academic Year 2020–2021 interns (Group A) underwent an online internship setting due to restrictions brought by the COVID-19 pandemic, while the Academic Year 2023–2024 interns (Group B) completed a traditional, face-to-face internship setting.

A total of 210 respondents participated in the study, consisting of 60 interns from Group A (online internship) and 150 interns from Group B (face-to-face internship). A purposive sampling technique was employed to ensure that only students who had fully completed their respective internship programs during the specified academic years were included in the study.

2.3 Research Instrument

Data were collected using a structured survey questionnaire designed to measure the perceived learning effectiveness of the respondents. The instrument consisted of two main sections: (1) demographic profile, and (2) indicators of learning effectiveness, which included knowledge acquisition, skills development, problem-solving and critical thinking, communication, and professional preparedness. The instrument was validated by experts in medical technology education to ensure clarity, relevance, and reliability.

2.4 Data Gathering Procedures

Prior to data collection, formal approval was sought from the institution and research adviser. The survey questionnaire was distributed to the respondents of both groups. For the online internship group (AY 2020–2021), questionnaires were distributed via online platforms, while for the face-to-face internship group (AY 2023–2024), distribution was conducted in person after securing proper coordination with faculty supervisors. Participation was voluntary, and informed consent was obtained from all respondents. Responses were collected within a one-month period and subsequently encoded for analysis.

2.5 Data Analysis

The data gathered were analyzed using descriptive and inferential statistics. Descriptive statistics, such as frequency counts, percentages, mean scores, and standard deviations, were used to present the demographic profile and perceived effectiveness ratings. To determine whether significant differences existed between the two groups, an independent samples t-test was performed at a 0.05 level of significance.

2.6 Ethical Considerations

The researchers ensured strict compliance with ethical research standards. Informed consent was obtained from all participants, and they were informed of their right to withdraw from the study at any time. The confidentiality and anonymity of all respondents were protected, as no identifying information was collected. Data were used strictly for academic purposes and in accordance with institutional ethical guidelines.

III. RESULTS AND DISCUSSIONS

To ensure a high-quality product, diagrams and lettering MUST be either computer-drafted or drawn using India ink.

Table.1: Demographic Profile

Sex	Frequency (f)	Percentage
Female	82	39.05%
Male	128	60.95%
Total	**210**	**100%**

The data in Table 1 shows that the majority of the respondents were female, comprising 128 or 60.95% of the total population, while male respondents accounted for 82 or 39.05%. This indicates that female students dominate the Medical Technology internship program in World Citi College, which reflects the common trend in allied health sciences where female enrollment tends to be higher compared to male counterparts.

Table.2: Frequency and Percentage Distribution of the Respondents in Terms of Age

Age Range	Frequency (f)	Percentage
20-21	68	32.38%
22-23	102	48.57%
24-24	35	16.67%
26 and above	5	2.38%
Total	**210**	**100%**

The data in Table 2 reveals that the majority of the respondents were within the age range of 22–23 years old, accounting for 102 or 48.57% of the total population. This is followed by those aged 20–21 years old with 68 or 32.38%, while 35 or 16.67% of the respondents were in the 24–25 age group. Only a small proportion, 5 or 2.38%, were aged 26 and above. This distribution suggests that most of the Medical Technology interns from World Citi College were in their early twenties, which aligns with the typical age of students completing undergraduate internship requirements.

Table.3: Frequency and Percentage Distribution of the Respondents in Terms of Internship Type

Exposure to Health Related Seminars/Training	Frequency (f)	Percentage
Yes	135	64.29%
No	75	35.71%
Total	**210**	**100%**

Table 3 shows that a majority of the respondents (64.29%) had exposure to health-related seminars or trainings, while 35.71% did not. This implies that most Medical Technology interns had prior opportunities to enhance their knowledge and skills through supplemental learning experiences, which may have contributed to their internship performance and readiness.

Table.4: Frequency and Percentage Distribution of the Respondents in Terms of Exposure to Health-related Seminars or Trainings

Internship Type	Frequency (f)	Percentage
Face-to-Face (2023-24)	150	71.43%
Online (2002-21)	60	28.57%
Total	**210**	**100%**

Table 4 shows that a larger proportion of respondents, 150 or 71.43%, experienced face-to-face internship, while 60 or 28.57% underwent online internship. This distribution reflects the transition from traditional to online internship during the COVID-19 pandemic, highlighting the shift in training modalities between different academic years.

Table.5: Shapiro–Wilk Test for Normality of the Variables

Variable	W Statistics	p-Value	Interpretation
Knowledge Acquisition	0.981	0.087	Normally Distributed
Skills Development	0.976	0.094	Normally Distributed
Problem Solving	0.972	0.072	Normally Distributed
Critical Thinking	0.968	0.041	Not Normally Distributed
Communication	0.983	0.067	Normally Distributed
Professional Preparedness	0.979	0.082	Normally Distributed

Table 5 presents the Shapiro–Wilk test results assessing the normality of the variables measuring learning effectiveness. With the exception of critical thinking ($p = 0.041$), all indicators yielded p-values greater than 0.05, suggesting that their distributions do not significantly deviate from normality. Thus, assumptions for parametric testing are satisfied for most variables, supporting the use of an independent samples t-test to compare the two groups. However, for variables not meeting normality assumptions, non-parametric alternatives may be considered to validate findings.

Table.6: Comparative Analysis of Perceived Learning Effectiveness Between Online and Face-to-Face Internship Groups

Indicators of Learning Effectiveness	Group A (Online)	Group B (Face-to-Face)	t-value	p-value	Interpretation
Knowledge Acquisition	3.65(0.72)	4.12(0.68)	-4.21	0.000	Significant
Skills Development	3.58(0.75)	4.25(0.63)	-5.18	0.000	Significant
Problem Solving	3.60(0.70)	4.05(0.65)	-3.84	0.000	Significant
Critical Thinking	3.55(0.80)	3.98(0.71)	-3.12	0.002	Significant
Communication	3.70(0.74)	4.15(0.60)	-3.87	0.000	Significant
Professional Preparedness	3.50(0.78)	4.20(0.66)	-5.35	0.000	Significant

Table 6 shows the results of the independent samples t-test comparing the perceived learning effectiveness of online and face-to-face internship groups. Across all six indicators—knowledge acquisition, skills development, problem-solving, critical thinking, communication, and professional preparedness—the face-to-face internship group reported significantly higher mean scores than the online internship group ($p < 0.05$ for all variables). These findings suggest that traditional, face-to-face internships provided more effective learning experiences for BS Medical Technology interns compared to online internship settings.

3.6.1.:Knowledge Acquisition

As shown in Table 6, the test rejects the null hypothesis since the p-value (0.000) is less than $\alpha = 0.05$. Therefore, there is a statistically significant difference in the perceived learning effectiveness on knowledge acquisition between the two groups ($t = -4.21$, $p < 0.001$). Group A (Online Internship) reported a mean of 3.65 (Moderately Effective), while Group B (Face-to-Face Internship) obtained a higher mean of 4.12 (Very Effective). This finding suggests that face-to-face internships provide stronger opportunities for Medical Technology interns to directly apply theoretical concepts in actual clinical settings, which enhances comprehension and long-term retention.

These results are consistent with studies emphasizing that experiential and hands-on learning fosters deeper knowledge integration compared to remote or simulated experiences. In the health sciences, direct engagement with laboratory procedures, diagnostic tools, and patient samples promotes a more comprehensive understanding of applied theories [14]. Furthermore, authentic practice settings allow for real-time feedback and clarification from supervisors, strengthening knowledge acquisition and reducing misconceptions that may arise in virtual environments [15].

3.6.2.: Skills Development

Table 6 shows that the null hypothesis is rejected since the p-value (0.000) is less than $\alpha = 0.05$. A significant difference was found in the perceived development of skills between the two groups ($t = -5.18$, $p < 0.001$). Group A (Online Internship) obtained a mean score of 3.58 (Moderately Effective), while Group B (Face-to-Face Internship) obtained a mean score of 4.25 (Very Effective). This highlights that traditional internships are more effective in equipping students with the practical skills needed in Medical Technology, particularly those requiring laboratory competence and manual precision

According to earlier research, hands-on training remains critical in medical and laboratory education, as it allows students to practice techniques that cannot be fully replicated in online modules [16]. Moreover, immediate access to mentors and clinical instructors provides students with corrective guidance and skill refinement, which is often limited in virtual settings [17]. Thus, the superiority of face-to-face internships in skill development is strongly supported by both the statistical results and existing literature.

3.6.3.: Problem Solving

As presented in Table 6, the null hypothesis is rejected since the p-value (0.000) is less than $\alpha = 0.05$. A significant difference exists in problem-solving effectiveness between the two groups ($t = -3.84$, $p < 0.001$). Group A (Online Internship) had a mean score of 3.60 (Moderately Effective), while Group B (Face-to-Face Internship) reported a higher mean of 4.05 (Very Effective). This suggests that face-to-face internships provide richer opportunities for students to engage in diagnostic reasoning and case-based problem-solving.

The literature supports this result, noting that problem-solving skills are better developed when students are exposed to unpredictable clinical situations that require immediate analysis and intervention [18]. Additionally, real-world settings allow collaboration with peers and supervisors, which fosters collective problem-solving and enhances cognitive flexibility—capabilities that are more difficult to cultivate in online simulations [14]. Thus, traditional internships create a learning environment where interns actively confront and resolve authentic challenges.

3.6.4.:Critical Thinking

Table 6 indicates that the null hypothesis is rejected since the p-value (0.002) is less than $\alpha = 0.05$. Therefore, a significant difference is observed in critical thinking between the two groups ($t = -3.12$, $p = 0.002$). Group A (Online Internship) reported a mean of 3.55 (Moderately Effective), while Group B (Face-to-Face Internship) reported a higher mean of 3.98 (Very Effective). This demonstrates that traditional internships strengthen the ability of Medical Technology students to think critically and evaluate complex cases.

Consistent with previous studies, exposure to actual laboratory workflows and patient-related scenarios helps students apply reflective judgment and higher-order reasoning [15]. Moreover, clinical practice enhances their decision-making by requiring them to weigh multiple variables under time pressure, thereby sharpening their analytical skills [16]. By contrast, online training—while effective in transmitting theoretical content—tends to offer structured and predictable scenarios, which limits the development of adaptive critical thinking.

3.6.5.: Communication

As reflected in Table 6, the test rejects the null hypothesis since the p-value (0.000) is less than $\alpha = 0.05$. A significant difference in communication skills exists between the groups ($t = -3.87$, $p < 0.001$). Group A (Online Internship) obtained a mean score of 3.70 (Moderately Effective), while Group B (Face-to-Face Internship) achieved a higher mean of 4.15 (Very Effective). These findings highlight that direct interpersonal interaction during traditional internships contributes significantly to the development of effective communication.

According to research, communication in clinical training is best cultivated in face-to-face contexts where students can practice professional dialogue with patients, collaborate with healthcare teams, and receive feedback on their communication style [17]. Furthermore, studies emphasize that non-verbal cues and professional etiquette—key components of effective healthcare communication—are best learned through in-person observation and participation [18]. This underscores why students in face-to-face internships reported stronger outcomes in communication development.

3.6.6.: Communication

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IV. CONCLUSION

This study demonstrated that face-to-face internships are more effective than online internships in enhancing the perceived learning effectiveness of BS Medical Technology students at the World Citi College Students in traditional internships reported higher levels of knowledge acquisition, skills development, problem-solving, critical thinking, communication, and professional preparedness. While online internships provided continuity of learning during pandemic restrictions, they were limited in offering hands-on practice and direct mentorship. These findings suggest that traditional internships remain essential for developing practical competencies and professional readiness, though online modalities can serve as a complementary tool to support theoretical learning. Institutions may consider hybrid approaches to maximize both accessibility and experiential learning opportunities.

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Numerical Simulation and Analysis of Gas-Liquid Two-Phase Flow in a Venturi Tube

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Keywords*— *Venturi tube, Fluent fluid analysis, gas-liquid two-phase flow.

***Abstract*— *The Venturi tube, a widely used cavitation-generating device in the petroleum and chemical industries, is valued for its simple structure and safe stability. During cavitation-induced gas-liquid two-phase flow, collapsing bubble clusters release high temperature and pressure energy with associated effects. This study uses Fluent to investigate the Venturi tube's internal flow field characteristics. By comparing pressure contours, velocity contours, and gas phase distributions under varying inlet-outlet pressure ratios, throat length-to-diameter ratios, and diffusion angles, it analyzes cavitation flow evolution. Results show: for a fixed-structure Venturi with constant outlet pressure, stronger cavitation effects occur with higher inlet pressure, larger throat length-to-diameter ratios, and smaller diffusion angles. These findings clarify internal flow patterns and the influence of hydraulic and structural parameters on cavitation intensity.*

I. INTRODUCTION

The Venturi tube is typically made of cast iron or steel. In its cross-sectional structure, the pipe section is larger at both ends than in the middle, with the smallest cross-sectional area being the throat. When fluid flows through the Venturi tube, due to the reduction of the pipe's cross-sectional area, the flow velocity increases, and the pressure correspondingly decreases, so the flow velocity is the greatest and the pressure is the lowest at the throat [1]. By leveraging the relationship between pressure difference and velocity in a horizontal state, the Venturi tube can be used to measure fluid velocity or flow rate, that is, the flow and velocity can be inferred from the pressure difference generated after the fluid flows through.

According to Bernoulli's law, in a steady and continuous flow field, the pressure must decrease where the flow velocity increases [2]. The Venturi tube operates on this principle: minimal pressure loss, no fouling, wide range, and capable of measuring large flows. It has now been widely applied in automotive carburetors, electrostatic precipitators, vacuum cleaners, coolers, dryers, and so on [3]. Based on these advantages, academic research on the Venturi tube continues to deepen. In 2013, Wang Changbin simulated the characteristics of cavitation gas-liquid two-phase flow in the Venturi tube through fluid mechanics simulation software and concluded that when other conditions remain unchanged, reducing the throat diameter or increasing the inlet pressure both increase the throat velocity and decrease the local static pressure, thereby enhancing cavitation; extending the length of the diffuser section delays the recovery of the adverse pressure gradient, prolonging the cavitation bubble growth and collapse process, and enhancing the cavitation gas-liquid two-phase flow effect. This conclusion has great reference value for actual engineering projects [4]. In 2014, Capocelli et al. proposed a comprehensive modeling method for estimating reactor performance, combining cavity dynamics with Bernoulli-type macroscopic flow calculations to estimate turbulent fluctuations, which provides a more effective framework for developing a general prediction model for cavitation reactors [5]. In 2016, Xianlin Li and Biao Huang studied the influence of orifice plate geometric parameters on cavitation in the Venturi tube and further explored the free radicals generated by cavitation effects, and the results showed that the throat diameter of the Venturi tube has a greater impact on cavitation effects than the throat length; the evolution intensity of cavitation-induced gas-liquid two-phase flow inside the Venturi tube is of great significance to the stable operation and structural integrity of engineering facilities [6]. In 2017, Long et al. and Brinkhorst et al. achieved high-speed visualization of cavitation onset and growth in Venturi tube devices through experimental research, clearly describing the development of cavitation and its impact on overall equipment operation from the perspectives of flow rate and pressure [7-8]. The Venturi cavitation reactor has become an experimental hotspot, attracting attention for its significant efficiency in wastewater treatment and various process enhancements.

In summary, while basic research on Venturi tubes has matured, the complex dynamics of cavitation-induced gas-liquid two-phase flow under special working conditions still require deeper exploration. This study uses Fluent to perform three-dimensional numerical simulations of cavitation cloud evolution, systematically adjusting key parameters like pressure ratios, diffusion angles, and throat length-to-diameter ratios. By extracting critical flow field features (such as cavitation volume fraction and pressure fluctuation patterns) and quantifying how structural design and operating conditions interact, the research provides valuable insights for both cavitation inhibition and energy utilization. These findings will directly support the optimized design of Venturi tubes, enhancing their operational economy and long-term reliability in practical applications.

II. RESEARCH METHODS

2.1 Establishment of the Physical Model and Parameter Selection

The specific structure of the Venturi tube studied in this paper is shown in Figure 1. Based on the actual working parameters of the Venturi tube, the inlet pressure is 0.3–0.6 MPa, and the outlet pressure is 0.1 MPa. The model defines the inlet diameter of the contraction section as D = 50 mm, the throat diameter as d = 10 mm, the throat length as L = 10 mm, the contraction angle α = 22.5°, and the diffusion angle β = 6° [9].

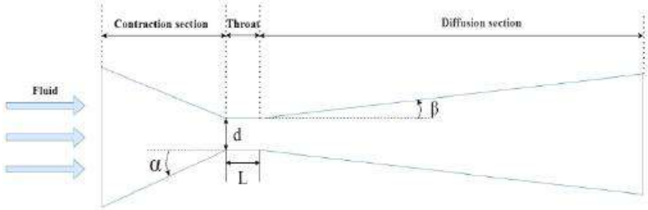

Fig.1 Venturi tube physical model

2.2 Establishment of the Mathematical Model

Liu Houlin et al. compared the application of three different models in cavitation flow calculations of centrifugal pumps and found that if the Zwart cavitation model is used for simulating the flow coefficient, the simulation results are closer to the experimental values [10]. The final form of the cavitation model proposed by Zwart-Gerber-Belamri is as follows:

If $P \leq P_V$

$$R_e = F_{vap} \frac{3\alpha_{nuc}(1-\alpha_v)\rho_v}{R_B} \sqrt{\frac{2}{3}\frac{P_V - P}{\rho_1}} \tag{1}$$

If $P > P_V$

$$R_C = F_{cond} \frac{3\alpha_v \rho_V}{R_B} \sqrt{\frac{2}{3}\frac{P - P_V}{\rho_1}} \tag{2}$$

where: R_e is the vaporization rate, R_B is the bubble radius, taken as R_B=$10^{-6}m$; α_{nuc} is the nucleation partial volume fraction, taken as α_{nuc}=5×; F_{vap} is the empirical correction coefficient for the evaporation term, taken as F_{vap}=50; F_{cond} is the empirical correction coefficient for the condensation term, taken as F_{cond} =0.001; P_V is the critical cavitation pressure; P is the flow field pressure; $\rho 1$ is the liquid phase density; R_C is the condensation rate; ρ_1 is the gas phase density.

When fluid flow passes through the wall surface, there is a viscous force that causes excessive gradient changes. In this region, the Reynolds number of turbulence becomes smaller, and a laminar effect will occur. The wall function is a set of semi-empirical formulas that derive the velocity physical quantities in this region [11]. The momentum equation for the wall function is:

$$U^* = \frac{1}{K_C} ln(E_C y^*) \tag{3}$$

U^* is the dimensionless velocity

$$U^* = \frac{U_P C_\mu^{\frac{1}{4}} K_P^{\frac{1}{2}}}{\frac{t_w}{\rho}} \tag{4}$$

y^* is the dimensionless distance from the wall

$$y^* = \frac{\rho C_\mu^{\frac{1}{4}} K_P^{\frac{1}{2}} y_P}{\mu} \tag{5}$$

where: K_C is the von Kármán constant, usually taken as 0.4187; E_C is the empirical constant, taken as 9.793; U_P is the average velocity at the wall surface node P; K_p is the turbulent kinetic energy near the wall surface node P; y_P is the distance from point P to the wall surface.

III. NUMERICAL SIMULATION

After obtaining the geometric model of the Venturi tube, mesh generation is also a key step: considering the abrupt pressure changes and complex flow field caused by cavitation, the computational dimension will increase exponentially with mesh refinement. Therefore, a non-structured mesh that is highly adaptable to arbitrary boundaries and easy to locally refine is adopted: the overall mesh is divided using the Fluent non-structured mesh, and the mesh quantity is refined in key areas such as the throat and diffuser section to ensure accuracy, while the contraction section is moderately sparse to reduce computational load and accelerate convergence, as shown in Figure 2 [12].

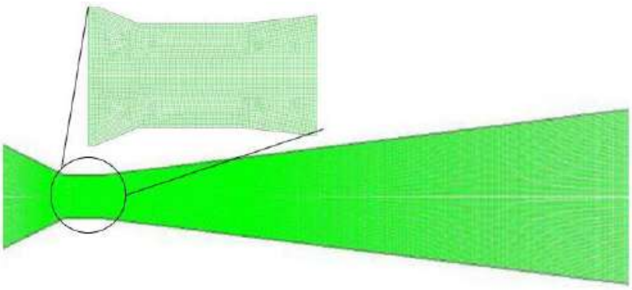

Fig.2 Venturi tube mesh generation

To simplify the model, the following assumptions are made for the control equations: the medium is steady-state, single-phase fluid with constant viscosity, density, and diffusion coefficient; there is no chemical reaction between the cavitation gas-liquid two-phase flow, and gravity is neglected. Based on these assumptions, the CFD software FLUENT is used to conduct numerical simulations of the flow field inside the Venturi tube.

3.1 Investigation of the Influence of Different Inlet Pressures on the Venturi Tube

Under other conditions remaining unchanged, the inlet pressure is set to 0.3 MPa, 0.4 MPa, 0.5 MPa, and 0.6 MPa respectively, to simulate and analyze the fluid velocity, pressure, and gas phase distribution inside the Venturi tube under different inlet pressures. The resulting diagrams are as follows.

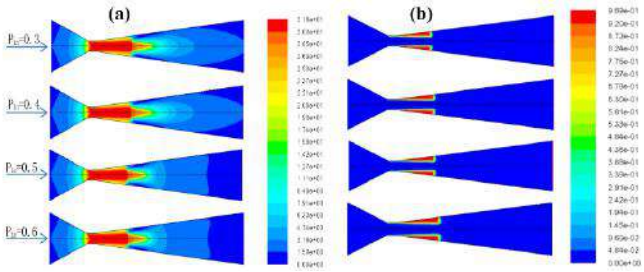

Fig.3 Velocity (a) and gas phase distribution (b) changes in the Venturi tube under different inlet pressures

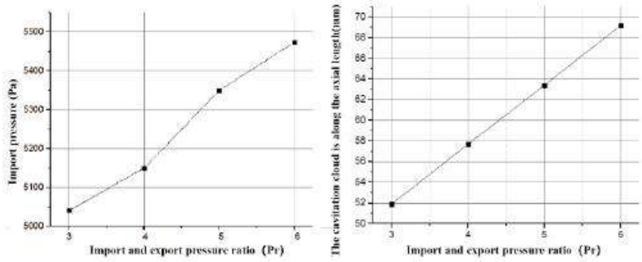

Fig.4 Pressure and cavitation cloud distribution along the axial length of the Venturi tube under different inlet and outlet pressure ratios

From the velocity contour in Figure 3(a), it can be seen that when the inlet and outlet pressure ratio is 6, the fluid velocity reaches a maximum of 31.6 m/s at the throat, and the maximum velocity increases with higher inlet pressure. The larger the inlet pressure, the larger the high-speed region at the throat. As the contraction section is entirely liquid, from the gas phase distribution in Figure 3(b), it can be observed that cavitation gas-liquid two-phase flow bubbles are generated at the junction of the contraction section and the front end of the throat, and more bubbles are produced at this junction than at the front end of the throat. After the front half of the diffuser section, the bubble diameter reduces to zero.

From Figure 4, it can be seen that under different inlet pressure conditions, the minimum pressure at the throat increases with the increase in inlet pressure, and the overall change is not very uniform. From the cavitation cloud diagram, it can be observed that as the inlet and outlet pressure ratio increases, the growth rate of the cavitation cloud length increases linearly.

3.2 Investigation of the Influence of Different Diffusion Angles on the Venturi Tube

With the throat length L = 10 mm, the contraction angle set to 22.5°, and the inlet pressure at 0.4 MPa, the diffusion angle is set to 6°, 9°, 12°, and 15° respectively. The simulation analysis of the fluid velocity, pressure, and gas phase distribution inside the Venturi tube under different inlet pressures is shown in Figure 5.

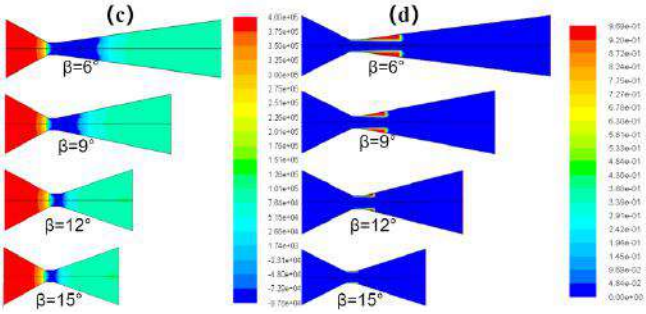

Fig.5 Pressure (c) and gas phase distribution (d) inside the Venturi tube under different diffusion angles

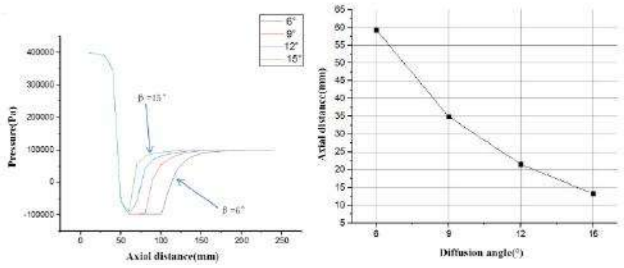

Fig.6 Axial pressure distribution and cavitation cloud length of the Venturi tube under different diffusion angles

As the diffusion angle of the Venturi tube increases, from the pressure contour (c), it can be seen that the low-pressure region decreases with the increase in the diffusion angle. Combined with Figure 3(a), it can be observed that the larger the diffusion angle, the faster the water flow velocity decays, the faster the pressure recovery in the diffuser section, and the smaller the low-pressure region. From the gas phase distribution diagram (d) of the Venturi tube, it can be seen that as the diffusion angle increases, the bubble range gradually decreases, and the starting point of generation gradually moves backward. That is, the smaller the diffusion angle of the Venturi tube, the greater the axial distance of the cavitation cloud length. Because bubbles can move further with the higher-velocity water flow and delay collapse, the cavitation gas-liquid two-phase flow bubble cloud region decreases with the increase in the diffusion angle.

From the axial pressure diagram of the Venturi tube in Figure 6, it can be seen that the diffusion angle has the greatest impact on the throat, and the larger the diffusion angle, the faster the pressure change. From the cavitation cloud length diagram, it can be more intuitively seen that as the diffusion angle increases, the axial distance of the cavitation cloud length decreases.

3.3 Investigation of the Influence of Different Throat Lengths on the Venturi Tube

The throat lengths are 0 mm, 10 mm, 20 mm, and 30 mm respectively, with other conditions remaining unchanged, the inlet pressure is 0.4 MPa, and the outlet pressure is 0.1 MPa.

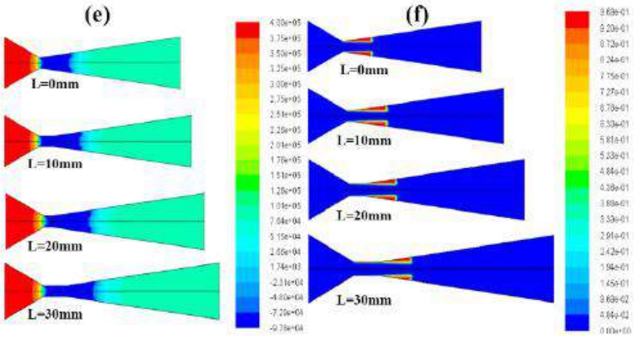

Fig.7 Pressure (e) and gas phase distribution (f) inside the Venturi tube under different throat lengths

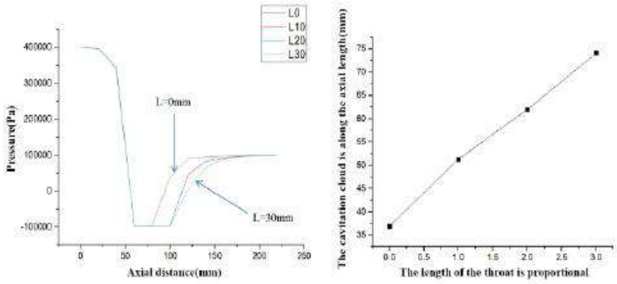

Fig.8 Axial pressure variation curve and cavitation cloud axial length of the Venturi tube under different throat lengths

The pressure contour (e) in Figure 7 reflects that as the throat length increases, the pressure recovery slows down, meaning that increasing the throat length within the Venturi tube delays pressure recovery. The gas phase distribution diagram (f) shows that bubbles are generated at both the throat inlet and outlet, with fewer bubbles at the throat inlet and larger bubble areas at the outlet.

From the axial pressure diagram in Figure 8, it can be seen that different throat lengths mainly affect the pressure at the end of the throat. When the throat length increases from 0–10 mm, the pressure changes rapidly, and then from 10–20 mm, the changes slow down. Overall, as the length increases, the rate of change tends to flatten. The cavitation cloud length diagram shows that the cavitation gas-liquid two-phase flow cavitation cloud length within the Venturi tube increases with the increase in the length-to-diameter ratio.

IV. CONCLUSION

This study employs the Fluent software to conduct numerical simulations of the fluid inside the Venturi tube, analyzing the basic characteristics of the flow field from three aspects: pressure, velocity, and phase diagrams. Using the numerical model, the generation and variation trends of cavitation gas-liquid two-phase flow under different structural designs and working conditions were analyzed. Through numerical simulation analysis, the following conclusions were drawn:

For the same Venturi tube with constant structural size and stable outlet pressure, as the inlet pressure increases, the area of the cavitation gas-liquid two-phase flow cloud also increases. Appropriately increasing the inlet and outlet pressure ratio is beneficial for enhancing the cavitation gas-liquid two-phase flow effect. The change in the throat length-to-diameter ratio (i.e., the ratio of throat length to throat diameter L/d) has little impact on the initial point of cavitation gas-liquid two-phase flow generation, but it helps to delay pressure recovery within the tube, allowing the cavitation cloud to develop better and collapse later. Under other conditions remaining the same, the cavitation gas-liquid two-phase flow cavitation cloud length within the Venturi tube increases with the increase in the length-to-diameter ratio L/d. Changes in the diffusion angle have a significant impact on the initiation and evolution of cavitation gas-liquid two-phase flow; a smaller diffusion angle is conducive to the generation and development of cavitation gas-liquid two-phase flow, causing cavitation to occur at lower pressures, advancing the starting point of cavitation, and subsequently providing more time and space for bubble generation and growth, with the final collapse region of the gas-liquid two-phase flow cavitation cloud moving backward.

Through the study of cavitation in the Venturi tube and combining the conclusions, in engineering fields such as wastewater treatment and food processing that require the enhancement and utilization of cavitation gas-liquid two-phase flow effects, we can strengthen the cavitation effect by increasing the inlet pressure, appropriately reducing the diffusion angle, and increasing the throat length-to-diameter ratio, thereby better applying the cavitation effect in industrial fields. In terms of reducing the damage caused by cavitation, such as in water conservancy projects, hydraulic machinery, and ships, we can weaken the cavitation effect by reducing the inlet pressure, appropriately increasing the diffusion angle, and decreasing the throat length-to-diameter ratio. In addition to these measures, reinforcing or adding wear-resistant coatings in areas prone to cavitation—where flow velocity increases sharply and pressure drops significantly—can also minimize the damage caused by cavitation gas-liquid two-phase flow effects.

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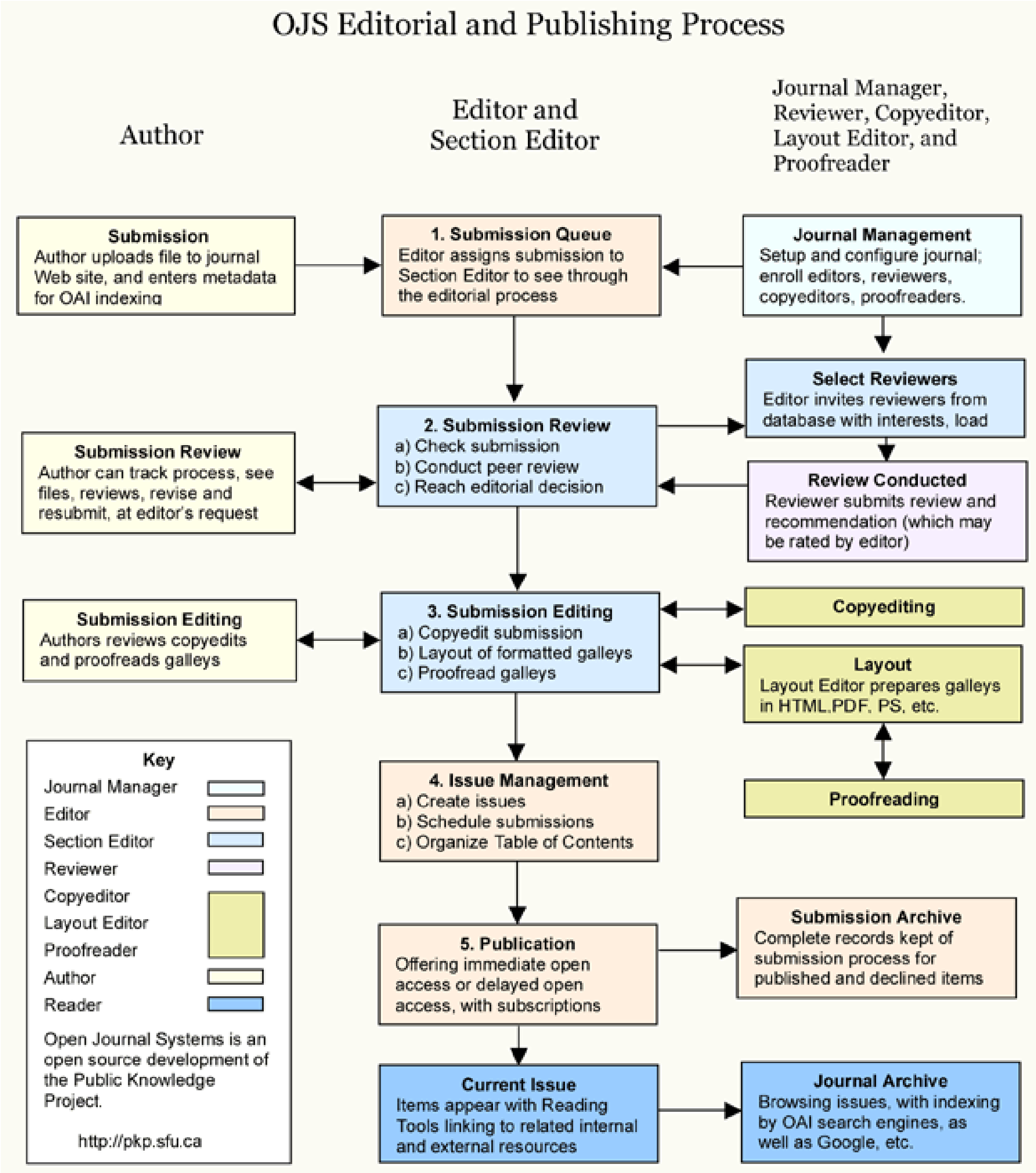

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