Journal of AI

e-ISSN : 3023-4018
Year: 2024 Volume:8 Issue: 1

INTERNATIONAL, OPEN ACCESS, PEER-REVIEWED JOURNAL

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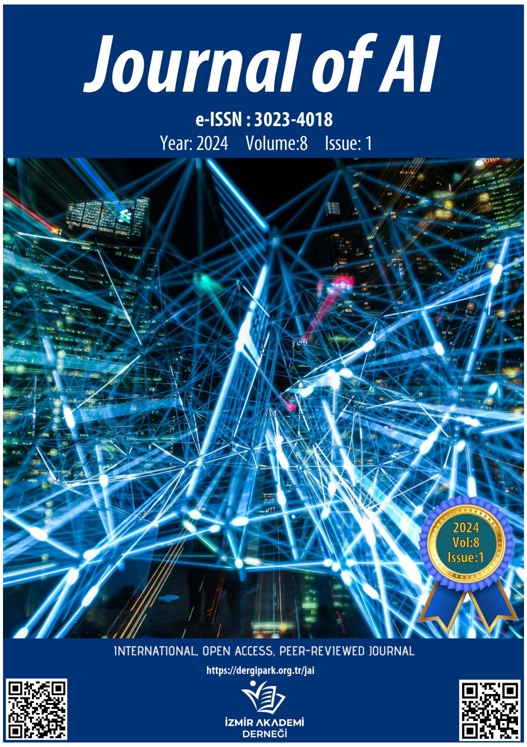
DERNEĞİ

Journal of AI (JAI)

e-ISSN: 3023-4018

Volume :8 Number:1 Year:2024



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JOURNAL OF AI

Volume: 8 **No:** 1 **Year:** 2024 **Period:** January-December

Head Office	: İzmir
Type of Publication	: It is published electronically once a year.
Publisher	: İzmir Akademi Derneği (www.izmirakademi.org)

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CONTENT

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***Volume:** 8, **Issue No:** 1, January-December 2024, **Pages:** 1-13*

Generative AI Professional Development Needs for Teacher Educators

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Received: 03.11.2023 Accepted: 25.12.2023 Online: 23.01.2024 Published: 31.12.2024

Research Article

Abstract

This study presents findings from a professional development (PD) webinar aimed at sensitizing and gathering teacher educators' knowledge of Generative Artificial Intelligence (GAI). The primary objective of the webinar was to deepen teacher educators' understanding and applications of GAI within the context of teacher education in Ghana and to identify areas requiring additional development. Three hundred and seven participants from a diverse group, including teacher educators, administrators, and in-service teachers participated in the PD session. The session was conducted online via Zoom. The video and audio recordings were transcribed and analyzed thematically using MAXQDA version 2022.4. Findings indicate a diverse range of familiarity with GAI among participants. While some expressed knowledge of GAI tools, others were learning about GAI for the first time. Further, the findings showed an increasing curiosity among participants for the inspiring functions of GAI in education, such as automatic scoring, academic writing, assisting teachers with image generation for their classroom practices, etc. The participants demonstrated a willingness to include GAI in their classroom practices and support their students. However, they also identified infrastructural gaps, such as the expense of premium GAI tools, training on GAI promptings, and ethical issues such as transparency, as potential barriers to the successful implementation of GAI in teacher education. Therefore, the study suggests that institutional support should be provided to teacher educators. This support would expand their access to various GAI tools and features. The study further recommends integrating GAI, including explainable GAI and prompt engineering, as a core component of teacher education and continuous professional development programs. Additionally, it emphasizes the importance of strengthening educators' skills in innovative assessment practices.

Keywords: *Generative Artificial Intelligence (GAI), Professional Development, Prompt Engineering, Teacher Education, Artificial Intelligence (AI), Assessment*

Cite this paper (APA)

Nyaaba, M., Zhai, X. (2024). Generative AI Professional Development Needs for Teacher Educators. Journal of AI. 8(1), 1-13. Doi: 10.61969/jai.1385915

1. INTRODUCTION

The emergence of GAI tools like ChatGPT and GPT-4 has reshaped various sectors, including education (Lim et al., 2023). Since the release of these GAI tools, there has been a plethora of concerns about their potential, especially in their applications in education (Zhai, 2023). As an emerging technology, there are many educators who have yet to experience GAI in education, especially in most developing countries like Ghana (Akanzire et al. 2023; Baidoo-Anu et al. 2023). Despite the potentials of GAI such as personalized learning and efficient knowledge transfer, educators are now faced with the challenge of integrating these advanced AI tools into their classroom practice (Kaplan-Rakowski et al., 2023; Liu et al., 2023).

Teacher educators are the professionals responsible for training student teachers for school systems at the tertiary level. As an open technology, it is assumed that student teachers may be exposed to GAI considering its open access and might be using it in an unethical manner in their academic work without awareness, particularly in their take-home assignments (Mogavi et al., 2023). To address this issue, it is crucial to highlight the importance of raising awareness of GAI among teacher educators, who hold the responsibility to support and educate student teachers to leverage GAI applications. This need is especially outstanding in places where digital literacy is still in the process of development, such as Ghana (Tounsi et al., 2023). Drawing upon this gap, we organized a webinar to sensitize teacher educators about GAI and to collect their insights, particularly in areas where they may seek assistance (Sancar et al., 2021; Koh et al., 2010).

Professional development sessions have been significant tools for teachers' engagement and professional learning in almost all levels of education (Avidov-Ungar, 2023), and so, this study reports the discussions from the professional development session organized to abreast teacher educators on the potential benefits and challenges of GAI, such as the ChatGPT and GPT-4. Based on these objectives, the following questions guided the study:

- What are Ghana teacher educators' perceptions and understanding of GAI applications in education after professional learning?
- What specific knowledge gaps do Ghana teacher educators need to enhance their GAI application?

2. DIFFUSION OF INNOVATIONS THEORY FOR GAI

The diffusion of innovations theory, formulated by Rogers in 1962, in conjunction with the technology acceptance model, lays the groundwork for understanding how new technologies and ideas permeate cultures (Smith et al., 2018). This theory, originating from the theory of reasoned action, predicts user attitudes, future intentions, and actual usage based on perceived usefulness and ease of use (Magsamen-Conrad & Dillon, 2020). Examining the incorporation of emerging technologies, such as GAI, into teacher education programs for teacher educators in Ghana, we found the diffusion of innovations theory became relevant to set a baseline for categorizing participants based on their inclination to embrace this novel technology on a spectrum from innovators to laggards (Magsamen-Conrad & Dillon, 2020).

Central to this theory is the "S-curve" depicting the adoption path: an initial slow uptake, a subsequent rapid adoption phase, and eventual stabilization. One of the key elements of this curve is perceived innovation attributes, such as relative advantage, compatibility, and complexity, which significantly dictate this diffusion. For instance, how the teacher educators in this study gauge the benefits of GAI compared to traditional teaching resources may be an essential element affecting their use of GAI (Dhirasasna & Sahin, 2021).

Again, factors like the ease of using GAI tools and observable results they produce play critical roles in shaping teacher educators' acceptance and subsequent integration into classroom practices (Stenberg, 2017). Therefore, determining the position of teacher educators on the adoption spectrum and identifying those factors influencing their perspective is critical. As posited by Kim et al. (2020), teacher educators' perspectives on technology adoption are essential in offering relevant recommendations for integrating GAI into teacher education programs (Zerfass et al., 2020).

3. FACTORS AFFECTING INNOVATION ACCEPTANCE

Teacher educators' perspective on the adoption, acceptance, and use of technology such as GAI is influenced by internal and external factors (Cerovski, 2016). Externally, factors such as flexibility of working with the GAI tools, provision of essential tools, the prospect of working with motivated students, availability of expertise in creating tech solutions, evaluating quality, teacher compensation, and funding play a role in the rate of adoption (Cerovski, 2016; Lawrence et al., 2018). Internal factors encompass learning anxiety, the inclination to interconnect, the acquisition of knowledge, and classroom interaction. Additionally, GAI adoption may be influenced by other internal factors like individual traits, which may include teacher educators' critical skills and complex problem-solving abilities (Alhumaid et al., 2023; Liang et al., 2021; Liu et al., 2021; Tyson & Sauers 2021). Eventually, it is highly assumed that these factors, whether internal or external, may have a great impact on teacher educators' perception towards the acceptance of GAI. This justifies the essence of continuous PD sessions to discuss the concerns and possible remedies. Research by Hung and Li (2017) highlights that most teachers possess a positive attitude towards professional development. This is because they perceive PD sessions as having a significant positive correlation with their capability to integrate innovation into their teaching (Ravhuhali et al., 2015).

4. METHOD

A qualitative research approach was adopted for this study. A recorded video from the PD session and a teacher survey were used as the tools for data collection. Heath et al. (2010) and Huber (2020) are of the view that video-based data collection is not only widely embraced in the academic research community but also commended for its potential to foster intimate interactions with research subjects. The PD session, which lasted almost two hours, was conducted as a webinar via Zoom for teacher educators in Ghana. Before the webinar, participants' demographic information was collected using a Google Form.

4.1 Participants

In total, 307 educators participated in the PD session. Though the study targeted teacher educators as the main participants, the participants included administrators in the field of education and teachers from Ghana's pre-tertiary education sector as well. The diverse nature of the participants ensured a multi-perspective dialogue informed by varying insights across the educational spectrum. The highest age brackets of the participants were 26-35 and 36-45 (see Figure 1).

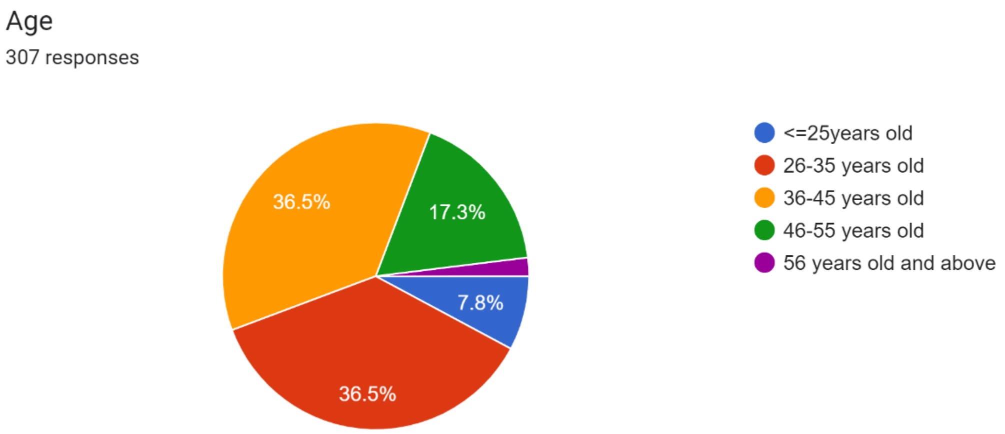

Figure 1. Age Brackets of Participants

According to Table 1, the colleges of education had the most representation of 121 representing 44.4%. Universities and polytechnics followed with 65 participants, representing 21.6%. The senior high schools and junior high schools had 36 participants representing 9.5%. Most of the participants were from the mathematics and ICT-related departments, with 106 participants representing 39.0%. The education department had 42 participants representing 12.5%. Twenty-four participants were from the technical and vocational, whiles 23 participants were from management and administration units. Twenty-one participants were categorized as 'specialized roles and others' represented 5.0% of the participants.

Table1. Frequency of Participant Demographics

Institutions	N (%)	Department and Units	N (%)	Designations	N (%)
Universities & Polytechnics	65 (21.6)	Mathematics and ICT-related	106 (39.0)	Teaching Roles	209 (79.8)
Colleges of Education	121 (44.4)	Science-related	43 (13.7)	Administrative Roles	41 (9.8)
Senior High Schools & Junior High Schools	36 (9.5)	Languages and Arts-related	48 (15.7)	Students & Academic Pursuits	29 (5.4)
Primary Schools & Basic Schools	25 (5.0	Education-related	42 (12.5)	Specialized Roles & Others	28 (5.0)
Other Institutions & Independent	60 (19.5)	Technical and Vocational	24 (5.8)		
		Management and Administration	23 (5.4)		
		Others	21 (7.9)		

4.2 Professional Development

The professional development was primarily initiated and organized through the collaborative efforts of the AI4STEM Education Center at the University of Georgina in the U.S., the Faculty of Education, University for Development Studies, Tamale in Ghana, the Gambaga College of Education in Ghana, and the Teacher Education Journal (TEJ), a wing of the National Teaching Council in Ghana. Together with these institutions, the TEJ led in the nationwide publicity of the webinar. During the PD session, the speaker delved into the definitions and applications of AI and Machine Learning (ML), emphasizing their capability to learn from experiences and make informed decisions through algorithms. He showcased Google Teachable Machine, illustrating how it enables the creation of ML models without necessitating coding skills while also highlighting its use in various sectors, such as disease diagnosis and refining teaching methodologies (Herdiska & Zhai, in press). He further led the discussion on using ML to assess student performance in science classes and shaping U.S. science education.

Also, he discussed how GAI has come as a game-changer yet with little empirical research done on its successful usage or threats in education (Zhai, 2023). The session discussed biases and pseudo biases of GAI and its essential components (Zhai & Krajcik, 2022), such as deviation from ground truth and systematic errors, and facial expression recognition errors. Examples were cited, such as the misclassification issues with Asian and black individuals, highlighting the limitations and potential pitfalls of AI algorithms.

4.3 Data Collection

Prior to the session, flyers with Google Form sign up links were distributed on various teacher educators' platforms in Ghana through their institutions and the Teacher Education Journal Newsletter. The registration process lasted for two weeks. Interested members filled out the Google form to provide some background information about themselves. The PD session was organized using Zoom. The features of Zoom were well managed to ensure there were smooth sessions without any external interruptions. The captions and record functions of Zoom were activated to enhance communication. The data saved from the session included video, audio, closed captions, and chat. These were used for the analysis.

4.4. Analysis

After the session, the video was transcribed and systematically analyzed using MAXQDA 2022.4. In support of the video transcripts, direct transcript from the Zoom recording was used to check for accuracies of the video transcripts. The thematic analysis was adopted for this study. The thematic analysis procedure mirrored the six phases of Clarke and Braun (2017) approach to thematic analysis. Therefore, the transcripts were initially coded by highlighting relevant sections with codes which represented specific ideas. These general initial codes were then grouped into potential themes. The themes were continuously reviewed and refined for coherence and consistency, ensuring they were representative of the data and aligned with the research questions. The analysis primarily concentrated on the participants' contributions, questions, and suggestions. This analysis helped to delve into the participants' perspectives, experiences, and views, distinct from the facilitator's (speaker of the webinars) presentation. To ensure the validity and reliability of the thematic analysis, the audit trail method and interrater of the transcripts were adopted. With these validity measures, documentation of the analysis process was maintained for transparency as well as a strict measure to capture the best accuracies through the Zoom transcripts and the Video transcripts from MAXQDA 2022.4. The demographic data collected from Google Forms were exported into Microsoft Excel and analyzed using frequency count and percentages. The demographic information was used to support the composition of the participants.

5. FINDINGS

The findings of the study stemmed from the research questions and the emerging themes from the transcripts as seen in Figure 2. Pseudo-names are used for direct quotes from the transcripts to support the findings.

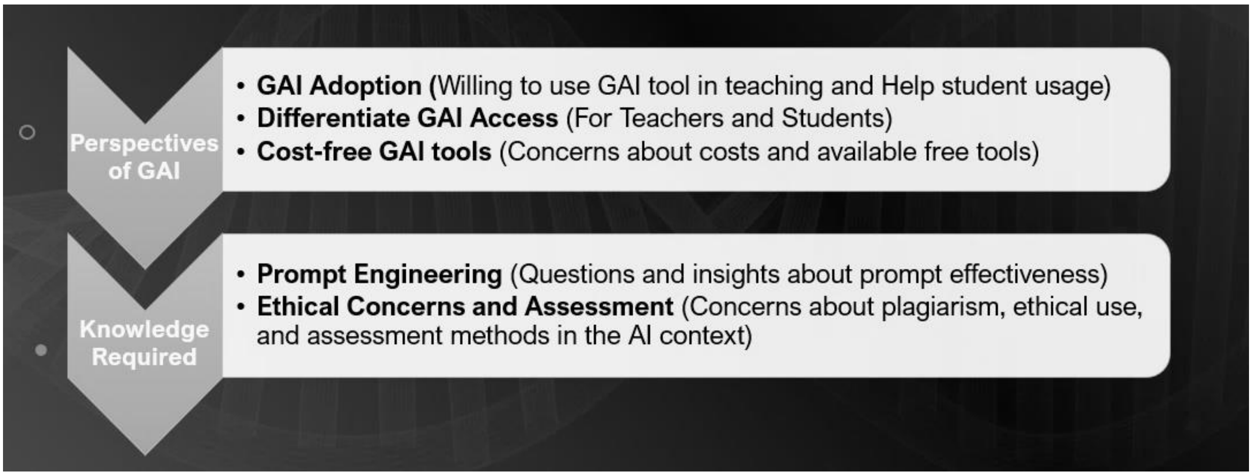

Figure 2. Teacher Educators Perspectives and Required Knowledge for GAI Application

5.1 Perspectives of GAI

The analysis revealed themes capturing the views of participants about GAI. For some of the participants, the session served as their introduction to GAI's capabilities despite having prior knowledge of its existence.

5.1.1 GAI Adoption

Some participants found the session enlightening. They expressed admiration for GAI's potential and demonstrated a willingness to include GAI in their classroom practices, as they believed that embracing GAI in education could revolutionize tasks like scoring, visualizing lessons, research writing, and enhancing subject matter expertise. They also advocated for continuous professional development in line with GAI.

> Participant 1: Thanks so much, Sir., for that great presentation. Please, Sir., we need special tools for the automatic scoring.

> Participant 3: Thanks so much, Sir., for that insightful presentation. In this regard, I think the world should rather find ways and means of embracing the use of AI generally and ChatGPT in particular, in education, we should rather have the conversation learning on how best we can continue the use of ChatGPT and AI in general in education, inculcating into our curricula, so that we do not seem to be stifling progress as far as technology or invention is concerned._

> Participant 2: I have a personal appeal to make to the National Teaching Council, Ghana, that they should try and encourage the use of AI in schools and keep teachers constantly updated so we don't become outdated.

> Participant 4: GAI can help teachers to get images to be used in the classroom.

5.1.2 Differentiate GAI Access

> The session had some participants suggesting different access to GAI tools between students and teachers. By this, they proposed teachers have exclusive features unavailable to students, which may potentially prevent situations where students might surpass their teachers in terms of derived content knowledge from GAI tools. However, there were other participants whose views were contrary to this suggestion. They suggested that students should be guided on the responsible use of GAI tools instead of differentiating access.

> Participant 3: The tools that we are using over here, especially ChatGPT. Is there the possibility that students could be allowed to have some restrictions as to how they can use the tools? And teachers will rather be given the full opportunity to use all the features in their way so that it doesn't end up that the students are having an upper hand on the teachers rather?

> Participant 6: The tools that we are using over here, especially ChatGPT. Is there the possibility that students could be allowed to have some restrictions as to how they can use the tools?

> Participant 7: The students should rather be guided on how to effectively use AI rather than restricting their access.

> Participant 8: Now that students have access to them; Tutors cannot restrict them.

5.1.3 Cost-free GAI tools

Also, some participants expressed interest in accessing a diverse range of GAI tools. However, they were interested in GAI tools that are available for free. The subscription costs associated with some GAI tools seem to pose a challenge for most of the participants. Presently, there are free versions of GAI tools, such as the ChatGPT, but the premium version requires users to pay for access. The GPT-4 is an advanced version of the ChatGPT free version and features significant improvements over ChatGPT in terms of the amount of data it was trained on, its size, and its capabilities. These improvements include a better understanding of context, more nuanced language generation, and increased accuracy in producing relevant and coherent responses for teacher education. Most of the participants only had knowledge about the ChatGPT free version and were interested in learning about other free versions since they couldn't afford to subscribe to the premium version, GPT-4.

> Participant 9: Apart from ChatGPT, what other free AI tools are available for use in education? People try to find answers to this question on social media but almost all turn out to be paid AIs.

> Participant 10: Give us examples of GAI tools we in the developing world like Ghana can use to facilitate effective teaching and learning.

5.2 Knowledge Required

Participants were concerned about the ethical issues that come with the use of GAI among teachers. Additionally, they highlighted the importance of prompt engineering, emphasizing that the accuracy of GAI responses improves with better responses. Furthermore, they believe innovative assessment practices would be beneficial in curtailing academic dishonesty among students regarding GAI use.

5.2.1 Prompt Engineering

A section of the participants was curious about how they could prompt AI chatbots to improve the quality of the responses they receive from the chatbots. These questions stemmed from the few participants who were privy to ChatGPT at the time of the PD session. Additionally, some participants raised concerns about the inaccuracies in ChatGPT responses and wanted to know how they could prompt ChatGPT to get the most accurate responses.

> Participant 11: How does a teacher utilize prompting to improve their GAI responses?

> Participant 12: The quality of your prompts determines the quality of the response from ChatGPT.

5.2.2 Ethical Concerns and Assessment

One of the major concerns raised by participants was the ethical use of GAI tools and the skills required to assess their students in the era of AI. The issue of plagiarism was a particular concern, with participants wanting to know whether they needed to reference information retrieved from GAI tools and how to approach this. They also expressed worries about students using these tools for their assignments and project works and were eager to find ways to address these issues, especially since not all information provided by GAI tools is accurate and could be misleading. They sought to acquire the best practices, including innovative assessment, that would help them assist their students to use GAI tools effectively and ethically.

> Participant 13: We would like to know if there are known ethical issues with the use of AI in education.

> Participant 14: how do we assess our students to get them to achieve educational outcomes?

6. DISCUSSION AND CONCLUSIONS

GAI tools are still in their nascent phase, and the fact that most of the teacher educators lacked familiarity with these tools was unsurprising. This is particularly the case given that it was not until November 2022 that ChatGPT catalyzed widespread discussions around GAI tools (Thorp, 2023; Simhadri & Swamy, 2023). As an emerging technology, it is crucial for teacher educators to acquaint themselves with these tools, not only to integrate them into their teaching but also to assist their students effectively (Florida, 2023). The finding indicated the teacher educators' curiosity towards the capabilities of GAI, especially with functionalities like automatic scoring, aiding students in academic writing, and image generation for instructional purposes (Kaplan-Rakowski et al., 2023). These findings about the potential of GAI to revolutionize teacher education align with the perceived usefulness element of the diffusion of innovation theory and the technology acceptance model (Smith et al., 2018). These models imply that technology or innovation will always be accepted once users find it useful in their practice.

Moreover, concerns about the potential misuse of GAI by students (Qadir, 2023) also support the prevailing belief about the challenges associated with technology diffusion, as outlined in the Diffusion of Innovations theory (Dhirasasna & Sahin, 2021). Consequently, these findings make it more prudent to equip teacher educators to adopt the best practices to effectively assist their students in using GAI tools. This finding supports Ng et al.'s (2023) assertion that teachers need AI competencies to integrate GAI effectively into classroom practices.

Additionally, prompting skill identified by the teacher educators as a significant skill resonates with Poola's (2023) assertion that crafting efficient prompts is vital in GAI usage and its outputs, given that GAI tools heavily depend on user input. This finding further confirms the perceived innovative attributes within the diffusion of innovation theory (Dhirasasna & Sahin, 2021), implying GAI compatibility of teacher educators' skills as an essential factor in the integration of GAI in their classroom practices (Dhirasasna & Sahin, 2021). Therefore, higher education institutions in Ghana, especially teacher education programs, must introduce courses or organize continuous professional development programs on prompt engineering (Meskó, 2023).

Moreover, the concerns about the costs of GAI tools may hinder teacher educators from gaining the best features of GAI tools. This is because most of the free GAI tools may lack the comprehensive features required for effective classroom integration (Whalen & Mouza, 2023). Hence, institutions are encouraged to incentivize premium versions of GAI tools and facilitate the integration of GAI in their programs (Brouwer et al., 2019).

Also, the findings suggest that many teacher educators lack a comprehensive understanding of GAI's operation, leading to less trust issues with its application (Gill et al., 2024; Samek & Müller, 2019). Therefore, efforts aimed at explaining the functions and mechanisms of GAI could substantially encourage its adoption among teacher educators. Explainable AI should be a core area in teacher education's continuous development programs about AI integration (Samek & Müller, 2019).

Assessment-related issues have consistently surfaced since the inception of GAI tools such as ChatGPT and GPT-4 (Zhai, 2022). Notably, certain studies, including those by Zhai (2022) and Zhai et al. (2023), have highlighted that GAI can outperform humans in tasks requiring substantial cognitive load, raising questions about its evaluation metrics and comparability to human capabilities. This aligns with the findings of this study, as the teacher educators were concerned about how GAI could potentially affect critical thinking and creative abilities among students. Therefore, the suggestion to adopt innovative assessment practices by the teacher aligned with Rudolph et al.'s (2023) findings, suggesting that GAI might decline traditional assessment practices at higher education levels.

In conclusion, the findings revealed an understanding of GAI by teacher educators and the essential knowledge they believe is crucial for the effective use of GAI. The finding indicated that teacher educators in Ghana are willing to include GAI in their classroom practices. They believe that embracing GAI could revolutionize tasks like scoring, visualizing lessons, research writing, and enhancing subject matter expertise. They further expressed their commitment to guiding students towards the effective and ethical use of GAI tools. However, the premium subscription costs associated with some GAI tools were seen as a challenge for several participants. Additionally, effective prompting engineering skills were identified by the teacher educators as one of the significant skills necessary for GAI application. They also called for innovative assessment practices to address the issue of academic dishonesty among students. Therefore, this study highlights the importance of institutional support in broadening the accessibility of GAI by addressing financial constraints that come with it, refining teacher educators'abilities through timely training; in prompt engineering and explainable AI courses whiles introducing innovative assessment practices. As GAI advances, it is crucial that teacher educators are adequately prepared to maximize the benefits of GAI in teacher education.

7. LIMITATIONS

While the study included 307 participants, the primary findings were predominantly derived from a subset of participants who actively engaged in the discussion session through questions, contributions, and clarifications. Therefore, researchers should be cautious to generalize the findings. Also, we suggest that future studies recruit a better representation of teachers to examine teacher educators' perceptions and understanding of GAI more comprehensively. Additionally, the duration of the session was limited, potentially restricting the depth and breadth of information that participants might have wanted to share.

ACKNOWLEDGEMENTS

The organization of the webinar that led to this study was supported by the Dean of Faculty of Education at the University for Development Studies, Tamale (Ghana), the Principal of Gambaga College of Education (Ghana), and the Editor of Teacher Education Journal (Ghana).

FUNDING

The study was partially funded by the National Science Foundation (NSF) (Award # 2101104, PI: Zhai). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF.

AUTHORS` CONTRIBUTIONS

All authors contributed equally to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors certify that there is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

REFERENCES

Adeshola, I., & Adepoju, A. P. (2023). The opportunities and challenges of ChatGPT in education. Interactive Learning Environments, 1-14. Doi:10.1080/10494820.2023.2253858

Akgun, S., & Greenhow, C. (2021). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. AI and Ethics, 1-10. Doi:10.1007/s43681-021-00096-7

Akanzire, N. B., Nyaaba, M. and Nabang, M. (2023). Perceptions and Preparedness: Exploring Teacher Educators' Views on Integrating Generative AI in Colleges of Education, Ghana). Available at SSRN: https://ssrn.com/abstract=4628153 or Doi:10.2139/ssrn.4628153

Alhumaid, K., Naqbi, S., Elsori, D., & Mansoori, M. (2023). The adoption of artificial intelligence applications in education. International Journal of Data and Network Science, 7(1), 457-466.

Avidov-Ungar, O. (2023). The professional learning expectations of teachers in different professional development periods. Professional Development in Education, 49(1), 123-134.

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. Journal of AI, 7(1), 52-62.

Baeesa, S. (2020). Perception of Neurosurgery Residents and Attendings on Online Webinars During COVID19 Pandemic and Implications on Future Education. World Neurosurgery, 146, e811 – e816. Doi:10.1016/j.wneu.2020.11.015

Betül B. (2014). "An investigation of using video vs. audio for teaching vocabulary." Procedia-Social and Behavioral Sciences 143: 450-457. Doi:10.1016/j.sbspro.2014.07.516

Bewersdorff, A., Zhai, X., Roberts, J., & Nerdel, C. (2023). Myths, mis-and preconceptions of artificial intelligence: A review of the literature. Computers and Education: Artificial Intelligence, 100143. Doi:10.1016/j.caeai.2023.100143

Brouwer, W., van Baal, P., van Exel, J., & Versteegh, M. (2019). When is it too expensive? Cost-effectiveness thresholds and health care decision-making. The European Journal of Health Economics, 20, 175-180.

Cerovski, J. (2016). The process of accepting technology innovation for rural teachers (Doctoral dissertation, Capella University).

Carvalho-Silva, D., García, L., Morgan, S., Brooksbank, C., & Dunham, I. (2018). Ten simple rules for delivering live distance training in bioinformatics across the globe using webinars. PloS Computational Biology, 14. Doi:10.1371/journal.pcbi.1006419.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. IEEE Access, 8, 75264-75278. Doi:10.1109/ACCESS.2020.2988510.

Chiu, T. (2021). A Holistic Approach to the Design of Artificial Intelligence (AI) Education for K-12 Schools. TechTrends, 65, 796 – 807. Doi:10.1007/s11528-021-00637-1.

Clarke, V., & Braun, V. (2017). Thematic analysis. The Journal of Positive Psychology, 12(3), 297-298. Doi:10.1080/17439760.2016.1262613

Dhirasasna, N., & Sahin, O. (2021). A system dynamics model for renewable energy technology adoption of the hotel sector. Renewable Energy, 163, 1994-2007. Doi:10.1016/j.renene.2020.10.088.

Emo, W. (2015). Teachers' motivations for initiating innovations. Journal of Educational Change, 16, 171-195. Doi:10.1007/S10833-015-9243-7.

Floridi, L. (2023). The Ethics of Artificial Intelligence: principles, challenges, and opportunities.

Gbemu, L. A., Sarfo, F. K., Adentwi, K. I., & Aklassu-Ganan, E. K. K. (2020). Teacher Educators' Self-Efficacy Beliefs and Actual Use of ICTs in Teaching in the Kumasi Metropolis. Turkish Online Journal of Educational Technology-TOJET, 19(2), 13-23.

Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., … & Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. Internet of Things and Cyber-Physical Systems, 4, 19-23. Doi:10.1016/j.iotcps.2023.06.002

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review, 61(4), 5-14. Doi:10.1177/0008125619864925

Heath, C., Hindmarsh, J., & Luff, P. (2010). Video in qualitative research. Sage Publications.

Herdiska, A., & Zhai, X. (in press). Artificial Intelligence-Based Scientific Inquiry. In X. Zhai & J. Krajcik (Eds.), Uses of Artificial Intelligence in STEM Education (pp. xxx-xxx). Oxford University Press.

Hristov, Kalin, Artificial Intelligence and the Copyright Survey (April 1, 2020). JSPG, Vol. 16, Issue 1, April 2020, Available at SSRN: https://ssrn.com/abstract=3490458 or Doi:10.2139/ssrn.3490458

Holzinger, A. (2019). Introduction to machine learning & knowledge extraction (make). Machine learning and knowledge extraction, 1(1), 1-20. Doi:10.3390/make1010001

Huber, M. (2020). Video-based content analysis. Analyzing group interactions: A guidebook for qualitative, quantitative and mixed methods, 37-48.

Kaplan-Rakowski, R., Grotewold, K., Hartwick, P., & Papin, K. (2023). Generative AI and Teachers' Perspectives on Its Implementation in Education. Journal of Interactive Learning Research, 34(2), 313-338.

Kenny, D. (2007). Student plagiarism and professional practice. Nurse education today, 27 1, 14-8. Doi:10.1016/J.NEDT.2006.02.004.

Kim, J., Merrill, K., Xu, K., & Sellnow, D. (2020). My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education. International Journal of Human–Computer Interaction, 36, 1902 – 1911. Doi:10.1080/10447318.2020.1801227.

Koh, J. H. L., Chai, C. S., & Tsai, C. C. (2010). Examining the technological pedagogical content knowledge of Singapore pre-service teachers with a large-scale survey. Journal of Computer Assisted Learning, 26(6), 563-573. Doi:10.1111/j.1365-2729.2010.00372.x

Lawrence, J. E., & Tar, U. A. (2018). Factors that influence teachers' adoption and integration of ICT in teaching/learning process. Educational Media International, 55(1), 79-105. Doi:10.1080/09523987.2018.1439712

Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. The International Journal of Management Education, 21(2), 100790.

Liu, M., Ren, Y., Nyagoga, L. M., Stonier, F., Wu, Z., & Yu, L. (2023). Future of education in the era of generative artificial intelligence: Consensus among Chinese scholars on applications of ChatGPT in schools. Future in Educational Research.

Magsamen-Conrad, K., & Dillon, J. M. (2020). Mobile technology adoption across the lifespan: A mixed methods investigation to clarify adoption stages, and the influence of diffusion attributes. Computers in Human Behavior, 112, 106456. Doi:10.1016/j.chb.2020.106456

Meskó, B. (2023). Prompt Engineering as an Important Emerging Skill for Medical Professionals: Tutorial. Journal of Medical Internet Research, 25, e50638. Doi:10.2196/50638

Mogavi, R. H., Deng, C., Kim, J. J., Zhou, P., Kwon, Y. D., Metwally, A. H. S., ... & Hui, P. (2023). Exploring user perspectives on chatgpt: Applications, perceptions, and implications for ai-integrated education. arXiv preprint arXiv:2305.13114. Doi:10.48550/arXiv.2305.13114

Natia, J., & Al-hassan, S. (2015). Promoting teaching and learning in Ghanaian Basic Schools through ICT. International Journal of Education and Development using ICT, 11(2).

Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. Educational technology research and development, 71(1), 137-161. Doi:10.1007/s11423-023-10203-6

Opfer, V., & Pedder, D. (2011). The lost promise of teacher professional development in England. European Journal of Teacher Education, 34, 24 – 3. Doi:10.1080/02619768.2010.534131.

Poola, I. (2023). Overcoming ChatGPTs inaccuracies with Pre-Trained AI Prompt Engineering Sequencing Process. . International Journal of Technology and Emerging Sciences (IJTES), 3 (3), 16-19.

Qadir, J. (2023, May). Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education. In 2023 IEEE Global Engineering Education Conference (EDUCON) (pp. 1-9). IEEE. Doi:10.1109/EDUCON54358.2023.10125121.

Ravhuhali, F., Kutame, A. P., & Mutshaeni, H. N. (2015). Teachers' perceptions of the impact of continuing professional development on promoting quality teaching and learning. International Journal of Educational Sciences, 10(1), 1-7. Doi:10.1080/09751122.2015.11890332

Rowland, D. R. (2023). Two frameworks to guide discussions around levels of acceptable use of generative AI in student academic research and writing. Journal of Academic Language and Learning, 17(1), T31-T69.

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?. Journal of Applied Learning and Teaching, 6(1).

Samek, W., & Müller, K. R. (2019). Towards explainable artificial intelligence. Explainable AI: interpreting, explaining and visualizing deep learning, 5-22.

Sancar, R., Atal, D., & Deryakulu, D. (2021). A new framework for teachers' professional development. Teaching and Teacher Education, 101, 103305. Doi:10.1016/j.tate.2021.103305

Stenberg, P. (2017). The purchase of Internet subscriptions in Native American households. Telecommunications Policy, 42, 51-60. Doi:10.1016/J.TELPOL.2017.08.003.

Simhadri, N., & Swamy, T. N. V. R. (2023). Awareness among teaching on AI and ML applications based on fuzzy in education sector at USA. Soft Computing, 1-9. Doi:10.1007/s00500-023-08329-z

Topor, D., & Budson, A. (2020). Twelve tips to present an effective webinar. Medical Teacher, 42, 1216 – 1220. Doi:10.1080/0142159x.2020.1775185.

Tounsi, A., Elkefi, S., & Bhar, S. L. (2023). Exploring the Reactions of Early Users of ChatGPT to the Tool using Twitter Data: Sentiment and Topic Analyses. In 2023 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET) (pp. 1-6). IEEE.

Thorp, H. H. (2023). ChatGPT is fun, but not an author. Science, 379(6630), 313-313. Doi:10.1126/science.adg7879

Wang, S. K., Hsu, H. Y., Reeves, T. C., & Coster, D. C. (2014). Professional development to enhance teachers' practices in using information and communication technologies (ICTs) as cognitive tools: Lessons learned from a design-based research study. Computers & Education, 79, 101-115. Doi:10.1016/j.chb.2004.02.005

Whalen, J., & Mouza, C. (2023). ChatGPT: Challenges, Opportunities, and Implications for Teacher Education. Contemporary Issues in Technology and Teacher Education, 23(1), 1-23.

Wong, S., Lim, S., & Quinlan, K. (2016). Integrity in and Beyond Contemporary Higher Education: What Does it Mean to University Students? Frontiers in Psychology, 7. Doi:10.3389/fpsyg.2016.01094.

Zhang, H. (2021). Exploring Automated Essay Scoring Models for Multiple Corpora and Topical Component Extraction from Student Essays (Doctoral dissertation, University of Pittsburgh).

Zhai, X., & Krajcik, J. (2022). Pseudo AI Bias. In arXiv preprint. Doi:10.48550/arXiv.2210.08141

Zhai, X., Shi, L., & Nehm, R. H. (2021). A meta-analysis of machine learning-based science assessments: Factors impacting machine-human score agreements. Journal of Science Education and Technology, 30, 361-379. Doi:10.1007/s10956-020-09875-z

Zhai, X. (2023). Chatgpt for next generation science learning. XRDS: Crossroads, The ACM Magazine for Students, 29(3), 42-46.

Zhai, X. (2022). ChatGPT user experience: Implications for education. Available at SSRN 4312418.

Zerfass, A., Hagelstein, J., & Tench, R. (2020). Artificial intelligence in communication management: a cross-national study on adoption and knowledge, impact, challenges and risks. Journal of Communication Management, 24(4), 377-389.

Journal of AI

Volume: 8, Issue No: 1, January-December 2024, Pages: 14-44

Reduction of Losses and Wastage in Seafoods: The Role of Smart Tools and Biosensors Based on Artificial Intelligence

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Received: 22.11.2023 *Accepted: 19.02.2024* *Online: 20.03.2024* *Published: 31.12.2024*

Review Article

Abstract

This paper reviews current knowledge on the role of smart tools and biosensors based on artificial intelligence in reducing seafood loss and wastage. This study shows that a variety of biosensors, categorised according to how they function, can be used to measure the quality of seafood. These include optical biosensors, enzyme-based biosensors, immunosensors, microbial biosensors, DNA-based biosensors, electrochemical biosensors, optical biosensors, tissue-based biosensors, and piezoelectric biosensors. Among these biosensors, optical biosensors, electrochemical biosensors, and mechanical biosensors are the most significant. Again, this study report that, for seafood traceability and management, a variety of smart solutions including blockchain technology, quick response (QR) codes, data analytics, digital twins, and radio frequency identification (RFID) tags can be utilised. Catch data, vessel tracking data, and data from the processing plant are some of the different data sources that can be utilised to trace seafood products. Artificial intelligence tools like neural networks, deep learning, machine learning, and others can be used to forecast and improve seafood quality. It is crucial to study the development of biosensors that can properly identify the earliest signs of seafood contamination or rotting.

Keywords: *Blockchain, Quick Response codes, Biosensors, Seafoods, Quality*

Cite this paper (APA)

Larbi Ayisi, C., Osei, S.A. (2024). Reduction of Losses and Wastage in Seafoods: The Role of Smart Tools and Biosensors Based on Artificial Intelligence. Journal of AI. 8(1), 14-44. Doi: 10.61969/jai.1394542

1. INTRODUCTION

Seafood is a colloquial and highly diverse food category which comprises of algae, cephalopods, cynobacteria, marine and freshwater finfish species, decapods and bivalves (Cooney et al., 2023). Seafoods are valuable protein source, especially in the case where other animal protein sources are expensive and scarce. Polyunsaturated fatty acids (PUFAs), which are known to influence prostaglandin synthesis and therefore promote wound healing, are among the necessary fatty acids found in seafoods (Kryzhanovskii and Vititnova, 2009; Zhang et al., 2010; Kindong et al., 2017). The demand for marine products (seafoods) is expanding substantially (Power at al., 2023). The increase in demand for seafoods could be attributed to consumers paying special attention towards consumption of foods that are healthy (Ghidini et al., 2019). The nutritional properties of seafoods could also be the cause of this increase in demand (Alamprese and Casiraghi, 2015). Despite the importance and significant increase in demand of seafoods, the resources available for wild catch are becoming scarce (Power at al., 2023).

Seafood losses is considered a serious challenge along the seafood value chain. The phenomenon of nutrient and economic losses along the seafood value chain results in serious wastage and has the tendency of posing health threats to consumers. Millions of people's diets are impacted by the loss of highly nutritious food or comprised, notably in areas where undernutrition and micronutrient deficiencies are widespread (Kruijssen et al., 2020).

As a result of the negative impact of seafood waste on the environment, rising demand for seafoods, coupled with its implication for marine conservation and policy, seafood wastage has gained global attention (Erasmus et al., 2021).

Wastage of seafoods have been attributed to some characteristics they possess. These characteristics that make seafoods prone to wastage includes fishing methods that result in by-catch, presence of digestive enzymes, oxidation as well as microbial spoilage (Ghaly et al., 2010; Love et al., 2015). Seafood loss can be enhanced by processing and storage conditions which can trigger microbial spoilage as well as sanitation (Tesfay and Teferi, 2017; Gyan et al., 2020).

In order to meet the current and future demands of seafoods at the global level, it is important to ensure loss and wastage are cut to minimum barest level. This can be achieved by applying technological innovations that can increase access to food that are cheap all year round without significant loss and wastage. Similarly, the amount of per capita food at the global level should be halved by 2030 at both the consumer and retail levels (Kruijssen et al., 2020). Also, along the production and supply chain levels, of which post-harvest is not an exemption, losses should be halved (United Nations, 2014).

Several smart tools and biosensors based on artificial intelligence have been applied in the seafood industry to cut down losses and wastage. These includes quick response (QR) codes, block chain technology, digital twin, data analytics, radio frequency identification (RFID) tags and FishNChip biosensor.

This article is aimed at providing an overview of smart tools and biosensors based on artificial intelligence that can be used to prevent losses and wastage of seafoods. This study is significant as it will serve as the basis and an established framework for further research work in the use of biosensors and smart tools based on artificial intelligence to reduce seafood loss and waste. In addition, creation of database on these possible biosensors and smart tools in reduction of seafood losses and wastage has the tendency to cause a notable improvement in the quality and quantity of seafoods produced.

2. METHODOLOGY

2.1 Literature search

For the purpose of achieving the objectives of this study, studies that had previously reported on application of various smart tools and biosensors based on artificial intelligence in monitoring seafood quality and food in general were searched and used. Papers published in only English were included in this study. No specific duration or date of publication was considered. Data bases such as IEEE, CAB abstracts, Ajol and Scopus were considered. Also, articles published in Elsevier, Taylor and Francis, and Wiley were considered.

2.2 Search strings

In order to identify papers relevant to this study several words and their combinations were used to search the above-mentioned databases. These words include ''internet of things'', wastage, seafood, losses, artificial intelligence, biosensor, deep, machine, learning, quick response scan, radio, frequency, identification, block, chain, technology, quality, supply, chain, electronic, monitoring, systems, neural, network, digital, twin.

3. BIOSENSORS FOR SEAFOOD QUALITY MONITORING

A biosensor is a quantitative analytical instrumentation approach that combines a physico-chemical transducer with a biologically derived sensing element (Surya et al., 2019). They are analytical tools that transform a biological response into an electrical signal (Mehrotra, 2016). Biosensors can measure chemical or biological reactions and turn the result into an electrical output (Bhalla et al., 2016; Franceschelli et al., 2021). By detecting minute changes and converting them into electric signals using signal conversion components like electrodes and optical devices, biosensors can measure specific target compounds quickly and easily (Grieshaber et al., 2008; Endo and Wu, 2019). Output signal, analyte, application, power source and sensor material are the different categories of sensors (Naresh & Lee, 2021; Saeed et al., 2022). Controlling the production environment and creating intelligent food packaging could both benefit from the use of biosensors (Wang et al., 2022).

Different types of biosensors are used in the monitoring of seafood quality. They are classified based on their working principles. These include optical biosensors, enzyme-based biosensors, immunosensors, microbial biosensors and DNA-based biosensors. Others include electrochemical biosensors, optical biosensors, tissue-based biosensors and piezoelectric biosensors. Biosensors with optical characteristics, mechanical biosensors, and electrochemical biosensors are the most significant types of biosensors (Ali et al., 2020). It is said that electrochemical biosensors are highly sensitive, simple to use, and fast to detect (Qiao et al., 2020). Electrochemical biosensors are however known for their precision, direct change detection based on the interaction of the sensor with the sample, low cost, and downsizing potential (Ali et al., 2020). Mechanical biosensors typically benefit from properties that scale well as physical size is decreased (Arlett et al., 2011). According to the chemical interactions between the sensor and the analyte, mechanical biosensors are often divided into four major categories: affinity-based assays, fingerprint assays, separation-based assays, and spectrometric assays (Arlett et al., 2011). When a biorecognition element interacts with an analyte, optical biosensors monitor for changes in phase, polarization, or frequency in the light field (Borisov and Wolfbeis, 2008; Purohit et al., 2020). This type of biosensors can be categorized into fluorescence, absorption and luminescence-based biosensors depending on the transduction mechanism used (Wang et al., 2018).

In addition to this, labelled versus label-free biosensors can be distinguished based on the purposes for which labels are used (Sadik et al., 2009). According to Purohit et al. (2020), labelled biosensors use a reporter or label to detect analytes such as enzymes (e.g., catalase, alkaline phosphatase, and horseradish peroxidase), electro-active substances, or fluorescent molecules. However, label-free approaches rely on BREs recognizing the target, and their straightforward design encourages the creation of portable devices (Purohit et al., 2020).

Some studies have been conducted with respect to the application of biosensors in seafood quality monitoring. Table 1 is a summary of studies reporting on the use of biosensors in seafood quality monitoring.

Table 1. Summary of studies on application of biosensors in monitoring of seafood quality.

Sensor	*Application*	*Findings*	*Reference*
Enzyme-based TMA (trimethylamine) biosensor	Analysing freshness of fish with extractions of horse-mackerel	◆ Due to the breakdown and decomposition of fish samples at 25 °C, sensor output increased with time.	Mitsubayashi et al. (2004)
Disposable biogenic amine biosensors	Determination of histamine in fish samples	◆ For histamine, diamine oxidase biosensors produced a linear concentration range of 9.9 × 10−6 to 1.1 × 10−3 M, while a monoamine oxidase-based sensor produced a linear concentration range of 5.6 × 10−5 to 1.1 × 10−3 M. ◆ Histamine levels and their recoveries determined in fish ranged from 100.0% to 104.6%.	Koçoğlu et al. (2020)
Amperometric biosensor	Determination of histamine in fish samples	◆ Excellent reproductibility and high ability was exhibited by the developed sensor ◆ Low limit of detection as well as high sensitivity was exhibited by the developed biosensor. ◆ Results obtained from the use of the biosensor to determine content of histamine was similar to that of ELISA (the reference method) for greater weever, mackerel and sardines.	Pérez et al. (2013)
Amperometric Enzyme Sensor	Redox-Mediated Determination of Histamine	◆ This selective sensor was effectively used to analyze spiked tuna and mackerel extracts, with recovery values of 99–100%. ◆ It had a low limit of detection (0.97 mg L^{-1}) and accurate and exact results. ◆ The sensor demonstrates good stability, retaining 87.7% of its initial signal after 35 days.	Torre et al. 2019
Amperometric Biosensor	Histamine Detection	◆ The biosensor exhibits great sensitivity (0.0631 A/M), a small detection limit (2.54 10'8 M), and a wide linear domain (0.1 to 300 M). ◆ The quantification of histamine in freshwater fish has been used to test the applicability of this enzyme sensor in natural complex samples and the analytical parameters. ◆ All freshwater fish samples tested showed excellent correlation between the results obtained with the new biosensor and those obtained with the traditional approach.	Apetrei and Apetrei (2016)
A Screen-Printed Disposable Biosensor	Selective Determination of Putrescine	◆ The determination of Put in anchovies and zucchini was successfully done using the biosensor.	Henao-Escobar et al. 2013
Electrochemical Biosensor with Nano-Interface for Xanthine Sensing-A Novel Approach	Estimation of Fish Freshness	◆ The biosensor displayed a peak response in less than 2 seconds and was impervious to ascorbic acid, urea, and sucrose interferences. ◆ It was discovered that the Michaelis-Menten constant (Km) is 1.3 nM. ◆ The limit of quantification is determined to be 8.3 pM and the limit of detection to be 2.5 pM.	Thandavan et al. 2013
Amperometric Biosensor	Detection of Fish Freshness	◆ After seven days, the fish showed very rapid degradation, and it was shown that the level of hypoxanthine increased with storage time.	Dolmacı et al. 2012
Amperometric Xanthine Biosensor	Detect xanthine in fish meat	◆ The biosensor showed optimal performance in 5 s at pH 7.0, 35 °C, and linearity for xanthine from 0.8 M to 40 M with a 0.8 M detection limit (S/E = 3). ◆ For xanthine oxidase, the Michaelis Menten constant (Km) was 13.51 M and the Imax value was 0.071 A. ◆ When kept at 4 °C, the biosensor, which detected xanthine in fish meat, lost 40% of its initial activity after 200 uses over a period of 100 days.	Devi et al. 2011

Sensor	Application	Findings	Reference
Xanthine Biosensor using Polymeric Mediator/MWCNT Nanocomposite Layer	Fish Freshness Detection	◆ The addition of MWCNT to the polymeric mediator film, which was crucial to the biosensor's efficacy, caused the biosensor to respond well to xanthine. ◆ The biosensor demonstrated strong storage stability and a decent level of anti-interference.	Dervisevic et al. 2015
Enzyme-based amperometric biosensor	Detect histamine and histamine-producing bacteria in tuna.	◆ The recovery of histamine from cultures and tuna samples was extremely high (mean bias 12.69 to 1.63%, with root-mean-square error 12%), and HPLC and biosensor techniques produced results that were comparable in the range from zero to 432 g/g (correlation coefficient, R^2 = 0.990). ◆ These findings unequivocally demonstrate that fresh tuna is frequently tainted with potent HPB. ◆ The operators of food businesses might use the histamine biosensor as a screening tool to find them and decide whether or not their process controls are sufficient.	Trevisani et al. 2019
Enzyme-based histamine biosensor	Changes in histamine and volatile amines of threadfin bream, mackerel, emperor bream, sardine, trevally and barracuda	◆ Neither the sensory changes nor the presence of volatile amines was correlated with the histamine concentration. ◆ It was discovered that the histamine production in trevally was quite high and comparable to that of mackerel. ◆ Prior to becoming organoleptically unsatisfactory, mackerel, sardine, and trevally may induce histamine poisoning issues.	Shakila et al. (2003)
DNA based biosensor	This study employed using existing seafood allergen detection method associated with DNA-based biosensor in comparisons to protein based and aptamer-based sensors	◆ Among them, the DNA-based detection approach is an indirect analysis that uses the allergen's gene as the object of detection and is distinguished by its high sensitivity and good stability.	Li et al. (2022).
	In order to identify Vibrio vulnificus in aquatic products, this study used DNA-based approaches.	◆ The proposed biosensor exhibited an excellent capacity to detect marine products contaminated with *V. vulnificus*.	Fan et al. (2021).
Optical biosensors	Detection of paralytic shellfish poisoning	◆ The decision limit (CCα) was 100 µg/kg, with the detection capability (CCβ) found to be ≤200 µg/kg. Repeatability and reproducibility were assessed at 200, 400, and 800 µg/kg and showed relative standard deviations of 8.3, 3.8, and 5.4 % and 7.8, 8.3, and 3.7 % for both parameters at each level, respectively.	Campbellet al. (2013).
Piezoelectric Biosensor	Detection of marine derived pathogenic bacteria	◆ By continuously monitoring frequency shifts, the sensor system was able to identify *V. vulnificus* in a dose-dependent way and within five minutes, bacterial cells were detected.	Hong & Jeong. (2014)
Immunusensor	Detecting tetrodotoxins in shellfish and European fish	◆ The immunosensor enabled the determination of TTXs at levels as low as 0.07 mg TTX equiv. kg−1 tissue, thus, well below the Japanese value of 2 mg TTX equiv. kg−1 tissue used as a criterion to consider puffer fish safe for consumption.	Reverté, et al. (2017)

4. SMART TOOLS FOR SEAFOOD TRACEABILITY AND MANAGEMENT

The safety of food is an important issue that affects health (Sahin et al., 2023). This is because approximately 420,000 people die annually from consuming contaminated food, with additional 600 million becoming ill (World Health Organization, 2019). There is therefore the need to consume foods that are healthy. Investigating the safety and quality of food products can help with this. For food supply chain management (SCM) systems, particularly for seafoods and live items, traceability is a crucial safety measure.

According to the Codex Alimentarius Commission (CAC, 2016), traceability is defined as the ability to follow the movement of a food through specified stage(s) of production, processing and distribution.

Traceability in the context of seafood is the tool that allow consumers, processors and seafood stakeholders to monitor the movement of seafoods along the value change; that is production, processing as well as distribution (Dopico et al., 2016).

For the most part, traceability has been viewed as a technological prerequisite for companies to comply with laws governing food safety, food recalls, and country-of-origin labelling (Tamm et al., 2016). In order to ensure the quality of seafoods are high, sustainable and safe, smart tools can be used to track seafood products from along the value chain from harvesting to sales or consumption point.

Traceability is important because it has been used globally as a tool to prevent and manage risk involved in the supply of food that is unsafe along the supply chain. It also aids in the recall or withdrawal of unsafe seafoods by regulators and manufacturers (Rao et al., 2022). Also, along the supply chain of the food system, traceability is essential as it helps in identification of sources of contamination and their routes (McMillin et al., 2012).

Different types of smart tools such as block chain technology, quick response (QR) codes, data analytics, digital twin and radio frequency identification (RFID) tags are used for traceability and management of seafoods. In this section, the characteristics of these useful smart tools and their application in seafood industry for traceability and management purposes are discussed.

4.1 Radio Frequency Identification (RFID) tags

Radio frequency identification (RFID) tags are small electronic devices that can be attached to seafood products to track their movement and location throughout the supply chain. RFID tags are also referred to as a transponder (Kumar et al., 2009). RFID is a catchall name for systems that identify objects using radio frequency signals. RFID offers extra space to store data and uses radio waves to automatically identify items in a flexible way. However, a variety of problems with regard to time and money demands as well as possibilities for fraud present challenges for RFID (Bilal and Martin, 2014; Mol 2014; Vo et al., 2020). With RFID, an object can be identified from a distance without a line of sight. RFID tags can be read by scanners and can provide real-time information about the product's origin, processing, and distribution. A tag, a reader, which collects data; and database and information management software are the three major components of a typical RFID model (Aydin & Dalkilic, 2018; Sedghy, 2019). Its technology is based on wireless communication, specifically radio frequency waves, between an interrogator and a tag attached to an object (Bibi et al., 2017; Aydin, 2019).

RFID sensors can be used to monitor the freshness of seafoods and to a larger extent its quality by observing the changes in the dielectric properties of each seafood (Potyrailo et al., 2012). This technology has been applied in the seafood industry with success over the past years. Several studies have been conducted with respect to Systems for Traceability Based on RFID (Hsu et al., 2008; Abad et al., 2009; Yan et al., 2012; Treber et al., 2013; Kokkinos et al., 2018; Zhang et al., 2019; Coronado Mondragon et al., 2021).

An RFID-enabled SCM tracking system for live fish had been suggested by Hsu et al. (2008). In this study, the data required for processing live fish was gathered, and ideas for the entire management system architecture, geared toward SME solutions, were developed. Each live fish was given an RFID tag in this manner to track its movement in the restaurants that sell live fish and logistic centers, as well as to give customers identity information.

Abad et al. (2009) created a real-time RFID smart tag for applications including the tracking and monitoring of cold-chain food. This process involved the use of a reader/writer and a smart tag, which was applied to the merchandise. These tags included an antenna for RFID tag transmission, integrated lighting, temperature and humidity sensors, a memory to store product data, and other components. The traceability information gathered by the sensors and stored in the memory chip. The investigation then used a wireless reader with a mobility option to read the food chain data that had been gathered from a distance of 10 cm. With the help of this technique, it was possible to automatically track records, read product data, and check the cold chain's temperature online. Furthermore, this approach eliminates the need to open the polystyrene containers holding the fish and smart tags, allowing the completely automated reader to read many tags at once. Additionally, the system makes sure that the temperature for frozen goods is kept below 0 ºC utilizing temperature sensors. Additionally, the system has humidity sensors, making it sensitive to changes in humidity around the storage environment.

Two separate examples of farmed fish tracking systems appropriate for small- and medium-sized enterprises (SMEs) were presented by Treber et al. (2011). In the first, a small business implemented an electronic RFID-enabled system in place of a manual data collection approach. This project produced an end-to-end SCM solution for farm fish that is beneficial to selling organizations and individual consumers. The second solution involved managing a portion of the automated fish packing process that was improved by RFID technology and branded with a barcode. In this instance, the goal was to transition from a manual data gathering approach to an RFID-enabled data collection method so that traceability could be extended to fish farms for breeding and on-growing.

Using IoT, RFID, and WSN, Kokkinos et al. (2018) created an aquatic product traceability solution. The system included an internet platform that could be accessed from mobile, intelligent devices like an RFID reader. To monitor and verify the security of aquatic products from their catch to the consumer's table, a system was developed. Through the use of the RFID system and the Arduino platform, several wireless sensors were integrated. For sustainable fisheries, the circumstances of the fisheries, the variety of capturing sites, and the quality of the fish products were all maintained. Also, routines relevant to the Greek sea were offered utilizing both traditional and contemporary Artificial Intelligence (AI) techniques, depending on the circumstances and quality assessment.

A smart traceability platform built on the Hazard Analysis and Critical Control Points (HACCP) standards was proposed by Zhang et al. in 2019. With this technique, quality control modelling and wireless facility monitoring were combined to improve fish quality as well as the security and openness of waterless fish transport. Therefore, to provide customers with traceability functions for any tracking-related inquiry, a QR code and the electronic product code (EPC) of the RFID tag were integrated. In this method, buyers were instantly given answers to questions about safe transportation, from aquaculture to markets. Sturgeon delivery trials in particular were evaluated and investigated.

For the fishery sector, Mondragon (2020) suggested a two-layer architectural approach. The surrounding energy consumption of a sensor network was modelled in this study using a sensor layer based on WSN theory. Data were gathered in the first phase from sensors used to monitor the water. Time series/scatter diagrams were used to examine the acquired data. Thus, the patterns and trends of snow crab catch settings were discovered. Finally, this study provided a set of resources for upcoming fisheries researchers to put together this strategy as a monitoring tool for SCM in fisheries leveraging on IoT solutions and RFID technology.

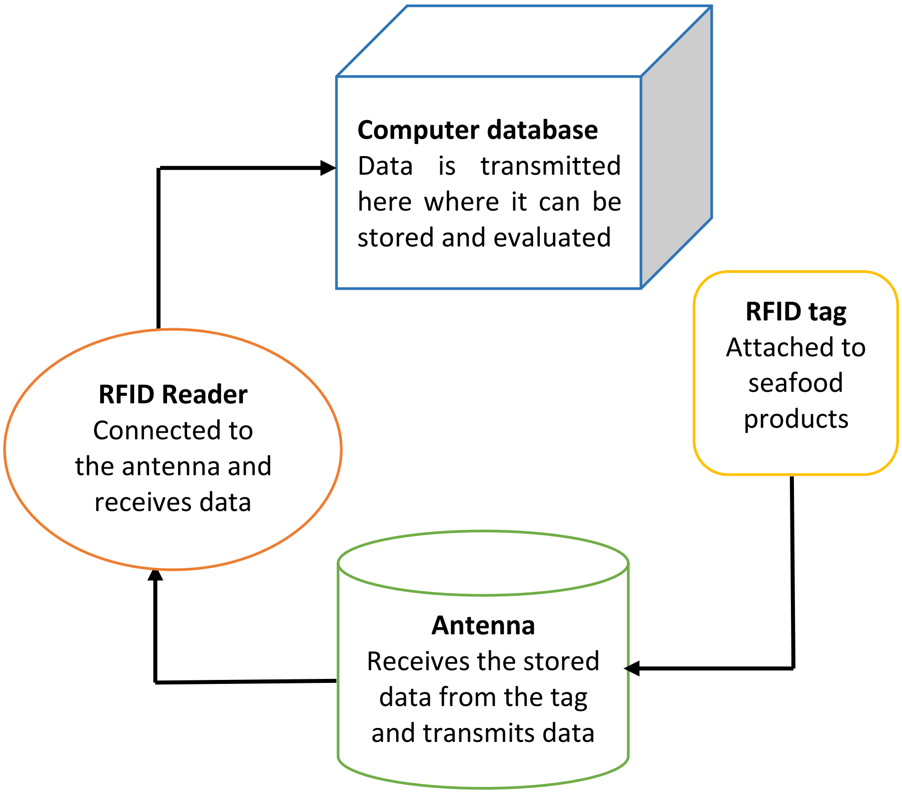

Figure 1. RFID process. Adapted from Rahman et al. (2021).

4.2 Quick Response (QR) codes

Quick Response (QR) codes are two-dimensional barcodes that can be printed on seafood packaging or labels. QR codes can be scanned by smart-phones or other devices to provide information about the product's origin, processing, and distribution. In reality, a QR code uses matrix bar-code technology. The QR Code can include text, video, ads, personal information, and more, allowing it to store significantly more data than a one-dimensional code (Kim and Woo, 2016). It is possible to read information from it, much like with matrix bar-codes (Demir et al., 2015). In order to assure the quality and safety of the products, the traceability connected with the use of the QR code may give information and transparency of the productive chains (Pieniak et al., 2011). The advantages of a QRC include great dependability (Chen et al., 2019; Waziry et al., 2023). The key advantage of this technology is its simplicity, since it simply requires the use of a Smartphone to scan the code in order to access the digitally accessible data (Machado et al., 2019).

Also, the benefit of QR codes is that they can hold a significant quantity of data. Any type of digital information that can be imagined can be embedded, including text, video, business card information, personal information, advertisements, etc. (Demir et al., 2015). Information systems can be accessed using QR-Code technology to add products produced by sellers (Liantoni et al., 2018). In order to assure the quality and safety of the products, the traceability connected with the use of the QR code may give information and transparency of the productive chains (Pieniak et al., 2011).

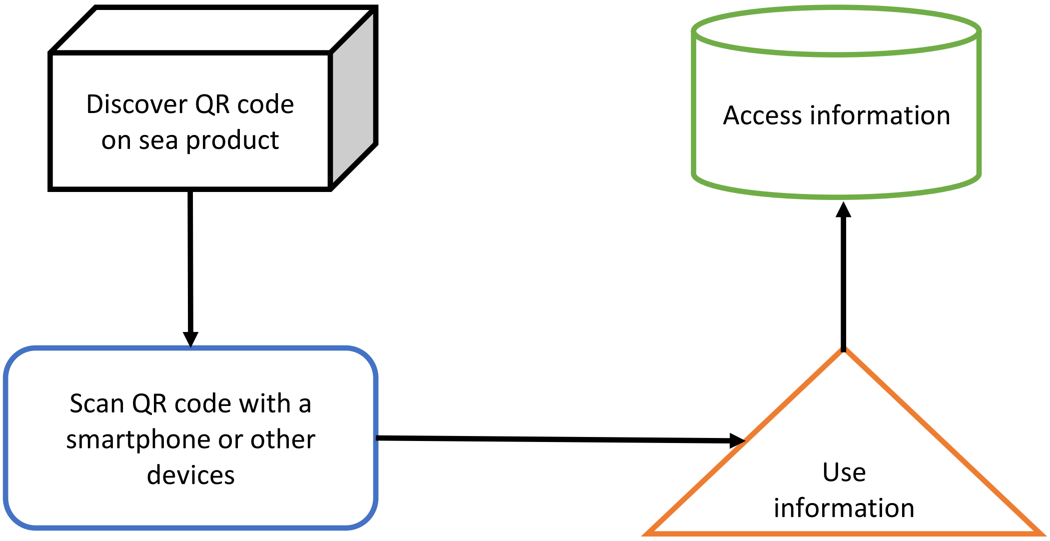

Figure 2. QR code process in seafoods. Adapted from Kochanska. (2020).

4.3 Blockchain technology

Block chain technology is defined as an open, distributed ledger that may effectively and permanently record transactions between two parties (Iansiti and Lakhani, 2017; Aydin and Yukcu, 2020; Friedman and Ormiston, 2022). The block chain technology also known as distributed ledger technology (DLT) was introduced in 2008 after the global financial crisis (Khan et al., 2022). Block chain technology is gaining traction as a cutting-edge invention that can promote sustainability in international supply chains (Saberi et al., 2019; Marsal-Llacuna, 2018; 2020). Block chain is an emerging technology in the agri-foods sector that has the potential to alter many facets of the agricultural industry (including fisheries and aquaculture) while also enhancing the safety and quality of agri-foods (Xu et al., 2020). By recording accountable information about food sustainability at all stages of the supply chain and enabling supply chain actors to query and verify specific food products, block chain, an emerging paradigm for immutable information storage and sharing, has the unique potential to improve sustainability communication (Cao et al., 2023). A decentralized digital ledger called a block chain can be used to securely and openly record and trace transactions. The supply chain can be made transparent and accountable by using block chain technology to produce a tamper-proof record of seafood products from their point of origin to their final destination. Researchers and professionals are becoming more aware of how block chain technology may inform and enhance the sustainability of the food supply chain (Cao et al., 2023). Block chain has arisen in this context as a promising technology that enables users to efficiently and effectively record the origin and movement of items as well as to totally eliminate or greatly reduce serious food fraud. Consumers can benefit from this development by receiving up-to-date, confirmed information in relation to the sources and delivery options of their purchases (Treiblmaier and Garaus, 2023). Applying block chain technology in seafood traceability could be beneficial as it could enhance higher automation in supply chain, lead to transparency and fraud protection. It also leads to positive influence on consumers, food authenticity, quality assurance and routine traceability (Patel et al., 2023). Furthermore, it can result in a decentralized network, a trustworthy trading system, making data much safe and unchangeable. . While different chain stakeholders have differing levels of adoption of this technology, implementing blockchain involves financial, technological, and organizational challenges (Sander et al., 2018; Kouhizadeh et al., 2021; Tolentino-Zondervan et al., 2022).

4.4 Electronic monitoring systems

Electronic monitoring, which is referred to as an integrated system of cameras and sensors on fishing vessels, can produce a thorough account of fishing activity that can help with fisheries management and guarantee that rules are being followed (Ruiz et al., 2015). Electronic monitoring systems can be used to track the movement and location of fishing vessels, and to monitor their catch and by-catch. Electronic monitoring systems can provide real-time information about the fishing activity and can help ensure compliance with regulations and sustainability standards. However, EM stands out due to the depth of data it can supply on fisheries activities and its thorough accountability.

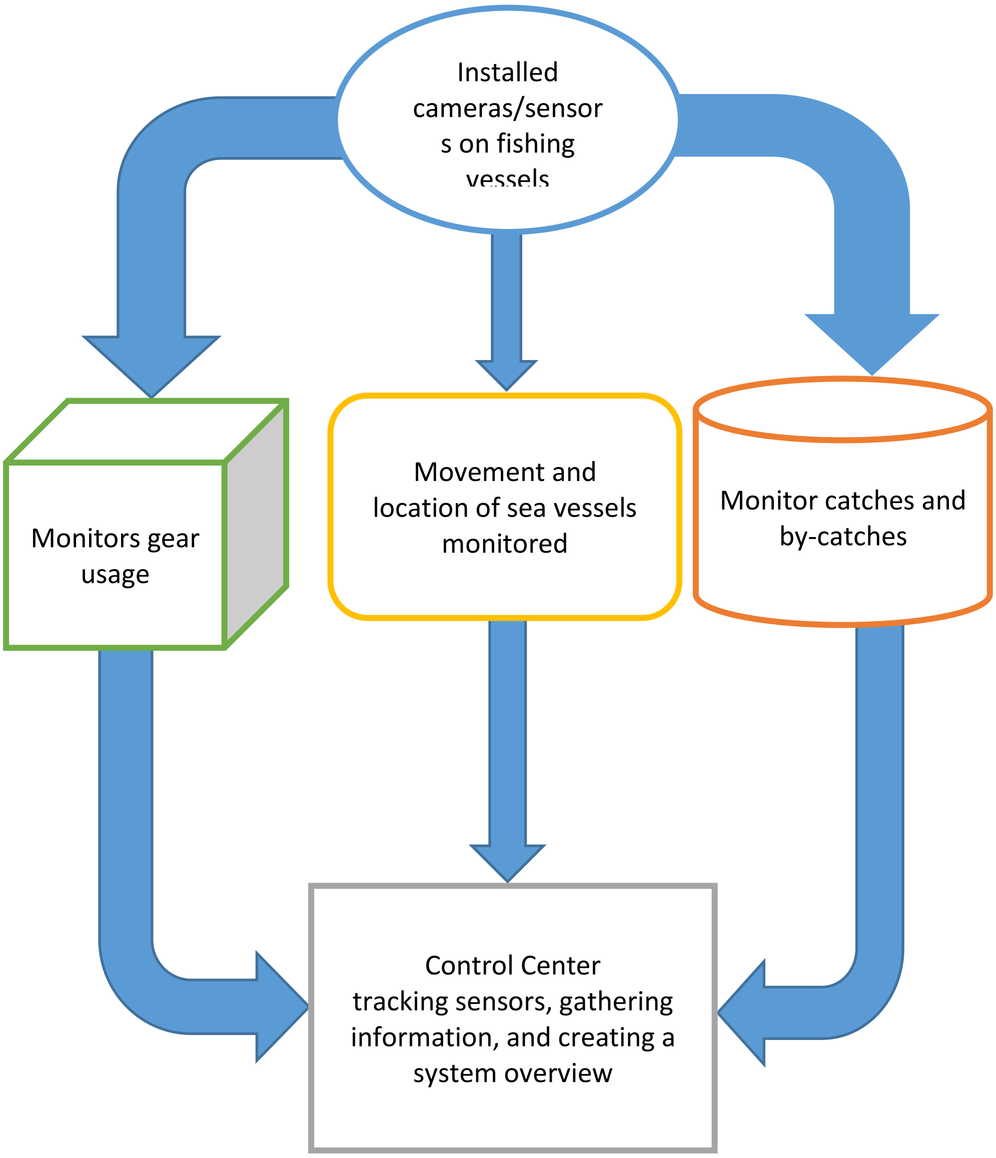

Figure 3. Electronic monitoring process in Seafoods. Adapted from van Helmond et al. (2020)

4.5 Digital twin

Grieves. (2014) initially proposed the digital twin concept. A reasonable definition of a digital twin is one that incorporates physical feedback data with artificial intelligence, machine learning, and software analysis to create a digital simulation within an educational platform. Despite differences in definitions, all definitions have three major elements namely; virtual space, physical space, and their connections of data and models (Liu et al., 2021). A digital twin is a virtual representation of a physical system that includes the environment and operational procedures and is updated by information exchanged between the physical and virtual systems. It is a gadget that constantly connects its virtual and physical equivalents (the twin) (Van der Burg et al., 2021; Neethirajan and Kemp, 2021; Melesse et al., 2023). The aim of digital twin is to characterize the behaviour of physical entities by leveraging on their virtual replica in real time (Liu et al., 2022). With the data fusion of each module, the digital twin keeps track of the state of the physical model in real time, which aids in the optimization and decision-making of physical items (Söderberg et al., 2017).

Digital twins are more responsive as a result of two-way communication. In order to automate and display the information to the human component in a way that is simple to understand, it is critical to capture expert decision making (Dyck et al., 2023). Using digital twins, physical and virtual items are combined in an effort to track and enhance resources and business operations (Autiosalo et al., 2020; Jones et al., 2020; Verdouw et al., 2021). Digital twins aid in identifying the post-harvest change of food quality that results, which is mainly unexplored. For exporters, retailers, and consumers, digital twins give data that may be used to make informed decisions about logistics and marketing, such as how long each shipment's shelf life will last (Defraeye et al., 2021). The twins also aid in the diagnosis and forecasting of potential supply chain issues that could lower food quality and result in food loss. In order to decrease retail and domestic food losses, twins may even recommend preventive shipment-tailored interventions (Defraeye et al., 2021). The visibility of the supply chain and the process monitoring would be significantly impacted by the deployment of digital twin technology in seafood traceability and management (Lezoche et al., 2020; Burgos et al., 2021; Agrawal et al., 2021).

5. DATA SOURCES FOR SEAFOOD TRACEABILITY

Data has been the foundation of the seafood industry and will continue to be. Obtaining the right information is an important step for traceability. Establishing or identifying reliable data sources is one way to increase openness. Based on this backdrop, the various sources of data that can be used to trace seafood products, such as catch data, vessel tracking data, and processing plant data are discussed in this section. In addition, advancements in technology, such as the Internet of Things (IoT), which keep making it easier to collect and analyze data is briefly discussed.

5.1 Sources of data for traceability

5.1.1 Catch data

Information on the fish or other marine animals that are caught by fishermen is referred to as catch data. The species, weight, and location of the catch, as well as details on the fishing boat and its crew, can all be included in this data. Catch information is crucial for tracking seafood items because it might reveal the product's origin and method of capture. Fishermen can collect catch data manually, or sensors and other technologies can do it automatically.

5.1.2 Vessel tracking data

Data on the movements of fishing vessels as they travel to and from fishing grounds is referred to as vessel tracking data. The location, speed, and direction of the vessel, as well as details on the weather and sea state, can all be included in this data. In order to trace seafood goods, vessel tracking data is crucial since it may be used to identify the product's origin and whether it was caught lawfully or illegally. Different technologies, including as satellite-based systems and automatic identification systems (AIS), can be used to gather data on vessel tracking.

Vessel monitoring systems (VMS) and the AIS can be used to track vessels (Orofino et al., 2023) in order to generate valuable information that are needed for seafood traceability. Vessel tracking can inform best practices, promote the fulfilment of important commitments, and improve transparency and traceability in operations in the seafood (Seafood Business for Ocean Stewardship, 2021).

5.1.3 Processing plant data

Information about the preparation and packaging of seafood items is referred to as processing facility data.

The location of the processing plant, the type and amount of the product, and the date and time of processing are just a few examples of the information that might be included. Data from the processing plant is crucial for tracking seafood items since it can be used to establish the chain of custody starting with the moment the product was captured and ending with the moment it was packaged and sent. Data collection in processing plants can be done manually or automatically using sensors and other technologies.

6. ARTIFICIAL INTELLIGENCE FOR SEAFOOD QUALITY PREDICTION AND OPTIMIZATION

A computing technology known as artificial intelligence (AI) aims to imitate human skills to sense their environment, analyze information, make decisions, and take actions to accomplish predetermined goals to varying degrees (Manning et al., 2022). Also, AI refers to a system for data analysis that automates skilful model creation (Li, 2021). Again, Chrispin et al. (2020) defined AI as the future made from pieces of the past. AI can take the role of human intelligence in problem-solving and decision-making (Kutyauripo et al., 2023). The ability of AI to accurately interpret external data, learn from it, and use that learning to accomplish specified objectives and tasks is one of its specialities (Hainlein and Kaplan, 2019). AI is increasingly being used to establish standards for current behaviours and the outcomes of those practices in the food sector and forecast how these elements will affect food supply and quality in the future (Karanth et al., 2023). The agriculture industry of which seafoods and crop production as well as harvesting and marketing are inclusive has seen tremendous improvement through the use of artificial intelligence (Goel et al., 2022). As a result of issues such as food safety, quality control, and classification as well as food sorting, the application of AI in the food industry keeps growing (Mavani et al., 2021).

Several AI are applied in the Prediction and Optimization of the quality of seafood. These includes neural networks, deep learning, machine learning, etc.

In this section, AI applied in predicting and optimization of seaweed quality are discussed. Special emphasis is laid on their description, advantages, disadvantages and application in seafood industry.

6.1 Machine learning

Computer science's sub-field of machine learning is categorized as an artificial intelligence technique (Chawla et al., 2023). Machine learning is the ability of a computer to learn without being taught for a particular job (El Naqa and Murphy, 2015; Anwar et al., 2023). Machine learning could either be supervised or unsupervised (Anwar et al., 2023). Samuel (1959) initially proposed the concept of machine learning, which is the study of how to enable computers to learn without being explicitly programmed. A subfield of artificial intelligence called machine learning makes use of a variety of factual and probabilistic approaches to teach computers how to discover hidden patterns (input-output linkages) in vast and frequently noisy data sets (Okafor et al., 2023). According to purposes and training methods, machine learning can be categorized into three broad approaches namely unsupervised learning, supervised learning and reinforcement learning (Chung et al., 2023). It has the benefit of allowing models to address issues that explicit methods cannot, and it may be used to a variety of fields (Chawla et al., 2023). M5-Prime regression tree, multiple linear regression, support vector regression, perceptron multilayer neural networks, and k-nearest neighbour are examples of machine learning employed in enhancing food. The development of selective fishing gear that lowers the accidental capture of non-target species can be facilitated by the application of machine learning algorithms. In addition to protecting biodiversity, this lowers fishermen's financial losses (Rossi, 2022). By analyzing data on the behavior and needs of individual species, machine learning algorithms enable individualized care while consuming the fewest resources possible. This strategy improves the industry's overall sustainability and efficiency (Neethirajan, 2020). It has proven possible to use machine learning to create chemometric discrimination tools by utilizing chemical pollutants and metal isotope ratios in eastern oysters (del Rio-Lavín et al., 2022)

6.2 Deep learning

An artificial neural network-based representation learning algorithm known as "deep learning" is a sub-field of machine learning (Deng and Yu, 2014). With numerous successful applications in image processing, speech recognition, object detection, and other fields, deep learning has established itself as a cutting-edge method for big data analysis (Zhou et al., 2019). Deep learning has demonstrated substantial benefits in automatically learning data representations, transfer learning, coping with the enormous amount of data, and achieving improved performance and higher precision (Ng et al., 2015; Kamilaris and Prenafeta-Boldu, 2018). Also, Jeevanandam et al. (2022) reported that due to the ability of deep learning to feature learning based on multi-layer artificial neural networks, it has received significant attention. In recent years, automatic identification of fish, sizing as well as counting has been performed by applying deep learning (Ovalle et al., 2022). Ovalle et al. (2022) investigated various Deep Learning (DL) based length estimation and species identification techniques. On the one hand, they modified the Mask R CNN method to the problem of fish species identification for the instance segmentation task. On the other hand, the length of each individual was estimated using the MobileNet-V1 convolutional neural network. The findings demonstrated that both the identification and length estimate algorithms can accurately measure the catch when individual overlap is modest to low. When there is a lot of overlap between individual fishes, the outcomes still need to be improved. The majority of recent studies on feeding decision-making with deep learning have focused mostly on image analysis. Machine vision can be used to create a better feeding plan that considers fish behavior. Such a device can stop the feeding process at more reasonable times, reducing labor waste and improving fish health (Zhou et al., 2018). Furthermore, behavior serves as a useful point of reference for fish welfare and harvesting. Relevant behavior monitoring can provide a nondestructive understanding and an early warning of fish status, especially for uncommon actions. Determining the condition of fish and deciding when to collect and feed them depend on real-time behavior monitoring. The ability of DL techniques to recognise visual patterns is considerable. employing DL to analyse behavior. RNNs, in particular, can solve the aforementioned issue successfully because of their strong modeling capabilities for sequential data (Yang et al., 2021).

6.3 Neural networks (NN)

Machine learning's neural network sub-field uses algorithms to analyse data and create abstractions that mimic thinking (Ma et al. 2022). It processes data, decodes spoken language, and visually identifies objects using multiple layers of algorithms. Each layer transmits information, with the output of one layer serving as the input for another (Zhou et al., 2019). As neural networks, one type of machine learning model, are naturally capable of handling such nonlinear phenomena, they have emerged as the model of choice for many researchers (Bali and Singla, 2021). In addition to achieving forward tracking and varied tracing for products in the supply chain, neural networks also assess food quality based on the related traceability data stored in the system. This can give consumers and related stakeholders more information, such as the product's quality level, to improve the consumer experience (Wang et al., 2017). It comprises a straight forward perceptive that calculates the weighted total of its inputs and outputs using mathematical operations (Zhu et al., 2021). The way an information flows across the network as well as the number of connection weights is determinant upon the architecture of the NN models (Maier et al., 2000). Multilayer perceptron which possess only three layers in most types of feed forward NN is the most widely and commonly used architecture (Csábrági et al., 2017).

Neural networks have a number of benefits, including high noise tolerance, the ability to generalize, and superior adaptation characteristics (Guiné, 2019). Incomprehensible model behavior, multi-source heterogeneous data, a lack of software with a food scientist-friendly interface are only a few of the primary issues faced by neural networks (Ma et al., 2022).

Hyperspectral photography was used by Liu et al. (2019) to investigate the use of a convolutional neural network for seafood species recognition. In this study, the usage of a convolutional neural network (CNN) to detect various seafood species using hyperspectral data is investigated. According to the study, CNN had a high degree of accuracy in its ability to identify various species of seafood.

In a similar vein, Chang and colleagues in 1999, investigated the use of neural networks to forecast shellfish demand. This study explores the use of a neural network to forecast consumer demand for various clam varieties based on previous sales information. The study discovered that the neural network could accurately estimate demand, and that this method might be helpful for supply chain management optimization.

Hussaine et al. (2020) investigated the use of blockchain and neural networks for seafood traceability. This study explores how to enhance seafood management and traceability using neural networks and blockchain technologies. The study suggests using neural networks to assess data on different types of seafood, fishing areas, and other variables.

7. APPLICATION OF AI IN ANALYSIS OF LARGE DATASETS OF SEAFOOD QUALITY

The Internet of Things (IoT) and recent developments in sensor networks have allowed for the collection of vast amounts of data (Rahmani et al., 2021). Big data has been created across many different locations via digital tools, platforms, apps, and human communications (Daniel, 2019; Luan et al., 2020).

More effective techniques with high analytical accuracy are required for the investigation of such vast amounts of data (Rahmani et al., 2021).

The main advantages of the big data revolution are frequently seen to be the extraction of useful knowledge and workable patterns from data (Mayer-Schönberger and Cukier, 2013; Jagadish et al., 2014). Big data analytics make use of a range of technologies and methods, including signal processing, image recognition, text analytics, social network analysis, data mining, visualization, predictive modelling as well as natural language processing (Chen and Zhang, 2014). The application of these AI technologies in the of large data sets in seafood quality monitoring and evaluation is discussed in this section.

7.1 Image recognition

Artificial intelligence is becoming increasingly proficient at applying image recognition, a digital picture or video procedure for identifying and detecting an object or feature (Bhardwaj et al., 2021). Based on visual signals including colour, texture, and shape, AI algorithms can be trained to identify various varieties of seafood and assess their quality.

An essential approach to verify the quality of fish is to analyze its color changes using imaging software, which is a non-hazardous, non-destructive common tool for analyzing data based on photography (Menesatti et al., 2010). One of the key approaches for enhancing raw photos from diverse sources, such as cameras or satellite sensors, space probes, aircraft, etc., is digital image processing (Awalludin et al., 2020). The use of a computer algorithm to perform image processing on a digital image is known as digital image processing. It deals with edge detection, edge sharpening, conversion, blurring, recognition, etc (Awalludin et al., 2020). The initial image's quality could be improved with the aid of image processing techniques, which also prepared the image for automated interpretation. The input images, pre-processing, segmentation, feature extraction, and classification of images are all dealt with by image processing techniques (Gamage, 2017).

Some studies have been conducted on the use of image recognition for monitoring seafood quality (Muhamad at al., 2009; Wang et al., 2013; Duta et al., 2016). Of these, Muhamad at al. (2009) proposed a fuzzy logic-based method for classifying the freshness of fish whilst Wang et al. (2013) suggested a regression-based technique on depending on the eye from samples of fish. Fuzzy logic technology was used in a 2009 study by Muhamad and colleagues to classify fish freshness based on image processing. To categorize the freshness of the fish in this study, the RGB color image processing data with a focus on the eye and gill of the fish was analyzed and simplified. A fuzzy logic technology has been applied to this goal. There are two different kinds of fuzzy input techniques that have been discussed: and involves two inputs, one of which is the mean RGB value for both the eye and the gill. There are six inputs where the input is an RGB value for the eye and gill, respectively. Results show that produce better results when compared to categorizing seafood freshness.

In order to cut expenses and time-consuming human inspection, the development of automatic fish sorting methods utilizing image analysis has been studied (Strachan and Kell, 1995). A study by Zion et al. (1999) created an image processing system based on moment-invariants combined with geometrical considerations for discriminating between photographs of three species of fish.

7.2 Predictive modelling

Predictive modelling is a crucial area of research in the seafood industry. For the food industry to increase productivity and minimize waste, the use of mathematical predictive models to evaluate microbial behaviour under various environmental circumstances is an intriguing approach. Predictive modelling can be used in a variety of contexts to improve the safety and quality of seafood, including quantitative (microbial) risk assessment, food chain modelling, quality and safety management, modelling of food processes, sampling, and plant design (Vasilis et al., 2013). Application of mathematical modelling for predicting shelf life necessitates adequate product rotting mechanism information has been reported (Koutsoumanis and Nychas, 2001). AI is able to find patterns and predict future seafood quality based on variables like temperature, water quality, and storage conditions by evaluating vast datasets of seafood quality metrics. One key field in the development of the food industry is predictive modelling (Membré and Lambert, 2008). Predictive models and their applications can be categorized into three namely; incident support to estimate the grade of impact on consumer safety or product quality, supporting food safety decisions that need to be made when implementing or running a food manufacturing operation and product innovation for assessing the rate of microbial proliferation (Calanche et al., 2020).

Some studies have been conducted to evaluate predictive modelling as a tool in the seafood industry (Koutsoumanis, 2001; Calanche et al., 2020; Giarratana et al., 2020; Garcia, 2022; Giarratana et al., 2022). Predictive modelling approaches have been used to determine the growth of pathogenic microorganisms in seafoods (Dalagaard et al., 2002).

According to Calanche and colleagues in 2020, the physico-chemical and microbiological parameters had a satisfactory correlation. The establishment of a shelf-life of 10 days, which corresponded to a poor grade (according to the European Community's system of grading fish for marketing purposes) with a freshness index below 50%, was made possible through sensory analysis and microbiological counts. Gill and flesh texture were the characteristics most susceptible to spoiling while storage in ice, according to sensory profiles. Following practical validation, the predictive models for the freshness index (%) and ice storage duration (h) showed an accuracy close to 90%.

Based on dynamic temperature conditions and a subsequent statistical analysis of the outcomes, Giarratana et al. (2022) built a deterministic mathematical model. The shelf-life of Atlantic mackerel was predicted using this model at certain storage temperatures. A total of 60 fresh fish were divided into two groups and held in ice for 12 days, one group at a constant temperature of 10.5°C and the other at a variable temperature of 1–7°C. At regular intervals, each fish had a microbiological examination and a sensory assessment using the Quality index method (QIM). After 9 days of storage for Group A and 3 days for Group B, a critical value of 6

Log cfu/g of spoilage bacteria (mostly psychoactive) linked with a considerable degradation of the sensory qualities was exceeded. By modelling the Quality index method (QIM) as a function of the behaviour of the spoilage bacteria, a trustworthy prediction of fish freshness was made possible. The spoilage bacteria load was converted into a Quality Index score using a coefficient of correlation.

In varied isothermal circumstances between 0° C and 15° C, Koutsoumanis (2001) observed the behavior of the natural microflora of Mediterranean gilt-head seabream (Sparus aurata) during aerobic storage. The influence of temperature on pseudomonad growth was modeled using a Belehradek type model employing the growth data of pseudomonads, which were established as the particular spoiling organisms of aerobically preserved gilt-head seabream. For the maximal specific growth rate (max) and the lag phase (tLag), the nominal minimum temperature parameters of the Belehradek model (Tmin) were found to be 11.8 and 12.8°C, respectively. By contrasting predictions with actual growth in dynamically changing tests, the model's applicability in forecasting pseudomonad growth on fish at shifting temperatures was assessed. Utilized were temperature scenarios created in the lab and simulations of actual temperature profiles seen in the fish chill chain. As comparison indices, bias and accuracy factors with corresponding ranges of 0.91 to 1.17 and 1.11 to 1.17 were utilized. For all temperature profiles studied, the average percent difference between shelf life experimentally measured by sensory analysis and shelf life projected based on pseudomonad development was 5.8%, demonstrating the model's accuracy in predicting fish quality under realistic circumstances.

7.3 Data clustering/Cluster analysis

A variety of exploratory multivariate statistical techniques that seek to isolate homogeneous groupings within a data set are collectively referred to as cluster analysis (Daniel and Gastón, 2014). A data-driven technique called cluster analysis is used to group people with comparable traits into groups. Based on quality criteria, AI can group together similar types of seafood, enabling researchers to find shared traits and potential quality-affecting variables. Since it may be used to categorise a set of samples according to many different features, cluster analysis is significant. Cluster analysis can also be used to more effectively evaluate huge data sets from instrumental measurements (Daniel and Gastón, 2014). In order to produce food products for particular consumer segments, cluster analysis is frequently used to identify groups of customers with varied preference patterns based on their liking of a collection of samples (Yenket et al., 2011).

Data mining, document retrieval, image segmentation, and pattern classification are only a few exploratory patterns analysis, grouping, decision-making, and machine learning applications where clustering is helpful (Jain, 2010). Clustering has been used to investigate genome data (Baldi and Hatfield, 2002) as well as group services delivery engagements for workforce management and planning (Hu et al., 2007).

7.4 Drone technology

Drones are revolutionizing land-based businesses; shops are looking into drone-based delivery systems, and realtors are using them to take aerial images of properties that are for sale. Underwater drones could bring about a similar transformation in the marine resources field by giving researchers eyes beneath the waves so they can monitor water quality and inexpensively remedy equipment issues (Whitt et al., 2020). These underwater drones will test dissolved oxygen levels and other physical and chemical data, and they will be outfitted with cameras to identify tears in nets before they get too serious, according to the drone creators (Orlowski, 2017). Divers may be put in danger during these checks, but the underwater drone is resistant to bad weather and much adverse weather conditions (Xiang et al., 2022). By using the drone's data on fish movements and environmental factors, fishermen may increase growth, reduce waste, and enhance accuracy. By examining fish stress levels, the data can also be utilized to reduce disease outbreaks and death (Fujita et al., 2018). Analyzing light conditions, on the other hand, can help control maturity and improve harvest quality (Ding & Ma, 2012). EyeROV TUNA, the first remotely operated underwater drone available for purchase in India, can send real-time footage of ships and other underwater structures to help with upkeep and repairs (Bagde & Pathan, 2023). The drone's capacity to navigate to a depth of 50 meters and take real-time HD video photos for underwater analysis has saved the usage of more costly and risky human examination by divers. One of the most cutting-edge systems, fishSHOAL, uses robot fish to find sources of underwater pollution (Müller-Schloer & Tomforde, 2017).

7.5 Data mining

Data mining is the technique of computing that identifies patterns in big data sets and extracts pertinent information (Kubat et al., 1998). It entails the application of both straightforward and sophisticated techniques, such as k-means clustering, k-nearest neighbour classification, support vector machine binary classifiers, dynamic prediction, modeling, artificial neural networks, and algorithm architecture, for the purpose of extracting useful data from relational, transactional, object-oriented, spatial, temporal, and relational databases, as well as from global information systems (Liao et al., 2012). Association, evolution, generalization, classification, characterisation, clustering, data visualization, pattern matching, and meta-rule guided mining are the main categories of data mining techniques (Gladju et al., 2022).

7.6 Robotic cages

For use in the open ocean, robotic cages are complete cages equipped with cameras, sensors, feeding and recirculation systems. A cage that fishermen can place their fish in before setting it adrift in the ocean (Føre et al., 2023). Brass mesh creates a cage, which prevents biofouling or the growth of algae and barnacles on submerged objects. By doing this, drag, and the requirement to clean the cages are reduced (Bagde & Pathan, 2023). Aquapods (Small Amphibious Robots with Sampling Capabilities) are a common name for robotic cages. These monitoring tools can be applied to aquaculture and exploration (Mackowiak, 2019). Data and AI will be necessary for commodity seafood markets, such as those for prawns and salmon, where international competition determines the price (Engle et al., 2016).

8. RESEARCH GAPS AND FUTURE OUTLOOK

Economic, technological, policy and ecological factors would greatly determine the contribution of seafood in meeting future food supply globally. A crucial issue that impacts both the commercial viability of the seafood business and the sustainability of seafood resources is the reduction of losses and wastage in seafoods. One viable answer to this challenge is the use of smart tools and biosensors based on artificial intelligence (AI) to enhance seafood processing and storage.

Although some progress has been made with respect to the use of AI based smart tools and biosensors in ensuring seafood are managed sustainably, lots of research gaps exist. There is therefore the need to fill these gaps to maximize the potential of biosensors and smart tools in reducing wastage and losses along the seafood value chain.

Analyzing and processing data in large quantities or amounts could be problematic. In this regard, researchers should focus on looking at tools that can analyze large amounts of data generated from the use of biosensors and smart tools based on artificial intelligence. In solving this challenge, there will be the need to conduct further studies to develop artificial intelligence algorithm that has the potential to produce insights that are actionable and can interpret complex data sets for sustaining production of seafoods.

Researchers should focus their studies on the utilization of deep learning, advanced molecular analysis methods like chromatography, electrophoresis, and spectroscopy, as well as genome characterization, to provide a revolutionary method for examining the quality dynamics of food ingredients.

Ability to detect fish spoilage which leads to great loss and wastage very early is important in ensuring food security. In this regards, it is important produce biosensors that can accurately detect early characteristics of contamination in seafood samples or seafood spoilage. Again it will be prudent to direct research towards development of biosensors that has the ability to detect varied range of microorganisms and compounds in seafood samples.

9. CONCLUSION

This review sort to highlight the role of smart tools and biosensors based on artificial intelligence in reduction of losses and wastage in seafood industry. The findings of this review demonstrate that a wide range of biosensors, grouped according to their modes of operation, can be used to assess the quality of seafood. These biosensors include microbial biosensors, optical biosensors, tissue-based biosensors, immunosensors, DNA-based biosensors, electrochemical biosensors, enzyme-based biosensors, optical biosensors, and piezoelectric biosensors. The most prominent of these biosensors are optical biosensors, electrochemical biosensors, and mechanical biosensors. Again, this study shows that a number of smart technologies are used for seafood traceability and management, including blockchain technology, quick response (QR) codes, data analytics, digital twins, and RFID tags. Data from the processing plant, vessel tracking information, and catch data are a few of the various data sources that can be used to track seafood products. The quality of seafood can be predicted and enhanced using artificial intelligence methods like neural networks, deep learning, machine learning, and others. There is a need to fill research gaps in the creation of biosensors capable of identifying a wide range of bacteria and chemicals in samples of seafood, even though some studies have been conducted regarding the role of smart tools and biosensors based on artificial intelligence that could reduce losses. Studying the creation of biosensors that can accurately detect the earliest indications of seafood contamination or rotting is essential.

ACKNOWLEDGEMENTS

None.

FUNDING

None.

AUTHORS` CONTRIBUTIONS

All authors contributed equally to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

Abad, E., Palacio, F., Nuin, M., De Zarate, A. G., Juarros, A., Gómez, J. M., & Marco, S. (2009). RFID smart tag for traceability and cold chain monitoring of foods: Demonstration in an intercontinental fresh fish logistic chain. *Journal of food engineering*, *93*(4), 394-399.

Agrawal, T. K., Kalaiarasan, R., Olhager, J., & Wiktorsson, M. (2021, August). Understanding Supply Chain Visibility Through Experts' Perspective: A Delphi Based Approach. In *IFIP International Conference on Advances in Production Management Systems* (pp. 189-196). Cham: Springer International Publishing.

Alamprese, C., and Ernestina Casiraghi, E. (2015). Application of FT-NIR and FT-IR spectroscopy to fish fillet authentication. LWT - Food Science and Technology, 63(1): 720-725. Doi: https://doi.org/10.1016/j.lwt.2015.03.021.

Anwar, H., Anwar, T., and Murtaza, S. (2023). Review on food quality assessment using machine learning and electronic nose system. Biosensors and Bioelectronics: X, 14: 100365. Doi: https://doi.org/10.1016/j.biosx.2023.100365.

Apetrei, I. M., & Apetrei, C. (2016). Amperometric biosensor based on diamine oxidase/platinum nanoparticles/graphene/chitosan modified screen-printed carbon electrode for histamine detection. *Sensors*, *16*(4), 422.

Arlett, J. L., Myers, E. B., & Roukes, M. L. (2011). Comparative advantages of mechanical biosensors. *Nature nanotechnology*, *6*(4), 203-215.

Autiosalo, J., Vepsäläinen, J., Viitala, R., & Tammi, K. (2020). A feature-based framework for structuring industrial digital twins, *IEEE Access 8*: 1193–1208.

Awalludin, E. A., Arsad, T. N. T., & Yussof, W. H. W. (2020, May). A review on image processing techniques for fisheries application. In *Journal of Physics: Conference Series* (Vol. 1529, No. 5, p. 052031). IOP Publishing.

Aydın, Ö. (2019). Enhancing Security in RFID. *PhD, Dokuz Eylül University, İzmir, Turkey*.

Aydın, Ö., Dalkılıç, G. (2018). A hybrid random number generator for lightweight cryptosystems: xorshiftLplus. The 3rd International Conference on Engineering Technology and Applied Sciences (ICETAS), 17-21 July 2018. Skpoje, Macedonia.

Aydın, Ö., & Yukcu, S. (2020). Siber Saldırı Önlemede Blokzinciri Teknolojisinin Fayda Maliyet Açısından Değerlendirilmesi. *MANAS Sosyal Araştırmalar Dergisi*, *9*(4), 2519-2530. Doi: https://doi.org/10.33206/mjss.740158

Bagde, P. S., & Pathan, J. G. K. (2023) The Role of Artificial Intelligence(AI) in Aquaculture: Improving Efficiency, Sustainability, and Profitability. *Chronicle of Aquatic Science*, *1*(1), 35-39.

Baldi, P., Hatfield, G. (2002). DNA Microarrays and Gene Expression. Cambridge University Press.

Bali, N., and Singla, A. (2021). Deep Learning Based Wheat Crop Yield Prediction Model in Punjab Region of North India. *Applied Artificial Intelligence,* *35*(15):1304–1328. Doi: https://doi.org/10.1080/08839514.2021.1976091

Bhalla N, Jolly P, Formisano N, Estrela P. (2016) Introduction to biosensors. *Essays Biochem, 60*(1):1-8. Doi: 10.1042/EBC20150001. PMID: 27365030; PMCID: PMC4986445.

Bibi, F., Guillaume, C., Gontard, N., and Sorli, B. (2017). A review: RFID technology having sensing aptitudes for food industry and their contribution to tracking and monitoring of food products. *Trends in Food Science & Technology, 62*: 91-103. Doi: https://doi.org/10.1016/j.tifs.2017.01.013.

Bilal, Z., & Martin, K. (2014). A hierarchical anti-counterfeit mechanism: securing the supply chain using RFIDs. In *Foundations and Practice of Security: 6th International Symposium, FPS 2013, La Rochelle, France, October 21-22, 2013, Revised Selected Papers* (pp. 291-305). Springer International Publishing.

Borisov, S. M., & Wolfbeis, O. S. (2008). Optical biosensors. *Chemical reviews*, *108*(2), 423-461. Doi: https://doi.org/10.1021/cr068105t.

Burgos, D., & Ivanov, D. (2021). Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review*, *152*, 102412.

CAC/GL60. (2006). Primciples for Traceability/product tracing as a tool within a food Inspection and certification system.

Calì, D., Condorelli, A., Papa, S., Rata, M., & Zagarella, L. (2011). Improving intelligence through use of Natural Language Processing. A comparison between NLP interfaces and traditional visual GIS interfaces. *Procedia Computer Science*, *5*, 920-925. Doi: https://doi.org/10.1016/j.procs.2011.07.128.

Campbell, K., Barnes, P., Haughey, S. A., Higgins, C., Kawatsu, K., Vasconcelos, V., & Elliott, C. T. (2013). Development and single laboratory validation of an optical biosensor assay for tetrodotoxin detection as a tool to combat emerging risks in European seafood. *Analytical and bioanalytical chemistry*, *405*, 7753-7763.

Cao, S., Johnson, H., & Tulloch, A. (2023). Exploring blockchain-based traceability for food supply chain sustainability: Towards a better way of sustainability communication with consumers. *Procedia Computer Science*, *217*, 1437-1445. Doi: https://doi.org/10.1016/j.procs.2022.12.342.

Chawla, P., Cao, X., Fu, Y., Hu, C. M., Wang, M., Wang, S., & Gao, J. Z. (2023). Water quality prediction of salton sea using machine learning and big data techniques. *International Journal of Environmental Analytical Chemistry*, *103*(18), 6835-6858. Doi: https://doi.org/10.1080/03067319.2021.1963713

Chen, C. P., & Zhang, C. Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information sciences*, *275*, 314-347. Doi: https://doi.org/10.1016/j.ins.2014.01.015

Chen, J., Huang, B., Mao, J., and Li, B. (2019). A novel correction algorithm for distorted QR-code image, in: 2019 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE), IEEE, 2019, pp. 380–384, Doi: https://doi.org/10.1109/EITCE47263.2019.9095073.

Chrispin, L.C., Jothiswaran, V. V.,Velumani, T., Angela, S.A.D., and Jayaraman R. (2020). Application of Artificial Intelligence in Fisheries and Aquaculture. Research Today 2(6): 499-502

Chung, D., Jeong, P., Kwon, D., and Han, H. (2023). Technology acceptance prediction of robo-advisors by machine learning. Intelligent Systems with Applications 18:200197

Cooney, R., Baptista de Sousa, D., Fernández-Ríos, A., Mellett, S., Rowan, N., Morse, A.P., Hayes, M., Laso, J., Regueiro, L., Wan, A.H.L., and Clifford, E. (2023). A circular economy framework for seafood waste valorisation to meet challenges and opportunities for intensive production and sustainability. Journal of Cleaner Production, 392: 136283. Doi: https://doi.org/10.1016/j.jclepro.2023.136283.

Coronado Mondragon, A. E., Coronado Mondragon, C. E., & Coronado, E. S. (2021). Managing the food supply chain in the age of digitalisation: A conceptual approach in the fisheries sector. *Production planning & control*, *32*(3), 242-255.

Csábrági, A., Molnár, S., Tanos, P., & Kovács, J. (2017). Application of artificial neural networks to the forecasting of dissolved oxygen content in the Hungarian section of the river Danube. *Ecological Engineering*, *100*, 63-72.

Dalgaard, P., Buch, P., & Silberg, S. (2002). Seafood Spoilage Predictor—development and distribution of a product specific application software. *International Journal of Food Microbiology*, *73*(2-3), 343-349.

Daniel, B. K. (2019). Big Data and data science: A critical review of issues for educational research. *British Journal of Educational Technology*, *50*(1), 101-113. Doi: https://doi.org/10.1111/bjet.12595.

Daniel, G., and Gastón, A. (2014). Mathematical and Statistical Methods in Food Science and Technology Cluster analysis: Application in food science and technology. 103–120. Doi: https://doi.org/10.1002/9781118434635.ch7

del Rio-Lavín, A., Weber, J., Molkentin, J., Jiménez, E., Artetxe-Arrate, I., & Pardo, M. Á. (2022). Stable isotope and trace element analysis for tracing the geographical origin of the Mediterranean mussel (Mytilus galloprovincialis) in food authentication. *Food Control*, *139*, 109069.

Demir, S., Kaynak, R., and Demir, R.K. (2015). Usage Level and Future Intent of Use of Quick Response (QR) Codes for Mobile Marketing among College Students in Turkey. Procedia - Social and Behavioral Sciences, 181: 405-413. Doi: https://doi.org/10.1016/j.sbspro.2015.04.903.

Deng, L. and Yu D. (2014) Deep learning: methods and applications. Foundations Trends in Signal Processing, 7, 197- 387.

Dervisevic, M., Custiuc, E., Çevik, E., & Şenel, M. (2015). Construction of novel xanthine biosensor by using polymeric mediator/MWCNT nanocomposite layer for fish freshness detection. *Food Chemistry*, *181*, 277-283.

Dervisevic, M., Custiuc, E., Çevik, E., Durmus, Z., Şenel, M., & Durmus, A. (2015). Electrochemical biosensor based on REGO/Fe3O4 bionanocomposite interface for xanthine detection in fish sample. *Food Control*, *57*, 402-410.

Devi, R., Thakur, M., & Pundir, C. S. (2011). Construction and application of an amperometric xanthine biosensor based on zinc oxide nanoparticles–polypyrrole composite film. *Biosensors and Bioelectronics*, *26*(8), 3420-3426.

Ding, W., Ma, Y. (2012). The Application of Wireless Sensor in Aquaculture Water Quality Monitoring. In: Li, D., Chen, Y. (eds) Computer and Computing Technologies in Agriculture V. CCTA 2011. IFIP Advances in Information and Communication Technology, vol 370. Springer, Berlin, Heidelberg. Doi: https://doi.org/10.1007/978-3-642-27275-2_56

Koçoğlu, I.O., Erdenc P.E., and Kılıç, E. (2020). Disposable biogenic amine biosensors for histamine determination in fish. Analytical Methods, 30 (12): 3802-3812. Doi: https://doi.org/10.1039/D0AY00802H.

Dolmacı, N., Çete, S., Arslan, F., & Yaşar, A. (2012). An amperometric biosensor for fish freshness detection from xanthine oxidase immobilized in polypyrrole-polyvinylsulphonate film. *Artificial Cells, Blood*

Substitutes, and Biotechnology, *40*(4), 275-279.

Dopico, D.C., Mendes, R., Silva, H.A. Verrez-Bagnis, V., Pérez-Martín, R., and Sotelo, C.G. (2016). Evaluation, signalling and willingness to pay for traceability. A cross-national comparison. Spanish Journal of Marketing - ESIC, 20 (2): 93-103. Doi: https://doi.org/10.1016/j.sjme.2016.07.001.

Dyck, G., Hawley, E., Hildebrand, K., and Paliwal, J. (2023). Digital Twins: A novel traceability concept for post-harvest handling. Smart Agricultural Technology,3:100079. Doi: https://doi.org/10.1016/j.atech.2022.100079.

EFSA Guidance for those carrying out systematic reviews European Food Safety Authority (EFSA). (2010). Application of systematic review methodology to food and feed safety assessments to support decision making. EFSA Journal, 8(6), 1637

El Naqa, I., Murphy, M.J. (2015). What Is Machine Learning?. In: El Naqa, I., Li, R., Murphy, M. (eds) Machine Learning in Radiation Oncology. Springer, Cham. Doi: https://doi.org/10.1007/978-3-319-18305-3_1

Endo, H., and Wu, H. (2019). Biosensors for the assessment of fish health: a review. Fisheries Science, Doi: https://doi.org/10.1007/s12562-019-01318-y

Engle, C. R., Quagrainie, K. K., & Dey, M. M. (2016). Seafood and aquaculture marketing handbook. John Wiley & Sons.

Erasmus, V.N., Kadhila, T., Gabriel, N.N., Thyberg, K.L., Ilungu, S., and Machado T. (2021). Assessment and quantification of Namibian seafood waste production. Ocean & Coastal Management, 199: 105402. Doi: https://doi.org/10.1016/j.ocecoaman.2020.105402.

Ercolini, D., Russo, F., Nasi, A., Ferranti, P., & Villani, F. (2009). Mesophilic and psychrotrophic bacteria from meat and their spoilage potential in vitro and in beef. *Applied and environmental microbiology*, *75*(7), 1990-2001.

Fan, S., Ma, C., Tian, X., Ma, X., Qin, M., Wu, H., ... & Wang, S. (2021). Detection of Vibrio vulnificus in seafood with a DNAzyme-based biosensor. Frontiers in Microbiology, 12, 655845.

Føre, M., Alver, M. O., Frank, K., & Alfredsen, J. A. (2023). Advanced Technology in Aquaculture–Smart Feeding in Marine Fish Farms. In Smart Livestock Nutrition (pp. 227-268). Cham: Springer International Publishing.

Franceschelli, L., Berardinelli, A., Dabbou, S., Ragni, L., Tartagni, M. (2021). Sensing Technology for Fish Freshness and Safety: A Review. Sensors, 21: 1373. Doi: https://doi.org/10.3390/s21041373

Tolentino-Zondervan, F., Ngoc, P. T. A., & Roskam, J. L. (2023). Use cases and future prospects of blockchain applications in global fishery and aquaculture value chains. *Aquaculture*, *565*, 739158. Doi: https://doi.org/10.1016/j.aquaculture.2022.739158.

Fujita, R., Cusack, C., Karasik, R., Takade-Heumacher, H., & Baker, C. (2018). Technologies for improving fisheries monitoring. Environmental Defense Fund, San Francisco, 71.

Gamage, P.T. (2017). Identification of brain tumor using image processing techniques Faculty of Information Technology, University of Moratuwa. https://www.researchgate.net/publication/276133543

Ghaly, A. E., Dave, D., Budge, S. & Brooks, M. S. (2010). Fish Spoilage Mechanisms and Preservation Techniques: Review. American Journal of Applied Sciences, 7(7), 859-877. Doi: https://doi.org/10.3844/ajassp.2010.859.877

Ghidini, S., Varrà, M.O., & Zanardi, E. (2019). Approaching Authenticity Issues in Fish and Seafood Products by Qualitative Spectroscopy and Chemometrics. Molecules, 24(9): 1812. Doi: https://doi.org/10.3390/molecules24091812

Giarratana, F., Nalbone, L., Ziino, G., Giuffrida, A., & Panebianco, F. (2020). Characterization of the temperature fluctuation effect on shelf life of an octopus semi-preserved product. *Italian journal of food safety*, *9*(1).

Giarratana, F., Panebianco, F., Nalbone, L., Ziino, G., Valenti, D., & Giuffrida, A. (2022). Development of a predictive model for the shelf-life of Atlantic mackerel (Scomber scombrus). *Italian Journal of Food Safety*, *11*(1). Doi: https://doi.org/10.4081/ijfs.2022.10019. PMID: 35284339; PMCID: PMC8883832.

Gill, C. O., & Newton, K. G. (1978). The ecology of bacterial spoilage of fresh meat at chill temperatures. *Meat science*, *2*(3), 207-217.

Gladju, J., Kamalam, B.S., and Kanagaraj, A. (2022). Applications of data mining and machine learning framework in aquaculture and fisheries: A review. *Smart Agricultural Technology, 2:100061*. Doi: https://doi.org/10.1016/j.atech.2022.100061.

Goel, N., Kumar, Y., Kaur, S., Sharma, M., Sharma, P. (2022). Machine learning-based remote monitoring and predictive analytics system for monitoring and livestock monitoring, in: Application of Machine Learning in Agriculture, *Academic Press, 2022*, pp. 47–67.

Grieshaber D, MacKenzie R, Vörös J, Reimhult E (2008) Electrochemical biosensors—sensor principles and architectures. *Sensors 8*:1400–1458

Guiné, R.P.F. (2019). The Use of Artificial Neural Networks (ANN) in Food Process Engineering. International *Journal of Food Engineering, 5*(1):15-21

Gyan, W. R., Alhassan, E. H., Asase, A., Akongyuure, D. N., & Qi-Hui, Y. (2020). Assessment of postharvest fish losses: The case study of Albert Bosomtwi-Sam fishing harbour, Western Region, Ghana. *Marine Policy*, *120*, 104120.

Hainlein, M. & Kaplan, A. (2019). A brief history of artificial intelligence: on the past, present, and future of artificial intelligence, *Calif. Manag. Rev. 61* (4): 5-14.

Henao-Escobar, W., Domínguez-Renedo, O., Alonso-Lomillo, M. A., & Arcos-Martínez, M. J. (2013). A screen-printed disposable biosensor for selective determination of putrescine. *Microchimica Acta*, *180*, 687-693.

Holzapfel, W. H. (1998). The gram-positive bacteria associated with meat and meat products. In A. Davies and R. Board (ed.), *The microbiology of meat and poultry, 31.*, 35-74. Blackie Academic & Professional, London, England.

Hong, S., & Jeong, H. D. (2014). Development of piezoelectric immunosensor for the rapid detection of marine derived pathogenic bacteria, Vibrio vulnificus. Journal of fish pathology, 27(2), 99-105.

Hsu, Y. C., Chen, A. P., & Wang, C. H. (2008, September). A RFID-enabled traceability system for the supply chain of live fish. In *2008 IEEE International Conference on Automation and Logistics* (pp. 81-86). IEEE.

Hu, J., Ray, B.K., Singh, M. (2007). Statistical methods for automated generation of service engagement staffing plans. *IBM J. Res. Dev. 51* (3), 281–293

Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R., et al. (2014). Big data and its technical challenges. *Commun. ACM. 57*, 86–94. Doi: https://doi.org/10.1145/2611567

Jain, A.K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters 31:* 651–666.

Jeevanandam, J., Agyei, D., Danquah, M.K., and Udenigwe, C. (2022). Food quality monitoring through bioinformatics and big data. Editor(s): Bhat, R. *Future Foods, Academic Press,* 733-744. Doi: https://doi.org/10.1016/B978-0-323-91001-9.00036-0.

Machado, J. G. D. C. F., Nantes, J. F. D., & Leonelli, F. C. V. Using Quick Response Code in Food Packaging for Traceability and Marketing Strategies. Glob J Nutri Food Sci. 1 (3): 2019. *GJNFS. MS. ID*, *515*.

Jones, D., Snider, C., Nassehi, A., Yon, J., and Hicks, B. (2020). Characterizing the digital twin: a systematic literature review, CIRP J. Manuf. Sci. Technol. 29: 320196–52.

Kaur, G., Tomar, P., and Tanque, M. (2021). Artificial Intelligence to Solve Pervasive Internet of Things Issues. Academic Press, Doi: https://doi.org/10.1016/C2018-0-04324-8

Khan, Md. A., Hossain, Md. E., Shahaab, A., and Khan, I. (2022). ShrimpChain: A blockchain-based transparent and traceable framework to enhance the export potentiality of Bangladeshi shrimp. Smart Agricultural Technology, 2, 100041. Doi: https://doi.org/10.1016/j.atech.2022.100041.

Kim, Y.G. & Woo, E. (2016). Consumer acceptance of a quick response (QR) code for the food traceability system: Application of an extended technology acceptance model (TAM). Food Research International, 85:266-272. Doi: https://doi.org/10.1016/j.foodres.2016.05.002

Kindong, R., Prithiviraj, N., Apraku, A., Ayisi, C.L., Dai, DX. (2017). Biochemical composition of Predatory carp (Chanodichthys erythropterus) from Lake Dianshan, Shanghai, China. Egyptian Journal of Basic and Applied Sciences, 4(4): 297-302. Doi: https://doi.org/10.1016/j.ejbas.2017.10.001.

Kochanska, A. (2020). Evaluation of the potential of emerging technologies for the improvement of seafood product traceability.

Kokkinos, K., Exadactylos, A., Vafidis, D., & Hatziioannou, M. (2018, November). Efficient traceability of aquatic products on the cold supply chain management via IoT and artificial neural networks. In *Proceedings of the 3rd International Congress on Applied Ichthyology & Aquatic Environment, Volos,* *Greece* (pp. 8-11).

Kouhizadeh, M., Saberi, S., Sarkis, J., (2021). Blockchain technology and the sustainable supply chain: theoretically exploring adoption barriers. *Int. J. Prod. Econ. 231*: 107831.

Koutsoumanis K, and Nychas G J E. (2001). Application of a systematic experimental procedure to develop a microbial model for rapid fish shelf life prediction. *Int J Food Microbiol. 60*:174–184.

Koutsoumanis K. (2001). Predictive Modeling of the Shelf Life of Fish under Nonisothermal Conditions. *Applied and Environmental Microbiology, 67*(4): 1821-1829. doi: Doi: https://doi.org/10.1128/AEM.67.4.1821-1829.2001

Kruijssen, F., Tedesco, I., Ward, A., Pincus, L., Love, D., and Thorne-Lyman, A.L. (2020). Loss and waste in fish value chains: A review of the evidence from low and middle-income countries. *Global Food Security, 26*: 100434. Doi: https://doi.org/10.1016/j.gfs.2020.100434.

Kryzhanovskii, S., andVititnova, M. (2009). x-3 polyunsaturated fatty acids and the cardiovascular system. *Hum Physiol, 35*:491–501. doi: Doi: https://doi.org/10.1134/S036211970904015X.

Kubat, M., Bratko, I., Michalski, R.S. (1998). A review of machine learning methods. Mach. Learn. Data Min., 3–69.

Kumar, S., and Solanki, A. (2023). A Natural Language Processing System using CWS Pipeline for Extraction of Linguistic Features. Procedia Computer Science 218 (2023) 1768–1777

Kutyauripo, I., Rushambwa, M., and Lyndah Chiwazi, L (2023). Artificial intelligence applications in the agrifood sectors. Journal of Agriculture and Food Research 11 (2023) 100502

Lezoche, M., Hernandez, J. E., Díaz, M. D. M. E. A., Panetto, H., & Kacprzyk, J. (2020). Agri-food 4.0: A survey of the supply chains and technologies for the future agriculture. *Computers in industry*, *117*, 103187.

Li, D. (2021). RETRACTED ARTICLE: Application of artificial intelligence and machine learning based on big data analysis in sustainable agriculture. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science*, *71*(9), 956-969. Doi: https://doi.org/10.1080/09064710.2021.1965650

Li, J., Wang, H., & Cheng, J. H. (2022). DNA, protein and aptamer-based methods for seafood allergens detection: Principles, comparisons and updated applications. *Critical Reviews in Food Science and Nutrition, 63*(2), 178-191.

Liantoni, F., Rosetya, S., & Rahmawati W.M. (2018). The Implementation of QR-Code Technology on Bulak Fish Center Information System. *Jurnal Online Informatika, 3*(2): 123-127

Liao, S.H., Chu, P.H., Hsiao, P.Y. (2012). Data mining techniques and applications–adecade review from 2000 to 2011, *Expert Syst. Appl. 39*(12): 11303–11311.

Liu, H., Xia, M., Williams, D., Sun, J., and Yan, H. (2022). Digital Twin-Driven Machine Condition Monitoring: A Literature Review. Journal of Sensors, Article ID 6129995, 13 pages, 2022. Doi: https://doi.org/10.1155/2022/6129995

Liu, M., Fang, S., Dong, H., & Xu, C. (2021). Review of digital twin about concepts, technologies, and industrial applications. *Journal of Manufacturing Systems, 58*:346–361.

Love, D.C., Fry, J.P., Milli, M.C., & Neff, R.A. (2015). Wasted seafood in the United States: Quantifying loss from production to consumption and moving toward solutions. *Global Environmental Change 35* 116–124

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S.J.H., Ogata, H., Baltes, J., Guerra, R., Li, P., Tsai, C-C. (2020). Challenges and Future Directions of Big Data and Artificial Intelligence in Education. *Frontiers in Psychology, 11*: Doi: https://doi.org/10.3389/fpsyg.2020.580820

Ma, P., Zhang, Z., Jia, X., Peng, X., Zhang, Z., Tarwa, K., Wei, C-I., Liu, F., and Wang, Q. (2022). Neural network in food analytics. *Critical Reviews in Food Science and Nutrition*, 1-19. Doi: https://doi.org/10.1080/10408398.2022.2139217

Maier, H. R., & Dandy, G. C. (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environmental modelling & software*, *15*(1), 101-124.

Manning, L., Brewer, S., Craigon, P.J., Frey, J., Gutierrez, A., Jacobs, N., Kanza, S., Munday, S., Sacks, J., and Pearson, S. (2022). Artificial intelligence and ethics within the food sector: Developing a common language for technology adoption across the supply chain. Trends in Food Science & Technology, 125: 33-42. Doi: https://doi.org/10.1016/j.tifs.2022.04.025.

Mavani, N. R., Ali, J. M., Othman, S., Hussain, M. A., Hashim, H., & Rahman, N. A. (2022). Application of artificial intelligence in food industry—a guideline. *Food Engineering Reviews*, *14*(1), 134-175. Doi: https://doi.org/10.1007/s12393-021-09290-z

Mayer-Schönberger, V., & Cukier, K. (2013). Big data: A Revolution That Will Transform How we live, Work, and Think. Boston, MA: Houghton Mifflin Harcourt.

McMillin, K.W., Lampila, L.E., & Marcy, J.A. (2012). Traceability in the meat, poultry and seafood industries. Editor(s): Kerry, J.P. In Woodhead Publishing Series in Food Science, Technology and Nutrition, Advances in Meat, Poultry and Seafood Packaging, Woodhead Publishing, 565-595. Doi: https://doi.org/10.1533/9780857095718.4.565.

Mehrotra, P. (2016). Biosensors and their applications- A review. Journal of Oral Biology and Craniofacial Research, 6(2): 153–159.

Melesse, T. Y., Franciosi, C., Di Pasquale, V., & Riemma, S. (2023). Analyzing the Implementation of Digital Twins in the Agri-Food Supply Chain. *Logistics*, *7*(2), 33.

Mitsubayashi, K., Kubotera, Y., Yano, K., Hashimoto, Y., Kon, T., Nakakura, S., Nishi, Y., and Endo, H. (2004). Trimethylamine biosensor with flavin-containing monooxygenase type 3 (FMO3) for fish-freshness analysis. Sensors and Actuators B 103: 463–467

Mol, A.P. (2014). Governing China's food quality through transparency: a review', Food control, 43:49-56

Muhamad, F., Hashim, H., Jarmin, R., & Ahmad, A. (2009, December). Fish freshness classification based on image processing and fuzzy logic. In *Proceedings of the 8th WSEAS International Conference on Circuits, Systems, Electronics, Control &* (pp. 109-115).

Müller-Schloer, C., & Tomforde, S. (2017). Organic Computing-Technical Systems for Survival in the Real World. Cham, Switzerland: Springer International Publishing.

Neethirajan, S. (2020). The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-Sensing Research, 29,* 100367.

Neethirajan, S.; Kemp, B. (2021). Digital Twins in Livestock Farming. *Animals, 11,* 1008.

Okafor, C.E., Iweriolor, S., Ani, O.I., Ahmad, S., Mehfuz, S., Ekwueme, G.O., Chukwumuanya, O.E., Abonyi, S.E., Ekengwu, I.E., Chikelu, O.P. (2023). Advances in machine learning-aided design of reinforced polymer composite and hybrid material systems. *Hybrid Advances, 2:* 100026. Doi: https://doi.org/10.1016/j.hybadv.2023.100026.

Orlowski, A. (2017). Drones making waves in aquaculture. SeafoodSource. https://www.seafoodsource.com/news/aquaculture/drones-making-waves-inaquaculture

Orofino, S., McDonald, G., Mayorga, J., Costello, C., and Bradley, D. (2023). Opportunities and challenges for improving fisheries management through greater transparency in vessel tracking. *ICES Journal of Marine Science, 0*:1–15. Doi: https://doi.org/10.1093/icesjms/fsad008

Ovalle, J.C., Vilas, C., and Antelo, L.T. (2022). On the use of deep learning for fish species recognition and quantification on board fishing vessels. *Marine Policy 139*: 105015

Patel, A.S., Brahmbhatt, M.N., Bariya, A.R., Nayak, J.B., and Singh, V.K. (2023). Blockchain technology in food safety and traceability concern to livestock products. *Heliyon, 9*(6), e16526. Doi: https://doi.org/10.1016/j.heliyon.2023.e16526.

Pérez S, Bartrolí J, Fàbregas E. (2013). Amperometric biosensor for the determination of histamine in fish samples. *Food Chem. 141*(4):4066-72. Doi: https://doi.org/10.1016/j.foodchem.2013.06.125.

Pieniak Z, Monika K, Kowrygo B, Verbeke W (2011) Consumption patterns and labelling of fish and fishery products in Poland after the EU accession. *Food Control 22*(6): 843-850.

Pieniak Z, Monika K, Kowrygo B, Verbeke W (2011). Consumption patterns and labelling of fish and fishery products in Poland after the EU accession. *Food Control 22*(6): 843-850.

Potyrailo, R.A., Nagraj, N., Tang, Z., Mondello, F.J., Surman, C. and Morris, W. (2012). Battery-free radio frequency identification (RFID) sensors for food quality and safety. *J Agric Food Chem, 60*(35): 8535–8543.Doi: https://doi.org/10.1021/jf302416y

Power, D.M., Taoukis, P., Houhoula, D., Tsironi, T., and Flemetakis, E. (2023). Integrating omics technologies for improved quality and safety of seafood products. *Aquaculture and Fisheries, 8*(4): 457-462. Doi: https://doi.org/10.1016/j.aaf.2022.11.005.

Purohit, B., Vernekar, P.R., Shetti, N.P. and Chandra, P. (2020). Biosensor nanoengineering: Design, operation, and implementation for biomolecular analysis. *Sensors International 1* (2020) 100040

Qiao, Z.; Fu, Y.; Lei, C.; Li, Y. (2020). Advances in antimicrobial peptides-based biosensing methods for detection of food-borne pathogens: A review. *Food Control.* 107116.

Qu, J-H., Liu, D., Cheng, J-H., Sun, D-W., Ma, J., Pu, H., and Zeng. X-A. (2014). Applications of near infrared spectroscopy in food safety evaluation and control: a review of recent research advances. Critical Reviews in Food Science and Nutrition, Doi: https://doi.org/10.1080/10408398.2013.871693

Rahman, L. F., Alam, L., Marufuzzaman, M., & Sumaila, U. R. (2021). Traceability of sustainability and safety in fishery supply chain management systems using radio frequency identification technology. *Foods, 10(*10), 2265.

Rahmani, A.M., Azhir, E., Ali, S., Mohammadi, M., Ahmed, O.H., Ghafour, M.Y., Ahmed, S.H., and Hosseinzadeh, M. (2021). Artificial intelligence approaches and mechanisms for big data analytics: a systematic study. *PeerJ Comput Sci. 2021*; 7: e488. Doi: https://doi.org/10.7717/peerj-cs.488

Rao, E.S., Seema Shukla, S., and Rizwana (2022). Food traceability system in India. *Measurement: Food 5:* 100019

Reverté, L., Campbell, K., Rambla-Alegre, M., Elliott, C. T., Diogène, J., & Campàs, M. (2017). Immunosensor array platforms based on self-assembled dithiols for the electrochemical detection of tetrodotoxins in puffer fish*. Analytica chimica acta, 989*, 95-103.

Rossi, S. (2022). Fishing and Overfishing-Sustainable Harvest of the Sea. In SDG 14: Life Below Water: A Machine-Generated Overview of Recent Literature (pp. 207-325). Cham: Springer International Publishing.

Ruiz, J., Batty, A., Chavance, P., McElderry, H., Restrepo, V., Sharples, P., Santos, J., and Urtizberea1 A. (2015) Electronic monitoring trials on in the tropical tuna purse-seine fishery*, ICES Journal of Marine Science, 72*(4):1201–1213. Doi: https://doi.org/10.1093/icesjms/fsu224

Sadik, O.A. Aluoch, A.O. and Zhou, A. (2009). Status of biomolecular recognition using electrochemical techniques, *Biosens. Bioelectron. 24* (2009) 2749–2765, Doi: https://doi.org/10.1016/j.bios.2008.10.003

Saeed, R., Feng, H., Wang, X., Zhang, X., and Fu, Z. (2022). Fish quality evaluation by sensor and machine learning: A mechanistic review. *Food Control, 137*:108902. Doi: https://doi.org/10.1016/j.foodcont.2022.108902.

Sahin, O.I., Saricaoglu, F.T., Dundar, A.N., and Dagdelen, A.F. (2023). Chapter 13 - Smart applications for fish and seafood packaging systems. Editor(s): Inamuddin, Tariq Altalhi, Jorddy Neves Cruz. Green Sustainable Process for Chemical and Environmental Engineering and Science, Elsevier, 211-227, Doi: https://doi.org/10.1016/B978-0-323-95644-4.000

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development, 3*(3), 210–229.

Sander, F., Semeijn, J., Mahr, D. (2018). The acceptance of blockchain technology in meat traceability and transparency. *Br. Food J. 120*(9), 2066–2079.

Seafood Business for Ocean Stewardship. (2021). Transparency and Governance of Sea BOS. https://seabos.org/task-forces/task-force-4/

Sedghy, B.M. (2019). Evolution of Radio Frequency Identification (RFID) in Agricultural Cold Chain Monitoring: A Literature Review. Journal of Agricultural Science; 11(3): 43-58. Doi: https://doi.org/10.5539/jas.v11n3p43

Shraddha Karanth, S., Benefo, E.O., Patra, D., & Pradhan A.K. (2023). Importance of artificial intelligence in evaluating climate change and food safety risk. Journal of Agriculture and Food Research 11: 100485.

Söderberg, R., Wärmefjord, K., Carlson, J.S., and Lindkvist, L. (2017). Toward a Digital Twin for real-time geometry assurance in individualized production, *CIRP Annals, 66* (1): 137-140. Doi: https://doi.org/10.1016/j.cirp.2017.04.038.

Strachan, N. J. C., & Kell, L. (1995). A potential method for differentiation between haddock fish stocks by computer vision using canonical discriminant analysis. *ICES Journal of Marine Science, 52*:145–149.

Surya, T., Sivaraman, B., Alamelu, V., Priyatharshini, A., Arisekar, U.and Sundhar, S. (2019). Rapid Methods for Histamine Detection in Fishery Products. *Int.J. Curr.Microbiol. App.Sci, 8*(3): 2035-2046

Tamm, E.E., Schiller, L., and Hanner, R.H. (2016). Chapter 2 - Seafood Traceability and Consumer Choice. Editor(s): Amanda M. Naaum, Robert H. Hanner, Seafood Authenticity and Traceability, *Academic Press,* 27-45, Doi: https://doi.org/10.1016/B978-0-12-801592-6.00002-4.

Tesfay, S. and Teferi, M., (2017). Assessment of fish post-harvest losses in Tekeze dam and Lake Hashenge fishery associations: northern Ethiopia. *Agric. Food Secur. 6,* 1–12.

Thandavan, K.; Gandhi, S.; Sethuraman, S.; Rayappan, J.B.B.; Krishnan, U.M. Development of Electrochemical Biosensor with Nano-Interface for Xanthine Sensing-A Novel Approach for Fish Freshness Estimation. *Food Chem. 2013*, 139, 963–969.

Torre, R., Costa-Rama, E., Nouws, H. P., & Delerue-Matos, C. (2020). Diamine oxidase-modified screen-printed electrode for the redox-mediated determination of histamine. *Journal of Analytical Science and Technology*, *11*, 1-8.

Trebar, M., Lotrič, M., Fonda, I., Pleteršek, A., & Kovačič, K. (2013). RFID data loggers in fish supply chain traceability. *International Journal of Antennas and propagation*, *2013*, 1–9.

Trevisani, M., Cecchini, M., Fedrizzi, G., Corradini, A., Mancusi, R., and Tothill, I.E. (2019). Biosensing the Histamine Producing Potential of Bacteria in Tuna. *Front Microbiol. 10:* 1844. Doi: https://doi.org/10.3389/fmicb.2019.01844

United Nations (2014). Open Working Group Proposal for Sustainable Development Goals. United Nations, New York City.

Van der Burg, S.; Kloppenburg, S.; Kok, E.J.; van der Voort, M. (2021). Digital Twins in Agri-Food: Societal and Ethical Themes and Questions for Further Research. *NJAS Impact Agric. Life Sci., 93*, 98–125.

van Helmond, A. T., Mortensen, L. O., Plet-Hansen, K. S., Ulrich, C., Needle, C. L., Oesterwind, D., ... & Poos, J. J. (2020). Electronic monitoring in fisheries: lessons from global experiences and future opportunities. *Fish and Fisheries, 21*(1), 162-189.

Vasilis, V., Cummins, E., and Frías, J. (2013). Editorial: Predictive Modelling of Quality and Safety Special Issue. *Food Control, 29*: 289.

Vazquez-Briseno, M., Hirata, F.I., Sanchez-Lopez, J.D., Jimenez-Garcia, E., Navarro-Cota, C., and Nieto-Hipolito, J.I. (2012). Using RFID/NFC and QR-Code in Mobile Phones to Link the Physical and the Digital World, IntechOpen, 2012. Doi: https://doi.org/10.5772/37447.

Verdouw, C., Tekinerdogan, B., Beulens, A., & Wolfert, S. (2021). Digital twins in smart farming. *Agricultural Systems*, *189*, 103046.

Vo S.A., Scanlan J. and Turner P. (2020). An application of Convolutional Neural Network to lobster grading in the Southern Rock Lobster supply chain. Food Control, Doi: https://doi.org/10.1016/j.foodcont.2020.107184.

Wang, F., Zang, Y., Wo, Q., Zou, C., Wang, N., Wang, X., & Li, D. (2013, March). Fish freshness rapid detection based on fish-eye image. In *PIAGENG 2013: Image Processing and Photonics for Agricultural Engineering* (Vol. 8761, pp. 52-56). SPIE.

Wang, J., Yue, H., Zenan Zhou, Z. (2017). An improved traceability system for food quality assurance and evaluation based on fuzzy classification and neural network, Food Control, 79: 363-370. Doi: https://doi.org/10.1016/j.foodcont.2017.04.013.

Wang, X., Li, F., Cai, Z., Liu, K., Li, J., Zhang, B., and He, J. (2018). Sensitive colorimetric assay for uric acid and glucose detection based on multilayer-modified paper with smartphone as signal readout, Anal. Bioanal. Chem. 410: 2647–2655

Wang, X., Luo, Y., Huang, K., and Cheng, N (2022). Biosensor for agriculture and food safety: Recent advances and future perspectives. Advanced Agrochem, 1(1): 3-6. Doi: https://doi.org/10.1016/j.aac.2022.08.002.

Waziry, S., Wardak, A.B., Rasheed, J., Shubair, R.M., Rajab, K., and Shaikh, A. (2023). Performance comparison of machine learning driven approaches for classification of complex noises in quick response code images. Heliyon, 9(4): e15108. Doi: https://doi.org/10.1016/j.heliyon.2023.e15108.

Whitt, C., Pearlman, J., Polagye, B., Caimi, F., Muller-Karger, F., Copping, A., ... & Khalsa, S. J. (2020). Future vision for autonomous ocean observations. Frontiers in Marine Science, 7, 697.

Xiang, Y., Sheng, J., Wang, L., Cai, Y., Meng, Y., & Cai, W. (2022). Research progresses on equipment technologies used in safety inspection, repair, and reinforcement for deepwater dams. Science China Technological Sciences, 65(5), 1059-1071.

Yan, B., Hu, D., & Shi, P. (2012). A traceable platform of aquatic foods supply chain based on RFID and EPC Internet of Things. *International Journal of RF Technologies*, *4*(1), 55-70.

Yang, L., Liu, Y., Yu, H., Fang, X., Song, L., Li, D. and Chen, Y. (2021). Computer vision models in intelligent aquaculture with emphasis on fish detection and behavior analysis: A review. Archives of Computational Methods in Engineering, 28, pp.2785-2816.

Yenket, R., Chambers IV, E. and Johnson, D.E. (2011) Statistical package clustering may not be best for grouping consumers to understand their most liked products. Journal of Sensory Studies 26, 209–225.

Zhang, Y., Wang, W., Yan, L., Glamuzina, B., & Zhang, X. (2019). Development and evaluation of an intelligent traceability system for waterless live fish transportation. *Food control*, *95*, 283-297.

Zhang, Z., Wang, S., Diao, Y., Zhang, J., Decheng, L.V. (2010). Fatty acid extracts from Lucilia sericata larvae promote murine cutaneous wound healing by angiogenic activity. Lipids Health Dis, 9:1–9.

Zhou, C., Xu, D., Lin, K., Sun, C. and Yang, X. (2018). Intelligent feeding control methods in aquaculture with an emphasis on fish: a review. Reviews in Aquaculture, 10(4), pp.975- 993.

Zhou, L., C. Zhang, F. Liu, Z. J. Qiu, and Y. He. (2019). Application of deep learning in food: A review. Comprehensive Reviews in Food Science and Food Safety 18 (6):1793–811. Doi: https://doi.org/10.1111/1541-4337.12492

Zhou, L., Zhang, C., Liu, F., Qiu, Z. and He, Y. (2019). Application of Deep Learning in Food: A Review. Comprehensive Reviews in Food Science and Food Safety, 18: 1793-1811. Doi: https://doi.org/10.1111/1541-4337.12492

Zhu, L., Spachos, P., Pensini, E.,& Plataniotis, K.N. (2021). Deep learning and machine vision for food processing: A survey. Current Research in Food Science 4:233–249

Zion, B., Shklyar, A., and Karplus, I. (1999). Sorting fish by computer vision. Computers and Electronics in Agriculture, 23(3): 175–187.

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***Volume:** 8, **Issue No:** 1, January-December 2024, **Pages:** 45-60*

Generative AI in Academic Research: A Descriptive Study on Awareness, Gender Usage, and Views among Pre-Service Teachers

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Received: 05.12.2023 Accepted: 20.04.2024 Online: 25.04.2024 Published: 31.12.2024

Research Article

Abstract

This study investigated the engagement of Pre-Service Teachers (PSTs) with Generative AI (GAI) tools in their research projects, focusing on their awareness, source of awareness, usage pattern based on gender, and views of GAI tools in academic research. We adopted a descriptive survey method to collect data from one hundred and four PSTs across five institutions in Ghana using a five-point Likert-type survey instrument, which included an open-ended question. The quantitative data were analyzed using means, frequencies, percentages, standard deviations, and an independent samples t-test. The findings revealed that PSTs are familiar with GAI tools, especially ChatGPT and Google Bard. They learned about these tools through personal searches, recommendations from friends, and social media platforms. The PSTs used these tools in writing all chapters of their research projects, with the Introduction Chapter being the most common area of application, followed by the Discussion and Findings Chapter, the Literature Review Chapter, Methodology, and Summary and Conclusion. We also identified a significant gender disparity in the use of GAI tools, with male PSTs exhibiting a higher frequency of use compared to their female counterparts. Nonetheless, both genders expressed a positive attitude towards GAI tools in academic research, noting among other benefits that these tools provided them with confidence and independence in their research writing. However, they also recognized inaccuracies in the information provided by GAI tools, which led to skepticism about relying solely on these tools for their research projects. Consequently, they expressed a preference for support from their research supervisors, highlighting the importance of a balanced approach that combines the use of GAI tools with human supervision in academic research. While we recommend the integrating of GAI tools in teacher education programs, we strongly suggest that such integration should be complemented with comprehensive guidance on how these tools can be effectively used by PSTs to conduct original and advanced research.

Keywords: *Generative AI, Research, Awareness, Use, Perspectives, Pre-service Teachers (PSTs), Gender*

Cite this paper (APA)

Nyaaba, M., Kyeremeh, P., Majialuwe, E.K., Owusu-Fordjour, C., Asebiga, E., A-ingkonge, B. (2024). Generative AI in Academic Research: A Descriptive Study on Awareness, Gender Usage, and Views among Pre-Service Teachers. Journal of AI. 8(1), 45-60. Doi: 10.61969/jai.1400867

1. INTRODUCTION

The journey to becoming a teacher in Ghana involves a critical rite of passage for Pre-service Teachers (PSTs), the completion of a research project in their final year (Armah, 2018; Hedges, 2002). This capstone project, a culmination of the research methodologies and pedagogical practices absorbed throughout their education, often takes the form of action research. Such projects are not merely academic exercises; they are extensions of the PSTs' field experiences, designed to address real classroom challenges with innovative solutions (Iddrisu et al. 2018). However, this process is not without its difficulties. Research writing has long been a daunting task for these students, often perceived as the most challenging aspect of their academic journey (Aydin & Karaarslan, 2023; Afful et al., 2022; Azila-Gbettor et al., 2015).

In recent years, the final year research project has been marred by a troubling trend of plagiarism (Aydin, 2023; Mosha & Laizer, 2021). A practice colloquially referred to as using 'grandfather' or 'grandmother' papers, where PSTs heavily rely on the work of their predecessors, has become a crutch due to a lack of confidence in their research writing abilities (Nketsiah et al., 2023; Armah, 2017). This trend points to a broader issue of inadequate research skills among PSTs, despite the guidance provided by their assigned supervisors (Yidaan, 2021).

The emergence of Generative Artificial Intelligence (GAI) such as ChatGPT is poised to revolutionize various sectors, including education (Zhai et al., 2023). GAI, characterized by its human-like cognitive functions across diverse tasks, offers significant potential to revolutionize teaching, learning, and research methodologies (Polat, 2023; Rahman & Watanobe, 2023). Yet, the conversation around GAI on teacher education has predominantly featured the voices of teacher educators (Nyaaba, M., & Zhai.2024; Akanzire, 2023), leaving a gap in understanding its impact from the perspectives of PSTs on how they are using it in their academic activities such as their nightmare activity; research (Zhai et al., 2023).

This study, therefore, seeks to bridge this gap by exploring PSTs' engagement with GAI toolsto assess their awareness, the channels through which they have encountered these tools, and their views on GAI tools in academic research. Goswami and Dutta (2015) literature review on gender differences in technology usage reveals that gender does play a crucial role in the acceptance of new technology in certain contexts, though not universally. In this study, we also aimed to determine whether GAI tools are embraced equally by PSTs of both genders. Based on these objectives we derived the following hypotheses:

Hypothesis

Based on the objectives of the study, the following hypothesis were formulated:

> ***H_O:** There is no statistically significant difference between male and female student teachers' use of AI tools for projects.*
>
> ***H_a:** There is a statistically significant difference between male and female student teachers' use of AI tools for projects*

2. THEORETICAL UNDERPINNING

2.1 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) was adopted for this study. This theory explores how technological acceptance is influenced by factors like performance expectations, effort expectations, social impact, and enabling circumstances. According to this theoretical paradigm, a user's behavioral purpose determines how they use technology. This theory is anchored on four essential constructs, including performance expectancy, effort expectancy, social influence, and facilitating conditions which directly impact the anticipated likelihood of technology adoption.

Venkatesh et al. (2003) hypothesized that an individual's performance expectancy is a measure of how much they think that using the system will enable them to improve their performance at work. The level of ease with which the system is to be used is known as effort expectancy. An individual's perception of how strongly influential others feel they should use the new method describes the social influence. An individual's level of confidence that organizations and technical infrastructure exist to facilitate the system's use describes their level of belief in facilitating conditions. Age, gender, experience, and readiness to use act as moderators of the effects of these variables (Venkatesh et al., 2003). We therefore aimed to use these variables to examine PSTs' awareness of, use of, and opinions of GAI, such as ChatGPT, GPT-4, etc (Haman & Školník, 2023). The aspects that influence student acceptability, choice of GAI tool, and ease of use of these technologies were explored in this study.

2.2 Potential Benefits of GAI

Globally, the 21st century has experienced a rapidly changing landscape in educational practices due to advancement in technology such as artificial intelligence (Petersen, 2021). The emergence of generative artificial intelligence gives more credence to this educational transformation. World Economic Forum (2023) conceptualizes GAI as the algorithms that generate new outputs based on the data they have been trained on. World Economic Forum (2023) further posits that unlike traditional AI systems that are designed to recognize patterns and make predictions, generative AI has the potential to create new content in the form of images, text, audio, and more to aid teaching and learning outcomes.

In addition, Alshater (2022) and Terwiesch (2023) hold that the use of GAI has gained impetus in many fields of professions including education, journalism, economics, engineering, medicine and finance etc. Chen et al. (2020) noted that GAI has the potential to influence personal tutoring. For them, GAI can be used to provide personalized tutoring and feedback to students based on their individual learning needs and progress. A study by Chen et al. (2020) demonstrated that a conversational agent based on a generative model (ChatGPT) could provide personalized math tutoring to students, resulting in improved learning outcomes. Their study further emphasized that the conversational agent could provide explanations tailored to students' misconceptions and could adapt to their level of understanding.

Similarly, Johnson et al. (2016), posit that GAI could help in language translation in educational practice. That is, GAI can be used to translate educational materials into different languages, making them more accessible to a wider audience. For Johnson et al. (2016), generative model trained on a dataset of bilingual sentence pairs could accurately translate between languages, achieving state-of-the-art results on several translation benchmarks. They hold further that; generative models were able to understand the meaning of sentences in one language and to generate accurate translations in another language to aid learning outcomes. Recent study by Zhai et al (2024) on Generative AI and ChatGPT revealed that these tools can outperform human on cognitive demand task in science.

2.3 Factors that affect Students' Use of Technology

Research has established that several factors affect students' use of technology. For example, Popescu and Badea's (2020) findings indicated students spend countless hours immersed in popular technologies such as social media channels, application software and internet browsers. For Popescu and Badea (2020), technology is becoming a more prominent form of learning among students globally. However, their efficacy in using technology is limited to identifiable factors.

Blankstein (2022) pointed out that one of the factors that affect student s use of technology is access. According to Blankstein (2022), students from lower socio-economic backgrounds may have limited access to technology and the internet. This can significantly affect their ability to use technology for educational purposes. Galindo-Dominguez (2021) also identified digital literacy and competence of students as factors that affect students' usage of technology. For Galindo-Dominguez (2021), students' digital literacy and competence with technology are fundamental factors influencing their ability to use it effectively to promote positive learning outcomes.

Galindo-Dominguez (2021) further posited that the pedagogical approaches adopted by schools play a critical role in students' usage of technology. They emphasize that the integration of technology into the curriculum is an important benchmark to influence students' ability to use technology. They concluded that in a meaningful pedagogically sound approach, students are more likely to engage with it. Montiel et al., (2020) linked students' effectiveness in the use of technology to cultural and societal factors. Montiel et al. (2020) further opined that cultural norms and values can influence students' perception of technology in education. For them, some cultures are more receptive to technology than others.

2.4 Gender and Digital Tools

The discourse on the digital gender divide presents a complex interplay of women's access to and use of digital tools, mostly in developing countries. Martin (2011) empirically challenges the notion of females being technophobic by demonstrating that, when controlling for employment, education, and income, women are more engaged users of digital tools than men. This suggests that the digital gender divide is less about an inherent reluctance among women to embrace technology and more about the structural barriers that limit their access and usage (Martin, 2011). Supporting this perspective, Goswami and Dutta (2015) highlight that gender plays a significant role in the intention to use technology in certain contexts, pointing towards a nuanced understanding of technology adoption that transcends simplistic binary distinctions (Goswami & Dutta, 2015). In addition, Liu's (2019) study finds no statistically significant gender difference in the knowledge of social media concepts among students in higher education yet notes gender-specific preferences in the use of social media tools, with males favoring resource-based platforms and females preferring relationship-building platforms (Liu, 2019). In the context of eHealth applications, Prinzellner and Simon (2022) emphasize the importance of gender-sensitive language and the display of medical information to ensure inclusivity for users with low eHealth literacy, underscoring the need for a gender-balanced approach in technology design and implementation (Prinzellner & Simon, 2022).

Khalid and Khan's (2022) findings recognize the broader digital divide exacerbated by the COVID-19 pandemic, indicating the urgency of addressing these gender disparities to achieve universal digital access and mitigate the adverse impacts on economic growth and social inclusion. These studies recognize gender differences in digital technology usage, and understanding these differences requires further investigation. GAI, as an emerging technology, could bridge the digital divide and promote gender equality in technology use in developing countries or elsewhere.

3. METHOD

We adopted a descriptive study using closed and open-ended survey. This approach helped us to systematically gather data from our target population, pre-service teachers (PSTs) in relation to our research objectives (Mishra & Alok, 2022; Pandey and Pandey., 2021). Specifically, this method aided us in obtaining the awareness, use, and views of PSTs about GAI (Borenstein & Howard, 2021; Creswell & Plano Clark, 2011).

4. PARTICIPANTS

The study involved one hundred and four (104) PSTs from five teacher education institutions in Ghana. The institutions included two research universities and three colleges of education. The PSTs were in the final years of their program and had either completed their research or were in the process of conducting their final research projects. PSTs in the colleges of education typically engage in research projects mostly in their final year of the program during or after their field teaching practice. The final research projects at teacher education institutions in Ghana involve students conducting an action research project after their teaching internship.

For convenience, the participants of this study were supervisees under the supervision of some of the authors in the various institutions during the research study. With this sampling technique, the participants were well-informed about the study and the survey before responding to them. However, we acknowledge the disadvantage of using convenience sampling as it is prone to biases (e.g., Donaldson et al., 2019; Ucar & Canpolat, 2019) and so the survey was opened to other interested members in the various institutions that met our criteria. The study involved 20 females representing 19.2% and 84 males representing 80.8%. Most participants fell within the age bracket of 21-25 years, representing 44.1%, followed by 26-30 years representing 29.9% and above 30 representing 25%, while the remaining fell within the age bracket of 16-20 years, with the least percentage of 1.0%. All of them were final-year students who had completed their research projects or were conducting their final research projects.

5. DATA COLLECTION

The main instrument for this study was a five-point Likert-type questionnaire with an open-ended item. We adapted An et al.'s (2023) Scale on "Modeling English teachers' behavioral intention to use artificial intelligence in middle schools" and Rowland's (2023) model on "stages of writing + possible model to guide thinking about the human-AI collaboration-collusion writing continuum" to construct the questionnaire items. Van Katwijk et al.'s (2023) findings on "Most Important Learning Outcomes of Pre-Service Teacher Research" also supported us in modifying the survey questions. Since some of the items were substantially changed from the adapted scales, we employed the help of two educational professors to check the content validity of the scale and advise us on any necessary revisions. The revised scale consisting of 15 items was used for this study. It solicited the demographic information of the participants, their familiarity with GAI tools, the areas of their research where they employ GAI assistance, and their general views of GAI in their research. These questions included closed-ended questions along with an optional open-ended question to gather the views of PSTs about GAI use in research at colleges of education.

We used Google Forms for data collection. Due to the physical distance between participating institutions and our participants, Google Forms provided the most convenient approach for us. Participants were asked for consent first and were given the option to participate or not. They were assured of anonymity, confidentiality, and the voluntary nature of their participation. The Google Forms survey link was shared with participants via their WhatsApp platforms, allowing them to respond at their convenience within two weeks.

6. DATA ANALYSIS

The data collected from closed-ended questions was analyzed using descriptive statistics. This involved calculating means, frequencies, standard deviations, and percentages to determine the distribution. The survey utilized a five-point Likert-type scale for PSTs' views on GAI, with weightings indicating Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), and Strongly Disagree (1). Negative items were rephrased; a mean score (M) above 3.0 indicates a positive view towards GAI, while a mean score below 3.0 indicates a negative view. Another five-point Likert-type scale was used to gauge PSTs' use of GAI with response options ranging from Never (1) to Very Often (5). The descriptive statistics of how frequently student teachers utilize GAI tools for projects were analyzed, and an independent samples t-test was conducted to examine potential differences between male and female PSTs in their use pattern. Open-ended questions were thematically analyzed to support the findings, initially coded into emerging themes. Quotations in the study were anonymized using pseudonyms for the participants' privacy.

7. FINDINGS

Addressing the first research question concerning pre-service teachers' (PSTs) familiarity with GAI tools, we explored their awareness and familiarity with these tools. Figure 1 illustrates the GAI tools that PSTs are aware of or familiar with. It shows that they are aware of numerous GAI tools but are particularly familiar with ChatGPT, followed by Google Bard. Figure 2 demonstrates how PSTs became acquainted with these tools, with a significant portion (39.2%) indicating they discovered the tools through personal research or readings. About 27.5% reported discovering the tools through their friends' recommendations, while 17.6% mentioned learning about them in their formal academic settings. A smaller percentage (12.7%) indicated they found out about GAI tools through social media platforms like WhatsApp, with the remaining learning about them through online courses or tutorials.

Figure 3 provides insight into how often PSTs employ GAI tools in their research projects. It was observed that 48.1% of PSTs sometimes use GAI tools in their research, while 13.9% use them often or very often. Notably, only a minority (14.8%) has never utilized GAI tools in their research projects. For those who have used these tools, they found them beneficial across all chapters or sections of their research projects. The chapters or sections where these tools were most helpful to them included introductory chapters, literature review chapters, findings and discussions, and data analysis and methodology chapters (as illustrated in Figure 4). This indicates that GAI tools are being employed by PSTs in all aspects of their research projects.

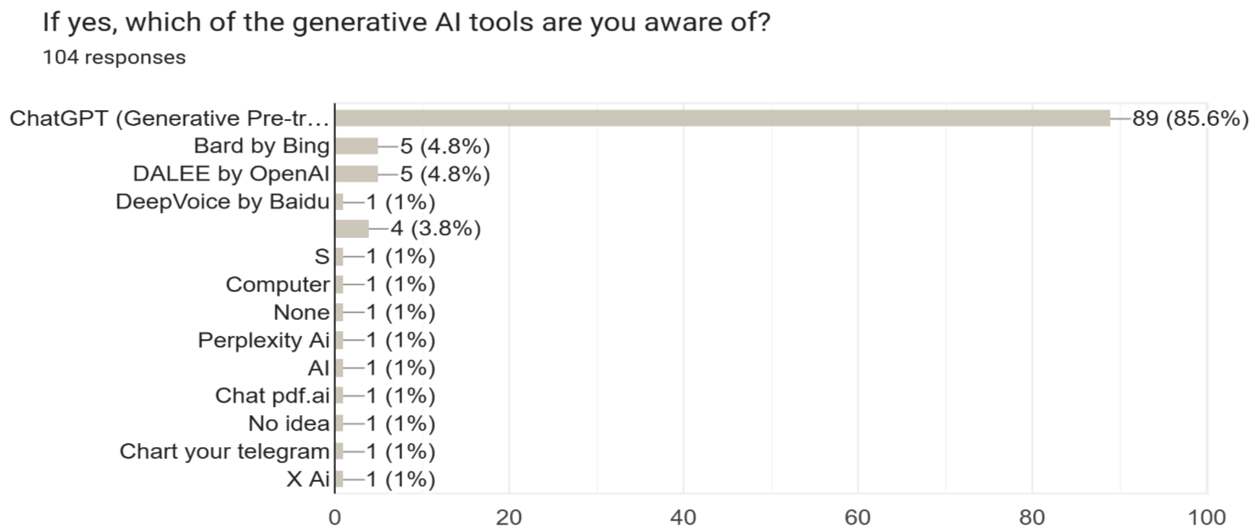

Figure. 1. PST Awareness of GAI tools

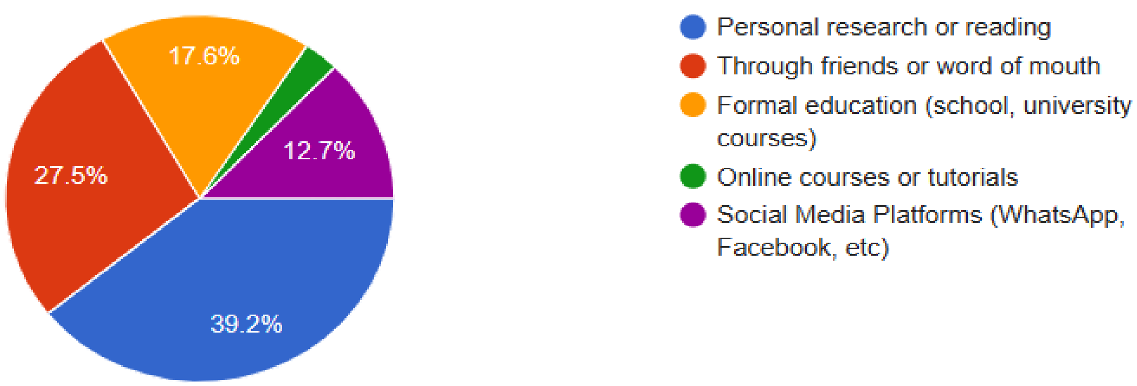

Figure. 2. How PSTs Got to Know about GAI tools

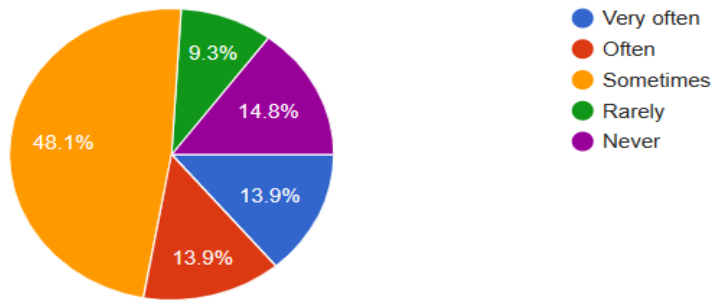

Figure. 3: Frequency of GAI Usage in Research Project by PST

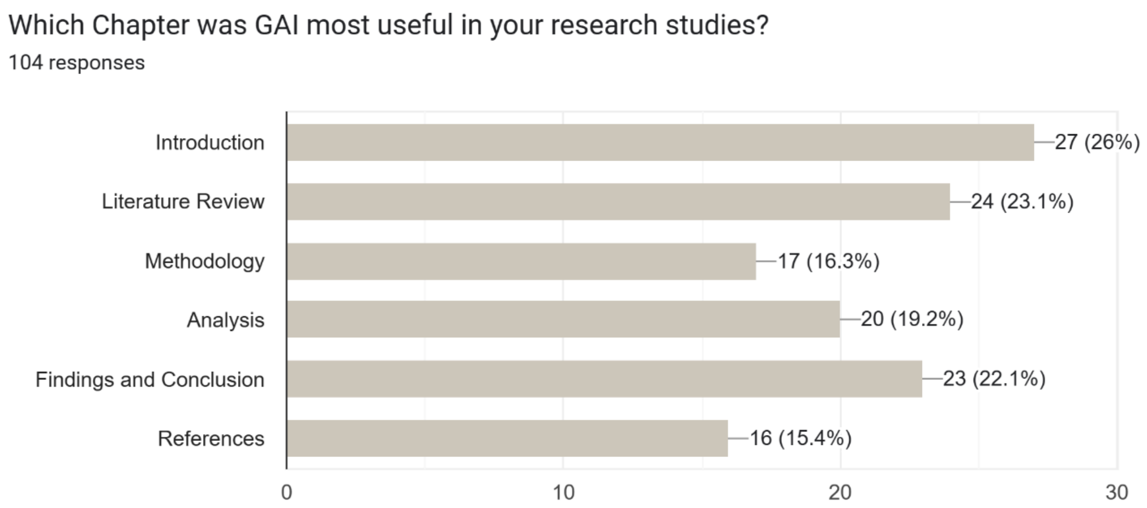

Figure. 4. *The Chapters of Research that PSTs Use GAI in Writing* igure 4). This indicates that GAI tools are being employed by PSTs in all aspects of their research projects.

7.1 Hypothesis

This hypothesis looked for a difference between two groups: male and female PSTs use of AI tools. Table 1 and Table 2 illustrate variability between the male and female PSTs use of AI tools for their research projects.

Table 1. Group Statistics of How Often PSTs Use GAI tools for projects

	Gender	N	Mean	Std. Deviation	Std. Error Mean
Use	Female	20	2.85	1.04	0.23
	Male	84	3.07	1.21	0.13

From the observation of the group means in Table 1, it could be indicated that male student teachers (*M* = 3.07, *SD* = 1.21) often use AI tools than their female counterparts (*M* = 2.85, *SD* = 1.04).

Table 2. Independent Samples T-Test of how often PSTs use GAI tools for research projects

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Diff.	Std. Error Diff.	95% Confidence Interval of the Difference	
									Lower	Upper
Use	Equal variances assumed	0.46	0.50	-0.75	102	0.45	-0.22	0.29	-0.80	0.36

An independent samples t-test was conducted to examine whether there was a significant difference between male and female student teachers on how often they use GAI tools for projects. The t-test results in Table 2, revealed a statistically significant difference between male and female PSTs' use of AI tools for their research projects (t = -0.75, df = 102, $p < 0.05$). Hence, we reject the null hypothesis and conclude that there was a statistically significant difference between male and female PSTs' use of AI tools for their research projects.

7.2 PSTs Views and Experiences of GAI

Table 3. Student teachers' views and experiences with the use of AI tools for research projects

Items	Group	N	Mean	Std. Dev.	t	Sig. value
GAI has the potential to positively impact students' assessments like research project	Female Male	20 84	3.45 3.54	1.23 1.04	-0.32	0.75
GAI has the potential to negatively impact students' assessments like research project	Female Male	20 84	2.45 2.96	1.0 1.12	-1.88	0.06
GAI helped me understand various complex parts of my research study better than I knew before	Female Male	20 84	3.65 3.58	0.88 1.04	0.26	0.79
With the help of GAI, the literature review section was an easy task for me	Female Male	20 84	3.55 3.39	0.76 1.01	0.65	0.51
I didn't require much assistance from anyone for my research once I started using GAI	Female Male	20 84	3.25 3.02	1.07 1.21	0.77	0.45
I felt more confident conducting my research with GAI's assistance	Female Male	20 84	3.45 3.50	0.83 0.94	-0.22	0.83
GAI tools explained things better than my supervisor had the time to do for me	Female Male	20 84	2.65 2.87	1.04 1.10	-0.81	0.42
It is expensive using GAI tools for research	Female Male	20 84	2.90 2.86	1.02 1.08	0.16	0.87
The information provided by GAI tools was not accurate enough, so I never trusted them	Female Male	20 84	2.40 2.82	0.88 0.98	-1.75	0.08
I suggest GAI tools be incorporated into our research courses, and students be taught how to use them in their research studies	Female Male	20 84	3.35 3.67	1.18 1.09	-1.15	0.25
Most students might not conduct original research due to GAI	Female Male	20 84	3.05 3.48	1.23 1.18	-1.44	0.15

Source: Field Data (2023)

From Table 3, it could be observed that both female and male PSTs had positive/ favourable views and experiences with the use of GAI tools for research projects. For example, female PST agreed to the statement 'GAI helped me understand various complex parts of my research study better than I knew before' with a mean and standard deviation of 3.65 and 0.88 respectively. On the other hand, male student teachers agreed to the same statement with a mean of 3.58 and a standard deviation of 1.04. The difference between the groups was found not to be statistically significant (t = 0.26, $p > 0.05$). The finding indicated that both female and male students have confidence in conducting their research with the assistance of GAI tools (female: M=3.45, SD=0.83), (male: M=3.50, SD=0.94). The t-value and significance level for this item indicate that the difference between genders is not statistically significant (t = -0.22, p > 0.05). Female PSTs reported a moderate level of independence in conducting their research with the help of GAI tools (female: M=3.25, SD=1.07), while male students reported a slightly lower level of independence (male: M=3.02, SD=1.21). The t-value and significance level for this item suggest that the difference between the genders is not statistically significant ($t = 0.77$, $p > 0.05$). A consensus emerged from the thematic analysis that GAI has the potential to enhance academic research and assist PSTs in completing their assignments, as indicated by one male participant (M1). This view was further echoed by a female participant (F1), who highlighted the efficiency and speed with which learning can be achieved using GAI. Participant M2 advocated for the utility of GAI in personal studies as a means of accessing supplementary information.

M1: AI is helping most of us not only with research work but assignments.

F1: GAI makes learning much easier and faster.

M2: It is good when doing your personal studies, it provides additional information for you.

However, the PSTs were somewhat neutral with a tendency towards disagreement on the effectiveness of GAI tools in explanation compared to their supervisors. Female students felt that GAI tools explained things somewhat better than their supervisors had time to do, with a slight disagreement on average (female: M=2.65, SD=1.04). Male PSTs were slightly more neutral with reservations about the ability of GAI tools to explain things (male: M=2.87, SD=1.10). The t-value and significance level indicate that the observed difference in opinions between genders is not statistically significant ($t = -0.81$, $p > 0.05$). Female PSTs expressed concerns about the accuracy of GAI tools, indicating a general mistrust (female: M=2.40, SD=0.88), and male students also showed some level of mistrust but to a lesser extent (male: M=2.82, SD=0.98). The t-value and significance level suggest that the difference in trust might be approaching significance, warranting further investigation ($t = -1.75$, $p < 0.10$). Furthermore, there was concern among female students that the use of GAI might lead to a lack of originality in research (female: M=3.05, SD=1.23), and male PSTs also shared this concern, though they were slightly more optimistic (male: M=3.48, SD=1.18). The t-value and significance level indicate that the difference between genders is not statistically significant, but it is approaching significance ($t = -1.44$, $p < 0.15$). The PSTs further expressed the view that GAI responses are not always accurate. They expressed concern that reliance on GAI could diminish students' critical thinking and logical reasoning skills. They warned that GAI could potentially ruin them if not used carefully, as they tend to prefer easier solutions and are reluctant to exert effort.

F2: It's good application software for students but its solutions are not accurate sometimes.

M3: We are becoming susceptible and vulnerable to GAI thereby alleviating our critical thinking and logical reasoning as students.

M4: In fact, GAI will spoil the youth, if care is not taken because they always want cheaper things. They don't want to stress themselves.

F3: AI can give students too much unverified information, which sometimes is wrong. Believing everything AI says can confuse them instead of helping them learn. So, AI might be doing more harm than good in schools.

M5: So sometimes is not everything you understand.

Nonetheless, the perception of the expense associated with using GAI tools for research was slightly disagreeable among female students (female: M=2.90, SD=1.02), and the same among male students (male: M=2.86, SD=1.08). The statistical test suggests no significant difference between the groups ($t = 0.16$, $p > 0.05$). Female students were positive about the suggestion to incorporate GAI tools into research courses (female: M=3.35, SD=1.18), and male students were even more favorable towards this suggestion (male: M=3.67, SD=1.09). The difference between genders was not statistically significant ($t = -1.15$, $p > 0.05$). The PSTs expressed uncertainty about any undiscovered methods of using GAI more effectively for their studies but expressed openness to welcoming such methods if they exist.

F5: If there's any other way of using GAI effectively, I don't know and have not yet discovered but if there's any other way to use GAI more effectively to help our studies, we welcome it.

8. DISCUSSION

The study showed that GAI tools have seen a significant uptick in awareness and usage among PSTs in Ghana, with most of them indicating awareness of OpenAI's ChatGPT, Google Bard, and DALLE (Strzelecki, 2023). This recognition of GAI tools among the PSTs reflects and confirms GAI tools' broader visibility and their applicability in educational settings (Strzelecki, 2023; Mansor et al., 2022). The prominence of ChatGPT in our findings is not surprising as it can be described as emerging GAI tools that bring much attention to AI in 2022. ChatGPT has capabilities in natural language processing and generation beneficial for research purposes (Seshadri & Swamy, 2023). The findings align with Venkatesh et al. (2003) UTAUT, which posits that awareness and adoption of new technologies follow a pattern influenced by social systems and communication channels (Kaminski, 2011). However, the few PSTs (14.8%) who have never used GAI tools in their research projects may reflect a gap in access or skills necessary to leverage these technologies effectively (Alam, 2021; Leese, 2010).

The pathways through which PSTs have come to learn about GAI tools are equally fascinating, with personal research or readings being the most common method, suggesting proactive engagement with technological advancements among the PSTs (Tapalova & Zhiyenbayeva, 2022). This also supports Venkatesh et al. (2003) UTAUT element on ease of use. This is an indication that GAI tools might not necessarily require any sophisticated skills in using them. The finding indicating that teacher education institutions play a lesser role in PSTs' awareness may point to a lag in the integration of emerging technologies in teacher education curricula or that the institutions are still in doubt about how to incorporate these tools in their curricula (Hwang & Shin, 2019; Nyaaba & Zhai, 2024; Kouame, 2012). The findings further highlight the role of digital media in PSTs' learning, emphasizing its growing influence as a medium for professional development and knowledge acquisition (Devi et al., 2022; Limna et al., 2022).

The disparity in the frequency of GAI tool usage between male PSTs and female counterparts confirms the wider discourse on gender differences in technology adoption and usage, suggesting that males are more inclined towards technology (Lee et al., 2022; Acilar & Sæbø, 2023). However, this finding appeared different from Martin's (2011) finding that females are more engaged users of digital tools than males (Ahn et al., 2022; Antonio & Tuffley, 2014). It tends to support Khalid and Khan's (2022) findings which recognized the broader digital divide between females indicating the urgency of addressing these gender disparities to achieve universal digital access and mitigate the adverse impacts on economic growth and social inclusion (Prinzellner & Simon, 2022). Addressing these disparities is crucial for ensuring equitable access to AI educational resources and for preparing all PSTs to effectively use AI in their future teaching practices, thereby fostering an inclusive digital literacy that is imperative for the 21st-century educator (Lee et al., 2022; Ahn et al., 2022).

The recognition and relevance of human supervisors expressed by the PSTs show a critical aspect of educational technology integration in teacher education programs (Molenaar, 2022). While GAI has been lauded for its potential to personalize learning and research by the PSTs (Seshadri & Swamy, 2023), the mentorship offered by human supervisors appears to remain indispensable (Kim et al., 2022; Zhai, 2023). This finding is consistent with Ausat et al.'s (2023) finding that emphasizes the irreplaceable value of human interaction in the development of critical thinking and research skills.

The PSTs' skepticism in the accuracy of information provided by GAI tools could be reflective of general hesitation to accept AI outputs as echoed in recent studies (Rahman & Watanobe, 2023; Nazaretsky et al., 2022). This aligns with the concerns raised about the impact of GAI on the originality of research as well

(Choung et al., 2023; Mosha & Laizer, 2021). This suggests a need for educational strategies that emphasize original thought and critical engagement with GAI-generated content, ensuring that the use of such tools enhances rather than diminishes the quality and originality of student research (Haider & Sundin, 2022).

The integration of GAI tools in research projects within teacher education programs is widely accepted among pre-service teachers (PSTs). This reflects the growing trend towards recognizing the benefits and acceptance of GAI in education, as highlighted by Çalışkan et al. (2022) and Escotet (2023). Moreover, the positive impact of GAI is further underscored by reports from both female and male student teachers, who have experienced increased confidence in conducting research with the support of these tools (Rahman & Watanobe, 2023; Tapalova & Zhiyenbayeva, 2022). PSTs also believe that GAI has the potential to significantly enhance assessments and advocate for its incorporation into their research courses. This consensus on the potential of GAI encourages educators to prepare students for technologically advanced research and practice (Sok & Heng, 2023; Zhai et al., 2023).

9. CONCLUSION

In this study, we explored PSTs engagement with GAI tools in their research projects: their awareness, how they learned about these tools, their usage based on gender and their overall views on GAI tools in academic research. The findings revealed that PSTs have a high level of familiarity with GAI tools, especially OpenAI's ChatGPT and Google Bard. The PSTs mostly learned about these tools through personal searches, from friends and social media platforms. These tools were primarily used in all chapters of their research projects, with the Introduction Chapter being the most common area of application, followed by the Discussion and Findings Chapter, the Literature Review Chapter, Methodology, etc.

There was also a significant difference in the use of GAI tools between male and female PSTs, with male PSTs exhibiting a higher frequency of use compared to their female counterparts. Despite this usage disparity, both genders agreed on the benefits of GAI, recognizing the confidence and independence it provided them in their research writing. However, they also acknowledged the potential inaccuracies in information that GAI tools could offer, leading to skepticism regarding relying entirely on them for support in their research projects. Consequently, they expressed a preference for support from their research supervisors, emphasizing the need for a balanced approach that combines GAI tools with human supervision in their research projects. Based on these findings, we recommend the integration of GAI tools into teacher education programs, accompanied by guidance on how they can be used effectively by PSTs to conduct original and advanced research.

10. LIMITATIONS OF THE STUDY AND IMPLICATIONS FOR FUTURE STUDIES

It is worth acknowledging the study's limitations as we interpret the findings. Though we appreciate the fact that convenience sampling, a non-probabilistic sampling can be used in quantitative research, it is prone to the challenges of representativeness thereby reducing the statistical power of the convenience sample. Also, this study was an online descriptive survey with a low response rate despite the efforts to get more PSTs involved in the survey. These suggest that the outcomes of the study cannot be generalized to the study's population. Considering this, future studies that employ probabilistic sampling techniques to give a fair representation of the study's population would be much needed.

ACKNOWLEDGEMENTS

N/A

FUNDING

No funding

AUTHORS` CONTRIBUTIONS

All authors contributed equally to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

All relevant data are within the paper and its Supporting Information.

REFERENCES

Acilar, A., & Sæbø, Ø. (2023). Towards understanding the gender digital divide: A systematic literature review. Global knowledge, memory and communication, 72(3), 233-249. https://doi.org/10.1108/GKMC-09-2021-0147

Afful, J. B. A., Ngula, R. S., Twumasi, R., Tetteh, G., & Mensah, F. (2022). Supervisors' perceptions of postgraduate students' thesis literature review writing in a Ghanaian university. Advances in Social Sciences Research Journal, 9(1), 267-289. http://dx.doi.org/10.14738/assrj.91.11120

Akanzire, B.N., Nyaaba, M. & Nabang, M. (2023). Perceptions and Preparedness: Exploring Teacher Educators' Views on Integrating Generative AI in Colleges of Education, Ghana (November 3, 2023). Available at SSRN: http://dx.doi.org/10.2139/ssrn.4628153

Alam, A. (2021, November). Possibilities and apprehensions in the landscape of artificial intelligence in education. In 2021 International Conference on Computational Intelligence and Computing Applications (ICCICA) (pp. 1-8). IEEE. https://doi.org/10.1109/ICCICA52458.2021.9697272

Alshater, M. (2022). Exploring the role of artificial intelligence in enhancing academic performance: A case study of ChatGPT. Available at SSRN: https://ssrn.com/abstract=4312358 or http://dx.doi.org/10.2139/ssrn.4312358

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. Education and Information Technologies, 28(5), 5187-5208. https://doi.org/10.1007/s10639-022-11286-z

Antonio, A., & Tuffley, D. (2014). The gender digital divide in developing countries. Future Internet, 6(4), 673-687. https://doi.org/10.3390/fi6040673

Armah, P. H. (2018). T-TEL Curriculum Reform Study.

Armah, P. H. (2017). Teacher education and professional learning in Ghana. The Institute for Education Studies (IFEST): Accra. Recuperado a partir de https://www.academia.edu/34610560/TEACHER_EDUCATION_AND_PROFESSIONAL_LEARNING_IN_GHANA.

Ausat, A. M. A., Massang, B., Efendi, M., Nofirman, N., & Riady, Y. (2023). Can chat GPT replace the role of the teacher in the classroom: A fundamental analysis. Journal on Education, 5(4), 16100-16106.

Aydin, Ö. (2023). Google Bard generated literature review: metaverse. Journal of AI, 7(1), 1-14.

Aydın, Ö., Karaarslan, E. (2022). OpenAI ChatGPT Generated Literature Review: Digital Twin in Healthcare. In

Ö. Aydın (Ed.), Emerging Computer Technologies 2 (pp. 22-31). İzmir Akademi Dernegi.

Aydin, Ö., & Karaarslan, E. (2023). Is ChatGPT leading generative AI? What is beyond expectations?. Academic Platform Journal of Engineering and Smart Systems, 11(3), 118-134.

Azila-Gbettor, E. M., Mensah, C., & Kwodjo Avorgah, S. M. (2015). Challenges of writing dissertations: Perceptual differences between students and supervisors in a Ghanaian polytechnic. International Journal of Education and Practice, 3(4), 182-198. DOI: 10.18488/journal.61/2015.3.4/61.4.182.198

Chan, C. K. Y., & Hu, W. (2023). Students' Voices on Generative AI: Perceptions, Benefits, and Challenges in Higher Education. arXiv preprint arXiv:2305.00290.

Chen, Y., Chen, Y., & Heffernan, N. (2020). Personalized math tutoring with a conversational agent. arXiv preprint arXiv:2012.12121.

Chen X, Zou D, Xie H, Cheng G, Liu C. Two decades of artificial intelligence in education. Educ Technol Soc. 2022;25(1):28-47.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human–Computer Interaction, 39(9), 1727-1739.

Devi, J. S., Sreedhar, M. B., Arulprakash, P., Kazi, K., & Radhakrishnan, R. (2022). A path towards child-centric Artificial Intelligence based Education. International Journal of Early Childhood, 14(3), 9915-9922.

Donaldson, J. L., Gallimore, L., & Swanson, D. (2019). National survey of extension 4-H professionals' perceptions of professional development factors. Journal of extensions, 57(1), 1-14. https://doi.org/10.34068/joe.57.01.27

Escotet, M. Á. (2023). The optimistic future of Artificial Intelligence in higher education. Prospects, 1-10.

Fisher, A., Exley, K., & Ciobanu, D. (2014). Using technology to support learning and teaching. London: Routledge. https://doi.org/10.4324/9780203074497

Goswami, A., & Dutta, S.(2015). Gender Differences in Technology Usage—A Literature Review. Open Journal of Business and Management, 04(1):51-59. doi: 10.4236/OJBM.2016.41006

Haman, M., & Školník, M. (2023). Using ChatGPT to conduct a literature review. Accountability in Research, 1-3. https://doi.org/10.1080/08989621.2023.2185514

Haider, J., & Sundin, O. (2022). Information literacy challenges in digital culture: conflicting engagements of trust and doubt. Information, communication & society, 25(8), 1176-1191.

Harris, C. J. (2016) The effective integration of technology into schools' curriculum. Distance Learning, (2), 27.

Hedges, J. (2002). The importance of posting and interaction with the education bureaucracy in becoming a teacher in Ghana. International journal of educational development, 22(3-4), 353-366.

Johnson, M., Schuster, M., Le, Q., Krikun, M., Wu, Y., Chen, Z., ... & Chen, Y. (2016). Google's neural machine translation system: Bridging the gap between human and machine translation.

Hwang, S., & Shin, J. (2019). Extending technological trajectories to latest technological changes by overcoming time lags. Technological Forecasting and Social Change, 143, 142-153.

Iddrisu, D. S., Bashiru, M., & Zakaria, A. (2018). The Impact of Transforming Teacher Education And Learning (T-Tel) In Enhancing Tamale College Of Education Tutors'competencies. Social Science Learning Education Journal, 3(4), 34-37.

Kaminski, J. (2011). Diffusion of innovation theory. Canadian Journal of Nursing Informatics, 6(2), 1-6.

Kanabar, V. (2023, June). An Empirical Study of Student Perceptions When Using ChatGPT in Academic Assignments. In International Conference on Computer Science and Education in Computer Science (pp. 385-398). Springer Nature Switzerland.

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2023). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. Review of Managerial Science, 1-32.

Khalid, U., & Khan, A. (2022). Understanding the Digital Divide in the Contemporary Digital World. Global Political Review, VII(IV):7-14. http://dx.doi.org/10.31703/gpr.2022(vii-iv).02

Kouame, B. J. (2012). Improving education with emerging technologies. Trafford Publishing.Latif E, Mai G, Nyaaba M, et al. Artificial General Intelligence (AGI) for Education. arXiv Prepr arXiv230412479. Published online 2023.

Lee, M. S., Guo, L. N., & Nambudiri, V. E. (2022). Towards gender equity in artificial intelligence and machine learning applications in dermatology. Journal of the American Medical Informatics Association, 29(2), 400-403.

Leese, M. (2010). Bridging the gap: Supporting student transitions into higher education. Journal of further and Higher Education, 34(2), 239-251.

Limna, P., Jakwatanatham, S., Siripipattanakul, S., Kaewpuang, P., & Sriboonruang, P. (2022). A review of artificial intelligence (AI) in education during the digital era. Advance Knowledge for Executives, 1(1), 1-9.

Liu, Y. (2019). Gender difference in perception and use of social media tools. In Gender and diversity: Concepts, methodologies, tools, and applications (pp. 1845-1858). IGI Global. http://dx.doi.org/10.4018/978-1-5225-6912-1.ch097

Mansor, N. A., Hamid, Y., Anwar, I. S. K., Isa, N. S. M., & Abdullah, M. Q. (2022). The awareness and knowledge on artificial intelligence among accountancy students. Int. J. Acad. Res. Bus. Soc. Sci, 12, 1629-1640.

Martin, H. (2011). Digital Gender Divide or Technologically Empowered Women in Developing Countries? A Typical Case of Lies, Damned Lies, and Statistics. Social Science Research Network,

Molenaar, I. (2022). The concept of hybrid human-AI regulation: Exemplifying how to support young learners' self-regulated learning. Computers and Education: Artificial Intelligence, 3, 100070.

Mosha, G., & Laizer, J. (2021). Undergraduate Students' Understanding of Plagiarism. Zambia Journal Of Library & Information Science (ZAJLIS), ISSN: 2708-2695, 5(1), 21-33. Retrieved from http://41.63.0.109/index.php/journal/article/view/47.

Nazaretsky, T., Cukurova, M., & Alexandron, G. (2022, March). An instrument for measuring teachers' trust in AI-based educational technology. In LAK22: 12th international learning analytics and knowledge conference (pp. 56-66). https://doi.org/10.1145/3506860.3506866

Nketsiah, I., Imoro, O., & Barfi, K. A. (2023). Postgraduate students' perception of plagiarism, awareness, and use of Turnitin text-matching software. Accountability in Research, 1-17.

Nyaaba, M., & Zhai, X. (2024). Generative AI professional development needs for teacher educators. Journal of AI, 8(1), 1-13. https://doi.org/10.61969/jai.1385915

Pandey, P., & Pandey, M. M. (2021). Research methodology tools and techniques. Bridge Center.

Petersen, J. (2021). Innovative assessment practices. Retrieved on 26 October 2023 from https://www.google.com/url?Innovative-Assessment-Whitepaper1.pdf&usg=AOvVaw1fWCFBStSE4BqDTXT5_Voi.

Polat, H. (2023). Transforming Education with Artificial Intelligence: Shaping the Path Forward. ISTES BOOKS, 3-20. Retrieved from https://book.istes.org/index.php/ib/article/view/26

Prinzellner, Y., & Simon, A. (2022). Secondary End-Users' Perspectives on Gender Differences in the Use of eHealth Applications in Older Adults. International Conference on Gender Research, 5(1): pp193-199. doi: 10.34190/icgr.5.1.149

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. Applied Sciences, 13(9), 5783.

Rashid, T., & Asghar, H. M. (2016). Full length article: Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. Computers in Human Behavior, 63604-612. http://dx.doi.org/1016/j.chb.2016.05.084.

Rowland, D. R. (2023). Two frameworks to guide discussions around levels of acceptable use of generative AI in student academic research and writing. Journal of Academic Language and Learning, 17(1), T31-T69. https://orcid.org/0000-0001-7854-476X

Sok, S., & Heng, K. (2023). ChatGPT for education and research: A review of benefits and risks. Available at SSRN 4378735.

Song, Y., & Kapur, M. (2017). How to Flip the Classroom – "Productive Failure or Traditional Flipped Classroom" Pedagogical Design? Educational Technology & Society, 20 (1), 292–305.

Tapalova, O., & Zhiyenbayeva, N. (2022). Artificial Intelligence in Education: AIEd for Personalised Learning Pathways. Electronic Journal of e-Learning, 20(5), 639-653.

Terwiesch, C. (2023). Would chat GPT3 get a Wharton MBA." A prediction based on its performance in the operations management course. Retrieved from https://mackinstitute.wharton.upenn.edu/wp-content/uploads/2023/01/Christian-Terwiesch-Chat-GTP.pdf

Simhadri, N., & Swamy, T. N. V. R. (2023). Awareness among teaching on AI and ML applications based on fuzzy in education sector at USA. Soft Computing, 1-9.

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. Interactive Learning Environments, 1-14.

Uçar, M. B., & Canpolat, E. (2019). Modelling Preservice Science Teachers' Environment-Friendly Behaviours. Australian Journal of Teacher Education, 44(2). https://doi.org/10.14221/ajte.2018v44n2.1

Van Katwijk, L., Jansen, E., & Van Veen, K. (2023). Pre-service teacher research: A way to future-proof teachers?. European Journal of Teacher Education, 46(3), 435-455.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425-478. https://doi.org/10.1080/02619768.2021.1928070.

Yidaan, P. Y. N. (2021). Experiences of Students Pursuing a Doctoral Program: Voices From a Private University in Ghana. Pan-African Journal of Education and Social Sciences, 2(2). Retrieved from https://journals.aua.ke/pajes/article/view/112

Zhai, X. (2023). ChatGPT and AI: The Game Changer for Education (March 15, 2023). Available at SSRN: https://ssrn.com/abstract=4389098

Zhai, X., Nyaaba, M., & Ma, W. (2024). Can generative AI and ChatGPT outperform humans on cognitive-demanding problem-solving tasks in science?. Science & Education, 1-22.https://doi.org/10.1007/s11191-024-00496-1

Journal of AI

Volume: 8, **Issue No:** 1, January-December 2024, **Pages:** 61-82

Cybersecurity in The Health Sector in The Reality of Artificial Intelligence, And Information Security Conceptually

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Received: 07.04.2024 *Accepted: 01.07.2024* *Online: 06.07.2024* *Published: 31.12.2024*

Review Article

Abstract

Healthcare service delivery, especially in terms of safeguarding personal data, requires ensuring the confidentiality of information. In this regard, establishing cybersecurity systems that ensure information security is highly necessary. The rapid advancement of technologies increases the likelihood of cyberattacks, and particularly, AI-supported threats can cause serious harm in service delivery. In the current era, attacks not only come from humans but also from AI tools, posing threats to information se curity. Considering that AI technology is expected to further advance in the future, it's evident that this technology could become even more menacing. This is especially pertinent to the healthcare sector. Cyberattacks can lead to breaches in healthcare system data and disrupt service delivery to the extent of paralyzing the healthcare system. Our study, which includes case examples, is a compilation-type research. Within the scope of our research, searches were conducted using the keywords healthcare sector, information security, and cybersecurity on Google Scholar and Web of Science. The most current topic headings intersecting information security with the healthcare sector were examined based on the articles found on the subject. Our study evaluates the following topics in order: information and cyber security concepts, cyber threats and public services, electronic health records and security, major cyber-attacks in the health sector, why healthcare data is attractive for cyberattacks, information security in the artificial intelligence era, and information security policies for Türkiye and other countries in the world. Ransomware holds a significant place among cyberattacks. Therefore, users within the healthcare system are advised to pay particular atte ntion to this issue. Attacks generally occur via email, starting with enticing the user into a cyber-threat through email. Artificial intelligence can also be used to get rid of such spam mails. Hence, it is strongly recommended that users in the healthcare sector undergo training on this matter. These trainings should be conducted regularly and continuously, with the institution's IT center offering an institutional approach in this regard.

Keywords: *Cyber attacks in health sector, health information, security policies, health sector, artificial intelligence, cyber threats, cyber security*

Cite this paper (APA)

Damar, M., Özen, A., Yılmaz, A. (2024). Cybersecurity in The Health Sector in The Reality of Artificial Intelligence, And Information Security Conceptuall. Journal of AI. 8(1), 61-82. Doi: 10.61969/jai.1466340

1. INTRODUCTION

In today's world, the widespread adoption of information technologies and their integration into various fields are changing the delivery styles of traditional public services and facilitating human life by providing practical opportunities (Cordella & Iannacci, 2010; Rosacker & Olson, 2008; Lindgren & Jansson, 2013). The rapid transformation in information and communication technologies significantly impacts the healthcare sector, as in all other domains (Iyanna et al., 2022; Herrmann et al., 2018). With advancements in information technologies, significant changes and transformations have occurred in the healthcare sector (Yılmaz et al., 2021; Iyanna et al., 2022). Moreover, with the influx of large amounts of data from many different systems, the role of data analytics in health informatics has increased in recent years (Galetsi et al., 2020; Jee & Kim, 2013). This has also led to an increased interest in building analytical, data-driven models based on machine learning in health informatics (Ravì et al., 2016). This has further increased the importance of concepts such as machine learning or artificial intelligence for the healthcare sector (Schwalbe & Wahl, 2020; Ali et al., 2023). Particularly, new technologies and methods enable improvements in treatment processes, communication with patients, processes related to health maintenance, and managerial processes of healthcare institutions (Ali et al., 2023). The rapidly evolving broadband internet and mobile connectivity solutions have virtualized processes such as appointments, follow-ups, and reporting in healthcare services, while cloud computing has overcome physical constraints for storing such data and similar information (Akalın & Veranyurt, 2020). However, developments in information and communication technologies are leading to an increasing number of attacks on individuals' privacy and data confidentiality.

In the context of data security, the security of Electronic Health Records (EHRs) is the first thing that comes to mind (Berber et al., 2009). Electronic health records consist of data used to automate a doctor's workflow (Öğütçü et al., 2011). According to Häyrinen et al. (2008), the concept of EHR encompasses a wide range of information systems, from the compilation of patient data from single departments to the long-term aggregation of patient records. In EHR systems, various data elements are documented, including daily schedules, medication administration records, physical assessments, admission nurse notes, nursing care plans, referrals, current complaints (such as symptoms), past medical histories, lifestyles, physical examinations, diagnoses, tests, procedures, treatments, medication therapies, discharge summaries, histories, logs, issues, findings, and vaccinations. In the future, it will be necessary to incorporate different types of standardized tools, electronic consultations, and nursing documentation systems into EHR systems.

All organizations must take active steps to protect the security and integrity of information resources, and this strategy is nowhere as critical as in hospitals, where issues of information accuracy and patient confidentiality are paramount (Stahl et al., 2012). The possibility of storing health information in electronic format increases concerns about patient privacy and data security. Therefore, any endeavor to implement computerized health service information systems must ensure the adequate protection of patient information privacy and integrity (Smith & Eloff, 1999). Naturally, the primary objective is to protect and securely store the privacy information of patients (Stahl et al., 2012). To ensure information and data security in healthcare services, the establishment of information security systems prevents unauthorized access to personal data, thus safeguarding data privacy. Like all data in electronic environments, security measures must be taken to mitigate risks that threaten personal health information (Par & Soysal, 2011).

The widespread use of Artificial Intelligence (AI) technologies in the healthcare sector makes information security and cyber security issues even more important. While the digitization of health data and the use of artificial intelligence algorithms enable more effective and efficient delivery of healthcare services, it also creates important responsibilities for the security of this data. AI can influence the field of information security both positively and negatively. Advanced threat detection and prevention, the evolution of malware and attacks, personal data privacy and security, AI-based social engineering, and AI-supported security solutions can be cited as positive examples. AI can be utilized to provide more effective and rapid responses in the field of information security. For instance, AI-based security systems that automatically detect and prevent attacks can be developed. However, in malicious applications, the opposite can occur. In conclusion, AI presents both new opportunities and new risks in the field of information security. Therefore, it is important for security experts to understand both the positive and negative aspects of AI technologies and to ensure information security by taking appropriate security measures.

Security is a pivotal concern in healthcare information systems, as most aspects of security become crucial and even critically important when processing healthcare information (Gritzalis, 1998). Previously, a data breach, a missing paper document, or a stolen computer would affect tens or thousands of patients, but today, as this content is digitized and accessible over many networks, a cyberattack has the capacity to harm millions of patients (Ganai et al., 2022). Although many studies have been conducted on the use of AI in the healthcare sector, it has been observed that there is a lack of research on information security and cybersecurity focusing on the healthcare sector in the context of AI. Limited research has focused on examining information security risks in the healthcare sector (Appari & Johnson, 2010). In this context our study evaluates the following topics in order: information and cyber security concepts, cyber threats and public services, electronic health records and security, major cyber-attacks in the health sector, why healthcare data is attractive for cyberattacks, information security in the artificial intelligence era, and information security policies for Türkiye and other countries in the world. The concept of information security within the healthcare sector has been comprehensively evaluated, as evident from the topic headings. As detailed in the methodology section, sources obtained through Google Scholar and Web of Science have been examined through abstracts and titles, followed by full-text readings, to discuss various approaches to information security in the healthcare sector. This topic has been thoroughly debated and evaluated within the framework of the literature. Our research aims to contribute to the literature by providing a comprehensive literature review in this regard.

2. METHODOLOGY

In our study, data security has been centered on from the perspective of the healthcare sector, and the issue of data privacy has been evaluated in detail. In this context, assessments have been made on how healthcare data can be protected using findings obtained through national and international literature research. This study addresses information security and cybersecurity issues in the health sector using literature review and conceptual analysis methods. Information from the relevant literature will be used to build a conceptual framework and evaluate current policy practices. Indeed, searches were conducted through Google Scholar and Web of Science using keywords such as healthcare sector, information security, artificial intelligence, and cybersecurity. The articles obtained through the relevant keywords on Google Scholar were accessed one by one and the full text of the articles deemed appropriate were accessed through the title and abstract. By reading the full texts, the titles that would contribute to our article were added to the article content and discussed. In the Web of Science search, a topic search was performed. The main search words used were “ts=(("health sector" and "artificial intelligence") or ("health informatics" and "artificial intelligence") or ("cyber security" and "artificial intelligence") or ("information security" and "artificial intelligence") or ("cyber security" and "health informatics"))”. The studies with the highest number of citations in the obtained data set were primarily focused on. Articles and other internet sources obtained within the scope of the topic are being evaluated in the research regarding the connection between information security and the healthcare sector. Our research is of a review type. As mentioned above, the titles and abstracts of the articles obtained from the search with the keywords on the relevant subject on Google Scholar and Web of Science were first accessed, and the full texts of the relevant articles were accessed. By reading within the subject, the issue of information security in the health sector in the reality of artificial intelligence was conceptually revealed with the subjective evaluation of the authors.

3. INFORMATION SECURITY AND CYBER SECURITY IN CONCEPTUAL TERMS

3.1 Information Security Concept

Information security is the set of measures taken to ensure the confidentiality, integrity and accessibility of information. This concept aims to control access to information and protect against malicious attacks with the use of information technologies. Information can exist in various forms. It can be written or printed on paper, stored electronically, shown in films, transmitted via electronic devices or mail, or spoken in conversations. Regardless of the type of information, it should always be appropriately protected. At this point, information security, conceptually expressed, involves implementing a set of controls including policies, procedures, processes, software and hardware functions, and organizational structures to protect information (ISO/IEC, 2005).

According to the definition provided by the National Security Telecommunications and Information Systems Security Committee, information security is the protection of all hardware and software systems that handle, transmit, store, or use information. Technically speaking, information security aims to safeguard the accuracy, availability, confidentiality, authenticity, integrity, and ownership of information. Of course, there are many threats to information security. These include, in order, unauthorized access to information, destruction of information, and alteration of information (Huang et al., 2010). In addition, Shchavinsky et al. (2023) also addressed the issue of the need for continuous development and improvement of the practical skills of cybersecurity professionals due to the continuous growth of threats to information and cybersecurity for organizations, businesses, society and government.

Within the historical development of information security, the McCumber Information Security Model stands out as a prominent framework for evaluating information security policies comprehensively. Since its inception in 1991, this model has remained valid and has served as the basis for subsequent models, addressing various dimensions of information security. The model encompasses three main elements: the characteristic, status, and security measures of information, inclusive of confidentiality, integrity, and availability. Confidentiality, the first element, refers to ensuring that information is accessible only to those authorized to access it. Integrity, the second element, pertains to maintaining the original state of information resources in any electronic environment or information center, ensuring that they remain unaltered by unauthorized individuals, thus preserving the integrity of the information. The third element, Availability, refers to accessibility and continuity, allowing users to access the information they need whenever they need it, provided they have the necessary authorization (Henkoğlu et al., 2013).

Since the implementation of health information systems, particularly considering the highly sensitive nature of their data, their security has been regarded as a significant concern. The possibility of storing health information electronically exacerbates concerns regarding patient privacy and data security (Smith & Eloff, 1999). Security, privacy, and access to personal data represent a critical area for the healthcare sector. Given that it serves a wide and large community, its importance in terms of information security is further heightened. It is perceived as a domain necessitating strategic management (Chiuchisan et al., 2017). Information security risks may include personnel leaving data assets unattended on-site, personnel losing a data asset, personnel sharing passwords to access patient data, personnel sending emails containing personal patient data to the wrong recipient, and unauthorized disclosure of data. Additionally, outsourcing data storage and processing processes to external servers for certain server services poses a significant information security risk. Emerging technologies such as cloud computing or RFID are prominent in this regard (Van Deursen et al., 2013). Gritzalis (1998) has viewed standardization as a significant tool for addressing the security gap in the healthcare sector.

3.2 Cyber Security Concept

In recent years, the terminology used to discuss the security aspects of digital devices and information has undergone significant changes. At the beginning of the century, the terms commonly used in this context were computer security, information technology security, or information security (Schatz et al., 2017). Indeed, in recent years, the term "cyber security" has been increasingly used in place of the previously mentioned terms. Of course, the widespread integration of the internet into various aspects of our lives has greatly influenced this shift.

Cybersecurity is an increasingly serious and complex issue at all levels (Caruson et al., 2012), requiring attention from all government levels (Chodakowska et al., 2022). In fact, cybersecurity is of paramount importance for maintaining business integrity, ensuring data security, and protecting cyber assets (Abdallah et al., 2021). Today, cybersecurity is considered one of the most significant socio-technological challenges faced by public institutions, crucial not only for the smooth functioning of government and local administrations but also for private companies using e-government services and the residents of relevant local administrations (Chodakowska et al., 2022).

Cyber security is the process of protecting computer systems, networks and other digital infrastructures from malicious attacks, data breaches and other threats. Cyber security is the set of measures that ensure the implementation of information security in the digital environment.

In a narrow sense, cybersecurity is the practice of protecting data and information resources. In a broader sense, it concerns the protection of digital content, information technology networks, business devices, and content transfer over the internet. The concept of cybersecurity emerged in the United States in the 1970s and spread worldwide by the late 1990s (Cavelty, 2010). Cybersecurity involves processes and technologies created to combat threats in cyberspace, primarily unauthorized access by cybercriminals, hackers, and terrorist hackers, aiming to protect computers, computer software, hardware, data, and networks from security vulnerabilities (Goutam, 2015). Cybersecurity is a term commonly used to protect against malware and hacker attacks (Bay, 2016). Indeed, cybersecurity and cyberspace are distinct concepts but closely related. Cybersecurity pertains to protecting internet-connected systems from cyberattacks, while cyberspace is the virtual realm used to store, share, and exchange information through the relevant physical infrastructure and network-connected systems. The place where internet activities occur is abstract and entirely virtual, serving as a medium for communication and information exchange. Therefore, cyberspace is a structure without boundaries that can expand rapidly without any political or physical constraints (Goutam, 2015).

The healthcare sector implements electronic health records for information sharing among relevant healthcare providers, updates them, establishes intranets, and also utilizes the internet to disseminate health-related information. Consequently, healthcare information systems become an integral part of all aspects of healthcare delivery (Smith & Eloff, 1999). Cybersecurity has various expectations in the health and medical sectors. Today's medical fields employ digital communication and documentation tools. It is imperative to ensure the highest possible protection of such documents. Healthcare systems possess sensitive information, necessitating the protection of these sensitive data from cyber threats (Pawar et al., 2024).

The healthcare sector is one of the most critical sectors for the Internet of Things (IoT). With the implementation of the Internet of Things in the healthcare sector, individuals have had to make efforts to develop platforms at both the hardware and software levels. Every sector is moving towards IoT integration, and this can create security vulnerabilities and threats in the healthcare sector. Ganai et al. (2022) statet that IoT is widely used in the healthcare sector to enhance service security. Similarly, IoT devices can also pose a security vulnerability and are increasingly prevalent in the healthcare sector, as in all sectors. The presence of an IoT device in a healthcare environment can provide an access point for illegal hacking attacks, thus creating a security loophole. The European legal framework applicable to IoT technologies in the healthcare sector is not clearly defined. Only two regulations, namely the General Data Protection Regulation (GDPR) and the Medical Device Regulation (MDR), are available (Casarosa, 2024).

3.2.1 Cyber Threats

Cyber threats are malicious activities that aim to damage computer systems and networks, steal data, and cause service interruptions. Cyber threats can occur through malware, ransomware, information leaks and other attack techniques (Aydın, 2020). Cybersecurity aims to protect against major cyber threats through internet-connected systems, including software, hardware, and data. These threats can be outlined as follows (Seemma et al., 2018; Goutam, 2015):

- *Cyber Terrorism*: These are attacks carried out by terrorist groups utilizing advancements in information technology to target computer systems, networks, and telecommunication infrastructures with the aim of advancing their political agendas.
- *Cyber Warfare*: This involves nation-states utilizing information technologies to infiltrate another nation's networks and cause harm. Cyber warfare is carried out by well-trained hackers with expertise in computer networks. In this type of cyber attack, networks are not shut down but are manipulated in ways that jeopardize the security of valuable data, disrupt infrastructure services, hinder trade, and sever communication channels.
- *Cyber Espionage*: This is the use of information technologies to obtain confidential information without the consent of individuals. It is the most commonly employed method for gaining economic, strategic, and military advantages. It is typically carried out using malicious software and hacking techniques.
- *Cyber Stalking*: This is a frequently conducted action aimed at forcibly intruding into individuals' personal lives to create anxiety, distress, and fear. Cyber stalkers take advantage of the anonymity of the internet to continue their activities without being detected. Cyber stalking, as it leads to psychological harassment of individuals, is also referred to as "psychological harassment" or "psychological terrorism."
- *Intellectual Property Theft*: This involves the theft of intellectual property, which includes new research, innovations, methods, formulas, or models with economic value, through cyberattacks.
- *Salami Attack*: In this type of cyberattack, cybercriminals or attackers steal small amounts of money from various bank accounts to accumulate substantial sums.
- *Identity Theft*: This is a type of cyberattack where an individual's important information, such as address, name, or credit card number, is stolen, allowing the perpetrator to impersonate that individual and commit crimes in their name.
- *Distributed Denial of Service (DDoS) Attack*: This involves suspending or temporarily interrupting services, rendering servers, computers, or network resources unavailable to authorized users.

3.2.2 Risks Posed by Cyber Threats to Public Services

As public services become increasingly digitalized, the risks of cyber attacks also escalate, potentially leading to serious disruptions in public services (Preis & Susskind, 2022). Indeed, the number of reported cybersecurity incidents and cyber attacks targeting government agencies continues to rise each year (Chałubińska-Jentkiewicz, 2021). However, despite cybersecurity being one of the most significant challenges facing governments today, visibility and public awareness remain limited (Bruijn & Janssen, 2017).

Cyber threats in public services can threaten the security and well-being of society. In particular, critical infrastructures such as healthcare can become the target of cyber-attacks and cause serious damage. Public institutions are responsible for ensuring the security of information technology networks and systems (Chałubińska-Jentkiewicz, 2021). The following factors should not be overlooked to ensure information security (ISO/IEC, 2005):

a) Establishing a security policy that reflects the organization's objectives,
b) Achieving a corporate approach to implementing, monitoring, improving, and sustaining information security,
c) Ensuring support and commitment from management at all levels,
d) Understanding information security requirements, risk management, and risk assessment,
e) Effectively conveying information security to all employees, managers, and other relevant parties to raise awareness,
f) Distributing guides on information security standards and policies,
g) Allocating funds to information security management activities,
h) Increasing awareness of information security through appropriate education and training,
i) Establishing an effective and efficient incident management process for information security.

4. ELECTRONIC HEALTH RECORDS AND HEALTH DATA

Electronic health records (EHRs) and health data form an important part of digitalization in the healthcare sector. EHRs digitally store patients' medical histories, diagnoses, treatments and other health information. Health data refers to all the information contained in these records and is an important source for the training and implementation of AI algorithms.

According to the definition provided by the Healthcare Information and Management Systems Society (HIMSS), EHRs are longitudinal electronic records of patient health information generated by one or more encounters in any care delivery setting. These records include the patient's gender, developmental notes, issues, treatments, vital signs, medical history, immunizations, laboratory data, and radiology reports. Electronic health records automate and streamline the doctor's workflow, making it more efficient (Öğütçü et al., 2011).

In private or public healthcare institutions, information about patients' medical histories, test results, diagnoses, treatments, and their durations are stored in digital format (Dülger, 2015). Access to patients' past diagnoses and treatments enables physicians to make accurate diagnoses and perform interventions more quickly and with less risk. As expressed in healthcare research, the accessibility of patient information provides significant benefits (Küzeci, 2019). Personal health data recorded in the system are shared among different institutions, allowing multiple individuals to access patient information (Yılmaz et al., 2021).

Electronic health record systems contain health data classified as sensitive information, encompassing individuals' most private details. When digitized, these data become useful for analysis and visualization, thereby creating new ways to provide better insights into a patient's condition and potential for improved decision-making. The digitization of healthcare services can be defined in four stages (Gopal et al., 2019):

- First Stage: At this stage, patient data is still recorded in paper-based format. This significantly limits the useful analytics of the information and restricts the efficient use of resources.

- Second Stage: In the second stage, the utilization of data begins. However, despite the acceleration of digitization in healthcare data, paper-based record-keeping still largely exists. Therefore, at this stage, opportunities for researching and analyzing the information are limited.
- Third Stage: The third stage sees full implementation of digitization. In this regard, organizations make healthcare services smarter by implementing analytics, next-generation data generation, Artificial Intelligence (AI), Machine Learning (ML) technologies, along with new service models aimed at improving business performance.
- Fourth Stage: At this stage, the healthcare system adopts a value-based healthcare approach rather than a fee-for-service or per capita payment approach, focusing on the value of healthcare services rather than the quantity.

The establishment of a rich health data foundation and achieving digital transformation in healthcare services are made possible through the use of advanced technologies such as analytics, portability, wearability, cloud computing, Machine Learning (ML), Internet of Things (IoT), and Artificial Intelligence (AI). For instance, the utilization of wearable compact devices that provide information to users via physical input or voice commands and assist in user interaction enables a continuous flow of data regarding individuals' physiology and kinesiology. As a result, self-monitoring of health conditions such as hypertension and stress becomes feasible, aiding in their prevention (Iqbal et al., 2016).

Another digital application is mobile health services. Mobile health (mHealth) involves the use of mobile devices to collect real-time health data from patients, with the collected data being stored and maintained on internet-connected network servers. Various heterogeneous groups such as hospitals and health insurance companies can access this data. These data are utilized by doctors to monitor, diagnose, and treat patients' conditions. With the integration of mobile health devices into the patient's environment, health abnormalities can be monitored simultaneously (Almotiri et al., 2016).

Cloud-based systems also stand out in digital applications. In areas where digital infrastructure is insufficient, cloud computing is a proven low-cost method that offers interoperability and scalability. Cloud-based platforms transmit data to cloud-based servers when the internet is disrupted, storing the data. This allows providers not only to monitor patients' conditions but also facilitates data sharing among providers. Cloud-based systems, especially those operable on phones, assist healthcare professionals in moni toring patients' conditions, providing them with an effective roadmap for decision-making, and streamlining workflow (Perednia et al., 1995).

Thanks to the digital health applications mentioned above, health data is continuously increasing. Indeed, health data accounts for nearly 30% of the total data volume worldwide. For each patient, thousands of files and data fields describing their health status are collected. A single patient generates about 80 megabytes of health data by utilizing electronic health record data. The largest sources of data used for diagnosis are images, proteomic information, and omics data (such as full genome sequence data). Developments in the Internet of Things, mobile technology, and sensors enable additional diagnostic informati on from connected medical devices and interpretation of Patient-Reported Outcomes from smartphones (Gopal et al., 2019).

Health data can be used for analyses that describe patients' characteristics. Analyzing rich data enables more diversified segmentation. For example, populations at high risk of future health issues (e.g., diabetes or cardiovascular events) can be identified (Gellerstedt, 2016).

4.1 Information Security in Healthcare in the Era of Artificial Intelligence

In today's world, information security has evolved from the mainframe era to the complex internet environment. Security issues now require a more coordinated and focused effort from national and international communities, governments, and the private sector. Therefore, it is critically important to continue strengthening technologies to overcome new challenges in information security (Dlamini, 2009).

Artificial intelligence refers to the simulation of human intelligence in machines. AI is revolutionizing healthcare services and becoming a transformative force (Mukherjee et al., 2022). Artificial intelligence plays an important role in the healthcare sector in improving healthcare services and diagnosing and treating diseases. Khan et al. (2023) stated that artificial intelligence has the potential to make significant progress towards the goal of making healthcare services more personalized, predictive, preventive, and interactive. Artificial intelligence can be utilized for diagnosis, drug development, personalized treatment, gene editing, disease prediction, and many other purposes. It aids in improving healthcare services by benefiting medical professionals, hospitals, and patients (Chikhaoui et al., 2022). Alugubelli (2016) stated that the rise of artificial intelligence has brought about a positive change in the sector by providing accurate data-driven decisions. In the healthcare sector, data obtained from large systems can be used for the early detection of chronic diseases, including cancer, diabetes, and cardiovascular diseases. However, the security of health data obtained through AI applications is a serious concern. Therefore, information security policies and practices are gaining importance in the healthcare sector in the era of AI. Machine learning has also had a significant impact in the healthcare sector alongside artificial intelligence. Machine learning is described as a technique used in the healthcare system to assist medical practitioners in patient care and clinical data management (Khan et al.,2023).

Deep learning, a technique based on artificial neural networks, has emerged in recent years as a powerful tool for machine learning. Deep learning also holds great promise for reshaping the future of artificial intelligence. Rapid advances in computational power, fast data storage and parallel processing capabilities have also contributed to a faster adoption of AI technology, with capabilities such as high-level features for predictive power and automatic optimization from input data (Ravì et al., 2016).

In the current era, attacks against information security can be carried out not only by humans but also by artificial intelligence tools. Moreover, considering that artificial intelligence technology is expected to advance even further in the future, it is evident that this technology could become even more threatening. Of course, this situation is even more relevant to the healthcare sector. The following are the types of impacts that may occur due to the misuse of healthcare data by artificial intelligence:

- *Privacy Violations*: Healthcare data contains personal and sensitive information. Artificial intelligence algorithms may encounter challenges in ensuring privacy while analyzing this data. This situation can lead to unauthorized access to the data and its malicious use.
- *Discrimination and Bias*: Artificial intelligence systems can learn biases from the datasets or create new forms of discrimination. For example, inadequate representation of certain ethnic groups or genders in some healthcare datasets may result in AI models failing to make accurate diagnoses and providing incorrect treatment recommendations for these groups.
- *False Results and Misdiagnoses*: AI models may produce incorrect results based on the data, leading to misdiagnoses, unnecessary treatments, or potentially harmful interventions.
- *Misuse and Harassment*: Artificial intelligence has the potential to misuse healthcare data and harass individuals. For instance, malicious actors who leak or gain unauthorized access to this data can pose threats based on personal information or exploit personal data.
- *Security Vulnerabilities*: The security of artificial intelligence systems can be challenging. These systems may be targeted by malicious actors for data manipulation or injection of malicious software, among other attacks.

To overcome these risks, strict security protocols and legal regulations are necessary for the collection, storage, and analysis of healthcare data. Additionally, transparency and accountability are essential during the training and evaluation of artificial intelligence algorithms. It is also crucial to design and implement artificial intelligence systems in accordance with ethical and justice principles. In this way, the risk of misuse of healthcare data by artificial intelligence can be reduced or prevented.

4.2 Major Cyber Attacks in the Healthcare Industry Around the World

The healthcare industry worldwide has become a target for cyber attackers. Cyber-attacks on major hospitals and healthcare organizations have caused serious consequences such as leakage of patients' health information, service interruptions and ransom demands. The healthcare sector has become increasingly vulnerable to cyber-attacks in recent years. Here are some major cyber-attacks targeting the healthcare sector in history:

- Stuxnet Attack (2010): Stuxnet was a cyber-attack targeting Iran's nuclear program, but one of its targets was also the control systems of medical devices associated with nuclear facilities in Iran. This attack had the potential to take control of and disable medical devices, particularly targeting vulnerabilities in industrial control systems used by Siemens, aiming to cause serious damage to targeted facilities (ELFANET, 2024).
- Tricare (2011): In late 2011, Science Applications International Corporation (SAIC), the federal government's military healthcare provider, announced a data breach affecting approximately 4.9 million military clinic and hospital patients registered with TRICARE. The data was stolen from a SAIC employee's car, impacting active and retired military personnel as well as their families. While no financial data was involved, the exposed sensitive information included Social Security numbers, phone numbers, home addresses, and other personal data (Digital Guardian, 2024).
- Advocate Health Care Data Breach (2013): Advocate Health Care fell victim to a series of data breaches following the theft of four personal computers storing unencrypted medical information of 4.03 million patients. The failure to implement the most basic cybersecurity practice of data encryption was a blatant violation of data protection standards outlined in the Health Insurance Portability and Accountability Act. As a consequence of such a misstep, the relevant institution was fined $5.55 million to send a strong message to other healthcare entities about the consequences of such lapses in security (Upguard, 2024).
- Premera Blue Cross (2014): In 2014, Premera Blue Cross experienced a significant data breach that led to unauthorized access to sensitive personal and medical information of millions of individuals, potentially putting them at risk. Regarded as one of the largest healthcare data breaches in history, the breach began with the simple opening of an email by an employee. Premera remained unaware of the breach for eight months. The attack resulted in a $74 million loss and impacted data of 11 million patients (Arcticwolf, 2023).
- Banner Health (2016): In 2016, hackers used malware to breach the payment processing system of Banner Health's food and beverage outlets. Subsequently, they utilized the system as a gateway to Banner Health's network and eventually gained access to servers containing patient data. The cyberattack went unnoticed for almost a month. The stolen data included highly sensitive information such as Social Security numbers, service and request dates, health insurance details, and more. The attack resulted in a $6 million loss and impacted data of 3.7 million patients (Arcticwolf, 2023).
- WannaCry Attack (2017): WannaCry can be cited as an example of ransomware, a type of malicious

software used by cybercriminals to extort money. It was a large-scale ransomware attack that affected numerous organizations worldwide. The healthcare sector, including hospitals and healthcare institutions, was significantly impacted by the attack. Many hospitals and clinics had their systems locked, disrupting patient care and medical services. As a result, the company faced significant financial and reputational repercussions, including a hefty fine levied by the Department of Health and Human Services' Office for Civil Rights (OCR). Responsible for enforcing the Health Insurance Portability and Accountability Act's (HIPAA) implementation, the OCR found that Premera violated many provisions of the HIPAA Security Rule (Kaspersky, 2024).

- Ryuk Attacks (2018-present): Ryuk is a ransomware attributed to the cybercriminal group WIZARD SPIDER, which poses a threat to governments, universities, healthcare, manufacturing, and technology organizations. These attacks target hospitals and healthcare systems, posing serious consequences that endanger patient care and disrupt healthcare services (Trend Micro, 2024).
- American Medical Collection Agency (2019): The data breach of the American Medical Collection Agency (AMCA) raised significant concerns in the healthcare sector. In June 2019, it was revealed that the third-party billing and collection services provider AMCA had caused a major data breach jeopardizing the personal and financial information of millions of individuals. This breach had serious consequences for both patients and healthcare service providers. The compromised data included names, addresses, birth dates, social security numbers, and payment card information (Getoppos, 2024). With the potential exposure of this sensitive information to unauthorized parties, individuals faced risks of identity theft, fraud, and other malicious activities. Consequently, this sensitive incident resulted in significant reputational damage and financial loss for the company. The attack is estimated to have caused $21 million in damages and affected the data of 21 million patients (Arcticwolf, 2023).
- University of California, Los Angeles (UCLA) Health (2023): The 2023 ransomware attack on UCLA Health was a significant cybersecurity incident that occurred at the University of California in Los Angeles. Ransomware is a type of malicious software that encrypts the victim's files and demands ransom payment in exchange for the decryption key. The impact of the ransomware attack was felt across the university, affecting critical systems and databases of various departments and services, leading to disruptions (Getoppos, 2024). The attack is estimated to have caused $7.5 million in damages and affected the data of 4.5 million patients (Arcticwolf, 2023).

These cyber-attacks have highlighted the cybersecurity vulnerabilities in the healthcare sector and underscored the need for healthcare organizations to strengthen their cybersecurity. Particularly, addressing issues such as the privacy of patient data, security of medical devices, and continuity of healthcare systems is crucial. Hospitals may have numerous entry points that hackers can exploit. Outdated computer systems, weak passwords, unpatched or outdated software, and stolen accounts from old computers can all play a role in this vulnerability. It should be noted that cybercriminals exploit any security gap to infiltrate and harm the hospital's network, and the most effective way to overcome this is through the implementation of an effective corporate information security policy and ensuring its sustainability.

4.3 Why Healthcare and Health Data Are Attractive for Cyber Attacks

Health records are significant and vulnerable, leading hackers to frequently target these records during data breaches. The lack of standardized guidelines for the ethical use of artificial intelligence and machine learning in healthcare services exacerbates this situation (Khan et al., 2023). The healthcare sector provides access to large amounts of sensitive health data, making it valuable targets for cyber attackers. Health data includes personal diagnostic information, medical histories and other sensitive information, making it attractive for malicious uses. The healthcare sector provides access to large amounts of sensitive health data, making it valuable Hospitals, in particular, are susceptible to cyberattacks because disruptions in their operations can pose life-threatening risks to patients, making them more likely to pay ransoms demanded by hackers. Additionally, budget constraints often leave healthcare facilities with limited resources and outdated IT infrastructure, making them more vulnerable to cyber threats. Furthermore, the increasing use of connected IoT devices in healthcare introduces new attack vectors for hackers. Insecurely connected medical devices can serve as entry points for cybercriminals to exploit security vulnerabilities and launch cyberattacks (Getoppos, 2024).

The most effective way to address this is for healthcare institutions to implement a robust information security policy within their organizations. In this process, the active participation of all healthcare personnel is crucial and of paramount importance. In a sustainable security policy, the responsibility does not solely fall on the information technology department or units. Certainly, these units have a critical role in ensuring the effective implementation of the existing or newly formulated information security policy. However, all personnel throughout the healthcare institution are actively involved in the information security policy. There are various aspects that users need to be mindful of, from the use of emails to the usage of portable storage devices. Therefore, periodic training sessions, sustainable and well-planned information security policies, and ideally accreditation by an information security institution for ISO27001 or similar standards are also recommended.

5. INFORMATION SECURITY POLICY PRACTICES IN HEALTH

With the advancement of technology, strides taken in all these healthcare services have also increased some of the risks caused by technology. This has led to the commodification of rights and the multi-dimensional nature of the relationship between physicians and patients. In order to provide better healthcare services in this regard, providing access to individuals' health data requires careful protection of health-related data seen as sensitive personal information. Security measures against risks threatening personal health information have become mandatory. Personal health information encompasses all health information acquired from before a person's birth to after their death. The technologies have heightened the risks of integrity, confidentiality, and accessibility of health information, endangering its security. Due to the primacy of privacy in personal health data, measures have been taken to minimize risks (Öztürk et al., 2014).

For ensuring security in information technology and information systems, countries develop information security policies. An information security policy is considered an increasingly important document that encompasses a series of security measures. The policy serves as a guiding document about the tools used in information security management and the desired outcomes. Additionally, it outlines the organization's approach to managing information security (Stahl et al., 2012).

5.1 Health Information Security Policies in Some Countries

Different countries have developed various policies and guidelines on health information security. These policies include various measures to ensure the security and privacy of health data. The World Health Organization has further developed the Helsinki Declaration, originally published in 1964, to express ethical principles in medical research and provide guidance to all participants. According to this declaration, "The dignity, privacy, and confidentiality of research subjects must always be respected. Every effort should be made to protect the privacy and confidentiality of subjects, minimize the impact of research on their physical and mental integrity and personality, and respect their integrity and personality". Accordingly, in the United States, national standards were established with the Health Insurance Portability and Accountability Act (HIPAA) enacted in 1996 for the storage of individuals' medical data and other personal health information. This national standard aims to reduce the misuse of data in the healthcare sector and protect the confidential information of US citizens (Uysal & Yorulmaz, 2018).

In 1999, the Institute of Medicine (IOM) in the United States published a report titled "To Err is Human: Building a Safer System," emphasizing the importance of ensuring patient safety in the healthcare sector. The report recommended establishing a center for patient safety, creating a reporting system nationwide, developing patient safety programs, and setting performance standards. It highlighted that the existing healthcare delivery organization fails to provide effective, safe, and efficient healthcare delivery to patients. Therefore, it underscored the need for restructuring healthcare delivery approaches and organizational structures to align with new goals (Korkmaz, 2018).

Building on the recommendations of the IOM report, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) initiated accreditation services to healthcare organizations worldwide in collaboration with the Joint Commission International (JCI) to implement patient safety goals outside the United States. JCI annually publishes and revises the International Patient Safety Goals (IPSG) with the guidance of an expert group. The goals, initially published in 2007 and updated in 2014, include initiatives such as verifying patient identity, ensuring effective communication, and promoting safety in the use of high-alert medications (Korkmaz, 2018).

In the United Kingdom, the British Standard BS-7799, which was significantly revised in 1999, was implemented to address health information security. This standard is a two-part framework that establishes, regulates, and documents security controls to protect the accuracy, confidentiality, and accessibility of information assets. The first part of the initial version published in 1999 describes working principles for information security, while the second part focuses on planning information security management systems and certification for such systems (Gerçeker, 2012). Another British Standard for information security management systems in the UK is BS7799-3:2005, titled "Rules for Information Security Management System Risk Management." This standard was developed to promote the adoption of the standard in small, medium, or large organizations. Its content includes topics such as identifying, assessing, monitoring, and controlling risks (Vural & Sağıroğlu, 2008).

The European Union adopts a method based on identifying threats and risks when formulating information security policies. Following analyses, numerous threats related to technology are identified, and the established policies are enacted into law and implemented. During the preparation phase of information policies, the main risks and threats are classified under three main headings. These were categorized by Henkoğlu & Yılmaz (2013) as unauthorized access to and intrusion into information systems, system disruption, obstruction, alteration, or destruction of data, and finally identity theft and misuse of personal data. The Luxembourg Declaration on Patient Safety, published in 2005, made the following recommendations to European Union institutions to preserve the confidentiality of patient records (European Union, 2005):

- Ensuring free, full access to patients' personal health data and ensuring the accuracy of the data.
- Implementing risk management routines taking into account the benefits of confidential reporting systems for potential risks.
- Promoting the use of new technologies, such as electronic health records.
- Establishing national forums with participation from relevant stakeholders to discuss national activities and patient safety.
- Ensuring the safe use of new surgical techniques and medical technologies.
- Integrating integrated procedures into the ongoing education of healthcare professionals, including continuous learning, a culture of patient safety, and improvement.

5.2 Health Information Security Policies in Türkiye

In Türkiye, reforms in the healthcare sector aimed at establishing health information systems began in the 1990s and gained momentum in the 2000s. The establishment of the health information system was addressed in the health sector section of the Eighth Five-Year Development Plan covering the years 2001-2005, stating that "All levels of healthcare service delivery will be improved in terms of human resources, infrastructure, management, and technology, and a health information system will be established." Additionally, the plan emphasized the need for establishing information infrastructure and setting policies in the public sector in line with the new role of the public in the information age, ensuring that information held by the public sector is disseminated to the public in accordance with principles of transparency and openness. In alignment with these principles, an action plan was prepared in 2003 (Sağlık Bakanlığı, 2004).

In 2003, the 58th Government prepared an Emergency Action Plan aimed at ensuring the provision of quality, cost-effective, continuous, widespread, and community-oriented healthcare services. The health reforms outlined in the plan were announced by the Ministry of Health under the name "Health Transformation Program" later that year, emphasizing the establishment of a health information system and access to effective information in decision-making processes as a significant component of digitalization in healthcare. Within this framework, fifteen objectives were listed for the development of the health information system as part of the e-Health project in 2004. These identified objectives were considered crucial for the establishment of the National Health System (Avaner & Fedai, 2017).

The Health Transformation Program envisaged eight fundamental components: (1) A Planning and Supervisory Health Ministry, (2) Universal Health Insurance that brings everyone under one roof, (3) A widespread, easily accessible, and friendly Healthcare Service System, (4) Health Human Resources Equipped with Information and Skills, Highly Motivated, (5) Education and Scientific Institutions Supporting the System, (6) Quality and Accreditation for Qualified and Effective Health Services to support the system, (7) Institutional Structuring in Rational Drug and Material Management, and (8) Access to Effective Information in Decision-Making - Health Information System. To ensure coordination and harmony among all these components, the establishment of an interconnected information system is required (Sağlık Bakanlığı, 2003).

In Türkiye, partial steps towards digital transformation have been taken by institutions through the implementation of the "E-Transformation Turkey" project, which binds public institutions affiliated with the Prime Ministry to its scope. Within the framework of the E-Transformation project, the Ministry of Health Project aims to ensure the security and continuity of financial, administrative, and clinical data shared in information systems, protect the institution's reputation and investments, and minimize legal risks arising from security breaches by establishing standards for information system security in all institutions affiliated with the Ministry of Health. The Ministry's information security policy consists of rules and methods established under 23 main headings, including antivirus systems, email security, and encryption (Marttin & Pehlivan, 2010). Within the framework of the National Health Information Systems established with the Health Transformation Program, there are applications such as the Basic Health Statistics Module, Hospital Information Management Systems, Core Resource Management System, and Family Medicine Information System under the name Health.net (Avaner & Fedai, 2017). Additionally, within the scope of the e-health project in the Health Transformation Program, various information systems such as e-Pulse, Telemedicine, and the Ministry of Health Communication Center (SABİM) are implemented (DPT, 2005). For example, Telemedicine enables the instant transfer of information between patients and healthcare providers, eliminating physical barriers (Perednia et al., 1995).

In addition to the activities carried out under the title of the Health Transformation Program in 2007, three new headings were added. These headings are listed below (Akdağ, 2008):

- Development of the healthcare sector towards a better future and the implementation of healthy life programs.
- Activation of stakeholders and the establishment of multilateral health responsibility for collaboration between sectors.
- Provision of cross-border health services to enhance the country's strength internationally.

In Türkiye, personal health data is collected and commodified through the Ministry of Health, Private Health Insurance, and the Social Security Institution (SGK) as a result of the privatization of healthcare services under the Health Transformation Program. Initially, personal health data collected in the electronic record system called MEDULA, meaning Health Network, which was primarily accounting-oriented, became more comprehensive and widespread over time. Starting from December 1, 2013, the Biometric Identity Verification System, which utilizes methods such as facial recognition, fingerprinting, voice recognition, and retinal scanning for biologically and irreversibly identifying individuals, was made mandatory for use in private hospitals by the SGK (İzgi, 2014). Additionally, in 2014, the Information Security Policies Directive and Guide, focusing on information security in healthcare services, came into effect with the approval of the Ministry of Health. The objectives outlined in this directive are as follows (Öztürk, 2014):

- Taking measures to ensure security in the collection, reporting, and sharing of information falling within the scope of the Ministry of Health's responsibilities.
- Ensuring protection against all external and internal threats to the integrity, confidentiality, and accessibility of information.
- Preventing human-caused damages by increasing awareness of information security among all managers and technical personnel involved in work on information networks and systems.
- Providing a computing infrastructure with ensured integrity, confidentiality, and accessibility.
- Preventing information and data losses through the achievement of sustainability.

Under the provisions of the Law on Protection of Personal Data dated 2016, the Regulation on Personal Health Data has been enacted to regulate the procedures and principles to be followed in practices carried out by the units of the Ministry of Health and the service providers affiliated with them, aiming to ensure data security in healthcare services. According to this regulation, a registration and notification system is established to enable individuals to monitor their health status and to effectively conduct healthcare services. The regulation stipulates that past health data cannot be disclosed except in cases required for the provision of healthcare services. Healthcare service providers must take necessary technical, physical, and administrative measures to prevent unauthorized individuals from accessing personal data belonging to others in service areas such as counters. Access to health data by healthcare personnel is limited to what is necessary for the service. In the event of death, the health data of a deceased individual is preserved for 20 years, and the legal heirs of the deceased, upon presenting a certificate of inheritance, are authorized to obtain this data (Mevzuat Bilgi Sistemi, 2016).

6. CONCLUSIONS AND RECOMMENDATIONS

Health data is continuously increasing worldwide, posing a risk of being vulnerable to cyber-attacks by hackers. Indeed, cyber-attacks can be likened to hurricanes that devastate an entire city's critical infrastructure or paralyze a nation. The losses incurred can be significant for a country. Considering that one-third of the world's population is widely interconnected through various platforms, including public institutions and services, cybersecurity plays a critical role in all forms of digitalization. Therefore, information security is of paramount importance for other services that are part of the digital transformation to perform their expected functions effectively and efficiently.

The increasing prevalence of viruses, spam, hackers, spyware, and numerous other threats to information security has led to millions of security issues. These problems result in companies suffering financial losses, human rights violations, and the collapse of entire information systems, causing serious impacts on society and the economy (Huang et al., 2010:221). Therefore, institutions holding health information data need to develop security software to protect against cyber-attacks and appoint individuals responsible for ensuring compliance with cybersecurity policies (Chatfield & Reddick, 2019). Additionally, a successful security system can be established through multiple security layers. These layers include physical security, personnel security, transaction security, communication security, network security, and data security (Goutam, 2015; Elattresh, 2022).

It is essential to recognize the intertwined nature of technology and information in healthcare and to continuously enhance security measures to safeguard information alongside technological advancements. Cyberattacks pose a significant threat to the healthcare sector, with hospitals being prime targets. Among the most prevalent threats are ransomware attacks, data breaches, and phishing attempts.

As evident, ransomware occupies a significant place among cyberattacks, particularly within the healthcare sector. Therefore, it is recommended that users within the healthcare system pay particular attention to this issue. Attacks typically commence through email methods, luring users into cyber threats via email. Therefore, it is strongly advised that users in the healthcare sector undergo training on this matter. These training sessions should be conducted regularly and continuously, with the institutional IT center providing a corporate approach in this regard. Additionally, users should promptly inform the IT department of any suspicious emails that may pose a threat.

Hospitals are prime targets for cybercriminals due to the wealth of valuable data they harbor, encompassing patients' personal and financial details, medical histories, and research findings. This data holds significant monetary value and thus makes healthcare facilities lucrative targets for cyberattacks. Factors contributing to such attacks include the critical nature of healthcare services, the multitude of entry points for exploitation, limited cybersecurity resources, and the proliferation of interconnected devices. To mitigate these risks and safeguard patients' sensitive information, healthcare organizations must implement robust security measures and enhance staff awareness. Investing in strong cybersecurity strategies is essential to protect sensitive data and ensure uninterrupted operation of critical systems. Although addressing this issue is complex, especially in developing countries, governments have a duty to find pragmatic solutions. Moreover, service providers should prioritize data protection, assess the security practices of third-party suppliers regularly, and take proactive measures to prevent future incidents. Above all, utmost care must be taken to safeguard patients' personal information.

ACKNOWLEDGEMENTS

M.Damar was supported by the Scientific and Technological Research Council of Türkiye (TUBITAK) under the TUBITAK 2219 International Postdoctoral Research Fellowship program. He would like to thank the Upstream Lab, MAP, Li Ka Shing Knowledge Institute at the University of Toronto for its excellent hospitality.

FUNDING

No funding

AUTHORS` CONTRIBUTIONS

All authors contributed equally to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

All relevant data are within the paper and its Supporting Information.

REFERENCES

Abdallah, Y. O., Shehab, E., & Al-Ashaab, A. (2021). Understanding Digital Transformation In The Manufacturing Industry: A Systematic Literature Review And Future Trends. Product: Management and Development, 19(1), 1-12.

Akalın, B., & Veranyurt, Ü. (2020). Sağlıkta Dijitalleşme Ve Yapay Zekâ. SDÜ Sağlık Yönetimi Dergisi, 2(2), 128-137.

Akdağ, R. (2008). Türkiye Sağlık Dönüşüm Programı ve Sağlık Hizmetleri Değerlendirme Raporu,1.Baskı, Ankara: Türkiye Cumhurieti Sağlık Bakanlığı.

Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M. A. A., & Dwivedi, Y. K. (2023). A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. Journal of Innovation & Knowledge, 8(1), 100333.

Almotiri, S. H., Khan, M. A., & Alghamdi, M. A. (2016). Mobile Health (M-Health) System in The Context of IoT. In 2016 IEEE 4th International Conference On Future Internet of Things and Cloud Workshops (Ficloudw) (Pp. 39-42). IEE, 22-24 Aug. 2016 Vienna, Austria.

Alugubelli, R. (2016). Exploratory study of artificial intelligence in healthcare. International Journal of Innovations in Engineering Research and Technology, 3(1), 1-10.

Appari, A., & Johnson, M. E. (2010). Information security and privacy in healthcare: current state of research. International journal of Internet and enterprise management, 6(4), 279-314.

Arcticwolf, (2023). The Top 15 Healthcare Industry Cyber Attacks of the Past Decade. https://arcticwolf.com/resources/blog/top-healthcare-industry-cyberattacks/. Access date: 06/04/2024.

Avaner, T., & Fedai, R. (2017). Sağlik Hizmetlerinde Dijitalleşme: Sağlık Yönetiminde Bilgi Sistemlerinin Kullanilmasi. Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 22(Kayfor 15 Özel Sayı), 1533-1542.

Aydın, Ö. (2020). Bilgisayar dünyasında hile, ihlal ve siber saldırılar. In Eds. Talan, T., & Aktürk, C. Bilgisayar Bilimlerinde Teorik ve Uygulamalı Araştırmalar (pp. 29-60). Efe Akademi.

Berber, L. (2009). Kişisel Sağlık Verileri ve Mahremiyet. 6. Ulusal Tıp Bilişimi Kongresi (TurkMIA '2009). 12-15 Kasım 2009, Antalya, Türkiye.

Berber, L., Ülgü. M.M, & Er, C. (2009). Elektronik Sağlık Kayıtları ve Özel Hayatın Gizliliği. İstanbul: İstanbul Bilgi Üniversitesi, Bilişim Teknoloji Uygulaması Hukuku Uygulama Araştırma Merkezi.

Caruson, K., Macmanus, S. A., & Mcphee, B. D. (2012). Cybersecurity Policy-Making at The Local Government Level: An Analysis of Threats, Preparedness, and Bureaucratic Roadblocks to Success. Journal of Homeland Security and Emergency Management, 9(2), 20120003. https://doi.org/10.1515/jhsem-

2012-0003

Casarosa, F. (2024). Cybersecurity of Internet of Things in the health sector: Understanding the applicable legal framework. Computer Law & Security Review, 53, 105982.

Cavelty, M. D. (2010). Cyber-Security. In The Routledge Handbook Of New Security Studies (pp. 154-162). Netherlands: Routledge.

Chałubińska-Jentkiewicz, K. (2021). Cybersecurity Policy. In K. Chałubińska-Jentkiewicz, In: Karpiuk, M. & Kostrubiec, J. (Eds.) The Legal Status Of Public Entities in The Field Of Cybersecurity in Poland. Maribor: Institute for Local Self-Government Maribor.

Chatfield, A. T., & Reddick, C. G. (2019). A Framework for Internet of Things-Enabled Smart Government: a Case of IoT Cybersecurity Policies and Use Cases in US Federal Government. Government Information Quarterly, 36(2), 346-357. https://doi.org/10.1016/j.giq.2018.09.007

Chikhaoui, E., Alajmi, A., & Larabi-Marie-Sainte, S. (2022). Artificial intelligence applications in healthcare sector: ethical and legal challenges. Emerging Science Journal, 6(4), 717-738.

Chiuchisan, I., Balan, D. G., Geman, O., Chiuchisan, I., & Gordin, I. (2017). A security approach for health care information systems. In 2017 E-health and bioengineering conference (EHB) (pp. 721-724). 22-24 June 2017, Bucharest, Romania.

Chodakowska, A., Kańduła, S., & Przybylska, J. (2022). Cybersecurity in The Local Government Sector in Poland: More Work Needs to Be Done: More Work Needs to Be Done. Lex Localis-Journal of Local Self-Government, 20(1), 161-192. https://doi.org/10.4335/m75jka54

Cordella, A., & Iannacci, F. (2010). Information systems in the public sector: The e-Government enactment framework. The Journal of Strategic Information Systems, 19(1), 52-66.

De Bruijn, H., & Janssen, M. (2017). Building Cybersecurity Awareness: The Need for Evidence-Based Framing Strategies. Government Information Quarterly, 34(1), 1-7. https://doi.org/10.1016/j.giq.2017.02.007

Digital Guardian, (2024). Top 10 Biggest Healthcare Data Breaches of All Time. https://www.digitalguardian.com/dskb/top-10-biggest-healthcare-data-breaches-all-time. Access date: 06/04/2024.

Dlamini, M. T., Eloff, J. H., & Eloff, M. M. (2009). Information Security: The Moving Target. Computers & Security, 28(3-4), 189-198.

DPT, (2005). E-Devlet Proje ve Uygulamaları. Ankara: Bilgi Toplumu Dairesi Yayını.

Dülger, M. V. (2015). Sağlık Hukukunda Kişisel Verilerin Korunması ve Hasta Mahremiyeti. İstanbul Medipol Üniversitesi Hukuk Fakültesi Dergisi, 1(2), 43-80.

Elattresh, J., A.M. (2022). Bilgi Güvenliği Hizmet Yönetimi: Bilgi Güvenliği Yönetimine Bir Hizmet Yönetimi Yaklaşımı Ve Bir Kurumun Müşterinin Memnuniyeti Ve Güvenirliği Üzerindeki Etkisi. Yayınlanmamış Doktora Tezi. Kastamonu Üniversitesi Fen Bilimleri Enstitüsü Malzeme Bilimi Ve Mühendisliği Ana Bilim

Dalı.

ELFANET, (2024). Stuxnet Nedir?. https://elfanet.com.tr/tr/main/article/stuxnet-nedir/105. Access date: 06/04/2024.

European Union, (2005). Patient Safety- Making It Happen Luxemburg Decleration on Patient Safety, S.1

Galetsi, P., Katsaliaki, K., & Kumar, S. (2020). Big data analytics in health sector: Theoretical framework, techniques and prospects. International Journal of Information Management, 50, 206-216.

Ganai, P. T., Bag, A., Sable, A., Abdullah, K. H., Bhatia, S., & Pant, B. (2022, April). A Detailed Investigation of Implementation of Internet of Things (IOT) in Cyber Security in Healthcare Sector. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1571-1575). 28-29 April 2022 Greater Noida, India.

Gellerstedt, M. (2016). The Digitalization of Health Care Paves The Way for Improved Quality of Life. Journal of Systemics, Cybernetics and Informatics, 14, 1-10.

Gerçeker, B. (2012). Sağlık Kuruluşlarında Örgüt İklimi Ve Bilgi Güvenliğinin İlişkisi. Dokuz Eylül Üniversitesi Sağlık Bilimleri Enstitüsü Sağlıkta Kalite Geliştirme ve Akreditasyon Ana Bilim Dalı. İzmir.

Getoppos, (2024). Cyber Attack in Hospitals: Biggest Healthcare Industry Cyber Threats. https://getoppos.com/cyber-attacks-in-hospitals/. Access date: 06/04/2024.

Gopal, G., Suter-Crazzolara, C., Toldo, L., & Eberhardt, W. (2019). Digital Transformation in Healthcare–Architectures of Present and Future Information Technologies. Clinical Chemistry and Laboratory Medicine, 57(3), 328-335.S.329

Goutam, R. K. (2015). Importance of Cyber Security. International Journal of Computer Applications, 111(7), 14-15

Gritzalis, D. A. (1998). Enhancing security and improving interoperability in healthcare information systems. Medical Informatics, 23(4), 309-323.

Häyrinen, K., Saranto, K., & Nykänen, P. (2008). Definition, structure, content, use and impacts of electronic health records: a review of the research literature. International journal of medical informatics, 77(5), 291-304.

Henkoğlu, T., & Yılmaz, B. (2013). Avrupa Birliği AB Bilgi Güvenliği Politikaları. Türk Kütüphaneciliği, 27(3), 451-471.

Herland, M., Khoshgoftaar, T. M., & Wald, R. (2014). A Review of Data Mining Using Big Data in Health Informatics. Journal of Big Data, 1(1), 1-35.

Herrmann, M., Boehme, P., Mondritzki, T., Ehlers, J. P., Kavadias, S., & Truebel, H. (2018). Digital transformation and disruption of the health care sector: Internet-based observational study. Journal of medical internet research, 20(3), e104.

Huang, D. L., Rau, P. L. P., & Salvendy, G. (2010). Perception of Information Security. Behaviour & Information Technology, 29(3), 221-232.

Iqbal, M. H., Aydin, A., Brunckhorst, O., Dasgupta, P., & Ahmed, K. (2016). A Review of Wearable Technology in Medicine. Journal of The Royal Society of Medicine, 109(10), 372-380.

Iyanna, S., Kaur, P., Ractham, P., Talwar, S., & Islam, A. N. (2022). Digital transformation of healthcare sector. What is impeding adoption and continued usage of technology-driven innovations by end-users?. Journal of Business Research, 153, 150-161.

İzgi, M. C. (2014). Mahremiyet Kavramı Bağlamında Kişisel Sağlık Verileri. Türkiye Biyoetik Dergisi, 1(1), 201425-201437.

Jee, K., & Kim, G. H. (2013). Potentiality of big data in the medical sector: focus on how to reshape the healthcare system. Healthcare informatics research, 19(2), 79-85.

Kaspersky, (2024). WannaCry fidye yazılımı nedir? https://www.kaspersky.com.tr/resource-center/threats/ransomware-wannacry. Access date: 06/04/2024.

Khan, B., Fatima, H., Qureshi, A., Kumar, S., Hanan, A., Hussain, J., & Abdullah, S. (2023). Drawbacks of artificial intelligence and their potential solutions in the healthcare sector. Biomedical Materials & Devices, 1(2), 731-738.

Kissi, J., Dai, B., Owusu-Marfo, J., Bediako, I. A., Antwi, M. O., & Akey, B. C. A. (2018). A Review of Information Security Policies and Procedures for Healthcare Services. Canadian Journal of Applied Science and Technology, 6(2), 812-819.

Korkmaz, A. Ç. (2018). Geçmişten Günümüze Hasta Güvenliği. İnönü Üniversitesi Sağlık Hizmetleri Meslek Yüksek Okulu Dergisi, 6(1), 10-19.

Küzeci, E. (2019). Kişisel verilerin korunması. Ankara: Seçkin Yayıncılık.

Lindgren, I., & Jansson, G. (2013). Electronic services in the public sector: A conceptual framework. Government Information Quarterly, 30(2), 163-172.

Marttin, V., & Pehlivan, İ. (2010). ISO 27001: 2005 Bilgi Güvenliği Yönetimi Standardı ve Türkiye'deki Bazı Kamu Kuruluşu Uygulamaları Üzerine Bir İnceleme. Mühendislik Bilimleri ve Tasarım Dergisi, 1(1), 49-56.

Mevzuat Bilgi Sistemi, (2016). Kişisel Verilerin Korunması Kanunu. https://www.mevzuat.gov.tr/mevzuat?MevzuatNo=6698&MevzuatTur=1&MevzuatTertip=5. Access date:01/03/2024.

Mukherjee, S., Chittipaka, V., Baral, M. M., Pal, S. K., & Rana, S. (2022). Impact of artificial intelligence in the healthcare sector. Artificial Intelligence and Industry 4.0, 23-54.

Öğütçü, G., Köybaşı, N. A. G., & Cula, S. (2011). Elektronik Sağlık Kayıtlarının İçeriği, Hassasiyeti ve Erişim Kontrollerine Yönelik Farkındalık ve Beklentilerin Değerlendirilmesi. VIII. Ulusal Tıp Bilişimi Kongresi, Tıp Bilişimi 2011. pp.88-97. 17-20 Kasım 2011, Xanadu Hotel, Belek, Antalya, Turkiye.

Özek, Ç. (1999). Düşünce Özgürlüğünden Bilgilenme Hakkına. İstanbul: AlfaYayınları.

Öztürk, H., Yüksek, C., & Aslan, M. (2014). Sağlık Bakanlığı Bilgi Güvenliği Politikaları Klavuzu, 2014. https://bilgiguvenligi.saglik.gov.tr/files/BilgiGüvenliğiPolitikalarıKılavuzu.pdf. Access date: 06/04/2024.

Par, Ö.E. & Soysal, E. (2011). Kişisel Sağlık Bilgilerinin Güvenliği Açısından Medula'da Kullanılan Yasa ve Standartların HIPAA ile Karşılaştırılması. VIII. Ulusal Tıp Bilişimi Kongresi, Tıp Bilişimi 2011. pp.82-87. 17-20 Kasım 2011, Xanadu Hotel, Belek, Antalya, Turkiye.

Pawar, J., Kulkarni, D., & Dhanwate, V. (2024). Understanding Cyber Security In Health Sector. Journal of Advanced Zoology, 45, 55-64.

Perednia, D. A., & Allen, A. (1995). Telemedicine Technology and Clinical Applications. JAMA, 273(6), 483-488.

Preis, B., & Susskind, L. (2022). Municipal Cybersecurity: More Work Needs to Be Done. Urban Affairs Review, 58(2), 614-629. https://doi.org/10.1177/1078087420973760

Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., & Yang, G. Z. (2016). Deep learning for health informatics. IEEE journal of biomedical and health informatics, 21(1), 4-21.

Rosacker, K. M., & Olson, D. L. (2008). Public sector information system critical success factors. Transforming Government: People, Process and Policy, 2(1), 60-70.

Sağlık Bakanlığı, (2003). Sağlıkta Dönüşüm, Ankara: Türkiye Cumhuriyeti Sağlık Bakanlığı.

Sağlık Bakanlığı, (2004). Türkiye Sağlık Bilgi Sistemi Eylem Planı. Bilgi İşlem Dairesi Başkanlığı. Ankara: Türkiye Cumhuriyeti Sağlık Bakanlığı.

Schwalbe, N., & Wahl, B. (2020). Artificial intelligence and the future of global health. The Lancet, 395(10236), 1579-1586.

Seemma, P. S., Nandhini, S., & Sowmiya, M. (2018). Overview of Cyber Security. International Journal of Advanced Research in Computer and Communication Engineering, 7(11), 125-128.

Shchavinsky, Y. V., Muzhanova, T. M., Yakymenko, Y. M., & Zaporozhchenko, M. M. (2023). Application Of Artificial Intelligence For Improving Situational Training Of Cybersecurity Specialists. Information Technologies and Learning Tools,97(5), 215-226.

Smith, E., & Eloff, J. H. (1999). Security in health-care information systems—current trends. International journal of medical informatics, 54(1), 39-54.

Smith, E., & Eloff, J. H. (1999). Security in health-care information systems—current trends. International journal of medical informatics, 54(1), 39-54.

Stahl, B. C., Doherty, N. F., & Shaw, M. (2012). Information Security Policies in The UK Healthcare Sector: A

Critical Evaluation. Information Systems Journal, 22(1), 77-94.

Stahl, B. C., Doherty, N. F., & Shaw, M. (2012). Information security policies in the UK healthcare sector: a critical evaluation. Information systems journal, 22(1), 77-94.

Tibodeau, P. (2014). Cyberattacks Could Paralyze US, Former Defence Chief Warns. https://www.computerworld.com/article/1612081/cyberattacks-could-paralyze-u-s-former-defense-chief-warns.html. Access date: 06/04/2024.

Trend Micro, (2024). RYUK fidye yazılımı nedir? https://www.trendmicro.com/tr_tr/what-is/ransomware/ryuk-ransomware.html. Access date: 06/04/2024.

Upguard, (2024). 14 Biggest Healthcare Data Breaches. https://www.upguard.com/blog/biggest-data-breaches-in-healthcare. Access date: 06/04/2024.

Uysal, B., & Yorulmaz, M. (2018). Sağlıkta Kalite Standartları ve Bilişsel Mahremiyet. Selçuk Üniversitesi Sosyal ve Teknik Araştırmalar Dergisi, (16), 24-33.

Van Deursen, N., Buchanan, W. J., & Duff, A. (2013). Monitoring information security risks within health care. Computers & Security, 37, 31-45.

Vural, Y., & Sağıroğlu, Ş. (2008). Kurumsal Bilgi Güvenliği ve Standartlari Üzerine Bir İnceleme. Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi, 23(2),507-522.

Yılmaz, D., Özkoç, E. E., & Öğütçü, G. (2021). Elektronik Sağlık Kayıtlarında Farkındalık. Hacettepe Sağlık İdaresi Dergisi, 24(4), 777-792.

Journal of AI

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***Volume:** 8, **Issue No:** 1, January-December 2024, **Pages:** 83-106*

Super AI, Generative AI, Narrow AI and Chatbots: An Assessment of Artificial Intelligence Technologies for The Public Sector and Public Administration

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Received: 09.07.2024 Accepted: 24.08.2024 Online: 24.08.2024 Published: 31.12.2024

Review Article

Abstract

Artificial intelligence encompasses a wide range of approaches, methodologies, and techniques aimed at mimicking human intelligence in machines. In recent times, the concepts of Generative Artificial Intelligence (AI), Super AI, and Narrow AI have attracted considerable attention. Undoubtedly, the success of ChatGPT in capturing all attention has played a significant role in this. Artificial intelligence technology has a profound impact on all sectors, and sector representatives are striving to adapt to this technology more quickly. It is projected that artificial intelligence could generate an economic size of 13 trillion American dollars by 2030. Developments in artificial intelligence technologies undoubtedly lead to significant improvements in the functioning of public institutions and access for citizens. Artificial intelligence has the potential to be used in many public services, including security and defense, healthcare services, education, transportation and infrastructure, environmental and natural resource management, law and justice systems, among others. Therefore, evaluating the types of artificial intelligence, Narrow AI applications, and chatbots for public use is seen as highly beneficial from the perspective of public administration and the public sector. In our study, the topics of super artificial intelligence, generative artificial intelligence, narrow artificial intelligence, and chatbots have been extensively evaluated within the context of the public sector and public administration. Utilizing findings from both Turkish and English literature reviews, the importance and potential impacts of artificial intelligence within the public sector, along with current trends, have been comprehensively assessed. This research delves into the concepts of artificial intelligence and its subsets—super AI, generative AI, narrow AI, and chatbots—within the general framework of the public sector. China and the United States are pioneering and leading countries in terms of investment. Although the U.S. stands out in many areas regarding investment, China's integration of artificial intelligence with national strategies and its policies indicate that it may play a more dominant role in the future. There are four main implementation areas of artificial intelligence in the public sector: efficiency and automation, service delivery, data-driven governance, and ethical and regulatory challenges. A review of the literature reveals that the ethical, legal, and social implications of implementing artificial intelligence in the public sector require more careful consideration. The study makes a significant contribution to the field of artificial intelligence discussions in public administration and the public sector, providing a comprehensive assessment of current discussions on artificial intelligence in the literature.

***Keywords:** Artificial intelligence, narrow ai, generative ai, chatbots, public administration*

Cite this paper (APA)

Damar, M., Özen, A., Çakmak, Ü.E., Özoğuz, E., Erenay, F. S. (2024). Super AI, Generative AI, Narrow AI and Chatbots: An Assessment of Artificial Intelligence Technologies for The Public Sector and Public Administration. Journal of AI. 8(1), 83-106. Doi: 10.61969/jai.1512906

1. INTRODUCTION

Artificial intelligence is now influencing daily lives, communities, and governmental structures more than ever before (Uzun et al., 2022). It enables groundbreaking developments in fields such as healthcare, agriculture, education, and transportation. Exponential growth is observed globally in consideration of artificial intelligence support. For instance, in the United States, the investment in entrepreneurial companies working in artificial intelligence increased by 20% in 2019, reaching $28.5 billion USD. The European Commission announced an annual investment of €20 billion for artificial intelligence in 2020. Moreover, it is said that artificial intelligence could increase the economic growth rates of the United States, Germany, and Japan by up to 2% in the next decade (Wirtz et al., 2019). Additionally, Bughin et al. (2018) forecasted that artificial intelligence could generate an economic size of $13 trillion by 2030. Developments in artificial intelligence technologies undoubtedly lead to significant improvements in the functioning of public institutions and access for citizens, enabling personnel to focus on more strategic tasks and facilitating faster service delivery (Yalçın, 2024).

Artificial intelligence is an enabling tool with the ability to take action and can be utilized in various fields within the public sector. Indeed, artificial intelligence can analyze large datasets, learn from them, and make decisions. Therefore, artificial intelligence can support many public employees in decision-making processes and even replace them (Maragno et al., 2023). Nowadays, with the adoption of the new doctrine of customer-oriented public administration, public managers aim to increase citizen satisfaction by improving the quality of services they provide (Suebvises, 2018). According to Wirtz et al. (2019), applying and implementing artificial intelligence technology in the public sector offers numerous opportunities to enhance efficiency. It is at this point that current artificial intelligence solutions emerge as strategic tools. Discussions regarding the implementation of artificial intelligence in the public sector are categorized into four main areas: application of artificial intelligence technology, artificial intelligence law and regulation, artificial intelligence ethics, and artificial intelligence society. Therefore, societal readiness in terms of legislation and laws regarding artificial intelligence is crucial.

According to Long & Magerko (2020), artificial intelligence is becoming increasingly integrated into user-oriented technology, yet public perception of these technologies remains limited. While artificial intelligence applications in the public sector are still limited, there are examples of exemplary applications in terms of productivity and efficiency (Maciejewski, 2017). Particularly, artificial intelligence applications supported by big data are noteworthy. In fact, big data has become a game-changer in modern public administration where it is used (Maciejewski, 2017). According to Uzun et al. (2022), governments have a responsibility as decision-makers in technological transformation to integrate artificial intelligence technology into public administration and policies. Busuioc (2021) stated that the low cost and efficiency of big data are decisive factors in public institutions' preference for artificial intelligence solutions in public services. Additionally, artificial intelligence systems have emerged in many applications thanks to big data (Goosen et al., 2018). Nowadays, projects utilizing natural language processing models based on artificial intelligence to improve efficiency and decision-making processes in public administration and to develop positive relationships with citizens are finding widespread application in many countries (Bozdoğanoğlu et al., 2024).

In a future where artificial intelligence transforms the way people interact, work, and live with both humans and machines, it's essential to assess the need for new skills. Particularly, with ChatGPT recently drawing all attention, debates arise regarding whether artificial intelligence technologies can replace human resources in all sectors. Many experts in various fields have become increasingly curious about recent developments within the age-old concept of artificial intelligence. Super artificial intelligence (Super AI), generative artificial intelligence (Generative AI), narrow or weak or applicable artificial intelligence (Narrow AI or Weak AI or Applicable AI), and chatbots are now frequently encountered in the literature. Hence, there arises a necessity for an in-depth analysis of artificial intelligence in public administration and the public sector. For these reasons, it is deemed necessary to evaluate super artificial intelligence, generative artificial intelligence, and narrow artificial intelligence, focusing on public administration and the public sector. In our planned study, artificial intelligence applications from around the world and in Türkiye will also be examined. It is believed that the study contributes significantly to the field of public administration, providing a comprehensive evaluation of current artificial intelligence discussions in the literature.

2. METHODOLOGY

In our study, the topics of super artificial intelligence, generative artificial intelligence, narrow artificial intelligence, and chatbots have been extensively evaluated within the context of the public sector and public administration. Utilizing findings from both Turkish and English literature reviews, the importance and potential impacts of artificial intelligence within the public sector, along with current trends, have been comprehensively assessed.

This research delves into the concepts of artificial intelligence and its subsets—super AI, generative AI, narrow AI, and chatbots—within the general framework of the public sector. It examines their applications, current debates, and emerging trends in Türkiye and globally, employing literature review and conceptual analysis methodologies. Information gathered from relevant literature serves to establish a conceptual framework and evaluate contemporary policy implementations. Specifically, searches were conducted using key terms such as public sector, public administration, artificial intelligence, productive artificial intelligence, super artificial intelligence, narrow artificial intelligence, and chatbots (e.g., ChatGPT, Google Gemini (Previously Google Bard (Aydin, 2023)), Claude) via Google Scholar and Web of Science.

Articles identified through these keywords were accessed individually to review full texts based on their titles and abstracts. Relevant contributions were integrated into the article's content after thorough reading and discussion of the full texts. Priority was given to highly cited works obtained from the research documents. The gathered articles and other internet sources were then evaluated in the context of their connection to information security and the healthcare sector.

Our research is of a review nature. The findings are organized using the deductive method to fill in the concepts of Super AI, Generative AI, Narrow AI, and Chatbots comprehensively, followed by evaluating the significance of artificial intelligence in the public sector within the literature. Current artificial intelligence applications and chatbot technologies from Türkiye and worldwide are specifically detailed. Insights into public sector applications from Türkiye and other countries were derived from research studies and internet sources, highlighting the advancements made by these nations. The discussion and conclusion sections provide an evaluation of all experiences and insights gained during our research, focusing on critical elements and areas worthy of further investigation.

3. SUPER AI, GENERATIVE AI, NARROW AI, CHATBOTS, PUBLIC ADMINISTRATION AND PUBLIC SECTOR

Miller (2024) defines artificial intelligence as the advancement of computer systems that can execute tasks typically requiring human intelligence. These systems strive to emulate human-like cognitive functions, including learning, problem-solving, decision-making, and language comprehension. Artificial intelligence encompasses intelligent systems focused on acquiring abilities conventionally linked with the human mind, such as language comprehension, learning, logical reasoning, and problem-solving (Saveliev & Zhurenkov, 2021).

Artificial intelligence encompasses a wide range of approaches, methodologies, and techniques aimed at mimicking human intelligence in machines. AI technologies, of course, operate according to specific models.

Significant advancements in language models have been made with the introduction of ChatGPT, developed and publicly released by OpenAI (Bilge, 2023). This language learning algorithm has excelled in understanding, analyzing, and responding to written and spoken communication, thereby attracting significant interest from users (Şentürk, 2023). Naturally, these language models and applications are not exclusive to ChatGPT. Google Gemini (Bard, using Google's LaMDA language family, is currently available in over 200 countries) and many other companies have entered the market and competition. How can these technologies be classified, and are these applications truly superior to the human brain? Furthermore, in what ways might these concepts transform the public sector and public administration? These are valuable questions that many researchers seek to answer.

3.1 Super Artificial Intelligence (Super AI) and Generative Artificial Intelligence (Generative AI)

For many years, mastering the ancient Chinese game of Go was considered extremely difficult, even deemed impossible for artificial intelligence. However, Google DeepMind's AI player AlphaGo has managed to defeat the best human competitors in this game. Initially, AI had to learn the game from humans. But this changed with DeepMind's new version. Now, AlphaGo Zero can learn and improve on its own by playing randomly instead of learning from humans. After three days and 4.9 million games, the world's best Go player became an AI (Revell, 2017). So, what are we experiencing and what kind of development are we witnessing? What kind of intelligence are we facing? For many, this can be frightening. Many average jobs in both the public and private sectors could come to life and confront us through intelligent technology, emerging from software and electronic circuits as robots. These robots could take over many average jobs across different sectors.

Advancements in artificial intelligence technology indicate the development of super intelligent machines that surpass human cognitive abilities (Aithal, 2023). Super intelligent machines refer to highly advanced and autonomous AI systems that possess intellectual capabilities far superior to humans in various domains (Wogu et al., 2018). The possibility that advancements in AI could eventually lead to the development of a super intelligent AI is a cause for concern among humanity. Such an AI could potentially dominate humanity and restrict freedom (Luck, 2024). While super intelligent AI does not yet seem feasible, it is likely that in the future, humans will contend with computers that are more intelligent than themselves. Another point of consideration is whether many problems that are currently unsolvable by the human mind can be resolved by super intelligent AI, which is itself a creation of humans. Dhara et al. (2023) have provided an assessment on this topic through health-related articles. Super intelligent computers could assist in the development of drugs and vaccines for numerous cancer cases and diseases, where the human mind currently falls short.

Artificial intelligence can be divided into three categories: super intelligent AI, general AI, and narrow AI. These categories are sometimes presented as four or nine categories in different sources. However, researchers generally focus on these three critical categories to comprehensively understand AI. Aithal (2023) lists the features of super intelligent machines as follows: enhanced cognitive abilities, self-learning and adaptability, autonomous decision-making, domain expertise and specialization, and ethical considerations. Super intelligent AI is often regarded as a utopian concept in the literature and is more of a goal to be achieved. Frerichs (2019) describes general AI as an AI capable of performing any general task that is asked of it. It is still in the developmental stage. Narrow AI, on the other hand, is designed to handle a specific task or set of tasks pre-defined by the programmer (Frerichs, 2019). Many of today's popular applications fall under this category.

Super intelligent AI surpasses human capabilities, whereas narrow AI is created for specific tasks. Generative AI is designed to match human-level intelligence in terms of breadth and adaptability, though it has not yet surpassed human capabilities. All practical solutions available today can be categorized as narrow AI (Buxmann & Schmidt, 2019; Moser, 2022). Today's AI is directly related to big data and deep learning technologies, involving extensive training and operation on large data sets. It also encompasses iterative modeling and deployment cycles. However, it appears to be constrained by static contexts and limited to predefined tasks (Moser, 2022).

Numerous nations and corporations have been dedicated to advancing super intelligent AI for an extended period. As an illustration, Lu et al. (2018) highlighted that China, through the development of native supercomputer systems, has formulated a self-governing system software covering fundamental components such as core drivers, operating systems, compilers, communication software, basic libraries, parallel programming environments, parallel file systems, resource management, and scheduling systems. Naturally, overcoming fresh hurdles in architecture, system software, and application technologies is imperative to facilitate the progression of supercomputer systems (Lu et al., 2018). In the literature, many studies involving super intelligent AI focus on ethical issues, the relationship between humans, society, and supercomputers, as well as philosophical evaluations of how the development of super intelligent AI will impact society.

3.2 Narrow (Weak or Applicable) Artificial Intelligence, Public Administration and Public Sector

Researchers have delineated between Narrow AI and artificial generative intelligence (AGI). Narrow AI pertains to systems tailored for particular tasks involving one or more decision-making processes, such as facial recognition in images or autonomous vehicles. On the other hand, AGI, which remains theoretical and unrealized, encompasses the defining characteristics of intelligence across a broad array of cognitive activities (Young et al., 2019). Narrow AI systems undergo training using machine learning algorithms like supervised learning or reinforcement learning to glean insights from extensive datasets, make decisions, or execute tasks based on established patterns and rules. As per Miller (2024), narrow AI, also referred to as weak or specialized AI, represents AI systems meticulously crafted and trained for specific tasks or domains. Unlike generative AI, which aims to emulate human-like intelligence across diverse tasks, narrow AI concentrates on excelling within a defined scope or efficiently carrying out a predetermined set of tasks. Applications of narrow AI encompass image or speech recognition, natural language processing, autonomous vehicles, and recommendation systems. Examples of narrow AI include smart personal assistants like Amazon's Alexa (Goosen et al., 2018) and Apple's Siri, which are tailored for specific functionalities. Machine learning plays a crucial role within narrow AI, enabling systems to learn from and interpret data, make predictions, and generate recommendations. However, models that perform predictive analytics or forecasting have existed prior to the development of narrow AI (Agrawal et al., 2019).

According to Saveliev & Zhurenkov (2021), narrow AI systems can execute complex computations but are limited to tasks constrained by operational environments and specific programming. Most narrow AI applications or machine learning systems are guided by five fundamental components: data input, data processing, predictive models, decision rules, and outputs (Frerichs, 2019). Additionally, there are limiting factors associated with these relevant artificial intelligences. Fischer et al. (2020) have outlined the limiting factors of today's machine learning-based artificial intelligences as follows: theory gap/statistical learning (lack of uniqueness, lack of confidence measure, lack of control of high-dimensional effects), theory-practice gap (narrow AI, data hungry, failure of big data assumption, limited data, bias, limited explainable AI), adoption gap (high adoption efforts, AI expert centric, reuse in its infancy, high initial costs), and social threats (skill gap, acceptance problems).

Applied artificial intelligence (AI) and narrow AI exhibit diverse methodological and application taxonomies, showcasing their extensive contributions across various sectors. Machine learning stands as a foundational technique in both realms, empowering systems to glean insights from data without explicit programming. These methodologies enable applications across sectors such as healthcare, finance, manufacturing, and autonomous systems. In the finance sector, for example, AI applications encompass fraud detection mechanisms, risk assessment models, algorithmic trading strategies, and customer service chatbots (Miller, 2024). AI has revolutionized business operations in finance, influencing service delivery, fraud detection, risk analysis, and more. Its utilization in financial services within the digital era impacts consumers and markets in numerous ways, including consumer protection, empowerment, financial crime prevention, competition, and market stability (Fernández, 2019; Rawat et al., 2023). Machine learning aids in investment risk assessment by identifying anomalies in financial data and supports automated trading systems. In the manufacturing sector, AI-driven models analyze sensor data to predict machine failures and optimize production processes (Miller, 2024).

Kaplan & Haenlein (2019), artificial intelligence (AI) as the ability of a system to interpret external data accurately, learn from these data, and use these learnings to achieve specific goals and tasks through flexible adaptation. One significant area where AI is relevant in the public sector is decision-making processes. Utilizing AI models allows public organizations to make rational decisions more efficiently in service delivery. An AI-enhanced information gathering model can facilitate access to maximum and accurate information for policy makers (Şahnagil, 2023). When examining the varieties of AI, it is possible to categorize types such as speech recognition, machine learning, natural language processing, and robotics (Önder & Saygılı, 2018).

The public sector can extensively benefit from artificial intelligence, particularly in areas such as firefighting, crime analysis using big data, and efficiently resolving citizen requests in call centers (Serçemeli, 2018; Önder & Saygılı, 2018; Yalçın, 2024; Özdemir, 2022; Bozdoğanoğlu et al., 2024; Ulaşan, 2023; Saveliev & Zhurenkov, 2021). Ingrams et al. (2022) have highlighted two primary ways in which AI can be beneficial to public administration. Firstly, they emphasize the instrumental effects of technological advancements on speed, efficiency, and service quality. Secondly, they suggest that AI contributes to enhancing the quality of government-citizen relationships by influencing public values development.

As per Uzun (2022), public administration holds the potential to foster the advancement of artificial intelligence, which is already undergoing adaptation across multiple sectors within the public domain. Although the integration procedures differ among nations, AI applications are progressively gaining prominence in diverse governmental functions. For example, AI-based automation capabilities simplify complex tasks for government agencies, eliminate redundancies, and enhance productivity for increased outputs.

Artificial intelligence technologies have become an integral part of our daily lives today. They are used in various fields such as voice assistants, translations, e-services, navigation, autonomous vehicles, and smart home devices (Serçemeli, 2018). In addition to these capabilities, it is anticipated that AI will continue to innovate and find applications across many sectors in the coming years. Currently, smart city initiatives are planned with the aim of advancing the information-communication sector globally, enhancing competitiveness in economic sectors, and thereby creating societies with high levels of welfare (Akpınar, 2023). Looking ahead, scenarios where expert and reliable Narrow AI applications manage towns or large cities, potentially overseeing tasks that could prevent unauthorized practices by mayors, could become a reality. Problems that mayors cannot solve alone might be addressed by a consortium of council members. While these scenarios may seem like scenes from a movie, they are not far from becoming reality.

3.3 Public Administration and the Public Sector Perspective on Chatbots: Chat GPT, Google Gemini (Previously Google Bard), Claude, and Others

A chatbot is a computer program utilizing natural language processing technology to interact with users (Shawar & Atwell, 2007). It represents a form of narrow artificial intelligence designed to extract meaningful information from free-text inputs based on user queries, discern the intent behind the user's question, and deliver an appropriate response (Goyal et al., 2018). Unlike generative artificial intelligence, which possesses capabilities at least comparable to humans, narrow AI is specifically engineered to execute a particular task (Hassabis et al., 2017; Lake et al., 2017; Aoki, 2020).

Chatbots are algorithm-based software designed to parse and interpret human language, aiming to enhance service quality, provide service delivery independent of time and place, and save time (Digital Transformation Office, 2023). One significant feature of chatbots is their incorporation of supervised learning algorithms. These algorithms aid chatbots in continuous learning from interactions with humans and in improving the accuracy of their responses (Androutsopoulou et al., 2019).

Three main combinations are utilized in creating chatbots: user interface, artificial intelligence, and integration (Digital Transformation Office, 2023). When examining types of chatbots, there are rule-based chatbots and AI-powered chatbots. Rule-based chatbot models were initially developed with simplicity in mind, yet they often fail to yield positive results in analyzing questions and providing responses. Therefore, they are typically used for defining simple tasks. However, they do have certain advantages, such as being cost-effective, easy to train, and facilitating human takeover if the chatbot veers off course. On the other hand, AI-powered chatbots are capable of responding to language traffic and answering questions in multiple languages, thereby handling big data. They are more efficient for advanced and nuanced tasks. Advantages of AI-powered chatbots include continually enhancing the information derived from previous interactions, analyzing various behaviors and languages, correcting spelling and grammar errors, generating responses to complex questions independently, and providing natural and more human-like responses compared to rule-based chatbots (Digital Transformation Office, 2023).

Generative AI has revolutionized many fields from text and content development to writing simple program codes, visualization, and video dubbing. Companies like Microsoft, Amazon, and Google are developing their own generative AI models (Livingston, 2023). These companies have integrated text-based Generative AI models into widely used service-oriented applications such as virtual assistants and chatbots (Lambert & Stevens, 2023). One of the most popular applications today is undoubtedly ChatGPT, which is publicly accessible. Productive artificial intelligence has the potential to change how we do things, and chatbots are one of its most popular applications. Despite companies like Google and Meta having their own chatbots, ChatGPT has become popular because it is open to the public (Aydın & Karaarslan, 2022; Aydın & Karaarslan, 2023).

Language models are artificial intelligence models trained on vast text datasets. These models learn the structure of a language, word usage, sentence formation rules, and other linguistic features. A chatbot like ChatGPT operates as a language model, generating meaningful responses based on user inputs. ChatGPT is a generative AI model and is one of the prominent large language models. Generative AI refers to artificial intelligence models that can generate new data or produce realistic content. Models like ChatGPT operate in the field of natural language processing, creating human-like texts.

Large language and multimodal models, sometimes referred to as foundational models, are a type of AI model trained on large amounts of data that can be adapted to various downstream applications, emerging as increasingly popular AI models. Models such as ChatGPT, DALL-E 2, and MakeA-Video have demonstrated impressive capabilities and are widely used in real-world scenarios (Maslej et al., 2023). A model like ChatGPT can be utilized for natural language generation and interacting with users. Figure 1 below illustrates the timeline and national connectivity of selected versions of these large language and multimodal models.

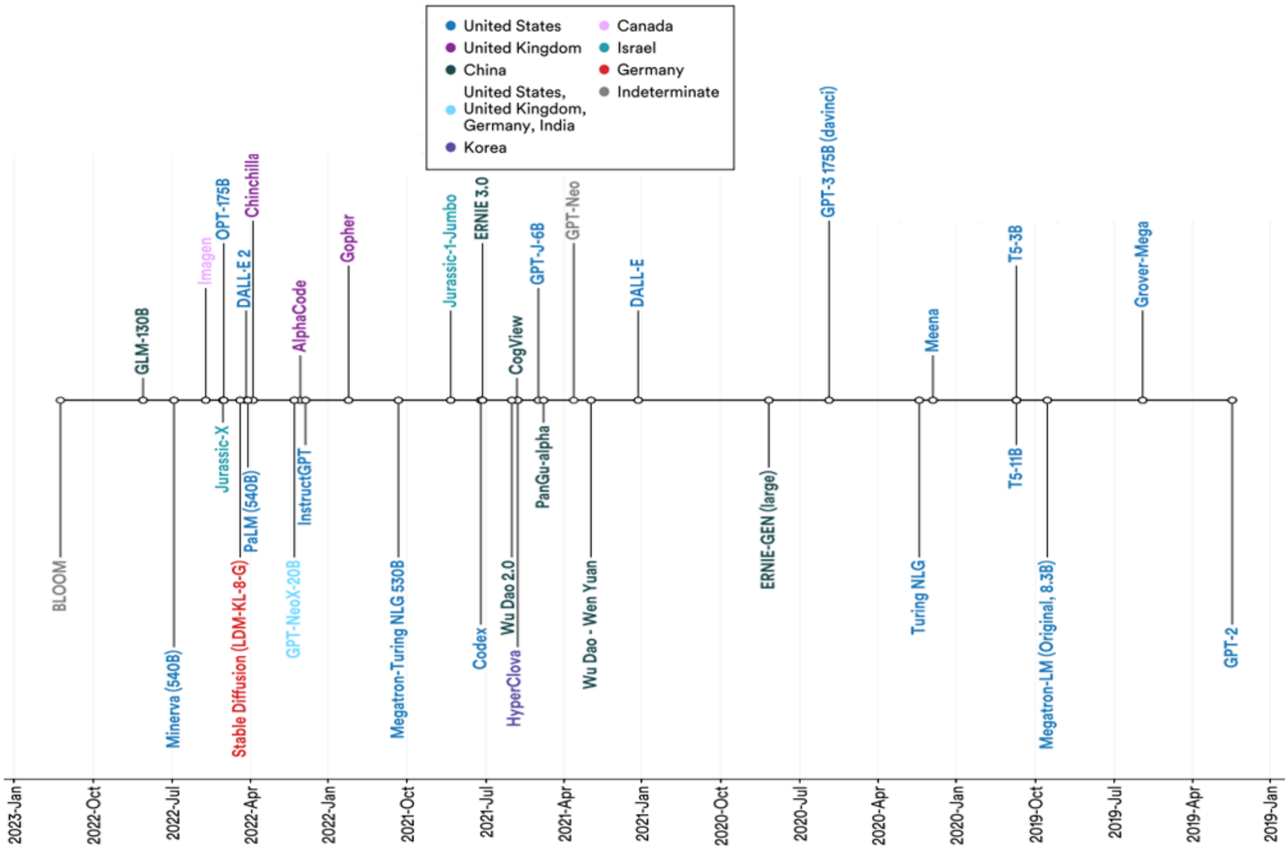

Figure 1. Timeline and National Affiliation of Select Large Language and Multimodal Model Releases (Maslej et al., 2023)

The discourse surrounding large language models and multimodal models often revolves around a specific theme, namely their associated costs. While artificial intelligence companies rarely discuss training costs explicitly, it is widely estimated that training these models can cost millions of dollars and becomes increasingly expensive as they scale (Maslej et al., 2023). Figure 2 below illustrates the selected training costs for prominent large language and multimodal models. For instance, the training cost is approximately 0.05 million dollars for GPT-2, whereas it is noted to be 1.80 million dollars for GPT-3.

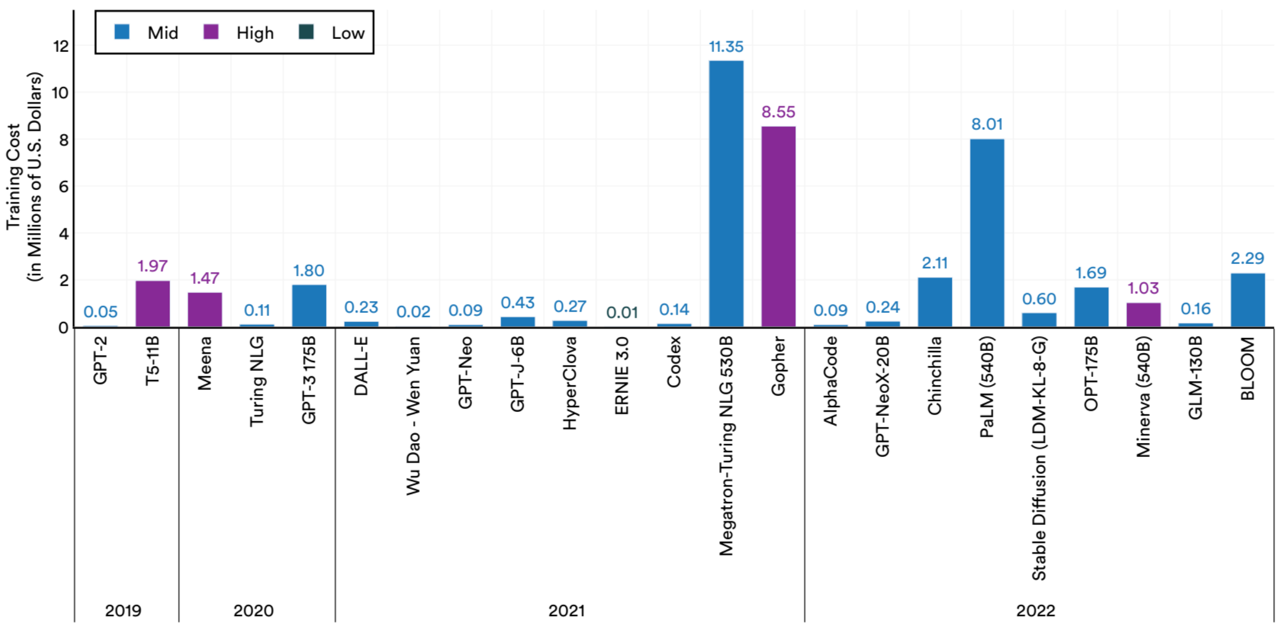

Figure 2. Estimated Training Cost of Select Large Language and Multimodal Models (Maslej et al., 2023)

Examining some features of the ChatGPT application, it can generate answers to questions, examine and debug errors, create text, classify texts, and provide translation, among other capabilities (Koçyiğit, 2023). Examples of applications similar to ChatGPT include MeetClaude developed by Antropic, ErnieBot developed by Baidu, CoPilot developed by Microsoft, Grok developed by XAI, and Google Gemini AI (formerly Google Bard AI) developed by Google, all of which have been launched in the past year by major technology companies developing Generative AI applications.

Artificial intelligence chatbots, leveraging large language models and machine learning, hold the potential to revolutionize our interactions with computers and digital systems. Proponents of these advancements argue that such applications can offer significant benefits to all (Bryant, 2023). Moreover, it is plausible to discuss the integration of chatbots within the public sector. AI applications utilizing public administration and chatbots in public settings have been present for over a decade (De Sousa et al., 2019). According to Misuraca and Van Noordt (2020), chatbots represent one of the most mature and extensively researched artificial intelligence solutions that transcend public boundaries. Indeed, chatbots are intelligent systems capable of handling vast datasets and addressing routine inquiries (Mehr et al., 2017).

Chatbots and other AI tools can assist public institutions in communicating more effectively with the public and delivering services. It is anticipated that they will increase the capacity to provide quick responses to citizens' questions (Yalçın, 2024). Maragno et al. (2023) have demonstrated the feasibility of chatbots for the customer service department of public organizations. Huang & Gan (2023) have stated that chatbots can contribute to service delivery in public institutions by addressing many needs effectively, potentially revolutionizing the public sector. Integration of chatbots into smart city applications such as waste management, transportation, and emergency services can enable citizens to access services efficiently and effectively in real time. Chatbots, widely used in sectors such as education, health care, tourism, banking, and marketing, are also rapidly gaining a foothold in the public sector today (Digital Transformation Office, 2023).

4. THE IMPORTANCE OF ARTIFICIAL INTELLIGENCE IN PUBLIC SECTOR AND SAMPLE APPLICATIONS

Artificial intelligence, with its various components such as machine learning, deep learning, neural networks, cognitive computing, and natural language processing, can be defined not merely as a single technology but as an "enabler." Indeed, it has widespread applications in many different sectors and areas of our daily lives, including health, industry, commerce, education, transportation, and more (Özdemir, 2022). Grace et al. (2018) suggest there is a 50% chance that artificial intelligence will surpass human performance in all tasks within 45 years and fully automate all human jobs within 120 years.

In their study, Wirtz et al. (2019) propose a model that categorizes the challenges of artificial intelligence into four main areas: (1) AI technology implementation, including AI safety, system/data quality and integration, financial feasibility, and the need for specialization and expertise; (2) AI law and regulations, covering the governance of autonomous intelligence systems, issues of responsibility and accountability, and concerns about privacy and safety; (3) AI ethics, addressing rulemaking for human behavior, the alignment of machine versus human value judgments, moral dilemmas, and AI discrimination; and (4) AI society, focusing on workforce substitution and transformation, social acceptance and trust in AI, and the evolution of interactions from human-to-machine and machine-to-machine.

According to Turchin (2018), the problem-solving ability of artificial intelligence stems not from its intelligence per se but from its access to large amounts of data and other resources. The application of big data in the public sector is structured according to the following administrative function systematics (Maciejewski, 2017): public audit (identifying irregularities and taking sensitive actions), public regulation (shaping social relations through prohibitions or orders), public service delivery (providing specific services or products).

While artificial intelligence varies sectorally in terms of its functions and applications, it offers certain advantages to institutions. Artificial intelligence contributes to organizations by providing recommendations and data for decision-making processes aligned with their goals and strategies, thereby enabling institutions to stay ahead in an increasingly competitive environment. Additionally, the contributions of artificial intelligence to institutions include: (1) automating business processes and enabling automated decision-making, (2) increasing efficiency and reducing costs, (3) boosting sales rates, (4) improving product or service quality, (5) optimizing processes such as supply chain and logistics, (6) enhancing customer satisfaction, loyalty, and experiences, (7) facilitating more efficient and advanced workforce allocation, (8) assisting in the execution of personalized marketing activities (Gtech, 2021). Indeed, the public sector stands among the most critical and important sectors.

Policy makers are defining new strategies to adapt to transformation. Public administration is redefining its duties and responsibilities to integrate into the digital transformation. The public sector is implementing reforms in policy and service delivery to adapt to this change seen in the private sector (Önder & Saygılı, 2018). In recent years, with the influence of the digitalization age, the concept of smart cities has gained significant attention from states. Smart cities use data analytics to enhance living standards, increase sustainability, and improve efficiency in various areas such as transportation, energy, health, and public services (Cuau, 2019). Indeed, such technological developments enhance efficiency, transparency, and accessibility in service delivery within the public sector, making it possible to address current problems and complexities in public administration more effectively (Tanrıverdi, 2021). Furthermore, the use and proliferation of digital service delivery contribute to the growth of public employment volumes (Sarıtürk, 2022).

Various examples of artificial intelligence applications exist in the public sector. For instance, Kouziokas (2016) applied artificial intelligence techniques in public administration to spatially predict crime to promote security management in public transport, and researchers found the developed solution to be highly beneficial. In the United States, the Atlanta Fire Rescue Department's predictive analytics application accurately predicted fires in buildings by 73%. In Canada, the City of Surrey developed an application via chatbot to help citizens find solutions to their municipal infrastructure-related issues (Ulaşan, 2023). Additionally, the Citizen Lab project in Belgium serves as an example of citizen participation in decision-making processes and the use of artificial intelligence technology in the chatbot field. This project automatically classifies and analyzes thousands of evaluations collected on citizen participation platforms using Natural Language Processing (NLP) and Machine Learning techniques. The application allows public officials to better see differences in priorities by separating results according to demographic groups and locations (Cuau, 2019). Of course, in addition to fully and ethically benefiting from natural language processing models based on artificial intelligence in public services, it is necessary to first have access to sufficient, high-quality, and unbiased data (Bozdoğanoğlu et al., 2024).

Another significant outcome of the development of artificial intelligence is unified and citizen-centric governance. In this model, artificial intelligence-based natural language processing models can be used in communication between institutions and citizens. Chatbots developed by public institutions exemplify this process. The progress made by artificial intelligence in natural language processing and deep learning has enabled the implementation of dialogue-based artificial intelligence applications. Communication speeds up with citizens through chatbots in public institutions, reducing the workload of employees (Şahnagil, 2023).

A study conducted by Harvard University identified five different use cases for chatbots in the public sector. These use cases include: answering citizens' questions and complaints through automatic customer support systems based on artificial intelligence, guiding citizens in document searches and form filling, accepting and directing citizen inputs to relevant institutions, translating information within the public sector, and designing documents for citizens to find answers to their questions (Androutsopoulou et al., 2019).

Bartosz Kopka (2011), who studied the advantages and disadvantages of AI-based chatbots, listed their advantages as: facilitating access to information for citizens, reducing costs in providing services to citizens in the public sector, and making the chatbot system more attractive to users, thereby encouraging more active use. He noted disadvantages such as the time-consuming nature of regularly processing new data and the inability to fully mimic human brains and behaviors in emulation.

5. THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE IN THE PUBLIC SECTOR IN TÜRKİYE AND EXAMPLES OF ARTIFICIAL INTELLIGENCE APPLICATIONS IN TÜRKİYE

Due to the global digital transformation, competition among countries has emerged. To avoid negative impacts on Türkiye from this competitive environment, it is crucial for the country to timely meet the demands of the era (Çarıkçı, 2010). In Türkiye, the integration of artificial intelligence (AI) in the public sector can be traced back to the e-government initiative. The e-government application aimed to leverage information and communication technologies in the public sector (Tamer & Övgün, 2020).

The e-government application was developed with three main objectives: facilitating citizen access to public services and increasing their availability; promoting citizen participation in service production and management processes, efficiently evaluating their preferences and choices; and ensuring rational and effective operation of public institutions. Additionally, transparency in public service delivery, cost savings, reduction of bureaucracy, acceleration of service delivery throughout the year, and increased citizen participation in public services can be listed as other objectives (Akçakaya, 2017).

In Türkiye, the Digital Transformation Office was established under Presidential Decree No. 1 on July 10, 2018, aiming to integrate technology advancements, societal demands, and digital transformation in the public sector. This initiative consolidated efforts previously conducted under different agencies related to digital transformation (e-government), national technologies, big data, cybersecurity, and artificial intelligence (AI) under one roof (Digital Transformation Office, 2024b).

The responsibilities of the Digital Transformation Office regarding artificial intelligence are outlined in Presidential Decree No. 48, which mandates the establishment of the Directorate of Big Data and Artificial Intelligence Applications. The tasks of this Directorate include developing strategies and coordinating efforts for effective use of big data and AI applications in public sectors, and leading AI applications in priority project areas (Akman & Çetin, 2019). Thus, the core task of digital transformation in this process is noted to manage collaboration and coordination among institutions.

Türkiye became one of the first 50 countries to publish its first national AI strategy, providing itself with a roadmap for 2021-2025, in August 2021. The primary goals of these initiatives are to increase societal welfare and strengthen national security (Özdemir, 2022). The policies defined under the 2021-2025 Türkiye Artificial Intelligence Strategy are categorized into six main headings, as outlined by the Digital Transformation Office (2024a): fostering advanced skills in AI, aligning the education system accordingly; increasing R&D activities in AI; enhancing entrepreneurship; ensuring access to high-quality data and technical infrastructure for AI; establishing an ethical and legal framework for AI; developing international collaborations in AI; managing the impact of AI on employment and professions; and transforming institutions and companies with AI applications.

Consequently, Türkiye 's level of AI readiness is progressing alongside these developments. According to the AI Readiness Index 2021, Türkiye improved its position by 14 places to 53rd among 160 countries, with a score of 55.49 compared to 46 in 2020. This rise can largely be attributed to the optimistic unveiling of its national strategy, which is seen as promising in both the short and long term (Özdemir, 2022).

In Türkiye, public institutions have implemented AI-based digital tools to serve the public. Examples include the Ministry of Foreign Affairs' development of the "Hızır" application under the digital diplomacy initiative, providing a chatbot-based application for citizens abroad to access services around the clock, without the constraints of office hours (Ministry of Foreign Affairs, 2024). Similarly, the Ministry of National Education has developed the MEB Assistant and EBA Assistant applications to provide effective service and assistance to citizens (Ministry of National Education, 2024). Additionally, the Ministry of Treasury and Finance's digital tax assistant "GİBİ" uses AI-based chatbot technology to answer taxpayer queries 24/7, providing updated regulatory information and saving time for citizens (Ministry of Treasury and Finance, 2024). Furthermore, Turkish public institutions have introduced AI-supported tools for smart transportation, energy management, environmental monitoring, education, healthcare, food sector, communication, and social projects, such as ASENA, GAMER, Muhatap, Uyuma, Kades, and NeyimVar (Yalçın, 2024).

To achieve a more effective development trend in AI in Türkiye, the Turkish Informatics Association has emphasized the need to establish a four-legged AI ecosystem. This ecosystem requires coordinated efforts among the supervisory public sector, flexible and dynamic private sector with production capabilities, universities developing creative and innovative technologies, professional chambers safeguarding societal values, and civil society organizations organizing joint activities (TBD, 2020). Overall, Türkiye is taking proactive measures to prepare public institutions for advancements in AI.

6. GLOBAL DEVELOPMENTS IN ARTIFICIAL INTELLIGENCE TECHNOLOGY

In the realm of global technological advancement, artificial intelligence has emerged as a transformative force promising to reshape industries, enhance efficiency, and foster innovation. While advanced countries progress in harnessing the potential of AI, its adoption and effective implementation in developing countries present a distinct set of challenges and opportunities. From infrastructure limitations and skill gaps to ethical considerations, the journey spans numerous opportunities across sectors such as health, education, agriculture, and beyond, uncovering and acknowledging the profound impact AI can have on these nations (Aderibigbe et al., 2023). AI has emerged as a powerful force shaping the global technological landscape, and adoption trends in developing countries are influenced by multiple factors (Pan, 2016). AI models today demonstrate significant potential to benefit humans across various fields, including education, medicine, and scientific research (Anderljung et al., 2023). It is evident that AI will have a direct impact on the international system and power distribution, as a global race spearheaded by the United States and China continues to unfold (Özdemir, 2022).

The United States introduced its national AI strategy, known as the American AI Initiative, via an Executive Order on February 11, 2019. This strategy aims to promote and protect AI technology and innovation in the United States through a collaborative approach. The government identified five key principles to drive AI development: sustaining investment in AI research and development, making federal AI resources available, eliminating obstacles to AI innovation, improving the American workforce through AI-focused education, and creating an international environment that supports American AI innovations and their responsible use. Additionally, the United States employs AI to improve the efficiency of federal government operations and public services (Saveliev & Zhurenkov, 2021). In the digital age, the competencies needed in the IT sector evolve over time in response to changes and transformations within the sector. This evolution also diversifies the characteristics required of human resources in the industry (Damar, 2022a; Damar, 2022b). A similar situation has been observed in the field of artificial intelligence and related sectors. Figure 3 below illustrates this change in the context of the USA.

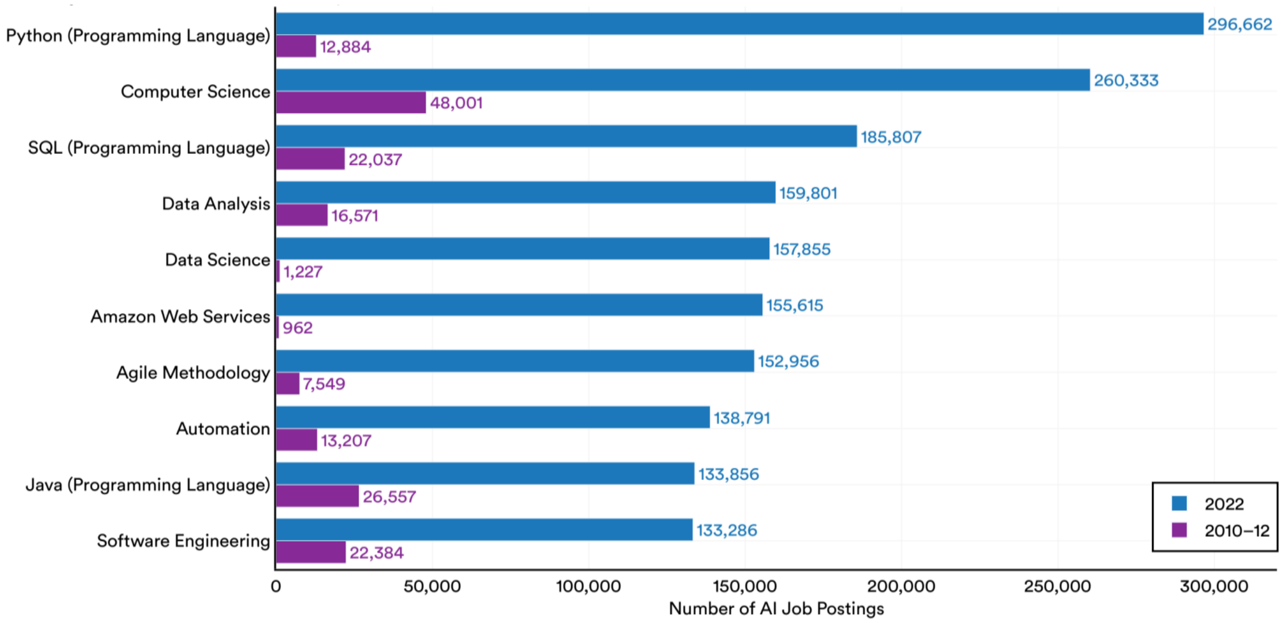

Figure 3. Top Ten Specialized Skills in 2022 AI Job Postings in the United States, 2010-2022

Table 1. Top Five Investment Activities, 2022 (Maslej et al., 2023)

Rank	Company Name	Headquarters Country	Focus Area	FA
AI Merger/Acquisition Investment Activities				
1	Nuance Communications, Inc.	United States	Artificial Intelligence; Enterprise Software; Healthcare; Medicine Learning	19.80
2	Citrix Systems, Inc.	United States	Data Management, Processing, and Cloud; HR Tech	17.18
3	Avast Limited	United States	Data Management, Processing, and Cloud; Fintech; Cybersecurity, Data Protection	8.02
4	AspenTech Corporation	United States	Manufacturing; Software; Supply Chain Management	6.34
5	Vivint Smart Home, Inc.	United States	Cybersecurity, Data Protection; Sales Enablement	5.54
AI Minority Stake Investment Activities				
1	AVEVA Group, PLC	United Kingdom	Chemical; Computer; Data Mining; Electronics; Industrial Manufacturing; Information Technology; Simulation; Software	4.68
2	Grupo de Inversiones Suramericana, SA	Colombia	Financial Services; Impact Investing; Insurance	1.48
3	Fractal Analytics Private Limited	India	Analytics; Artificial Intelligence; Big Data; Business Intelligence; Consulting; Machine Learning	0.35
4	Atrys Health, SA	Spain	Medical and Healthcare	0.28
5	R Systems International, Ltd.	India	Analytics; Information Technology; IT Management; Software	0.17
AI Private Investment Activities				
1	GAC Aion New Energy Automobile Co., Ltd.	China	Automotive; Clean Energy; Electric Vehicle; Manufacturing	2.54
2	Idience Co., Ltd.	South Korea	Emergency Medicine; Healthcare; Pharmaceutical	2.15
3	Uali	Argentina	Drones; Cloud Computing	1.50
4	Anduril Industries, Inc.	United States	Cybersecurity, Data Protection; AR/VR; Drones	1.50
5	Celonis, GmbH	Germany	Retail; Industrial Automation, Network; HR Tech; Insurtech	1.22
AI Public Offering Investment Activities				
1	ASR Microelectronics Co., Ltd.	China	Semiconductor; VC	1.08
2	iSoftStone Information Technology (Group) Co., Ltd.	China	Data Management, Processing, and Cloud; Cybersecurity, Data Protection	0.73
3	Jahez International Company for Information Systems Technology	Saudi Arabia	Artificial Intelligence; E-Commerce; Food and Beverage; Food Delivery; Information Technology; Logistics	0.43
4	Fortior Technology (Shenzhen) Co., Ltd.	China	Electronics; Machine Manufacturing; Semiconductor	0.30
5	Beijing Deep Glint Technology Co., Ltd.	China	Cybersecurity, Data Protection; Music, Video Content	0.29

**FA: Funding Amount (in Billions USD)*

While the United States leads in investments globally, a notable reality in recent years, as in many fields, is China's prominence. Saveliev & Zhurenkov (2021) highlighted Chinese companies as among the most popular among international technology investors, listing leading firms in AI investment such as Sense Time ($1.2 billion in 2018), UBTech Robotics ($820 million), Megvii Technology ($600 million), YITU Technology ($300 million), alongside American companies Dataminer ($391 million), CrowdStrike ($200 million), and Pony.ai ($214 million). China aims to become a global innovation leader in AI by 2030, with ambitious investment plans totaling 1 trillion yuan ($147.8 billion), aiming to establish itself as a "scientific and technical superpower" in AI, leading in all AI domains (English Gov, 2017).

Since 2013, the United States has led in private artificial intelligence investments with $248.9 billion, followed by China with $95.1 billion and the United Kingdom with $18.2 billion. Then, in order, they are Israel ($10.83 billion), Canada ($8.83 billion), India ($7.73 billion), Germany ($6.99 billion), France ($6.59 billion), South Korea ($5.57 billion), Singapore ($4.72 billion), Japan ($3.99 billion), Hong Kong ($3.10 billion), Switzerland ($3.04 billion), Australia ($3.04 billion), and Spain ($1.81 billion) (Maslej et al.,2023). Additionally, Table 1 shows the top five investment activities by country and firm name.

Additionally, another table below illustrates the Top AI Private Investment Activities for the USA, China, European Union, and United Kingdom (Table 2).

Table 2. Top AI Private Investment Events for United States, China, European Union and United Kingdom (Maslej et al.,2023)

Rank	Company Name	Focus Area	FA
United States			
1	Anduril Industries, Inc.	Cybersecurity, Data Protection; AR/VR; Drones	1.50
2	Faire Wholesale, Inc.	Fintech; Retail; Sales Enablement	0.82
3	Anthropic, PBC	Artificial Intelligence; Information Technology; Machine Learning	0.58
4	Arctic Wolf Networks, Inc.	Data Management, Processing, and Cloud; Cybersecurity, Data Protection	0.40
5	Jing Chi, Inc.	Data Management, Processing, and Cloud; AV; AR/VR	0.40
China			
1	GAC Aion New Energy Automobile Co., Ltd.	Automotive; Clean Energy; Electric Vehicle; Manufacturing	2.54
2	GAC Aion New Energy Automobile Co., Ltd.	Automotive; Clean Energy; Electric Vehicle; Manufacturing	1.11
3	Beijing ESWIN Technology Group Co., Ltd	Data Management, Processing, and Cloud; Industrial Automation, Network; Semiconductor; Marketing, Digital Ads; Sales Enablement	0.58
4	Zhejiang Hozon New Energy Automobile Co., Ltd.	Data Management, Processing, and Cloud; Cybersecurity, Data Protection; Sales Enablement	0.44
5	Zhejiang Hozon New Energy Automobile Co., Ltd.	Data Management, Processing, and Cloud; Cybersecurity, Data Protection; Sales Enablement	0.32
European Union and United Kingdom			
1	Celonis, GmbH	Retail; Industrial Automation, Network; HR Tech; Insurtech	1.22
2	Content Square, SAS	Analytics, Artificial Intelligence: CRM: Data Visualization; Digital Marketing; SaaS	0.60
3	Retail Logistics Excellence - RELEX Oy	Retail	0.57
4	Cera Care Limited	Medical and Healthcare	0.32
5	Babylon Holdings Limited	Medical and Healthcare; Music, Video Content	0.30

**FA: Funding Amount (in Billions USD)*

The European Union (EU), not wanting to fall behind in AI technologies led by the U.S. and China, has identified strategic areas to secure a larger share of the market and allocated substantial budgets accordingly. The EU supports early-stage AI research with grants up to €2 million, and provides up to €100 million in support for companies to commercialize positive outcomes after prototype or concept validation (TBD, 2020). Anderljung et al. (2023) emphasized the need for increased regulation and management of AI across various policy domains, prompting the EU to pursue appropriate legal frameworks such as the GDPR, AI Act, Digital Services Act (DSA), Digital Markets Act (DMA), Data Governance Act (DGA), Data Act (DA), and

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European Health Data Space (EHDS), positioning itself as a global leader in regulating digital innovation and potential harms (Sharon & Gellert, 2023).

Russia, while taking significant steps in AI, predominantly focuses these efforts within state-controlled frameworks. Over the past decade, Russia has conducted approximately 1,400 AI scientific projects, mostly by non-profit organizations. The country allocated approximately $343 million to AI R&D in the last decade, compared to around $200 million annually from U.S. state budgets for AI research (Saveliev & Zhurenkov, 2021).

In the United Kingdom, a system developed based on AI has proven highly profitable, generating £1.4 billion in additional revenue for the British treasury in its first year, despite its initial cost of £45 million (Caldwell, 2014). The system, Connect, developed by His Majesty's Revenue and Customs, utilizes social network analysis software and data mining techniques to detect fraudulent or undisclosed activities by cross-referencing tax records with other databases (Sanghrajka, 2024). Babuta et al. (2020) suggested that the use of AI within the framework of powers granted to government institutions may raise additional privacy and human rights considerations under existing legal and regulatory frameworks. Currently, however, the concept of responsibility concerning AI remains legally undefined globally (Saveliev & Zhurenkov, 2021). Similar systems have been implemented in different periods in India and Poland (Maciejewski, 2017).

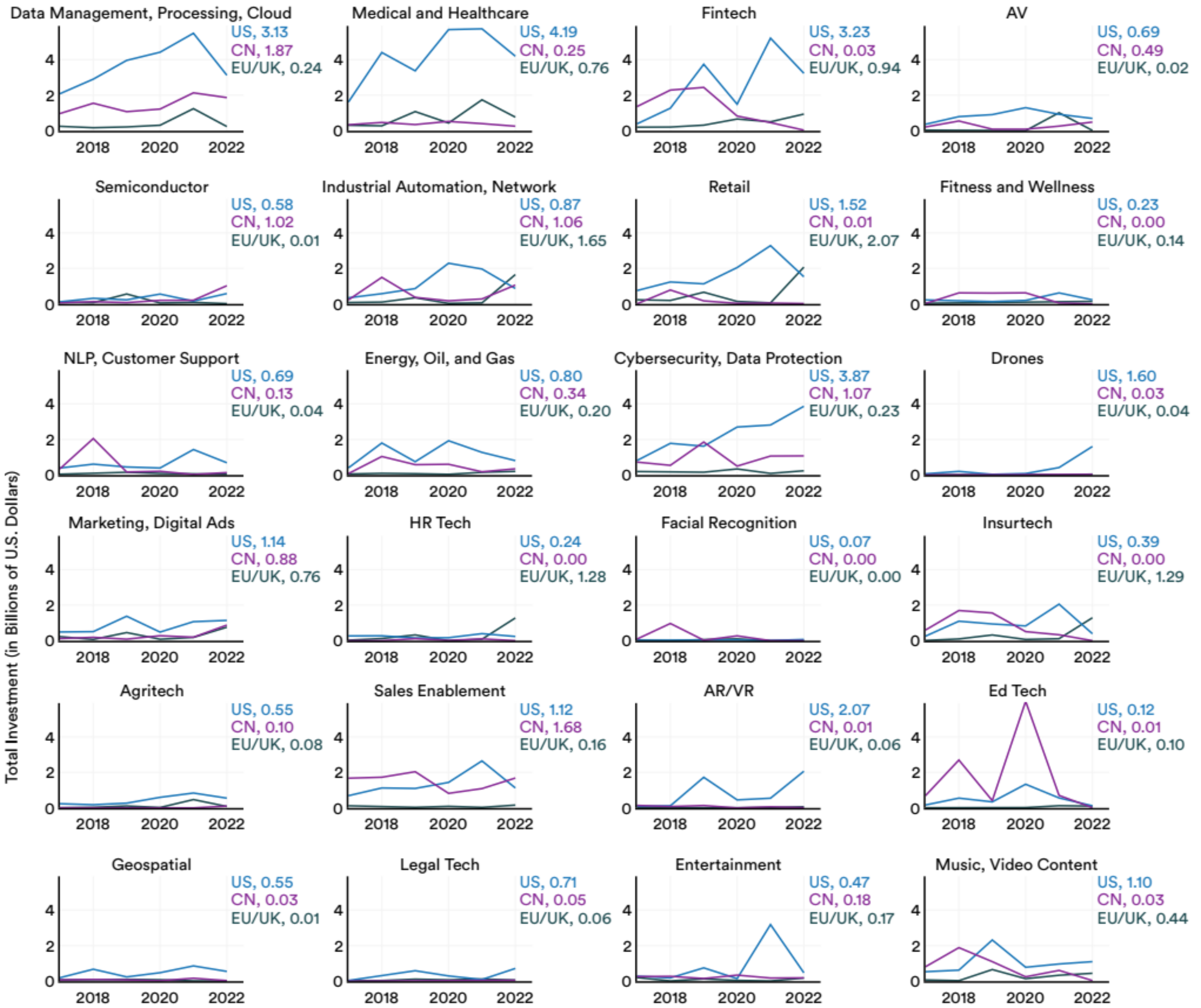

Figure 4. Private Investment in AI by Focus Area and Geographic Area (US: United States, CN: China, EU/UK: European Union/United Kingdom), 2017-22 (Maslej et al.,2023)

Each country invests significantly in artificial intelligence, both through private sector initiatives and government support. The investments made by the United States, European Union, United Kingdom, and China in 24 different areas of artificial intelligence are depicted in Figure 4.

The countries and groups mentioned above can be evaluated as exemplary applications of AI development. Nevertheless, advancements in AI are centered around human welfare. Examples of big data applications have demonstrated exceptional improvements in the effectiveness and efficiency of public administration, suggesting that big data could significantly enhance overall public governance (Maciejewski, 2017). However, the development of AI is progressing towards large-scale, complex distributed systems from relatively limited independent systems. Yet, potential risks such as hardware and software failures, design flaws, malicious attacks, and goal misalignment may arise. Moreover, systems controlled by advanced AI may become unpredictable, leading to ethical risks when making decisions regarding operational matters (Page et al., 2018). In this regard, it is highly valued that policymakers exercise caution in initiatives within public administration concerning artificial intelligence.

In developing countries, the challenges and opportunities of artificial intelligence extend beyond national borders. Global collaboration is essential to share knowledge, best practices, and resources. International organizations, technology companies, and research institutions can play a significant role in supporting developing countries on their AI journeys. Consequently, the integration of artificial intelligence in developing countries is a dynamic journey that requires coordinated efforts, strategic planning, and a commitment to inclusivity (Aderibigbe et al., 2023). The potential benefits of AI technology are substantial not only for the public sector but also for all sectors and countries. Additionally, it serves as a significant and critical catalyst for sustainable development goals globally.

7. DISCUSSION AND CONCLUSION

If we evaluate artificial intelligence technologies for the public sector, they can be applied in various domains such as security and defense for enhancing surveillance capabilities, in healthcare for medical diagnostics and treatment processes, in education for personalized learning materials, in improving public services, in transportation and infrastructure for traffic management and planning, in environmental and natural resource management for assessing environmental risks and natural disaster scenarios, in legal and justice systems for optimizing court decisions and identifying overlooked factors, in conducting financial analyses and economic predictions, among numerous other areas. Therefore, countries worldwide show significant interest in and allocate substantial resources for such a beneficial technology, also outlining national AI strategy action plans.

Artificial intelligence represents a revolutionary technological development with the potential to deeply impact all aspects of our lives. Both private and public sectors have recognized this, resulting in substantial investments in AI in recent years. For instance, according to the International Data Corporation's Worldwide Artificial Intelligence Spending Guide covering 32 countries and 19 industries, global spending on AI was $50.1 billion in 2020 and $85.3 billion in 2021, with projections to exceed $204 billion by 2025. The study highlights that countries like the United States and China are expected to lead in AI spending and reap significant economic gains from AI advancements (Özdemir, 2022).

In Türkiye, efforts are underway to integrate AI into digital transformation and public administration (Avaner & Çelik, 2021). Yalçın (2024) suggests that AI adoption in Turkish public institutions will shape through policies aligned with these institutions' goals and objectives. According to the Turkish Informatics Association's AI report, achieving a competitive global position in AI and swiftly implementing AI solutions in critical sectors require coordinated efforts among supervisory public sector bodies, the dynamic production capacity of the private sector, innovative technology-generating universities, professional chambers safeguarding societal values, and non-governmental organizations (TBD, 2020). Analyzing the opportunities and threats posed by AI technologies, which bring many innovations to public administration and are expected to continue doing so in the future, is crucial (Gezici, 2023).

The software sector ranks among the leading industries in creating new opportunities and adding value to developing countries. Countries like Türkiye, with a young and dynamic population, have a significant advantage in harnessing this potential (Damar & Özdağoğlu, 2021). In this context, Turkish universities have an important role to play. Their role in supporting scientific advancement is indisputable, and governments should view universities as a strategic tool for capturing current technologies and staying abreast of innovations (Damar & Aydın, 2021; Damar et al., 2020; Damar & Özdağoğlu, 2021). Despite approximately 200 computer science, software engineering, information technology, and AI departments across Turkish universities, many of these departments lack sufficient faculty members (TBD, 2020). Increasing AI-focused departments and integrating AI and machine learning courses into compulsory curricula such as statistics, mathematics, computer science, electrical engineering, electronic engineering, and telecommunications is strongly recommended. It is crucial to appoint academicians to these critical roles based on merit and ensure that appointed individuals are expert researchers in their fields, as they are critical for the country's future.

Furthermore, it is recommended that Türkiye significantly and rapidly enhance its bilateral interaction with China in international cooperation. Suggestions include increasing embassy numbers in G8 countries and countries like China and India, as well as establishing technology intelligence units in these large embassies (TBD, 2020). Additionally, increasing the number of researchers sent to China and India should be encouraged, particularly supporting technology-focused doctoral studies and post-research studies where China and India are pioneers. Civil society organizations such as the Turkish Informatics Association and the Software Industrialists Association are encouraged to engage with China and India, creating special investment and entrepreneurship reports on these countries, which are believed to support cross-border commercial initiatives. Trade and professional chambers should prioritize bilateral cooperation with these countries.

To expedite the integration of AI in the public sector, efforts should focus on accelerating the data cycle, enhancing AI for public policy development, coordinating the workforce with AI, harmonizing public administrations with AI, and prioritizing cybersecurity (Erbaş, 2023). AI investments should be incentivized. Besides resolving operational challenges in AI service delivery and supporting policies, AI is expected to actively create solutions in areas such as risks, crimes, pandemics, natural disasters, etc. (Efe, 2022). To create public value, all levels of government should consciously guide public sector knowledge, skills, and experiences to shape a more diverse and inclusive workforce for current and future capabilities (Lundy et al., 2021). Furthermore, for AI technologies to be developed, effectively used, and thereby ensure comprehensive development, it is imperative to swiftly establish a national AI ecosystem based on transparency (TBD, 2020). Thus, AI can make public services more efficient, use resources more effectively, and provide better services to citizens.

Given that AI technology is rapidly evolving and to plan for the future, it is essential for individuals to not only consider what AI can currently accomplish but also envision its potential future applications. Imagining AI and contemplating the global impacts of such applications are believed to be highly beneficial.

ACKNOWLEDGEMENTS

M.Damar was supported by the Scientific and Technological Research Council of Türkiye (TUBITAK) under the TUBITAK 2219 International Postdoctoral Research Fellowship program. He would like to thank the Upstream Lab, MAP, Li Ka Shing Knowledge Institute at the University of Toronto for its excellent hospitality.

FUNDING

No funding

AUTHORS` CONTRIBUTIONS

All authors contributed equally to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

All relevant data are within the paper and its Supporting Information.

REFERENCES

Aderibigbe, A. O., Ohenhen, P. E., Nwaobia, N. K., Gidiagba, J. O., & Ani, E. C. (2023). Artificial intelligence in developing countries: bridging the gap between potential and implementation. Computer Science & IT Research Journal, 4(3), 185-199.

Agrawal A., Gans, J., & Goldfarb, A. (2019). Prediction machines: the simple economics of artificial intelligence. USA: Harvard Business Review Press.

Aithal, P. S. (2023). Super-Intelligent Machines-analysis of developmental challenges and predicted negative consequences. International Journal of Applied Engineering and Management Letters (IJAEML), 7(3), 109-141.

Akçakaya, M. (2017). E-Devlet Anlayışı Ve Türk Kamu Yönetiminde Edevlet Uygulamaları. Yüzüncü Yıl Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, (3), 8-31.

Akman, E., & Çetin, M. (2019). Yeni Kamu Yönetimi Anlayışının Bir Yansıması Olarak Dijital Dönüşüm Ofisi. IV. Uluslararası Stratejik ve Sosyal Araştırmalar Sempozyumu Kitabı, (pp.223-231), December, 19th, 2024, Burdur, Türkiye. https://www.isasor.org/ISASOR%20IV%20ABSTRACT%20BOOK.pdf

Akpınar, M. T. (2023). Akıllı Şehirler ve Yapay Zeka. TYB Akademi Dil Edebiyat & Sosyal Bilimler Dergisi, (37), 14-25.

Anderljung, M., Barnhart, J., Leung, J., Korinek, A., O'Keefe, C., Whittlestone, J., ... & Wolf, K. (2023). Frontier AI regulation: Managing emerging risks to public safety. arXiv preprint arXiv:2307.03718.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. Government information quarterly, 36(2), 358-367.

Aoki, N. (2020). An experimental study of public trust in AI chatbots in the public sector. Government information quarterly, 37(4), 101490.

Avaner, T., & Çelik, M. (2021). Türkiye'de dijital dönüşüm ofisi ve yapay zeka yönetimi: Büyük Veri ve Yapay Zeka Daire Başkanlığı'nın geleceği üzerine. Medeniyet Araştırmaları Dergisi, 6(2), 1-18.

Aydın, Ö. (2023). Google Bard Generated Literature Review: Metaverse. Journal of AI, 7(1), 1-14. https://doi.org/10.61969/jai.1311271

Aydın, Ö., & Karaarslan, E. (2023). Is ChatGPT leading generative AI? What is beyond expectations?. Academic Platform Journal of Engineering and Smart Systems, 11(3), 118-134.

Aydın, Ö., Karaarslan, E. (2022). OpenAI ChatGPT Generated Literature Review: Digital Twin in Healthcare . In Ö. Aydın (Ed.), Emerging Computer Technologies 2 (pp. 22-31). İzmir Akademi Dernegi. Emerging Computer Technologies 2, Pp. 22-31

Babuta, A., Oswald, M., & Janjeva, A. (2020). Artificial intelligence and UK national security: policy considerations. Technical Report. RUSI, London.

Bilge, A. C. (2023). Bir yapay zekâ destekli dil modeli olan chatGPT'nin turizm sektöründe potansiyel ve hayata geçen uygulamaları. Journal of Recreation and Tourism Research, 10(3), 139-155.

Bozdoğanoğlu, B., Haspolat, İ., & Yücel, A. Kamu İdarelerinde Yapay Zekâ Kullanımının Ülke Uygulamaları ve Temel Kamusal İlkeler Çerçevesinde Değerlendirilmesi. Ankara Hacı Bayram Veli Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 26(1), 1-32.

Bryant, A. (2023). AI Chatbots: Threat or Opportunity?. Informatics, 10(2), 49. https://doi.org/10.3390/informatics10020049

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute, 4. https://www.mckinsey.com/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20frontier%20Modeling%20the%20impact%20of%20AI%20on%20the%20world%20economy/MGI-Notes-from-the-AI-frontier-Modeling-the-impact-of-AI-on-the-world-economy-September-2018.pdf

Busuioc, M. (2021). Accountable artificial intelligence: Holding algorithms to account. Public administration review, 81(5), 825-836.

Buxmann, P., & Schmidt, H. (2021). Grundlagen der Künstlichen Intelligenz und des Maschinellen Lernens. In: Buxmann, P., Schmidt, H. (eds) Künstliche Intelligenz. Springer Gabler, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-61794-6_1

Caldwell, K. (2014). Are you next on the taxman's hitlist. The Telegraph, 10. https://www.telegraph.co.uk/finance/personalfinance/tax/11092959/HMRC-targets-Are-you-next-on-the-taxmans-hitlist.html

Cuau, C. (2019). Applying artificial intelligence to citizen participation: the Youth4Climate case study. Citizenlab. Erişim Tarihi:25/05/2024. https://www.citizenlab.co/blog/civic-engagement/youth-for-climate-case-study/

Çarıkçı, O. (2010). Türkiyede e-devlet uygulamalari üzerine bir araştirma. Süleyman Demirel Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, (12), 95-122.

Damar, M. (2022a). Dijital çağda bilişim sektörünün ihtiyacı olan yetkinlikler üzerine bir değerlendirme. Journal of Information Systems and Management Research, 4(1), 25-40.

Damar, M. (2022b). Dijital Dünyanın Dünü, Bugünü Ve Yarını: Bilişim Sektörünün Gelişimi Üzerine Değerlendirme. Nevşehir Hacı Bektaş Veli Üniversitesi SBE Dergisi, 12(Dijitalleşme), 51-76.

Damar, M., & Aydın, Ö. (2021). Türkiye'nin 2010 Sonrası Yönetim Bilişim Sistemleri Alanında Uluslararası Q1 Dergilerinde Durumu. İzmir İktisat Dergisi, 36(4), 811-842.

Damar, M., & Özdağoğlu, G. (2021). Yazılım Sektörü ve Uluslararasılaşma, Politika Önerileri. Editörler, Ömer Aydın, Çağdaş Cengiz, Teknoloji ve Ululararası İlişkiler. İzmir: Nobel Yayın Evi.

Damar, M., Özdağoğlu, G., & Özveri, O. (2020). Üniversitelerde Dönüşüm Süreci Ve Araştırma Üniversitesi Yaklaşımı. Uluslararası Medeniyet Çalışmaları Dergisi, 5(2), 135-159.

De Sousa, W. G., de Melo, E. R. P., Bermejo, P. H. D. S., Farias, R. A. S., & Gomes, A. O. (2019). How and where is artificial intelligence in the public sector going? A literature review and research agenda. Government Information Quarterly, 36(4), 101392.

Dhara, S.K., Giri, A., Santra, A., Chakrabarty, D. (2023). Measuring the Behavioral Intention Toward the Implementation of Super Artificial Intelligence (Super-AI) in Healthcare Sector: An Empirical Analysis with Structural Equation Modeling (SEM). In: Tuba, M., Akashe, S., Joshi, A. (eds) ICT Infrastructure and Computing. ICT4SD 2023. Lecture Notes in Networks and Systems, vol 754. Springer, Singapore. https://doi.org/10.1007/978-981-99-4932-8_42

Digital Transformation Office, (2023). Chatbot Uygulamları ve ChatGPT Örneği. Ankara: Türkiye Cumhuriyeti Cumhurbaşkanlığı Dijital Dönüşüm Ofisi.

Digital Transformation Office, (2024a). Türkiye Cumhuriyeti Cumhurbaşkanlığı Dijital Dönüşüm Ofisi. Ulusal Yapay Zekâ Stratejisi (UYZS) 2021-2025. Erişim Tarihi:25/05/2024. https://cbddo.gov.tr/SharedFolderServer/Genel/File/TR-UlusalYZStratejisi2021-2025.pdf.

Digital Transformation Office, (2024b). T.C. Dijital Dönüşüm Ofisi. T.C. Dijital Dönüşüm Ofisi. Erişim Tarihi:25/05/2024. https://cbddo.gov.tr/hakkimizda/

Efe, A. (2022). Yapay Zekâ Ortamındaki Dijital Kamu Yönetiminin Yol Haritası. Kamu Yönetimi ve Teknoloji Dergisi, 4(1), 99-130.

English Gov, (2017). China issues guideline on artificial intelligence development. The State Council The Peoples Republic of China. Erişim Tarihi: 25/05/2024. http://english.www.gov.cn/policies/latest_releases/2017/07/20/content_281475742458322.htm

Erbaş, M. S. (2023). Türk Kamu Yönetiminde Stratejik Yönetim ve Dijital Dönüşüm Bağlamında Yapay Zekanın Kullanımı. Türk İdare Dergisi,95(496),185-215.

Erdoğan, G. (2021). Yapay zekâ ve hukukuna genel bir bakış. Adalet Dergisi, (66), 117-192.

Fernández, A. (2019). Artificial intelligence in financial services. Banco de Espana Article, 3, 19.

Fischer, L., Ehrlinger, L., Geist, V., Ramler, R., Sobiezky, F., Zellinger, W., ... & Moser, B. (2020). Ai system engineering—key challenges and lessons learned. Machine Learning and Knowledge Extraction, 3(1), 56-83.

Frerichs, J.T.M. (2019). Empowering Our Recruiters: Leveraging Narrow Artificial Intelligence and Cloud-based Customer Relationship Management Tools to Enhance Systematic Recruiting. United States Marine Corps School of Advanced War.fighting Marine C01ps University. Quantico, Virginia, USA.

Gezici, H. S. (2023). Kamu yönetiminde yapay zeka: Avrupa Birliği. Uluslararası Akademik Birikim Dergisi, 6(2), 111-128.

Goosen, R., Rontojannis, A., Deutscher, S., Rogg, J., Bohmayr, W., & Mkrtchian, D. (2018). Artificial Intelligence Is A Threat To Cybersecurity. It's Also A Solution. Boston Consulting Group (BCG), Tech. Rep. https://boston-consulting-group-brightspot.s3.amazonaws.com/img-src/BCG-Artificial-Intelligence-Is-a-Threat-to-Cyber-Security-Its-Also-a-Solution-Nov-2018_tcm9-207468.pdf

Goyal, P., Pandey, S., & Jain, K. (2018). Deep learning for natural language processing. New York: Apress.

Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: when will aI exceed human performance. EvidencefromaIexperts. Journal of Artificial Inteligence Research,62(2018), 729-754.

Gtech, (2021). Yapay Zeka Nedir, Yapay Zeka Hakkında Bilmeniz Gerekenler. Erişim Tarihi: 25/05/2024. https://www.gtech.com.tr/yapay-zeka-nedir-yapay-zeka-hakkinda-bilmeniz-gerekenler/

Hassabis, D., Kumaran, D., Summerfield, C., & Botvinick, M. (2017). Neuroscience-inspired artificial intelligence. Neuron, 95(2), 245-258.

Huang, C., & Gan, K. (2023). Enhancing Citizen Engagement in Smart Cities with Chatbot. International Journal of Smart Systems, 1(1), 34-39.

Ingrams, A., Kaufmann, W., & Jacobs, D. (2022). In AI we trust? Citizen perceptions of AI in government decision making. Policy & Internet, 14(2), 390-409.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business horizons, 62(1), 15-25.

Koçyiğit, A., & Darı, A. B. (2023). Yapay zekâ iletişiminde chatgpt: insanlaşan dijitalleşmenin geleceği. Stratejik Ve Sosyal Araştırmalar Dergisi, 7(2), 427-438.

Kopka, B. (2011). Theoretical aspects of using virtual advisors in public administration . 3rd International Conference – New Economic Challenges. Masaryk University, Faculty of Economics and Administration, Brno, Czech Republic

Kouziokas, G. N. (2016). Artificial intelligence and crime prediction in public management of transportation safety in urban environment. In Proceedings of the 3rd conference on sustainable urban mobility (pp. 534-539). Volos: University of Thessaly.

Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2017). Building machines that learn and think like people. Behavioral and brain sciences, 40, e253.

Lambert, J., & Stevens, M. (2023). ChatGPT and generative AI technology: A mixed bag of concerns and new opportunities. Computers in the Schools, (Online),1-25. https://doi.org/10.1080/07380569.2023.2256710

Livingston, C. (2023). ChatGPT, The rise of generative AI. Erişim Tarihi: 2/05/2024. https://www.cio.com/article/474809/chatgpt-the-rise-of-generative-ai.html

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In CHI '20: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. April 25 - 30, 2020, Honolulu, USA.

Lu, Y., Qian, D., Fu, H., & Chen, W. (2018). Will supercomputers be super-data and super-AI machines?. Communications of the ACM, 61(11), 82-87.

Luck, M. (2024). Freedom, AI and God: why being dominated by a friendly super-AI might not be so bad. AI & Society, Online(2024),1-8.

Lundy, J., Keast, R., Farr-Wharton, B., Omari, M., Teo, S., & Bentley, T. (2021). Utilising a capability maturity model to leverage inclusion and diversity in public sector organisations. Australian Journal of Public Administration, 80(4), 1032-1045.

Maciejewski, M. (2017). To do more, better, faster and more cheaply: Using big data in public administration. International Review of Administrative Sciences, 83(1_suppl), 120-135. https://doi.org/10.1177/0020852316640058

Maragno, G., Tangi, L., Gastaldi, L., & Benedetti, M. (2023). AI as an organizational agent to nurture: effectively introducing chatbots in public entities. Public Management Review, 25(11), 2135-2165.

Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., ... & Perrault, R. (2023). Artificial intelligence index report 2023. arXiv preprint arXiv:2310.03715.

Mehr, H., Ash, H., & Fellow, D. (2017). Artificial intelligence for citizen services and government. Ash Center for Democratic Governance and Innovation. Harvard Kennedy School, no. August, 1-12. https://creatingfutureus.org/wp-content/uploads/2021/10/Mehr-2017-AIforGovCitizenServices.pdf

Miller, S. (2024). Unveiling the Synergy: Exploring Advances in Applied Artificial Intelligence and Narrow AI (No. 11651). EasyChair. https://easychair.org/publications/preprint_download/d1PB

Ministry of Foreign Affairs. (2024). Hızır yapay zekâ uygulaması. Hızır yapay zekâ uygulaması. Erişim Tarihi:25/05/2024. http://www.konsolosluk.gov.tr/UseFulLinks/Index

Ministry of National Education. (2024). T.C. Milli Eğitim Bakanlığı. Eba ve MEB asistan. Erişim Tarihi:25/05/2024. https://www.meb.gov.tr/eba-asistan-uzaktan-egitimde-cevapsiz-soru-birakmayacak/haber/20829/tr

Ministry of Treasury and Finance. (2024). T.C. Hazine ve Maliye Bakanlığı. GİBİ uygulaması. Erişim Tarihi: 25/05/2024. https://www.gib.gov.tr/mobil-uygulamalar-0

Misuraca, G., & Van Noordt, C. (2020). AI Watch-Artificial Intelligence in public services: Overview of the use and impact of AI in public services in the EU. JRC Research Reports, (JRC120399).

Moser, B. (2022). Modeling & Engineering Beyond Narrow AI. Erişim Tarihi: 25/05/2024.

https://www.software-center.se/wp-content/uploads/2022/05/2022-05-09-SC_BeyondNarrowAI.pdf

Önder, M., & Saygılı, H. (2018). Yapay Zekâ Ve Kamu Yönetimine Yansimalari. Türk İdare Dergisi, 2(487), 629-670.

Özdemir, G. S. (2022). Yapay Zekada Küresel Gelişmeler ve Trendler: Türkiye'nin Yeri Nedir?. Erişim Tarih: 25/05/2024. https://kriterdergi.com/dosya-teknoloji/yapay-zekada-kuresel-gelismeler-ve-trendler-turkiyenin-yeri-nedir

Page, J., Bain, M., & Mukhlish, F. (2018). The risks of low level narrow artificial intelligence. In 2018 IEEE international conference on intelligence and safety for robotics (ISR) (pp. 1-6). IEEE, 24-27 Aug. 2018, Shenyang, China.

Pan, Y. (2016). Heading toward artificial intelligence 2.0. Engineering, 2(4), 409-413

Rawat, R., Goyal, H. R., & Sharma, S. (2023). Artificial Narrow Intelligence Techniques in Intelligent Digital Financial Inclusion System for Digital Society. In 2023 6th International Conference on Information Systems and Computer Networks (ISCON) (pp. 1-5). IEEE, Mathura, India, March 3-4, 2023.

Revell, T. (2017). Go-playing super AI transcends humanity. New scientist, (3148), 1-9.

Sanghrajka J. (2024). Taxation UK, HMRC's Connect computer and investigations. Erişim Tarihi: 25/05/2024. https://www.taxation.co.uk/articles/hmrc-s-connect-computer-and-investigations

Sarıtürk, M. (2022). Dijital Dönüşüm Döneminde Kamu Yönetimi ve Dijital Hükümet. Adıyaman Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, (42), 555-603.

Saveliev, A., & Zhurenkov, D. (2021). Artificial intelligence and social responsibility: the case of the artificial intelligence strategies in the United States, Russia, and China. Kybernetes, 50(3), 656-675.

Serçemeli, M. (2018). Muhasebe Ve Denetim Mesleklerinin Dijital Dönüşümünde Yapay Zekâ. Electronic Turkish Studies, 13(30),369-386.

Sharon, T., & Gellert, R. (2023). Regulating Big Tech expansionism? Sphere transgressions and the limits of Europe's digital regulatory strategy. Information, Communication & Society, (Online),1-18. https://doi.org/10.1080/1369118X.2023.2246526

Shawar, B. A., & Atwell, E. (2007). Chatbots: are they really useful?. Journal for Language Technology and Computational Linguistics, 22(1), 29-49.

Suebvises, P. (2018). Social capital, citizen participation in public administration, and public sector performance in Thailand. World Development, 109, 236-248.

Şahnagil, S. (2023). Kamu Yönetimi ve Yapay Zekâ İlişkisi. Editör Ö. Dündar, İktisadi ve İdari Bilimler Alanında Teori, Uygulama ve Güncel Tartışmalar (ss.23-40). Ankara: Gazi Kitabevi.

Şentürk, Ö. (2023). İç Denetim Faaliyetlerinde Yapay Zekadan Beklentiler: Chatgpt Uygulaması Örneği. TIDE AcademIA Research, 4(2), 51-82.

Tamer, H. Y., & Övgün, B. (2020). Yapay zeka bağlamında dijital dönüşüm ofisi. Ankara Üniversitesi SBF Dergisi, 75(2), 775-803.

Tanrıverdi, A. (2021). Yapay zekânın kamu hizmetinin sunumuna etkileri. Adalet Dergisi, (66), 293-314.

TBD, (2020). Türkiye'de Yapay Zekanın Gelişimi İçin Görüş ve Öneriler. Türkiye Bilişim Derneği Kavramsal Rapor. Erişim Tarihi: 25/05/2024. https://www.tbd.org.tr/pdf/yapay-zeka-raporu.pdf

Turchin, A. (2018). Narrow AI Nanny: Reaching Strategic Advantage via Narrow AI to Prevent Creation of the Dangerous Superintelligence. Erişim Tarihi: 25/05/2024. https://philpapers.org/rec/TURNAN-3

Ulaşan, F. (2023). Koronavirüsle Mücadelede Yapay Zekânin Yerinin Kamu Yönetimi Temelinde Değerlendirilmesi. In International Mediterranean Congress.(Ed. B. Arslan and M. Erdoğan). Mersin: Iksad Global.

Uslu, H. (2023). Dijital Dönüşüm ve Kamu Hizmetleri Yönetimde Yenilikçi Yaklaşımlar ve Zorluklar. Uluslararası Politik Araştırmalar Dergisi, 9(3), 15-31.

Uzun, M. M., Yıldız, M., & Önder, M. (2022). Big Questions of AI in Public Administration and Policy. Siyasal: Journal of Political Sciences, 31(2), 423-442.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. International Journal of Public Administration, 42(7), 596-615.

Wogu, I. A. P., Misra, S., Assibong, P. A., Ogiri, S. O., Damasevicius, R., & Maskeliunas, R. (2018). Super-Intelligent Machine Operations in Twenty-First-Century Manufacturing Industries: A Boost or Doom to Political and Human Development?. Towards Extensible and Adaptable Methods in Computing, 209-224.

Yalçın, A. (2024). Türkiye'de Kamu Kurumlarının Toplum İçin Geliştirdiği Yapay Zekâ Uygulamaları. İstanbul Aydın Üniversitesi Sosyal Bilimler Dergisi, 16(2), 185-215.

Young, M. M., Bullock, J. B., & Lecy, J. D. (2019). Artificial discretion as a tool of governance: a framework for understanding the impact of artificial intelligence on public administration. Perspectives on Public Management and Governance, 2(4), 301-313.

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Journal of AI

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Volume: 8, **Issue No:** 1, January-December 2024, **Pages:** 107-137

Artificial Intelligence in Cancer: A SWOT Analysis

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Received: 01.05.2024 *Accepted: 07.09.2024* *Online: 19.09.2024* *Published: 31.12.2024*

Review Article

Abstract

Cancer, a collection of maladies that has undergone extensive examination over centuries, remains a formidable challenge. Despite the array of available pharmacological and therapeutic interventions, the intricate molecular dynamics and heterogeneity of cancer continue to challenge the scientific community. Artificial Intelligence (AI) emerges as a promising avenue, offering the potential for expedited, precise diagnostics devoid of human expertise. Additionally, AI facilitates the tailoring of patient-specific therapeutic strategies targeting various facets of cancer, spanning macroscopic to microscopic levels. Nonetheless, it is imperative to scrutinize the potential benefits and limitations of AI technologies in this context. This review undertakes a comprehensive Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis of AI's application in cancer. An extensive compilation of AI applications encompasses predictive modeling, diagnostic capabilities, prognostic assessments, and personalized therapeutic modalities, spanning genomic analyses to individualized treatment regimens. The synthesis of evidence suggests that the advantages of AI outweigh its drawbacks; nevertheless, obstacles to its widespread integration persist.

Keywords: *Artificial intelligence, cancer, deep learning, machine learning, precision oncology, SWOT analysis*

Cite this paper (APA)

Torkay, G., Fadlallah, N., Karagöz, A., Canlı, M., Saydam, E., Mete, A., Kızılışık, F., Darici, H., Yeşil, Y. (2024). Artificial Intelligence in Cancer: A SWOT Analysis. Journal of AI. 8(1), 107-137. Doi: 10.61969/jai.1469589

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1. INTRODUCTION

Since Alan Turing's seminal inquiry into the capabilities of machines to exhibit intelligence (Turing and Haugeland, 1950), substantial progress has been made in domains such as computational biology and evolutionary algorithms (Yang, 2012). Turing's question spurred scientific endeavors, leading to the development of advanced artificial intelligence (AI) algorithms that now find application across diverse industries, including healthcare (Bohr and Memarzadeh, 2020).

In the 1980s, rudimentary, rule-based AI systems emerged, albeit with limited computational prowess, rendering them inadequate for addressing the complex challenges encountered in healthcare, such as disease diagnosis, decision-making, and image processing (Davenport and Kalakota, 2019). Notably, computer vision, a branch of AI facilitating the extraction of meaningful insights from visual data like digital images, relies on Deep Learning (DL) and Convolutional Neural Networks (CNNs), subfields within the broader domain of machine learning (ML), demanding substantial data volumes. Herein, image processing research assumes significance within the healthcare sector.

ML, a subset of AI, enables software to acquire knowledge autonomously through exposure to representative data, yielding predictive capabilities that can be refined through iterative practice. ML classifications encompass supervised, unsupervised, and reinforcement learning (RL). Supervised learning delves into establishing correlations between input features and desired outcomes, effectively addressing classification and regression challenges. Unsupervised learning is geared towards uncovering patterns, clustering data, discovering rules, and facilitating information extraction from data without prior guidance (Sarker, 2021). In contrast, RL centers on decision-making strategies that maximize cumulative rewards, successfully applied in domains like robotics, autonomous vehicles, and strategic games. Concurrently, DL, a facet of ML, employs multi-layered artificial neural networks (ANNs) to tackle problems spanning object recognition, speech analysis, and natural language processing (NLP). It is essential to recognize the interrelatedness of these technologies, as depicted in Figure 1.

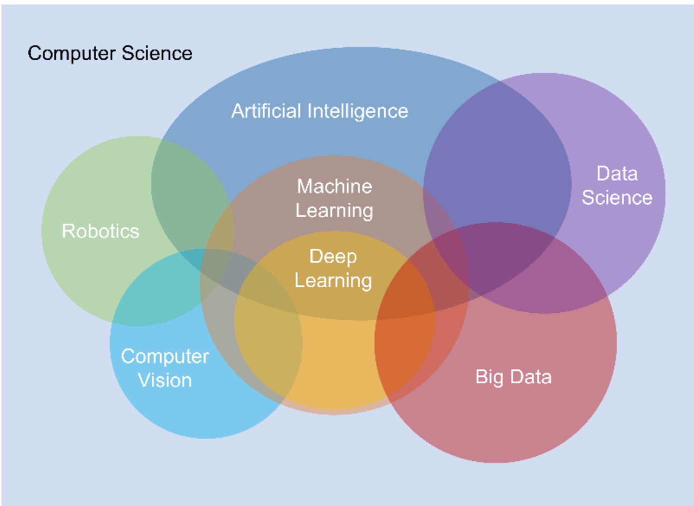

Figure 1: Current approaches and interdisciplinary interactions in computer science.

Over the past decade, AI has permeated diverse industrial domains, with research and development efforts promptly extending into healthcare, owing to the potential advantages of AI in medical practice. AI has, thus far, applied every facet of medical processes, ranging from disease prediction to treatment to hospital administration (Jiang et al., 2017). A noteworthy area of medical integration for AI is in the domain of oncology.

Cancer, a spectrum of diseases with historical origins, has challenged researchers for centuries, characterized by unregulated cell proliferation and the loss of cellular control mechanisms. Its classification into various distinct types and subtypes underscores the complexity of treatment, necessitating individualized therapeutic strategies dictated by factors such as cancer type, stage, molecular phenotype, and patient profile.

Dysregulation in the mechanisms governing physiological events, including cell proliferation, growth, apoptosis, and deoxyribonucleic acid (DNA) repair can catalyze the transformation of normal cells into cancerous ones. Genetic and epigenetic changes play pivotal roles in tumor initiation and progression, contributing to metastasis, drug resistance, autocrine signaling, and the initiation of vascular networks. Consequently, AI algorithms find utility in predicting cancer prognosis at the molecular level (Kourou et al., 2014). The intricate landscape of cancer genomics research, characterized by epigenetic alterations, variations in mutations, signaling pathway aberrations, and the consequent tumor subgroup diversity, can be effectively navigated using big data, statistical methods, and AI, as evidenced by recent literature (Catto et al., 2010; Dlamini et al., 2020; Khalifa et al., 2020; Zhang et al., 2020; Zhao et al., 2020).

Cancer development is influenced by genetic and environmental factors, including smoking, viral infections, obesity, sun exposure, alcohol consumption, chemical agents, and DNA damage (Parsa, 2012). Commonly diagnosed cancers include lung, breast, and colorectal, with leading causes of cancer-related mortality being lung, liver, and stomach cancers (Ferlay et al., 2019). Given the substantial patient population and mortality rates associated with cancer, there is a pronounced need for AI-based models that span the entire spectrum of cancer care, from prevention to treatment.

In the realm of cancer diagnostics, methods and devices such as immunohistochemistry (IHC), frozen section analysis in pathology, polymerase chain reaction (PCR), DNA microarrays, computer tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) play pivotal roles (Goyal et al., 2006). However, the selection of specific diagnostic methods depends on the type of cancer, each demonstrating varying levels of sensitivity and specificity. For instance, breast cancer diagnosis may suffice with manual examination and mammography, while colon cancer may necessitate colonoscopy and biopsy.

Cancer treatment predominantly involves surgery and radiotherapy, with surgery aimed at tumor removal, while radiotherapy employs ionizing radiation to target specific areas and induce cell damage through DNA disruption (Keam et al., 2020). Chemotherapy, though generally not targeted to a specific location of the body, remains a gold standard for cancer treatment for inhibiting cancer cell proliferation (DeVita and Chu, 2008).

Despite the unique developmental processes and molecular intricacies inherent to each cancer type, the fundamental principles underlying the disease remain consistent. Hanahan and Weinberg's definition and subsequent revisions of the hallmarks of cancer, elucidating molecular and biochemical processes (Hanahan and Weinberg, 2000; Hanahan and Weinberg, 2011), continue to guide our understanding. In January 2022, Hanahan expanded on these hallmarks, introducing "New Dimensions" (Hanahan, 2022). Figure 2 provides a reinterpretation, encapsulating the transition from the traditional "10 hallmarks of cancer" to the "10 hallmarks of AI in cancer" as a summary.

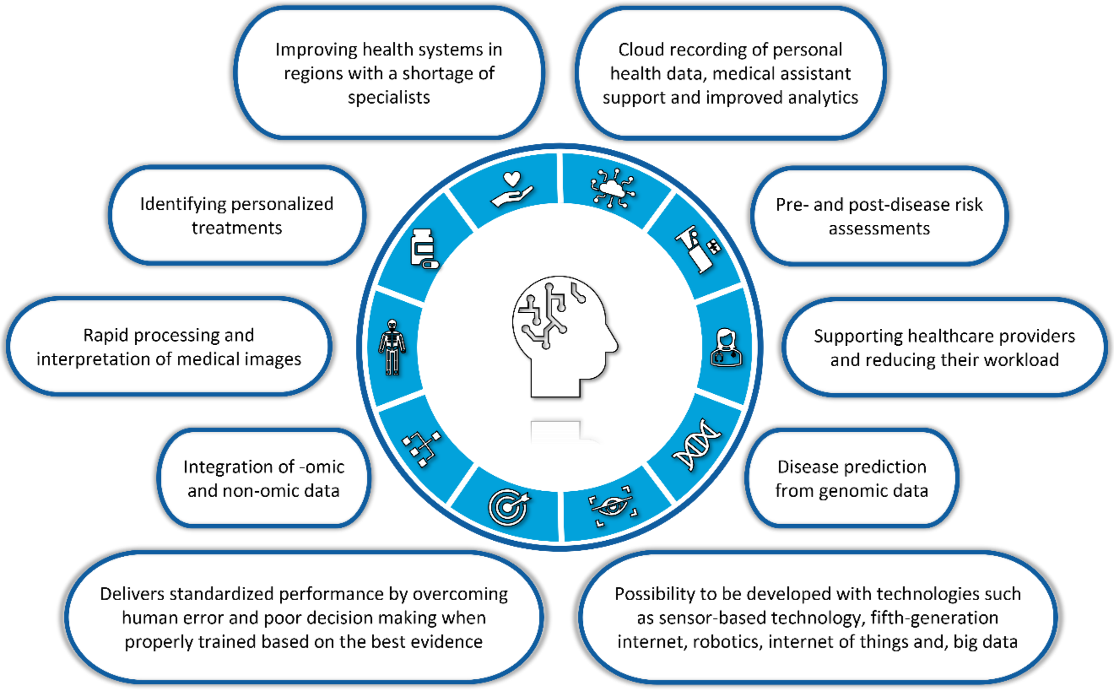

Figure 2: Areas where AI can aid cancer research.

CNNs are designed to emulate the human brain's mechanisms for object recognition, with ANNs serving as their foundational building blocks (Lindsay, 2021). In the human brain, each neuron encodes specific information collectively contributing to the comprehension of distinctive features within an image. To illustrate, consider a CNN model tasked with recognizing 'cats' and 'dogs' in images. This model comprises interconnected layers that interact sequentially. The initial layer serves as the input layer, receiving images of cats and dogs. During training, these images are labeled as either 'cat' or 'dog.' Subsequent layers are responsible for identifying specific features in the images. For instance, one neuron might specialize in identifying triangular ears, while another focuses on tail shape or whiskers. Further layers delve into finer details, aptly termed hidden layers, as the precise characteristics sought by individual neurons remain opaque to developers. With each image passing through these layers, a score is assigned based on the similarity between various aspects of the image and the neuron's feature. At the output layer, the model aggregates these scores to determine the image's category. Throughout the training process, these scores are compared to the provided labels, and mathematical formulas compute a loss function, allowing for the recalibration of each neuron's contribution (referred to as weights) to the image's overall score. This iterative process continues until training concludes, usually when the validation error is no longer decreasing (O'Shea and Nash, 2015). Subsequently, during model usage, images traverse the same layers and neurons, with the score calculated based on their similarity to each neuron's feature, but no further alterations are made to the model. In a similar vein, for a CNN model designed to identify brain tumors in MRI scans, each neuron can scrutinize specific features associated with tumor shapes or cerebral anomalies. The model aggregates scores for every small detail within the MRI, enabling it to accurately detect even minute irregularities and distinguish tumors from other abnormalities (Ranjbarzadeh et al., 2021). Figure 3 provides a simplified and schematic representation of an artificial neuron and a neuron in the human brain's structure.

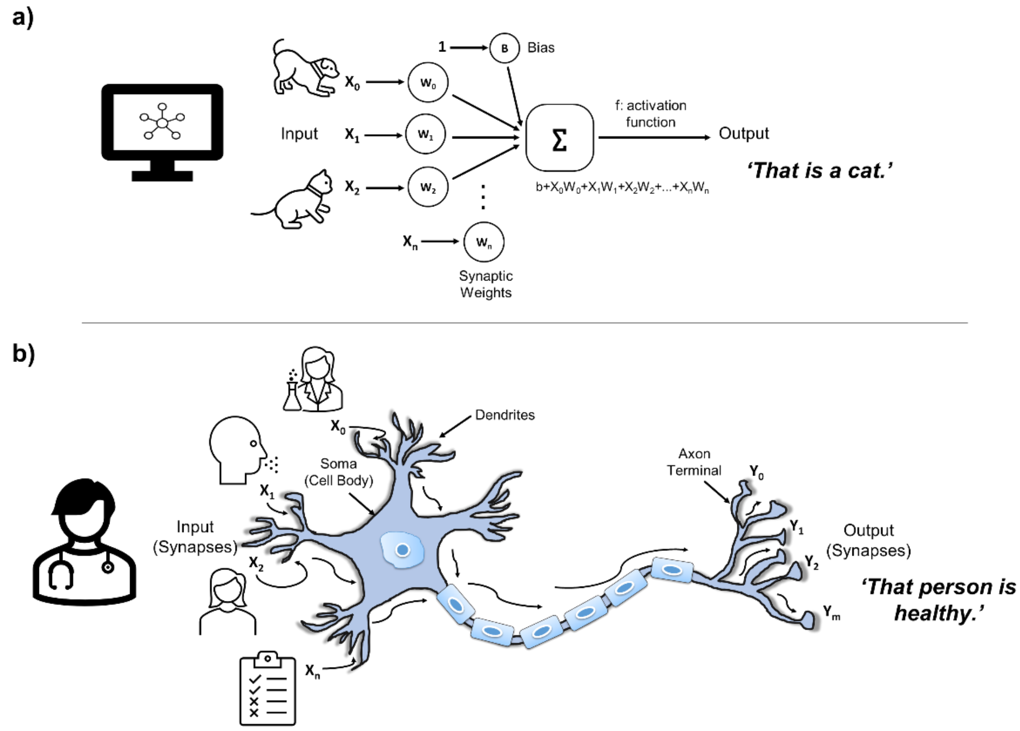

Figure 3: The similarity between an artificial neuron and a neuron. A neuron in a biological nervous system is a processing element in ANNs. Dendrites correspond to the summation function, while the cell body corresponds to the activation function. Biological synapses, that is, intercellular connection areas, correspond to weights in ANNs. Axons are the output region. Learning for an ANN can be expressed as updating the weight coefficients between synapses and dendrites. a) In an ANN, each of the input values (x_i) is multiplied by the weights (w_i), and the bias value (B) is added to the obtained information. The output value is acquired by applying the activation function (f) to the result. b) In the human brain, the learning process produces new axons by stimulating axons or changing the strength of existing axons. A doctor interprets data based on life experience and decides whether a person is healthy or not.

2. AI IN CANCER AND MEDICINE

The paradigm of evidence-based medicine revolves around the formulation of therapeutic judgments rooted in prior knowledge and accumulated experience. While traditional statistical methodologies leverage various mathematical techniques to discern these patterns, AI introduces approaches for uncovering intricate correlations that resist easy translation into mathematical equations. Neural networks, akin to the human brain, encode data through a vast interconnection of neurons, enabling ML systems to approach complex problems with a semblance of clinical acumen. Additionally, these systems can assimilate knowledge from each new case they encounter and amass exposure to a greater number of examples in a brief span than a human physician can accumulate in a lifetime (Buch et al., 2018). This holds true for clinical processes in oncology, where AI augments existing methods with enhanced sophistication. Nonetheless, it remains uncertain whether complex algorithms trained on extensive data sets consistently yield more precise predictions than human clinicians. Key requisites include the accuracy of labels and the cleanliness of data. Figure 4 delineates the conventional methods employed in the overarching disease process alongside the potential contributions of AI.

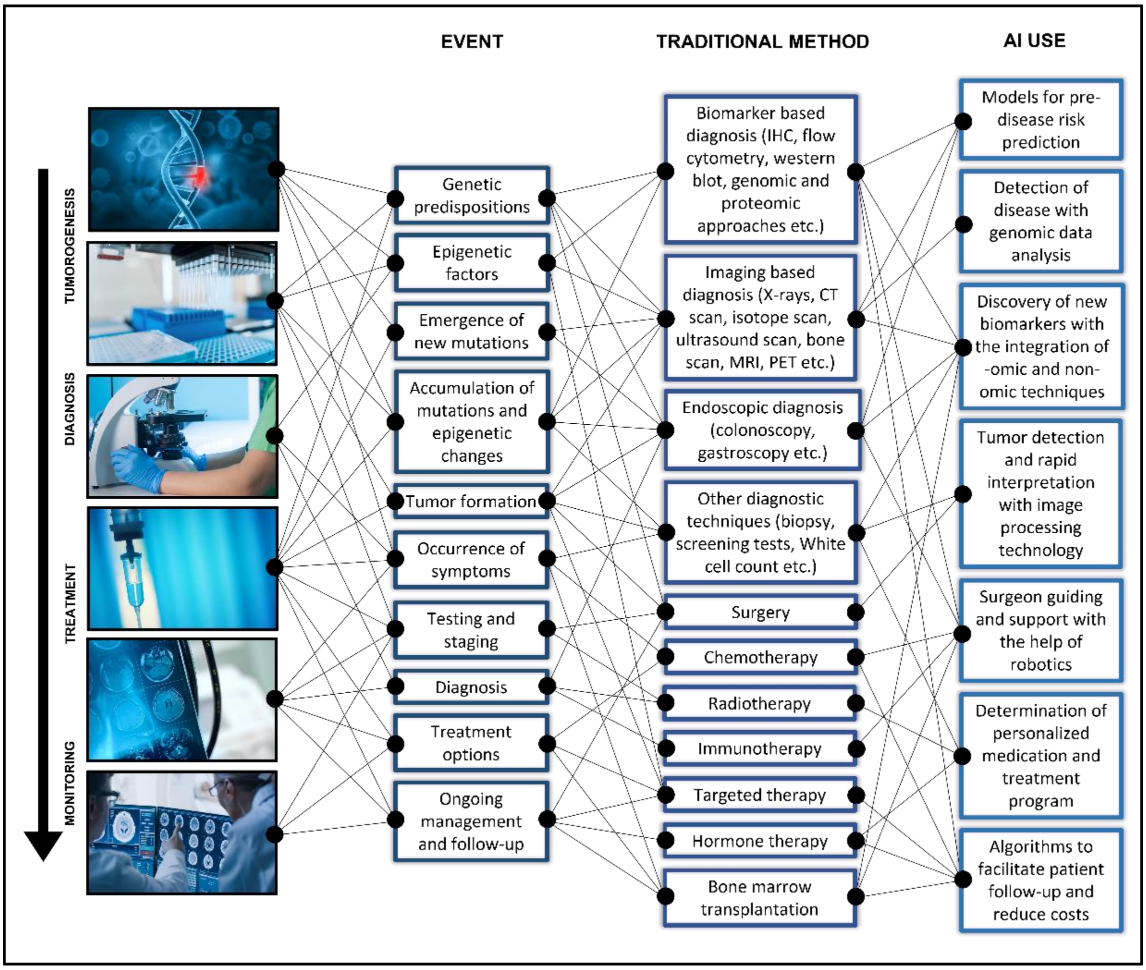

Figure 4: The diagram of the events that occur in the cancer process, the traditional methods used in this process, and possible AI approaches (Neural connections are added for visual purposes alone; they have no meaning.).

2.1 Personalized Medicine

AI assumes a pivotal role in the advancement of personalized medicine, predicated on its capacity for in-depth data analysis, thereby elucidating targeted objectives and intervention strategies. The realization of AI's potential in personalized medicine hinges not only on the refinement of pertinent assays but also on the effective storage, collection, accessibility, and subsequent integration of data (Schork, 2019). Digital health records, interconnected for diagnostic and treatment decision-making, serve as reservoirs for AI, which leverages patient data to discern optimal treatment plans and tailored therapeutic solutions (Amisha et al., 2019). The substantial cost involved in drug development, estimated at approximately $2.6 billion, with a high attrition rate between trial phases and regulatory approvals, underscores the pressing need for more efficient methodologies (Fleming, 2018).

Various machine intelligence methodologies have been harnessed to guide resource-intensive traditional experiments. ML tools have emerged, capable of swiftly and cost-effectively identifying potential bioactive molecules from vast pools of candidate compounds, exemplified by quantitative structure-activity relationship (QSAR) modeling. However, the advent of the 'big' data era in drug discovery has precipitated a transformation in ML approaches, ushering in the era of DL, which offers enhanced efficacy and potency in handling extensive datasets (Zhang et al., 2017). In a bid to streamline costly and time-consuming conventional experiments, multiple machine intelligence technologies have been employed. Notable among these is QSAR modeling, a ML technique adept at identifying physiologically active molecules from among millions of candidate compounds, thus promising cost-effective pre-clinical cost reduction and risk mitigation through virtual screening, activity scoring, and diverse drug design strategies. Beyond the prediction of molecular attributes, DL methodologies are enlisted for the generation of tailored molecules, further catalyzing AI's role in drug design (Zhong et al., 2018). ANNs such as deep neural networks (DNNs) and repetitive networks, particularly in the realm of drug discovery, assume a prominent role, underscoring AI's potency. The synergy of synthesis planning and facile synthesis avenues has become a reality, heralding the prospect of computer-aided drug discovery in the near future (Hessler and Baringhaus, 2018).

2.2 Diagnosis

AI diagnostic systems assume paramount significance for several compelling reasons. Given the global shortage of highly skilled specialists such as radiologists, the quest for rapid and dependable solutions has become imperative. AI systems, unlike their human counterparts, possess the capacity to analyze vast datasets within remarkably short timeframes, while consistently upholding high levels of accuracy and precision. Their prowess in comprehending extensive datasets enables the discernment of intricate relationships and the identification of subtle details that often elude human perception. Predominantly, AI's application in clinical diagnosis is exemplified through image analysis, a domain where AI algorithms, particularly CNNs, have outshone radiologists in terms of swiftness and accuracy.

There are many examples where AI is used in cancer diagnosis. For instance, in a study conducted at Stanford Academic Medical Center, while radiologists took an average of 240 minutes to label 420 images, the AI model under investigation labeled the same dataset in a mere 1.5 minutes (Rajpurkar et al., 2018). Su and colleagues (2020) created a DL model for the diagnosis of hydronephrosis from ultrasound images. Yadav and Jadhav (2019) used CNN networks to diagnose multiple lung diseases from X-ray images. Coudray and colleagues (2018) created a classification and segmentation model for lung cancer histopathology. Bien and colleagues (2018) developed a diagnostic model for knee MRIs.

AI's remarkable precision and reliability stem from its immunity to fatigue and distractions, attributes inherently human. Furthermore, AI exhibits a capacity for rapid adaptation, facilitating the diagnosis of novel diseases within a relatively short time frame (Davenport and Kalakota, 2019). This adaptability is exemplified by the prolific generation of scientific publications and AI models dedicated to the diagnosis of the novel coronavirus (COVID-19) within a month of its declaration as a pandemic. For instance, Chen and colleagues (2020) swiftly developed a CNN model capable of diagnosing COVID-19 on CT scans with a high degree of accuracy a mere few months after the initial case was reported.

In the realm of medical applications, AI engineers undertake the training of CNNs using a vast repository of medical images, meticulously annotated by domain specialists. Medical image processing predominantly serves two core functions: diagnosis classification and segmentation. In the classification paradigm, the AI model endeavors to categorize the input image into predefined classes. These classes may assume a binary form, as exemplified in the diagnosis of COVID-19, where classes are defined as "healthy" or "not healthy" (Islam et al., 2020). Alternatively, multiple classes may be employed, encompassing categories like "healthy," "COVID," or "pneumonia" (Jin et al., 2020). Conversely, segmentation models are tasked with delineating and annotating affected regions within the image, akin to the discerning eye of a radiologist, surpassing the sole provision of class labels. A quintessential instance is the diagnosis of COVID-19 through the precise delineation of afflicted areas (Yan et al., 2020). The quintessential segmentation DL algorithm is Unet, expressly designed for the nuanced demands of medical data (Ronneberger et al., 2015). By meticulously orchestrating the CNNs in a specific sequence, these models attain highly accurate segmentation of regions of interest (ROIs), with the training data being enriched with medical images annotated by seasoned professionals, explicitly highlighting ROIs.

Both classification and segmentation techniques undergo an initial training phase on extensive datasets, followed by testing on novel data samples constituting approximately one-third of the training dataset's size. The test dataset serves as the crucible for evaluating the model's accuracy, generalizability, precision, and other pivotal metrics. In medical applications, an additional crucial step precedes the model's deployment, involving the validation of the newly tested data by domain specialists, commonly referred to as establishing the "ground truth." This ground truth can be ascertained through primarily two approaches. The first entails a panel of experts validating the model's outputs, typically employing a consensus voting mechanism. The second approach involves validation by subjecting the samples to another, typically superior test and comparing the outcomes. For instance, in the context of X-ray image classification, the model's results may be corroborated by performing a concurrent CT scan. Following the validation step, the model's performance is comprehensively re-evaluated, thereby determining its suitability as a bona fide AI model or necessitating further optimization.

2.3 Decision Making

Decision-making constitutes a pivotal aspect of human existence, essential for navigating diverse situations. In the context of healthcare, clinical decision-making (CDM) emerges as a cornerstone of healthcare providers' responsibilities, wielding a direct influence on the diagnosis, prognosis, formulation of treatment plans, and post-treatment care. The complexity of the CDM process encompasses various modes, spanning from intuitive and heuristic to analytical and evidence-based (Gigerenzer and Kurzenhaeuser, 2005; Nalliah, 2016). While technological advancements in the healthcare industry have significantly enhanced global well-being, a knowledge gap persists concerning the identification of optimal methods or approaches tailored to specific patient conditions and temporal dynamics. However, there is still a lack of knowledge about finding the best method or approach in specific conditions and times for each patient.

The ascendancy of AI has been unfolding over decades, catalyzed by the proliferation of potent hardware and the deluge of data. A watershed moment occurred in the latter half of the 1990s when IBM's Deep Blue triumphed over world chess champion Garry Kasparov. This victory heralded a rapid acceleration in AI's evolution, with particular strides achieved in the domain of DL and the concurrent escalation of computing power. These advancements empowered AI researchers to grapple with copious datasets and tackle profoundly intricate problems, with some AI applications attaining nearly perfect accuracy in select cases (Odusami et al., 2021). Nonetheless, the opacity inherent in AI decision-making, coupled with the substantial costs associated with false negatives and false positives, has prompted a shift in focus. Rather than replacing human specialists with AI systems for definitive decision-making, the primary objective has transitioned towards the development of Clinical Decision Support Systems (CDSSs). These systems aim to enhance the accuracy and reliability of healthcare providers' decisions, mitigating the risks associated with erroneous judgments (Wijnhoven, 2021).

2.4 Treatment

AI has found application in the analysis of diverse data types, including documents, sensory information, and medical images, with the overarching aim of augmenting the accuracy of CDM. Notably, NLP emerged as an initial foray in healthcare, focusing on knowledge extraction from repositories like the Electronic Health Record (EHR) system, encompassing patient treatment records, laboratory reports, diagnoses, and medical visits (Demmer-Fushman et al., 2009). Various applications of NLP have been devised, spanning disease-treatment classification (Reddy and Baskar, 2018), influenza detection (Ye et al., 2017), prediction models for asymptomatic populations (Hong et al., 2017), and the creation of decision support systems (DSS) (Gatt et al., 2009). While a diverse array of ML algorithms underpin NLP applications, DNNs have particularly excelled in discerning intricate word relationships. Recurrent Neural Networks (RNNs), a subtype of DL, have gained prominence for processing time-series data, exemplified by their utility in handling electroencephalogram (EEG) signals and data from wearable garments. RNN architectures, endowed with robust problem-solving capabilities, hold promise for the development of CDSSs, owing to their aptitude for tackling complex issues. Various RNN applications have been elucidated (Ilbay et al., 2011; Choi et al., 2017; Bhavya and Pillai, 2019; Snorovikhina and Zaytsev, 2020).

Furthermore, the domain of medical image processing stands as a prevalent and influential domain for AI deployment in diagnostic decision-making and the selection of treatment strategies. CNNs stand as the predominant models in this arena, adept at tasks ranging from anomaly detection and classification to segmentation. While medical image processing exists as a distinct field from CDSS, it exerts a direct impact on the decision-making process by furnishing healthcare professionals with supplementary insights and knowledge essential for diagnosis and treatment planning.

3. SWOT ANALYSIS

It is apparent that AI embodies numerous advantageous characteristics, yet it remains an imperfect disruptive technology. While the allure of its attributes such as speed, accuracy, reliability, repeatability, and accessibility are undeniable, challenges persist in the form of data standardization issues, applicability complexities, and hardware dependencies that remain unresolved. The scientific community's accumulation of open-source data has been facilitated by researchers' enthusiastic engagement in the field and the rapid expansion of AI and ML studies in recent years. The escalating processing power, which not only adheres to but often surpasses Moore's Law, empowers users to analyze vast datasets with greater ease (Shalf, 2020). This progression reverberates in the realm of medicine, where AI serves as a means to bridge the gap created by the scarcity of human specialists and their inherent limitations. However, as AI increasingly assumes a pivotal role, questions regarding the allocation of responsibility for the outputs, data security, and ethical concerns come to the fore. Consequently, it becomes imperative to adopt a balanced perspective, acknowledging both the benefits and potential challenges. In this review, we have undertaken a comprehensive exploration of AI in a general context, elucidating its prospects in healthcare, with a specific focus on its strengths, weaknesses, opportunities, and threats—a succinct SWOT analysis—pertaining to AI in medicine, particularly within the domain of cancer research.

3.1 Strengths

The insufficiency of human resources in terms of both capacity and time to conduct intricate analyses has prompted the adoption of AI and ML as alternative tools to supplant human labor as much as possible. When summarizing the strengths inherent to AI, it is evident that it offers remarkable attributes, including speed, precision, reproducibility, accessibility, and the capacity to discern relationships among concepts. Furthermore, AI possesses additional advantages, such as its independence from remuneration, its capability to operate around the clock without the need for breaks, its immunity to emotional fluctuations, and its capacity to autonomously generate standardized responses.

3.1.1 Speed

One of the paramount strengths of AI resides in its capacity to swiftly analyze vast quantities of data, a quality of particular significance in the realm of healthcare, and notably, in the context of diagnosis, as acknowledged by the Food and Drug Administration (FDA). In the domain of medical imaging diagnosis, AI's speed is particularly compelling when addressing intricate tasks, such as the precise pixel-by-pixel segmentation of medical images to identify potential tumor regions. The time required by radiologists to perform a comparable task is substantially greater (Zhang et al., 2021). Consequently, AI, when employed within healthcare facilities, can expedite the medical imaging analysis process, serving either as a decision support tool for diagnosis or by offering potential ROIs for expert examination.

In the analysis of genetic sequences from biopsy samples, AI-driven models, particularly those based on DL, demonstrate their efficacy in reducing interpretation time, as exemplified by the work of Karim et al. (2021). Another noteworthy application involves the use of AI to aid pathologists in diagnosis, wherein pathology slides can be digitized through slide scanners and subjected to AI algorithms for preliminary assessments, thus expediting the diagnostic process (Komura and Ishikawa, 2018). These algorithms can either streamline the diagnostic process by presenting ROIs or trigger the initiation of pertinent tests before the samples are scrutinized by expert pathologists (Bera et al., 2019).

Early diagnosis in the initial stages of cancer treatment is of paramount importance, affording patients ample time for intervention. Sun and colleagues (2019) have developed a model incorporating a DNN based on genetic variations for 12 types of cancer, facilitating the assessment of cancer risk before a formal diagnosis, thereby expediting treatment.

Drug discovery, characterized by its complexity, stands as another domain where AI's efficacy surpasses human capabilities in terms of speed. AI-facilitated in silico studies have the potential to identify drug molecule targets objectively and evidentially on a large scale. This approach holds promise for significantly abbreviating protracted drug development processes, primarily by streamlining operations and minimizing resource utilization (Workman et al., 2019). However, it is worth noting that this field remains a work in progress (Bender and Cortés-Ciriano, 2021).

In the field of biomedicine, Ko and colleagues (2018) conducted a study that assessed the performance of supervised ML in the analysis of cross-sectional clinical data for multicolor flow cytometry, an essential prognostic factor for measuring minimal residual disease which is an important prognostic factor and aimed to avoid the disadvantages of manual interpretation. Their developed algorithm achieved a remarkable accuracy of nearly 90% within a mere 7 seconds, a stark contrast to the 20 minutes required for human manual interpretation.

3.1.2 Accuracy

The concept of accuracy, which denotes the precision of a measurement system, holds paramount significance within the field of medical science. Recent AI models consistently exhibit levels of accuracy that are on par with human capabilities (Kheradpisheh et al., 2016). However, AI's precision in discerning minute details confers upon it a substantial advantage, as it meticulously analyzes data at the pixel and digit level. This enables AI models to achieve a sensitivity that surpasses human capabilities. An illustrative example in the domain of disease diagnosis involves a recent study proposing a model that outperforms 72% of general practitioners on written test cases (Richens et al., 2020).

Beyond accuracy, the performance of AI models in cancer research must be evaluated using a range of metrics tailored to the specific problem at hand, such as sensitivity, specificity, and other metrics used in classification, segmentation, and object detection tasks (Goyal et al., 2020). For instance, in breast cancer screening, sensitivity measures the model's ability to correctly identify true cancer cases, ensuring that no malignancies are missed, while specificity ensures that healthy tissues are not incorrectly flagged as cancerous. This balance is crucial in clinical settings to minimize both false positives and false negatives. Moreover, in the context of MRI-based brain tumor segmentation, metrics like the Dice coefficient and Intersection over Union (IoU) assess how closely the AI-generated segmentations align with actual tumor boundaries (Güvenç et al, 2023). Such metrics are vital in guiding precise surgical interventions. Similarly, in object detection tasks, such as identifying lung nodules in CT scans, the ROC curve and AUC score are often employed to evaluate the model’s performance across different threshold settings, which is particularly important for early-stage lung cancer detection (Srivastava et al., 2023). These diverse evaluation metrics provide a comprehensive understanding of an AI model’s strengths and weaknesses, enhancing its applicability in different aspects of cancer research.

Two critical facets of accuracy are sensitivity and specificity in the context of diagnosis. As part of cancer, sensitivity represents the ratio of correctly identifying cancer samples from the total number of cancer cases within the patient pool. Specificity pertains to the accuracy of diagnosing cancer cases selected from the entire patient sample. To facilitate a deeper comprehension of these concepts, Figure 5 can be taken into consideration.

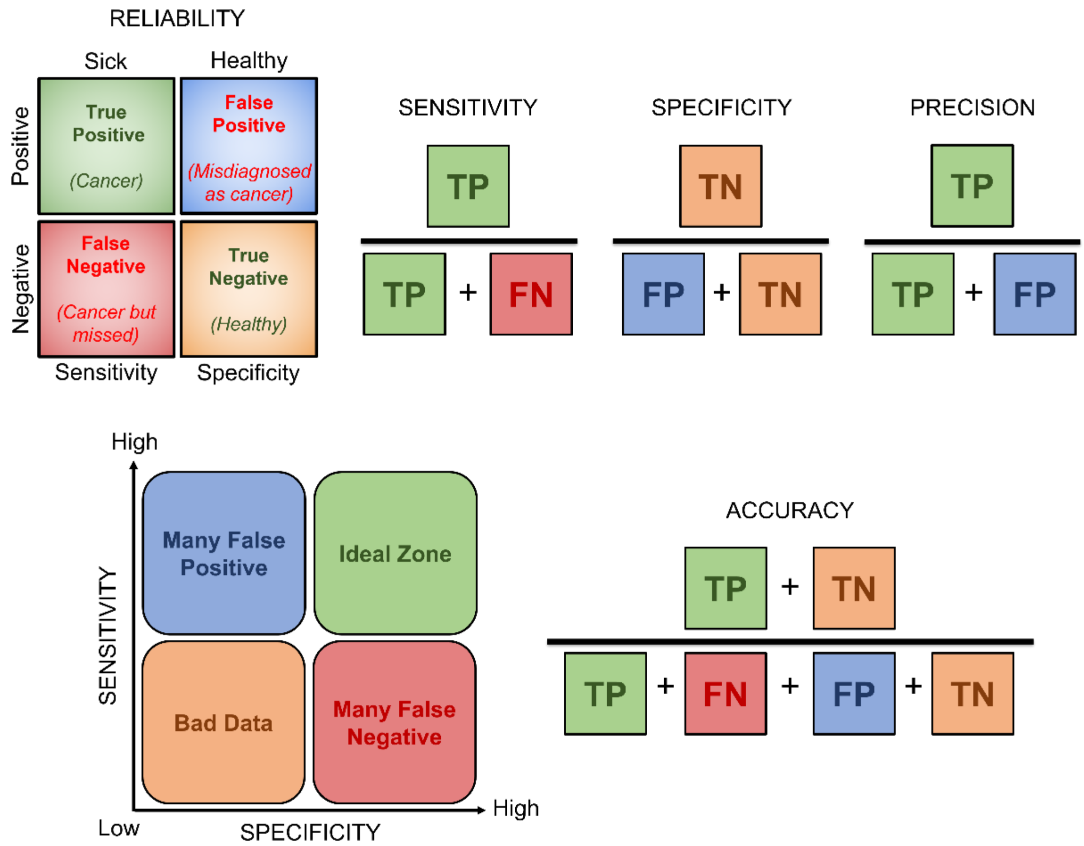

Figure 5: Statistical reliability standards encompass key attributes, namely accuracy, precision, specificity, and sensitivity. While these concepts are distinct, they are often evaluated in conjunction. Precision pertains to the reliability of a method when it yields consistent results upon repeated analyses using the same samples. Such consistency indicates that the results can be replicated reliably. Specificity, on the other hand, measures a test's ability to correctly identify and exclude samples that lack a particular characteristic. A highly specific test minimizes the occurrence of false-positive results. Sensitivity, conversely, gauges a test's effectiveness in correctly identifying samples possessing a specific characteristic. A test with high sensitivity minimizes the occurrence of false-negative results. The overarching concept of accuracy, which can be perceived as an evaluation encompassing all these attributes, essentially assesses whether a method can measure what it is intended to measure accurately and reliably.

Clinicians heavily rely on their knowledge and experience in diagnosing patients, which is acquired gradually over time. Consequently, newly graduated clinicians may lack the years of experience that their more seasoned colleagues possess. Furthermore, not all physicians encounter the same diversity of cases throughout their careers. For instance, physicians practicing in smaller locations may have limited exposure to a variety of patient cases. This situation can be likened to an AI model trained with insufficient data. A study conducted by Liang and colleagues (2019) grouped physicians by their level of experience and compared their performance with an AI system. The findings revealed that the AI-based model outperformed the two groups of less experienced physicians but exhibited lower accuracy than the three groups of senior physicians, with an average accuracy score of 88.5%. These results suggest that AI models may assist young physicians in diagnosis but may not perform as proficiently as experienced physicians (Liang et al., 2019). Additionally, aside from a lack of experience, human errors stemming from physical and psychological conditions can also lead to diagnostic inaccuracies.

Prognosis holds a critical role in cancer treatment, and the accuracy of prognosis predictions must be reliable. To achieve more accurate results, the development of AI models that comprehensively analyze the data commonly used in prognosis is imperative. In clinical settings, prognosis relies on genetic tests and histological images, but predictions based on these tests can remain subjective. DL models that integrate histological and genomic data can offer a more objective perspective on prognosis. Although models combining histological and genomic data yield more accurate results than clinicians, further refinement is needed to enhance objectivity. For instance, in a study by Mobadersany and colleagues (2018), experts were still required to identify ROIs on slides, indicating that human expertise remains essential in AI training. While algorithms can be developed to automate the selection of ROI regions, this process still necessitates expert input, underscoring the ongoing need for time to mature these processes.

As an illustration, computer-aided systems can assist in detecting polyps and adenomas during colonoscopy procedures. In a study by Liu and colleagues (2020), patients were randomized for colonoscopy, and a DL-based computer-assisted system was used in one of the groups. The study observed significant increases in the detection rate of adenomas, the average number of adenomas, the number of small adenomas, and the number of proliferative polyps compared to the control group (Liu et al., 2020). Such systems can offer decision support to endoscopists in challenging circumstances. Nevertheless, further randomized controlled studies and extensive datasets are required to bolster reliability.

3.1.3 Repeatability and Accessibility

AI models, even though trained on specific datasets, exhibit a remarkable ability to perform effectively on data beyond their initial training scope. Transfer learning (TrLe) techniques are employed to extend the utility of AI models trained for specific applications to different domains (Kim et al., 2020). For instance, an object detection model initially trained on common objects can be further trained on medical images, delivering high accuracy since the primary training data focus on extracting general features rather than domain-specific nuances. This versatility contributes to the repeatability and reproducibility aspects of AI models, as they can consistently perform with accuracy over multiple uses and can serve as building blocks for more complex models. An example of this is demonstrated by Namikawa and colleagues (2020), who efficiently classified gastric cancers and ulcers using their AI-based diagnostic system. In their study, they developed and re-validated algorithms previously obtained in another study, resulting in a model with improved specificity (Namikawa et al., 2020). This showcases how previously generated algorithms can be adapted and enhanced using new datasets.

Moreover, AI's inherent accessibility is of paramount importance in the realm of healthcare, especially for reaching remote areas where skilled clinicians may be scarce or unavailable. Additionally, ANNs possess online learning capabilities, allowing them to autonomously learn and adapt continuously. As previously mentioned, computers are immune to human limitations like stress, fatigue, hunger, or institutional pressures. This makes AI more reliable in hazardous environments and during times of crisis.

3.1.4 Learning Relationships

AI possesses a remarkable advantage that sets it apart from other technologies: its ability to approximate nonlinear relationships and unveil even the subtlest connections within vast datasets. Leveraging its talents in pattern association, classification, and sample clustering, AI aids in understanding the intricate biological causation required for various applications. As a result, new studies are conducted continuously to train AI through the development of novel models. One noteworthy model in this regard is TrLe, which mitigates data scarcity challenges by utilizing a pre-trained model in a related problem context (Hutchinson et al., 2017).

Unlike humans, AI demonstrates the capacity to meticulously analyze extensive datasets, enabling it to perform tasks such as clustering, classification, and the discovery of new patterns. This capability empowers the resolution of complex medical problems, including medical imaging analysis, prognosis, and drug discovery. Furthermore, AI can uncover novel relations between symptoms, diseases, or drugs, as it doesn't rely on understanding causation to reveal these connections, a feature distinct from medical professionals. This opens up new possibilities for expediting our comprehension of current and future diseases.

The complex and variable molecular and genetic mechanisms underlying cancer present one of the most challenging aspects of cancer treatment. These intricate and variable systems are pivotal for personalized treatment, drug development, and generate vast datasets that defy analysis through classical methods. To address this challenge, cutting-edge sequencing technologies and AI are employed for data analysis (Fountzilas and Tsimberidou, 2018). Additionally, predicting the prognosis of highly heterogeneous cancers like hepatocellular carcinoma (HCC) can be exceptionally challenging. While various molecular subtypes of HCC have been identified through multi-omic studies, some exhibit similar survival outcomes. Consequently, identifying HCC subtypes sensitive to survival and evaluating multi-omic data are crucial for prognosis prediction and treatment planning. Chaudhary and colleagues (2018) harnessed DL computing frameworks to address these challenges using multi-omic HCC data. Using ribonucleic acid (RNA) sequencing, micro-RNA (miRNA) sequencing, and methylation data from The Cancer Genome Atlas (TCGA), their study resulted in the identification of two optimal subgroups with distinct survival outcomes (Chaudhary et al., 2018). In their review of the roles of AI in prostate cancer, Goldenberg and colleagues (2019) demonstrated that AI not only enhances image processing-mediated diagnosis but also supports researchers and clinicians in various aspects, ranging from molecular biology and genetics to robotic surgery, thereby improving disease prognosis and saving valuable time for patients.

Leveraging computational biology for prognostic evaluations can significantly expedite the process for both patients and clinicians. Recent advancements in algorithms enable the swift and highly accurate synthesis of data that may be challenging to integrate and interpret or time-consuming to analyze. For instance, Daemen and colleagues (2008) integrated microarray and proteomic analyses with computational biology techniques using samples from rectal cancer patients at different stages of treatment. Their models achieved a remarkable sensitivity of 96% in predicting treatment responses (Daemen et al., 2008). Evaluating multiple types of data simultaneously is a key strategy to enhance predictive power. Genomic, proteomic, metabolomic data, histopathological samples, clinical outcomes, and even patient questionnaires can be synthesized to develop diverse prognostic scores. To achieve this, we can leverage the latest advancements in molecular biology techniques and AI.

In summary, AI's strengths collectively contribute to bridging gaps in human efforts to achieve accurate and unbiased healthcare. AI-driven DSSs aim to mitigate all facets of human error, accelerate expert decision-making, and enhance the overall quality of healthcare.

3.2 Weaknesses

AI, while boasting numerous strengths, also exhibits certain weaknesses and areas that necessitate improvement. One prevalent issue is the system's incapacity to scrutinize its own functioning and the possibility of failing to learn effectively. This predicament can be addressed through adjustments to the datasets and models employed. Although machines possess extensive storage capacity and formidable processing capabilities, they lack human-like cognitive faculties entirely. AI networks excel at detecting minuscule anomalies in images, often imperceptible to humans. However, they struggle to establish cause-and-effect relationships with these anomalies, which presents a formidable challenge, particularly in the context of medical images (Shvetsova et al., 2021). Furthermore, AI models, crafted with highly specific data for particular purposes, prove susceptible to even minor alterations, rendering replicability challenging under varying conditions. Disparate learning methods, datasets, ROIs, and even different software developers can all influence outcomes. Therefore, method standardization holds significant importance. Moreover, certain domains, such as healthcare, may encounter difficulties in acquiring data, and AI consistently relies on hardware for data processing. Lastly, the substantial energy consumption associated with large-scale AI models has undeniable implications for global warming, posing a threat to human health.

3.2.1 Causality

To address the weaknesses of DL and traditional ML, it's crucial to delve into the concept of causality. In the real world, humans inherently strive to discern cause-and-effect relationships between events because comprehending the underlying reasons empowers them to make decisions that can shape a better future. ML algorithms excel at identifying patterns and correlations between inputs and outputs, and they are adept at predicting outcomes. However, this capacity is not synonymous with understanding causation. Recent research emphasizes the necessity for AI systems to construct causal models that facilitate explanation and comprehension (Lake et al., 2017).

ML algorithms do not possess an intrinsic understanding of genuine causal relationships or how inputs and outputs are intrinsically linked; instead, they tend to memorize the relationship between inputs and outputs, which can lead to overfitting (Ying, 2019). Overfitting occurs when an analysis is tailored too closely to a specific dataset, rendering it less adaptable to new, unseen data. Causality can aid ML in mitigating overfitting while enhancing accuracy and interpretability. It does so by mitigating the adverse impacts of selection bias, interobserver variability, and other factors on accuracy, and by facilitating a genuine comprehension of the data's significance. Outputs should be comprehensible and interpretable not only to programmers but also to other researchers (Azuaje, 2019).

However, a significant challenge arises in the form of the "black box" problem, which stems from the non-transparency of the information processing systems used by AI to solve problems. This opacity hampers researchers' ability to precisely understand why a particular output is generated. Engineers are actively working on solutions to this problem, advocating for the use of more interpretable models (Rudin, 2019). For instance, studies involving AI and the cancer genome are burgeoning, yet scientists remain essential for interpreting the outcomes produced by these models (Liu et al., 2018).

3.2.2 Reproducibility

In ML, the process of training algorithms and fine-tuning hyperparameters is crucial to achieving optimal results. Equally important is the ability to consistently obtain the same outcomes when using identical data, algorithms, and hyperparameters, which is referred to as reproducibility. Reproducible AI algorithms play a pivotal role in enhancing the comprehensibility, interpretability, accuracy, and dependability of the workflow (Cutillo et al., 2020).

The term "reproducibility" gained prominence following a 2016 study conducted by Baker, which revealed that over half of scientists struggled to replicate their own experiments, and seven out of ten encountered difficulties when trying to reproduce experiments conducted by other researchers (Baker, 2016). Achieving reproducibility in AI is indeed challenging because it hinges on factors such as training data, the selection or generation of features, algorithmic procedures, hardware, and software configurations, and is influenced by variations between laboratories and population diversity. For instance, the Watson for Oncology system, which was initially trained in the United States, exhibited slight inconsistencies when applied to different cases and evaluated by various experts in India. However, these disparities might also be attributed to differences in treatment approaches between countries and variations in demographics (Somashekhar et al., 2018).

3.2.3 Data Availability (Annotations & Privacy Restrictions)

DL algorithms often demand large volumes of data during the training process, yet the biomedical field frequently encounters limitations in terms of the quantity of available data (Huang et al., 2020). While there are some publicly available anonymized datasets for research purposes, these datasets are often insufficient in size to achieve the high levels of accuracy and precision required for applications in the healthcare industry. Moreover, there are various other sources of medical data, such as electronic health records, experimental data, physiological monitoring data, and medical imaging data, which are stored in secure databases (Hulsen et al., 2019). Accessing such data is hindered by strict regulations and privacy concerns surrounding medical data, making it challenging to obtain the necessary datasets for training ML algorithms in healthcare. To address these data limitations, researchers have explored alternative approaches such as TrLe and leveraging different portions of the same pathological sections in ML education. Additionally, the use of synthetic images generated through Generative Adversarial Networks (GANs) has been investigated as a means to augment training datasets (Iqbal and Ali, 2018). Some studies have shown that even experts have difficulty distinguishing between real and artificial images (Abdelhalim et al., 2021).

Beyond data availability, data annotation presents another significant challenge in the medical field. Annotating medical data, such as segmenting tumors in medical images, requires the expertise of professionals, often experienced radiologists. Finding professionals with the available time for annotation work can be a substantial challenge. Efforts to increase data standardization and facilitate access to clean data are essential but remain ongoing processes. Converting examples into numerical values and selecting appropriate methods for data preprocessing and activation functions are also critical aspects that rely on the programmer's experience. Moreover, the lack of highly accurate reference datasets, which include meticulously characterized tumors and detailed clinical annotations, is a significant concern. Furthermore, collecting extensive personal health data raises security and privacy concerns, making it susceptible to potential security breaches (Rigaki and Garcia, 2020). Blockchain applications have been explored as a potential solution to enhance data security (Saldanha et al., 2022).

In summary, the challenges in data science, particularly in the context of medical data, are more prominent than the lack of AI capabilities. Addressing issues related to data quantity, quality, standardization, annotation, and security is crucial for advancing AI applications in healthcare.

3.2.4 Applicability

The applicability of AI models in healthcare often faces challenges due to a gap between AI engineers and the healthcare system. While AI models may hold theoretical promise in medical applications, they may not align with the practical processes and quality metrics of the healthcare system (He et al., 2019). For instance, historically, computer scientists have aimed to achieve automatic diagnosis or CDSS for medical purposes since the 1960s (Miller, 1994). However, AI models typically lack an understanding of causality and rely on observed data relationships, which contrasts with the diagnostic process in healthcare. In medical diagnosis, the emphasis is on comprehending the biological causal relationships between symptoms and diseases rather than merely identifying correlations in data. Consequently, computer science shifted its focus to computer-aided diagnosis systems, where AI models serve as decision assistants rather than decision-makers. This shift aligns more closely with practical healthcare applications.

Additionally, evaluation metrics and quality assurance criteria differ significantly between engineering and medical sciences. While an AI model that is 100 times faster than traditional methods but has an 80% accuracy rate may seem like a significant advancement in engineering contexts, medical applications demand a different standard. In clinical settings, achieving a 99% accuracy rate with low precision is not acceptable. The medical field prioritizes precision and reliability over raw speed. Moreover, the testing and quality assurance process for AI in medicine is more complex because even minor malfunctions can have critical consequences. AI models in medicine require periodic testing and ongoing performance monitoring to ensure that they consistently meet the required standards over time. Unfortunately, not all AI models have robust methods for conducting stability analyses, which further complicates quality assurance efforts.

3.2.5 Hardware Dependence

ML algorithms require powerful hardware at various stages, including data storage, data preprocessing, training, and deployment. The training of ML models, especially those dealing with large datasets or complex tasks like image processing, demands substantial storage capacity and efficient processors, such as graphics processing units (GPUs) and tensor processing units (TPUs) (Jawandhiya, 2018). These specialized hardware components are capable of handling the intense computational workloads required during training.

The ability to perform parallel processing is another critical factor in ML performance, and it depends on the processors' ability to run in parallel. For example, DL models, particularly ANNs, distribute memory across network connections and weight values. The information processed by the network is encoded in the connections and weights of neurons, and individual links or neurons do not carry meaningful information on their own. Therefore, determining the appropriate number of neurons and layers in a neural network can impact the computational load. Adding extra layers increases the computational time required for training and inference.

In practice, many ML applications are deployed to cloud services due to their advantages in terms of hardware availability, cost efficiency, and scalability. However, there are challenges related to deploying ML models in the medical domain. Medical data processing and storage in the cloud can be subject to regulatory restrictions and privacy concerns. Additionally, real-time applications may not use cloud services because of data transfer delays, as immediate response times are crucial in such scenarios. These considerations underscore the importance of selecting the right hardware and deployment strategies for specific ML applications, particularly in healthcare settings where data privacy and real-time decision-making are paramount.

3.3 Opportunities

The burgeoning success of AI algorithms in recent decades can be attributed to the confluence of advancements in hardware technology and the opportunities afforded to AI researchers. These opportunities are underscored by notable progress in data generation, scientific publications, and financial investments within the domains of both cancer research and AI. AI, having benefited significantly from these favorable conditions, has now matured to offer invaluable contributions to healthcare professionals and cancer patients alike.

Within ANNs, information is not confined to conventional files or databases but is rather distributed and retained throughout the network via intricate connections. This unique attribute ensures a robust fault tolerance mechanism, where meaningful information remains intact even in the event of cell malfunction. Moreover, ANNs obviate the need for distinct mathematical models, distinguishing them from traditional programming paradigms. In essence, the distinctive programming logic of ANNs mitigates conventional challenges, ushering in novel prospects for AI in healthcare and beyond.

3.3.1 Amount of Produced Data

The exigent demand for vast datasets to effectively train AI networks is now being met, driven by an unprecedented surge in data production. This surge is catalyzed by several factors, including the widespread adoption of technology-driven devices, ubiquitous internet connectivity enabling data sharing among individuals and devices, and the proliferation of capacious data storage repositories such as cloud services. Notably, the medical domain has witnessed an extraordinary expansion in data generation, chiefly due to the pervasive digitization of medical instruments, resulting in an unparalleled proliferation in the quantity and caliber of data. Concurrently, research institutions have played a pivotal role in augmenting this data deluge. For instance, the repositories of gene sequencing data and the cumulative knowledge amassed in drug discovery endeavors have reached unprecedented levels. Consequently, the burgeoning volumes of healthcare-related data represent golden opportunities for AI researchers to craft increasingly sophisticated neural networks.

3.3.2 Number of Publications in AI and Cancer

The landscape of AI research has been evolving over several years, but it is within the past two decades that ML in healthcare has witnessed a remarkable surge in momentum (as depicted in Figure 6). Following the proven success of its AI, the number of people working in this field has also increased (Tran et al., 2019), and the increase rate of publications is 45.15% from 2014 to 2019 (Guo et al., 2020). This upswing in activity has been underpinned by a confluence of factors, including the burgeoning volumes of digitized data generated worldwide and the availability of formidable computational hardware capable of processing these data troves. Furthermore, the practice of openly disseminating the outcomes of AI research has significantly contributed to this growth, as it allows subsequent researchers to build upon the foundational work of their peers rather than reinventing the wheel. This collaborative and information-sharing ethos has emerged as a substantial boon, particularly in the field of healthcare. The domain of oncology, notably, has been a focal point for researchers over the years, with knowledge in this sphere accumulating incrementally. The diminishing costs associated with technologies like next-generation sequencing have facilitated the acquisition of data, including genomic data, with increased ease, making it more accessible for reuse and further research endeavors.

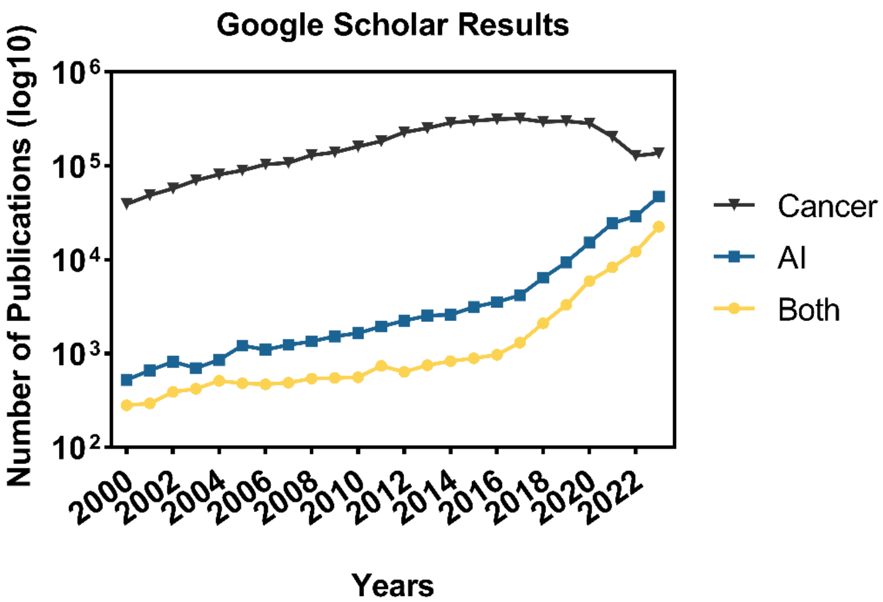

Figure 6: The trend in cancer and AI-related publications since 2000, as revealed by a Google Scholar search conducted in May 2024, indicates a consistent and gradual increase in research activities in the field of cancer up until the year 2013. Notably, there has been a concurrent increase in publications that encompass both AI and cancer, a trend that has gained substantial momentum, particularly after the year 2015. For ease of visualization, the number of articles is presented in a logarithmic base.

3.3.3 Number of Organizations and Money Spent on Cancer Research and AI

Cancer, often referred to as the second leading cause of death after cardiovascular diseases in contemporary times, is a disease with a documented history dating back to as early as the 400s BC. It continues to be a focal point of extensive research efforts and represents a significant segment of the pharmaceutical industry.

Recent data indicates that The American Cancer Society, for instance, has made substantial investments, amounting to nearly $5 billion, in cancer research since its inception in 1946. Governments and scientific research institutions worldwide annually allocate substantial funding and resources for cancer research and clinical investigations. Despite the persistent challenges in completely eradicating this disease, the wealth of data and research possibilities in this field offer a ray of hope for cancer patients and their families. Concurrently, AI and ML technologies have garnered increasing attention from researchers and investors alike in recent years. Numerous grants and funding opportunities are being awarded across various sectors to advance these technologies. When the realms of cancer research and AI converge, a highly compelling and vital research domain emerges, holding immense promise for the future of cancer diagnosis, treatment, and care.

3.3.4 Available Computation Power

Since the inception of computers, there has been a consistent and impressive surge in processing power. Advancements in semiconductor technology, coupled with increased processor efficiency, have rendered computers thousands of times faster than their early counterparts. Furthermore, the advent of graphics processors has significantly bolstered computers' parallel processing capabilities, while the cost of computers and servers has simultaneously plummeted. The availability of cloud service providers has further streamlined access to essential hardware for operations demanding substantial processing power. This shift, away from multi-million-dollar investments in infrastructure, towards efficient pay-as-you-go models, has revolutionized computing. These developments empower computers with the capability to process vast datasets, a task that far exceeds the capacity of the human brain. Consequently, clinicians, despite their extensive knowledge and experience, cannot consistently guarantee the precision of their diagnoses when dealing with such immense data volumes (Huang et al., 2020).

In this context, AI models and ML technologies emerge as pivotal tools for achieving accurate disease diagnosis and prognosis. For instance, while prognosis reliant on genomic and histological analyses by clinical experts may retain subjectivity, Mobadersany and colleagues (2018) have achieved more objective prognosis outcomes through their DL approaches. These DL methods adeptly integrate histological and genomic data, ushering in a new era of precision in prognosis (Mobadersany et al., 2018).

3.3.5 Early Diagnosis

Early diagnosis constitutes a pivotal determinant for favorable treatment outcomes in various types of cancer. Typically, patients seek medical attention only when severe symptoms manifest, resulting in missed opportunities for early detection. AI technology offers the potential to identify cancer risk before the disease's clinical onset, affording ample time for intervention. A prospective paradigm could involve routine non-invasive screenings, followed by AI-driven analyses. Eisner and colleagues (2013), for instance, devised a metabolic profiling approach to construct an ML predictor utilizing relatively straightforward samples such as urine. This innovation allows the prediction of patients who may or may not require a colonoscopy, an invasive diagnostic method for colorectal cancer precursor polyps. While their clinical research yielded specificity and sensitivity rates nearing 60%, this study hints at the possibility of clinicians deploying a preliminary DSS, providing a faster and less burdensome alternative to fecal-based testing prior to colonoscopy (Eisner et al., 2013).

In a retrospective study, Liu and colleagues (2005) conducted a comprehensive analysis of complex protein profiles extracted from serum samples obtained from individuals with astrocytoma, benign brain tumors, and healthy subjects. Employing AI-driven protein fingerprinting techniques, their models were trained to discern potential biomarkers capable of distinguishing glioma patients from healthy individuals and distinguishing astrocytoma from benign brain tumors. The outcomes of their endeavors demonstrated sensitivities and specificities exceeding 85%, underscoring the vital role AI can play in the identification of disease biomarkers, particularly when early and straightforward diagnoses are essential (Liu et al., 2005).

The scope of AI's contributions to early cancer diagnosis extends across various stages of the disease. Genomic studies strive to unveil cancer risk before its clinical manifestation, while medical imaging and image processing techniques aim to pinpoint cancer's location, size, stage, and grade from its incipient stages. A hallmark feature of AI is its remarkable speed and precision when applied to tasks it has learned, rendering it invaluable not only for early diagnosis but also for addressing challenges encountered during treatment, such as drug resistance and metastasis, in the domain of precision oncology. Notably, next-generation sequencing (NGS) techniques play a prominent role in this context (Dlamini et al., 2020). AI's utility extends beyond clinical and patient settings to encompass pre-clinical investigations, *in vitro* studies, and *in vivo* research, lending crucial support to basic science researchers as they explore novel diagnostic and treatment avenues.

3.3.6 Reducing Work Loads of Healthcare Providers

The COVID-19 pandemic has underscored the immense burden faced by healthcare professionals, highlighting the potential for AI to alleviate their workload in the future. AI holds promise in streamlining various healthcare processes, including the reduction of documentation tasks for clinicians. Additionally, AI-driven tools, particularly those incorporating virtual reality (VR) and augmented reality (AR), such as case simulations, can enhance the education of young physicians in clinical diagnosis and decision-making. However, it's important to acknowledge that significant advancements are still required in this domain (Baniasadi et al., 2020).

In the field of medical imaging and preparations, AI-driven scanning can facilitate the selection of specific ROIs, potentially reducing the time needed for examination. Pathologists and physicians can optimize their time by focusing on regions flagged as high-risk by AI or on patients identified as high-risk. Moreover, looking ahead, robotic systems have the potential to revolutionize surgical procedures by minimizing invasiveness and assuming responsibility for routine tasks, thereby reducing surgeons' workloads. Nevertheless, it's essential to recognize that Robot-assisted Surgery (RAS) applications entail intricate procedures necessitating seamless human-robot interaction, multitasking capabilities, preparedness, and rapid responses to diverse stimuli and unforeseen scenarios (Shafiei et al., 2020).

The shortage of specialists for specific cancer types and the time constraints preventing specialists from staying current with the ever-expanding body of knowledge pose significant limitations in cancer treatment. CDSSs address this challenge by leveraging computational reasoning approaches to evaluate the mounting volume of information, providing critical support to clinicians in oncology treatment (Somashekhar et al., 2018). An exemplary CDSS is IBM's Watson for Oncology system, which acquires knowledge by comprehensively reviewing the literature, protocols, and patient charts, and learning from test cases and experts at institutions like the Memorial Sloan Kettering Cancer Center. Remarkably, this system has demonstrated high consistency in providing breast cancer treatment recommendations for diverse patients beyond its original training context. AI-driven CDSSs hold considerable potential for enhancing cancer treatment, particularly in regions facing shortages of specialized expertise.

3.4 Threats / Risks

The integration of clinical expertise with AI capabilities remains a challenge, as clinicians typically possess limited knowledge of AI, while data scientists and engineers may lack clinical insights. Overcoming these barriers necessitates the establishment of multidisciplinary collaboration frameworks. Moreover, the field of AI grapples with significant legal constraints, particularly concerning health data, as governments impose increasingly stringent regulations. Researchers bear substantial legal responsibilities in this context. Furthermore, as previously mentioned, the vulnerability of health data to potential cyberattacks poses a major threat. Beyond legal responsibilities, the allocation of liability for potential consequences arising from AI applications is a contentious issue that requires careful consideration.

3.4.1 Legal Restrictions

A paramount challenge hindering the advancement of AI systems in medical applications pertains to the realm of laws and regulations. Data sharing, a pivotal factor for accelerating research and enhancing accuracy, is currently constrained by ethical and financial considerations (Fountzilas and Tsimberidou, 2018). Concerns about the implications of new technologies, particularly those related to medical data, have given rise to apprehensions among social scientists. Varying regulations already exist across countries regarding the use of medical data (Essén et al., 2018). In the United States, federal laws delineate health data in the Privacy Rule established under the Health Insurance Portability and Accountability Act (HIPAA). The Privacy Rule stipulates that only specific entities, such as physicians and healthcare providers, may handle health data under tightly defined circumstances. Conversely, European Union laws encompass health data within their broader data privacy regulations (Price and Cohen, 2019). With the growing integration of AI in healthcare settings, it is plausible that additional laws and restrictions will be enacted governing the collection, annotation, training, and utilization of data. The extent to which these laws may constrain the open AI community's ability to develop medical systems remains to be determined, as these decisions are influenced by myriad factors, including AI systems' performance within the healthcare landscape, as well as social and political considerations (Renda, 2019). At present, openly accessible medical data are anonymized through the removal of at least patient names and identification information. However, this anonymization approach is imperfect, as there are techniques for re-identifying anonymized data. Consequently, there is a pressing need to identify more robust methods for safeguarding patient privacy without impeding the utilization of medical data for AI systems. The utilization of secure personal health data marketplaces employing blockchain technologies, which have garnered increased attention in recent years, offers a potential solution. Such marketplaces can both mitigate regulatory challenges and facilitate developers' access to the requisite data set.

3.4.2 Ethics and Legal Responsibility

Since the inception of AI, there has been a persistent curiosity regarding its capacity to address ethical questions and adhere to an ethical framework. A prominent example of this conundrum is the ethical dilemmas posed by autonomous vehicles, where decisions might involve choosing between jeopardizing the lives of passengers or pedestrians. In the field of medical applications, ethical concerns encompass several key aspects: obtaining informed consent from patients for the use of AI-based models in their healthcare, ensuring the safety and transparency of AI models, addressing issues of fairness and bias in AI models, and safeguarding data privacy (Gerke et al., 2020).

Additionally, the question of responsibility, both ethical and legal, looms large when it comes to deploying AI models. Determining who is accountable for mistakes made by or resulting from AI, and how to establish legal liability, remains a pivotal issue that can hinder the adoption of AI technologies in various institutions. In medical contexts, the significance of this question varies; for instance, the responsibility associated with a DSS is considerably different from that of a surgical robot. However, even in the case of highly advanced AI-based models employed in critical applications, a similar chain of responsibility can be applied, drawing parallels with established norms in other automated domains such as aviation. This chain typically entails the user of the model, followed by the manufacturer, and ultimately the parent company. This approach is grounded in the understanding that, despite their sophistication, AI technologies remain contingent on human trainers and operators who impart their acquired intelligence.

Nevertheless, ethical considerations are intrinsic to any undertaking involving humans or living entities, encompassing research, treatment, surgical interventions, and beyond. As such, the solicitation of consent forms from patients and/or their relatives is a customary practice. It is reasonable to extend a similar principle to AI. Algorithms that learn from human decisions, or more precisely, are trained by humans, inevitably inherit human fallibility. Therefore, it is imperative that AI systems undergo continuous scrutiny by experts to verify their proper functioning. Instances of overdiagnosis, underdiagnosis, or misdiagnosis underscore the potential risks, as patient lives may hang in the balance. Consequently, the question arises whether AI can ever entirely supplant human experts, a prospect that, for the foreseeable future, remains a distant possibility.

3.4.3 Data Dependence

AI fundamentally operates on data and its performance, accuracy, precision, and speed are intricately tied to data quality. It relies on a constant influx of new data to refine its capabilities. Learning in AI occurs through exposure to examples, and these examples must comprehensively represent the problem domain. When AI models trained on specific types of data encounter different data types or data presented in a dissimilar manner, achieving the desired level of accuracy becomes challenging. This challenge is particularly evident in radiomics studies where medical images yield tens of thousands of features. The selection of input features for training an AI network is crucial, as varying feature combinations can significantly impact model accuracy, even when derived from the same set of images.

Moreover, AI models tend to be highly specialized and are typically proficient only in the tasks they were trained for. Consequently, the dependence on data is a limiting aspect of AI. Although various models have been developed to address this limitation, the maturity required for extensive healthcare applications has not yet been attained. For instance, attempting to predict drug sensitivity or intolerance based solely on gene expression profiles or specific gene mutations may prove inadequate. In precision oncology, a comprehensive prognosis necessitates consideration of a patient's genomic and demographic attributes, alongside -omic profiles like epigenomics, proteomics, and metabolomics, along with non-omic data such as histopathology. AI can play a pivotal role in integrating and standardizing these diverse data sources, offering invaluable support to clinicians, and aiding in more accurate treatment decisions.

However, the integration and standardization of such multifaceted data pose formidable challenges. Researchers are actively engaged in addressing these issues, with precision oncology emerging as a prominent application area for AI. Nevertheless, it is essential to acknowledge that AI has a substantial distance to cover in overcoming these obstacles, and traditional methods continue to serve as the gold standard in oncology. The complexities of pre-processing and integrating data, coupled with the need to grasp the phenotypic status of patients, underscore the extensive journey ahead for AI in the field of oncology (Patel et al., 2020).

4. TAKE-HOME POINTS

As a conclusion to this paper, Figure 7 summarizes the SWOT analysis of AI in cancer (and many other medical fields).

Figure 7: SWOT analysis of the use of AI in cancer.

- Cancer, comprising numerous diverse types, remains a formidable challenge due to the elusive causes and absence of definitive treatments. This complexity renders the entire journey from diagnosis to treatment an arduous task for both healthcare practitioners and patients.
- In recent years, AI has made its presence felt in the healthcare sector, promising transformative impacts across various medical processes, encompassing diagnostics, decision-making, personalized therapy, and treatment.
- The heterogeneity of cancer types, each characterized by distinct genetic and epigenetic traits, further complicates the treatment landscape, underscoring the imperative for personalized approaches tailored to individual cases.
- In this challenging landscape, the fusion of big data and AI offers newfound hope to both patients and clinicians grappling with the intricacies of cancer diagnosis and treatment. Precision oncology, in particular, leverages AI to assimilate and process extensive datasets emanating from multi-omics analyses.
- AI's remarkable strengths include its speed, capacity for high-precision training, repeatability, accessibility, and proficiency in deciphering intricate data relationships that often confound human comprehension.
- However, certain unresolved weaknesses persist, such as the lack of causal understanding, insatiable data requirements, obstacles to accessing healthcare data, ethical and legal quandaries, issues regarding applicability, hardware prerequisites, and the intricate problem of explainability epitomized by the black box conundrum.
- Notwithstanding these challenges, AI offers manifold opportunities. The burgeoning volume of data generation, the availability of open-source code, escalating AI-related funding, and expanding programming capabilities augur a promising future. AI has the potential to enhance early diagnosis rates, elevate treatment success probabilities, and alleviate the burdens on healthcare professionals through automated processes.

- Key impediments to the extensive implementation of AI in healthcare encompass legal responsibilities, regulatory constraints, and ethical dilemmas.
- To usher in an era of more widespread AI utilization in cancer care, enhancing data accessibility and integrity, along with securing healthcare data to requisite levels, stands as a paramount imperative.
- Healthcare professionals grapple with substantial workloads, a challenge thrown into stark relief during events like the COVID-19 pandemic. While AI applications cannot fully supplant human expertise at present, they can significantly augment healthcare delivery. Ongoing research and technological advancements hold promise for the field of oncology.
- Anticipations point to a future where AI becomes an increasingly ubiquitous presence in the healthcare sector, further revolutionizing the landscape and enhancing patient care.

ACKNOWLEDGEMENTS

Gülşah Torkay would like to acknowledge the financial support from the Scientific and Technological Research Council of Turkey (TUBITAK) 2210-A General Domestic Graduate Scholarship Program and 2211-E National PhD Scholarship Program for Former Undergraduate and MSc/MA Scholars (App No: 1649B022101483 and App No: 1649B032304943).

FUNDING

There is no funding for this study.

AUTHORS` CONTRIBUTIONS

All authors contributed to the manuscript and read and approved the final version of this paper.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

There is no raw data associated with this review article.

REFERENCES

Abdelhalim, I. S. A., Mohamed, M. F., & Mahdy, Y. B. (2021). Data augmentation for skin lesion using self-attention based progressive generative adversarial network. *Expert Systems With Applications*, *165*, 113922.

Amisha, P. M., Pathania, M., & Rathaur, V. K. (2019). Overview of artificial intelligence in medicine. Journal of family medicine and primary care, 8(7), 2328.

Azuaje, F. (2019). Artificial intelligence for precision oncology: beyond patient stratification. *NPJ precision oncology*, *3*(1), 1-5.

Baker M. (2016). 1,500 scientists lift the lid on reproducibility. Nature, 533(7604), 452–454. https://doi.org/10.1038/533452a

Baniasadi, T., Ayyoubzadeh, S. M., & Mohammadzadeh, N. (2020). Challenges and practical considerations in applying virtual reality in medical education and treatment. *Oman Medical Journal*, *35*(3), e125.

Bender, A., & Cortés-Ciriano, I. (2021). Artificial intelligence in drug discovery: what is realistic, what are illusions? Part 1: ways to make an impact, and why we are not there yet. *Drug discovery today*, *26*(2), 511-524.

Bera, K., Schalper, K. A., Rimm, D. L., Velcheti, V., & Madabhushi, A. (2019). Artificial intelligence in digital pathology—new tools for diagnosis and precision oncology. *Nature reviews Clinical oncology*, *16*(11), 703-715.

Bhavya, S., & Pillai, A. S. (2019, December). Prediction models in healthcare using deep learning. In International Conference on Soft Computing and Pattern Recognition (pp. 195-204). Springer, Cham.

Bien N, Rajpurkar P, Ball RL, Irvin J, Park A, et al. (2018) Deep-learning-assisted diagnosis for knee magnetic resonance imaging: Development and retrospective validation of MRNet. PLOS Medicine 15(11): e1002699. https://doi.org/10.1371/journal.pmed.1002699

Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In Artificial Intelligence in healthcare (pp. 25-60). Academic Press.

Buch, V. H., Ahmed, I., & Maruthappu, M. (2018). Artificial intelligence in medicine: current trends and future possibilities. British Journal of General Practice, 68(668), 143-144.

Catto, J. W., Abbod, M. F., Wild, P. J., Linkens, D. A., Pilarsky, C., Rehman, I., ... & Hamdy, F. C. (2010). The application of artificial intelligence to microarray data: identification of a novel gene signature to identify bladder cancer progression. European urology, 57(3), 398-406.

Chaudhary, K., Poirion, O. B., Lu, L., & Garmire, L. X. (2018). Deep Learning-Based Multi-Omics Integration Robustly Predicts Survival in Liver Cancer. Clinical cancer research: an official journal of the American Association for Cancer Research, 24(6), 1248–1259. https://doi.org/10.1158/1078-0432.CCR-17-0853

Chen, J., Wu, L., Zhang, J., Zhang, L., Gong, D., Zhao, Y., Chen, Q., Huang, S., Yang, M., Yang, X., Hu, S., Wang, Y., Hu, X., Zheng, B., Zhang, K., Wu, H., Dong, Z., Xu, Y., Zhu, Y., Chen, X., … Yu, H. (2020). Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography. Scientific reports, 10(1), 19196. https://doi.org/10.1038/s41598-020-76282-0

Choi, E., Schuetz, A., Stewart, W. F., & Sun, J. (2017). Using recurrent neural network models for early detection of heart failure onset. Journal of the American Medical Informatics Association: JAMIA, 24(2), 361–370. https://doi.org/10.1093/jamia/ocw112

Coudray, N., Ocampo, P.S., Sakellaropoulos, T. et al. Classification and mutation prediction from non–small cell lung cancer histopathology images using deep learning. Nat Med 24, 1559–1567 (2018). https://doi.org/10.1038/s41591-018-0177-5

Cutillo, C. M., Sharma, K. R., Foschini, L., Kundu, S., Mackintosh, M., & Mandl, K. D. (2020). Machine intelligence in healthcare—perspectives on trustworthiness, explainability, usability, and transparency. *NPJ digital medicine*, *3*(1), 1-5.

Daemen, A., Gevaert, O., De Bie, T., Debucquoy, A., Machiels, J. P., De Moor, B., & Haustermans, K. (2008). Integrating microarray and proteomics data to predict the response on cetuximab in patients with rectal cancer. Pacific Symposium on Biocomputing. Pacific Symposium on Biocomputing, 166–177.

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future healthcare journal, 6(2), 94.

Demner-Fushman, D., Chapman, W. W., & McDonald, C. J. (2009). What can natural language processing do for clinical decision support?. *Journal of biomedical informatics*, *42*(5), 760-772.

DeVita, V. T., Jr, & Chu, E. (2008). A history of cancer chemotherapy. Cancer research, 68(21), 8643–8653. https://doi.org/10.1158/0008-5472.CAN-07-6611

Dlamini, Z., Francies, F. Z., Hull, R., & Marima, R. (2020). Artificial intelligence (AI) and big data in cancer and precision oncology. Computational and Structural Biotechnology Journal.

Eisner, R., Greiner, R., Tso, V., Wang, H., & Fedorak, R. N. (2013). A machine-learned predictor of colonic polyps based on urinary metabolomics. BioMed research international, 2013, 303982. https://doi.org/10.1155/2013/303982

Essén, A., Scandurra, I., Gerrits, R., Humphrey, G., Johansen, M. A., Kierkegaard, P., ... & Ancker, J. S. (2018). Patient access to electronic health records: differences across ten countries. *Health policy and technology*, *7*(1), 44-56.

Ferlay, J., Soerjomataram, I., Dikshit, R., Eser, S., Mathers, C., Rebelo, M., Parkin, D. M., Forman, D., & Bray, F. (2015). Cancer incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012. International journal of cancer, 136(5), E359–E386. https://doi.org/10.1002/ijc.29210

Fleming, N. (2018). How artificial intelligence is changing drug discovery. Nature, 557(7706), S55-S55.

Fountzilas, E., & Tsimberidou, A. M. (2018). Overview of precision oncology trials: challenges and opportunities. Expert review of clinical pharmacology, 11(8), 797–804. https://doi.org/10.1080/17512433.2018.1504677

Gatt, A., Portet, F., Reiter, E., Hunter, J., Mahamood, S., Moncur, W., & Sripada, S. (2009). From data to text in the neonatal intensive care unit: Using NLG technology for decision support and information management. Ai Communications, 22(3), 153-186.

Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial Intelligence in Healthcare, 295–336. https://doi.org/10.1016/B978-0-12-818438-7.00012-5

Gigerenzer, G., & Kurzenhaeuser, S. (2005). Fast and frugal heuristics in medical decision making. Science and medicine in dialogue: Thinking through particulars and universals, 3-15.

Goldenberg, S. L., Nir, G., & Salcudean, S. E. (2019). A new era: artificial intelligence and machine learning in prostate cancer. Nature Reviews Urology, 16(7), 391-403.

Goyal, L., Hingmire, S., & Parikh, P. M. (2006). Newer Diagnostic Methods in Oncology. Medical journal, Armed Forces India, 62(2), 162–168. https://doi.org/10.1016/S0377-1237(06)80062-6

Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. (2020). Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities. Computers in biology and medicine, 127, 104065.

Guo, Y., Hao, Z., Zhao, S., Gong, J., & Yang, F. (2020). Artificial intelligence in health care: bibliometric analysis. *Journal of Medical Internet Research*, *22*(7), e18228.

Güvenç, E., Ersoy, M., & Çetin, G. (2023). BRAIN TUMOR SEGMENTATION ON FLAIR MR IMAGES WITH U-NET. Mugla Journal of Science and Technology, 9(1), 34-41.

Hanahan, D. (2022). Hallmarks of Cancer: New Dimensions. *Cancer Discovery*, *12*(1), 31-46.

Hanahan, D., & Weinberg, R. A. (2000). The hallmarks of cancer. cell, 100(1), 57-70.

Hanahan, D., & Weinberg, R. A. (2011). Hallmarks of cancer: the next generation. cell, 144(5), 646-674.

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature medicine*, *25*(1), 30-36.

Hessler, G., & Baringhaus, K. H. (2018). Artificial Intelligence in Drug Design. Molecules (Basel, Switzerland), 23(10), 2520. https://doi.org/10.3390/molecules23102520

Hong, S. N., Son, H. J., Choi, S. K., Chang, D. K., Kim, Y. H., Jung, S. H., & Rhee, P. L. (2017). A prediction model for advanced colorectal neoplasia in an asymptomatic screening population. PloS one, 12(8), e0181040.

How the American Cancer Society Funds Research. https://www.cancer.org/research/how-american-cancer-society-research-funding-works.html#:~:text=In%202019%2C%20you%20helped%20us,vital%20patient%20services%20and%20programs Accessed 2 February 2022.

Huang, S., Yang, J., Fong, S., & Zhao, Q. (2020). Artificial intelligence in cancer diagnosis and prognosis: Opportunities and challenges. Cancer Letters, 471, 61-71.

Hulsen, T., Jamuar, S. S., Moody, A. R., Karnes, J. H., Varga, O., Hedensted, S., ... & McKinney, E. F. (2019). From big data to precision medicine. *Frontiers in medicine*, *6*, 34.

Hutchinson, M. L., Antono, E., Gibbons, B. M., Paradiso, S., Ling, J., & Meredig, B. (2017). Overcoming data scarcity with transfer learning. *arXiv preprint arXiv:1711.05099*.

Ilbay, K., Übeyli, E. D., Ilbay, G., & Budak, F. (2011). A new application of recurrent neural networks for EMG-based diagnosis of carpal tunnel syndrome. Recurrent Neural Networks for Temporal Data Processing, 37.

Iqbal, T., & Ali, H. (2018). Generative adversarial network for medical images (MI-GAN). *Journal of medical systems*, *42*(11), 1-11.

Islam, M. Z., Islam, M. M., & Asraf, A. (2020). A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images. *Informatics in medicine unlocked*, 20, 100412.

Jawandhiya, P. (2018). Hardware design for machine learning. *Int. J. Artif. Intell. Appl*, *9*(1), 63-84.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare:

past, present and future. Stroke and vascular neurology, 2(4).

Jin, C., Chen, W., Cao, Y. et al. Development and evaluation of an artificial intelligence system for COVID-19 diagnosis. Nat Commun 11, 5088 (2020). https://doi.org/10.1038/s41467-020-18685-1

Karim, M. R., Beyan, O., Zappa, A., Costa, I. G., Rebholz-Schuhmann, D., Cochez, M., & Decker, S. (2021). Deep learning-based clustering approaches for bioinformatics. *Briefings in Bioinformatics*, *22*(1), 393-415.

Keam S, Gill S, Ebert MA, Nowak AK, Cook AM. Enhancing the efficacy of immunotherapy using radiotherapy. Clin Transl Immunology. 2020 Sep 10;9(9):e1169. doi: 10.1002/cti2.1169. PMID: 32994997; PMCID: PMC7507442.

Khalifa, N. E. M., Taha, M. H. N., Ali, D. E., Slowik, A., & Hassanien, A. E. (2020). Artificial intelligence technique for gene expression by tumor RNA-Seq data: a novel optimized deep learning approach. IEEE Access, 8, 22874-22883.

Kheradpisheh, S. R., Ghodrati, M., Ganjtabesh, M., & Masquelier, T. (2016). Deep networks can resemble human feed-forward vision in invariant object recognition. *Scientific reports*, *6*(1), 1-24.

Kim, Y. G., Kim, S., Cho, C. E., Song, I. H., Lee, H. J., Ahn, S., ... & Kim, N. (2020). Effectiveness of transfer learning for enhancing tumor classification with a convolutional neural network on frozen sections. *Scientific Reports*, *10*(1), 1-9.

Ko, B. S., Wang, Y. F., Li, J. L., Li, C. C., Weng, P. F., Hsu, S. C., Hou, H. A., Huang, H. H., Yao, M., Lin, C. T., Liu, J. H., Tsai, C. H., Huang, T. C., Wu, S. J., Huang, S. Y., Chou, W. C., Tien, H. F., Lee, C. C., & Tang, J. L. (2018). Clinically validated machine learning algorithm for detecting residual diseases with multicolor flow cytometry analysis in acute myeloid leukemia and myelodysplastic syndrome. EBioMedicine, 37, 91–100. https://doi.org/10.1016/j.ebiom.2018.10.042

Komura, D., & Ishikawa, S. (2018). Machine learning methods for histopathological image analysis. *Computational and structural biotechnology journal*, *16*, 34-42.

Kourou, K., Exarchos, T. P., Exarchos, K. P., Karamouzis, M. V., & Fotiadis, D. I. (2014). Machine learning applications in cancer prognosis and prediction. Computational and structural biotechnology journal, 13, 8–17. https://doi.org/10.1016/j.csbj.2014.11.005

Lake, B. M., Ullman, T. D., Tenenbaum, J. B., & Gershman, S. J. (2017). Building machines that learn and think like people. *Behavioral and brain sciences*, *40*.

Liang, H., Tsui, B. Y., Ni, H., Valentim, C. C., Baxter, S. L., Liu, G., ... & Xia, H. (2019). Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. *Nature medicine*, *25*(3), 433-438.

Lindsay, G. W. (2021). Convolutional neural networks as a model of the visual system: Past, present, and future. Journal of cognitive neuroscience, 33(10), 2017-2031.

Liu, J., Cheng, Y., Wang, X. et al. Cancer Characteristic Gene Selection via Sample Learning Based on Deep Sparse Filtering. Sci Rep 8, 8270 (2018). https://doi.org/10.1038/s41598-018-26666-0

Liu, J., Zheng, S., Yu, J. K., Zhang, J. M., & Chen, Z. (2005). Serum protein fingerprinting coupled with artificial neural network distinguishes glioma from healthy population or brain benign tumor. Journal of Zhejiang University. Science. B, 6(1), 4–10. https://doi.org/10.1631/jzus.2005.B0004

Liu, W. N., Zhang, Y. Y., Bian, X. Q., Wang, L. J., Yang, Q., Zhang, X. D., & Huang, J. (2020). Study on detection rate of polyps and adenomas in artificial-intelligence-aided colonoscopy. Saudi journal of gastroenterology: official journal of the Saudi Gastroenterology Association, 26(1), 13–19. https://doi.org/10.4103/sjg.SJG_377_19

Mamoshina, P., Ojomoko, L., Yanovich, Y., Ostrovski, A., Botezatu, A., Prikhodko, P., ... & Zhavoronkov, A. (2018). Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare. *Oncotarget*, *9*(5), 5665.

Miller, R. A. (1994). Medical diagnostic decision support systems—past, present, and future: a threaded bibliography and brief commentary. *Journal of the American Medical Informatics Association*, *1*(1), 8-27.

Mobadersany P, Yousefi S, Amgad M, Gutman DA, Barnholtz-Sloan JS, Velázquez Vega JE, et al. Predicting cancer outcomes from histology and genomics using convolutional networks. Proceedings of the National Academy of Sciences of the United States of America. 2018;115(13): E2970–E2979.

Nalliah, R. P. (2016). Clinical decision making–choosing between intuition, experience and scientific evidence. British dental journal, 221(12), 752-754.

Namikawa, K., Hirasawa, T., Nakano, K., Ikenoyama, Y., Ishioka, M., Shiroma, S., Tokai, Y., Yoshimizu, S., Horiuchi, Y., Ishiyama, A., Yoshio, T., Tsuchida, T., Fujisaki, J., & Tada, T. (2020). Artificial intelligence-based diagnostic system classifying gastric cancers and ulcers: comparison between the original and newly developed systems. Endoscopy, 52(12), 1077–1083. https://doi.org/10.1055/a-1194-8771

O'Shea, K., & Nash, R. (2015). An Introduction to Convolutional Neural Networks. ArXiv, abs/1511.08458.

Odusami, M., Maskeliūnas, R., Damaševičius, R., & Krilavičius, T. (2021). Analysis of Features of Alzheimer's Disease: Detection of Early Stage from Functional Brain Changes in Magnetic Resonance Images Using a Finetuned ResNet18 Network. *Diagnostics*, *11*(6), 1071.

Parsa, N. (2012). Environmental factors inducing human cancers. Iranian journal of public health, 41(11), 1.

Patel, S. K., George, B., & Rai, V. (2020). Artificial intelligence to decode cancer mechanism: beyond patient stratification for precision oncology. *Frontiers in Pharmacology*, *11*, 1177.

Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., … Lungren, M. P. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Medicine, 15(11). https://doi.org/10.1371/journal.pmed.1002686

Ranjbarzadeh, R., Kasgari, A. B., Ghoushchi, S. J., Anari, S., Naseri, M., & Bendechache, M. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Scientific Reports, 11(1), 1-17.

Reddy, E. M., & Bhaskar, P. (2018). Able Machine Learning Method for classifying Disease-Treatment Semantic Relations from Bio-Medical Sentences. *vol*, *5*, 5.

Renda, A. (2019). *Artificial Intelligence. Ethics, governance and policy challenges*. CEPS Centre for European Policy Studies.

Richens, J.G., Lee, C.M. & Johri, S. Improving the accuracy of medical diagnosis with causal machine learning. Nat Commun 11, 3923 (2020). https://doi.org/10.1038/s41467-020-17419-7

Rigaki, M., & Garcia, S. (2020). A survey of privacy attacks in machine learning. *ACM Computing Surveys*.

Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, *1*(5), 206-215.

Saldanha, O. L., Quirke, P., West, N. P., James, J. A., Loughrey, M. B., Grabsch, H. I., ... & Kather, J. N. (2022). Swarm learning for decentralized artificial intelligence in cancer histopathology. *Nature Medicine*, 28(6), 1232-1239.

Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. SN Computer Science, 2(3), 1-21.

Schork, N. J. (2019). Artificial intelligence and personalized medicine. In Precision Medicine in Cancer Therapy (pp. 265-283). Springer, Cham.

Shafiei, S. B., Elsayed, A. S., Hussein, A. A., Iqbal, U., & Guru, K. A. (2020). Evaluating the Mental Workload During Robot-Assisted Surgery Utilizing Network Flexibility of Human Brain. *IEEE Access*, *8*, 204012-204019.

Shalf, J. (2020). The future of computing beyond Moore’s law. Philosophical Transactions of the Royal Society A, 378(2166), 20190061.

Shvetsova, N., Bakker, B., Fedulova, I., Schulz, H., & Dylov, D. V. (2021). Anomaly detection in medical imaging with deep perceptual autoencoders. *IEEE Access*, *9*, 118571-118583.

Snorovikhina, V., & Zaytsev, A. (2020, October). Unsupervised anomaly detection for discrete sequence healthcare data. In International Conference on Analysis of Images, Social Networks and Texts (pp. 391-403). Springer, Cham.

Somashekhar, S. P., Sepúlveda, M. J., Puglielli, S., Norden, A. D., Shortliffe, E. H., Rohit Kumar, C., Rauthan, A., Arun Kumar, N., Patil, P., Rhee, K., & Ramya, Y. (2018). Watson for Oncology and breast cancer treatment recommendations: agreement with an expert multidisciplinary tumor board. Annals of oncology: official journal of the European Society for Medical Oncology, 29(2), 418–423. https://doi.org/10.1093/annonc/mdx781

Srivastava, D., Srivastava, S. K., Khan, S. B., Singh, H. R., Maakar, S. K., Agarwal, A. K., ... & Albalawi, E. (2023). Early Detection of Lung Nodules Using a Revolutionized Deep Learning Model. Diagnostics, 13(22), 3485.

Su, Jilian & Liu, Yuanhui & Wang, Junmei. (2020). Ultrasound image assisted diagnosis of hydronephrosis based on CNN neural network. Journal of King Saud University - Science. 32. 10.1016/j.jksus.2020.04.005.

Sun, Y., Zhu, S., Ma, K. et al. Identification of 12 cancer types through genome deep learning. Sci Rep 9, 17256 (2019). https://doi.org/10.1038/s41598-019-53989-3

Tran, B. X., Vu, G. T., Ha, G. H., Vuong, Q. H., Ho, M. T., Vuong, T. T., La, V. P., Ho, M. T., Nghiem, K. P., Nguyen, H., Latkin, C. A., Tam, W., Cheung, N. M., Nguyen, H. T., Ho, C., & Ho, R. (2019). Global Evolution of Research in Artificial Intelligence in Health and Medicine: A Bibliometric Study. Journal of clinical medicine, 8(3), 360. https://doi.org/10.3390/jcm8030360

Turing, A. M., & Haugeland, J. (1950). Computing machinery and intelligence (pp. 29-56). Cambridge, MA: MIT Press.

US Food and Drug Administration. (2020). Artificial intelligence and machine learning in software as a medical device. *Content current as of January*, *28*, 2020. https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-software-medical-device Accessed 3 February 2022.

Wijnhoven, F. (2021). Organizational Learning for Intelligence Amplification Adoption: Lessons from a Clinical Decision Support System Adoption Project. *Information Systems Frontiers*, 1-14.

Workman, P., Antolin, A. A., & Al-Lazikani, B. (2019). Transforming cancer drug discovery with Big Data and AI. Expert opinion on drug discovery, 14(11), 1089–1095. https://doi.org/10.1080/17460441.2019.1637414

Yadav, S.S., Jadhav, S.M. Deep convolutional neural network based medical image classification for disease diagnosis. J Big Data 6, 113 (2019). https://doi.org/10.1186/s40537-019-0276-2

Yan, Q., Wang, B., Gong, D., Luo, C., Zhao, W., Shen, J., ... & You, Z. (2021). COVID-19 chest CT image segmentation network by multi-scale fusion and enhancement operations. IEEE transactions on big data, 7(1), 13-24.

Yang, X. S. (Ed.). (2012). Artificial intelligence, evolutionary computing and metaheuristics: in the footsteps of Alan Turing (Vol. 427). Springer.

Ye, Y., Wagner, M. M., Cooper, G. F., Ferraro, J. P., Su, H., Gesteland, P. H., ... & Tsui, F. (2017). A study of the transferability of influenza case detection systems between two large healthcare systems. *PloS one*, *12*(4), e0174970.

Ying, X. (2019, February). An overview of overfitting and its solutions. In *Journal of Physics: Conference Series* (Vol. 1168, No. 2, p. 022022). IOP Publishing.

Zhang, D., Liu, X., Shao, M. et al. The value of artificial intelligence and imaging diagnosis in the fight against COVID-19. Pers Ubiquit Comput (2021). https://doi.org/10.1007/s00779-021-01522-7

Zhang, L., Tan, J., Han, D., & Zhu, H. (2017). From machine learning to deep learning: progress in machine intelligence for rational drug discovery. Drug discovery today, 22(11), 1680–1685. https://doi.org/10.1016/j.drudis.2017.08.010

Zhang, Z., Li, J., He, T., & Ding, J. (2020). Bioinformatics identified 17 immune genes as prognostic biomarkers for breast cancer: application study based on artificial intelligence algorithms. Frontiers in oncology, 10, 330.

Zhao, Y., Pan, Z., Namburi, S., Pattison, A., Posner, A., Balachander, S., ... & George, J. (2020). CUP-AI-Dx: A tool for inferring cancer tissue of origin and molecular subtype using RNA gene-expression data and artificial intelligence. EBioMedicine, 61, 103030.

Zhong, F., Xing, J., Li, X., Liu, X., Fu, Z., Xiong, Z., Lu, D., Wu, X., Zhao, J., Tan, X., Li, F., Luo, X., Li, Z., Chen, K., Zheng, M., & Jiang, H. (2018). Artificial intelligence in drug design. Science China. Life sciences, 61(10), 1191–1204. https://doi.org/10.1007/s11427-018-9342-2