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FULL PAPER

Artificial intelligence (AI): cancer treatment revolution in India

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Cancer is well-recognized as a leading cause of morbidity and mortality on a worldwide scale. Significant progress has been made in the areas of screening, diagnosis, treatment, and survivorship in recent decades. Nevertheless, there are still obstacles to overcome in delivering individualized and data-driven healthcare. Artificial intelligence (AI), a subfield of computer science focused on prediction and automation, has emerged as a promising option for enhancing the healthcare journey and advancing precision in healthcare. The utilization of artificial intelligence (AI) in oncology encompasses several areas, such as enhancing cancer research, refining clinical practices (e.g., forecasting the correlation between numerous factors and outcomes, such as prognosis and response), and deepening our comprehension of tumor molecular biology. This study aims to explore the significance of artificial intelligence (AI) in cancer research within the Indian context. To fulfill the objective of this study, a diverse range of medical experts was taken into consideration, and the perspectives articulated by the participants are presented above. The study revealed that artificial intelligence (AI) assumes a significant role in the provision of health care services, particularly in the domain of cancer treatment.

KEYWORDS

AI; cancer; NFS; NMS; HSF; HSM.

Introduction

Cancer is responsible for a substantial burden of illness and death on a global scale. According to available data, it has been approximated that there were around 19.3 million newly diagnosed instances of cancer in 2020 [1]. It is anticipated that this number will witness a rise in the next decades. According to projections, it is anticipated that there will be a total of 30.2 million newly diagnosed cancer cases in 2040. Despite significant advancements in the diagnosis and treatment of cancer [2], the promotion of innovation in healthcare, particularly in the field of cancer care, is of utmost importance. The timely detection of cancer continues to be a significant global obstacle. The efficacy of screening activities is constrained by factors such as public acceptance, financial backing, and the incomplete coverage of all groups at risk [3]. Nevertheless, implementing screening programs without evidence-based justification might result in a substantial financial strain and the inefficient allocation of resources within health systems with limited resources [4].

Recognizing the inherent limitations in the cognitive capabilities of the human brain, it is imperative to promptly adopt alternative methodologies for effectively managing the vast quantities of contemporary big data, which encompasses both organized and unorganized data streams that inundate the healthcare sector daily. The proliferation of data, coupled with advancements in storage and computing capabilities, has significantly contributed to the advancement of data-processing methodologies, including machine learning (ML) and artificial intelligence (AI). These techniques have gained prominence as crucial instruments in addressing intricate challenges within the realm of cancer care. An increasing number of research investigations emphasize the utilization of artificial intelligence (AI) as a burgeoning instrument for the customization of cancer-care methods through the analysis of existing data. According to a recent study, a total of 97 clinical studies have been found which focused on the use of artificial intelligence (AI) in cancer detection. The majority of these trials were initiated after 2017 [5].

Artificial intelligence has exhibited considerable significance in medical fields that encompass the examination of images, particularly within the realms of radiology and pathology [6]. The subject of radiology encompasses several uses of artificial intelligence (AI), with a specific focus on deep learning (DL) methods. These algorithms are employed for the analysis of imaging data acquired during routine cancer treatment. Deep learning algorithms are utilized in several domains such as categorizing illnesses, detecting diseases, segmenting medical images, characterizing medical conditions, and monitoring health status [7,8].

Image classification plays a crucial role in cancer screening studies since it enables the accurate categorization and identification of cancerous cells or tissues. Artificial intelligence (AI) has the potential to enhance the radiologists' performance by improving results, reducing time requirements, and facilitating the categorization of minor lesions. In addition, it can contribute to the development of an enhanced organizational process, such as the identification of a high-priority set of reports that require examination and reporting. Several studies have demonstrated the efficacy of integrating artificial intelligence (AI) with human expertise in enhancing mammography screening for breast cancer [9-10].

The utilization of artificial intelligence (AI) has the potential to enhance the detection process by assisting in the identification of malignant tumors that may otherwise go unnoticed by human observers. For example, it can be utilized to detect pulmonary nodules [11] or cerebral metastases on magnetic resonance imaging (MRI) scans [12]. The detection process is dependent on the use of bounding boxes to identify a lesion or item of interest. Artificial intelligence (AI) aids physicians in the interpretation of medical pictures, such as lung nodules, facilitating the detection process [13].

Segmentation is a crucial process that involves the classification of individual pixels based on their association with certain organs or lesions. This process enables the accurate identification and measurement of lesions, allowing for the determination of their volume and size. Brain gliomas necessitate the use of quantitative indicators to effectively manage, stratify risk, and prognosticate outcomes [14].

Characterization: The utilization of deep learning techniques in the analysis of medical pictures enables the extraction of a multitude of aspects that may elude human detection. This has the potential to reveal previously unrecognized illness traits and patterns. The area of radiomics pertains to the study of these characteristics, and there is a burgeoning interest in integrating these characteristics with clinical genetic data. The use of radiomics techniques has the potential to contribute valuable insights to predictive models that effectively forecast both treatment response and potential adverse effects resulting from cancer therapies [15]. Radiomics has the potential to be employed in several forms of cancer, including liver, brain, and lung tumors [16,17]. The use of radiometric characteristics extracted from brain MRI in deep learning models demonstrates comparable performance to those of expert neuroradiologists in distinguishing between brain gliomas and brain metastases.

Generative adversarial networks (GANs) refer to artificial intelligence (AI) models that possess the capability to produce novel pictures using diverse datasets. One potential application is the production of synthetic computed tomography (CT) images derived from magnetic resonance imaging (MRI) scans. The aforementioned technology exhibits the capacity to facilitate the process of radiation planning [18]. Furthermore, it has been demonstrated to be beneficial in the automation of dose distribution for intensity-modulated radiation therapy (IMRT) in the treatment of prostate malignancies [19].

Moreover, it should be noted that generative networks, which encompass various architectural types like autoencoders (AEs) and vibrational autoencoders (VAEs), possess the potential to enhance the process of acquiring multimodality imaging data, such as MRI and CT scans. This improvement is achieved by reducing the radiation dose and minimizing the need for intravenous contrast [20-21]. Given that patients undergoing cancer treatment are required to undergo regular scans to determine the stage of their tumors, the implementation of adverse event (AE) and vaccine-associated event (VAE) monitoring systems has promise in terms of both reducing healthcare expenditures and enhancing patient safety.

Moreover, deep learning models have the potential to be utilized for the prediction of future cancer progression. The care gap refers to the situation when patients get regular scans or MRIs for unrelated disorders, and certain artificial intelligence (AI) models have previously been created to forecast diseases, such as cardiovascular scores derived from CT scans [22, 23]. The study investigated the capacity of deep-learning convolutional neural networks (CNNs) to accurately forecast the likelihood of developing breast cancer over five years based on normal mammograms [24]. The potential of accurately predicting future occurrences of cancer based on a normal scan is highly encouraging and holds significant potential for making a substantial influence on the general population.

Artificial intelligence (AI) models may also be utilized in pathology and photography. In their study, Golatkar *et al.* (2023) presented findings on the performance of a deep learning model utilizing convolutional neural networks. The model demonstrated a classification accuracy of over 90% in distinguishing between benign and malignant histology in hematoxylin and eosin (H&E) stained breast biopsy samples [25]. Dermoscopic pictures have been utilized for categorizing lesions as either benign or malignant, and have demonstrated comparable accuracy levels to those achieved by professional dermatologists [26].

At now, several artificial intelligence (AI) applications have been successfully integrated into clinical practice [27-29]. There is a need for more progress, enhancement, and use of artificial intelligence (AI) concerning real-world data. The accomplishment of this objective necessitates a workforce that has received proper training, emphasizing the critical need for educating the upcoming generation of physician-scientists in the fields of artificial intelligence (AI) and cancer [30].

Artificial intelligence (AI) may also be leveraged to optimize cancer diagnostics. The utilization of AI technology in colonoscopy procedures has demonstrated its cost-effectiveness as it effectively detects and distinguishes benign polyps, eliminating the need for excision [31]. Not only would this measure conserve healthcare expenditures, but it would also decrease the occurrence of negative outcomes resulting from a more intrusive treatment strategy. The precise identification of malignant and pre-malignant lesions enables the reduction of excessive therapeutic measures. In this regard, it is worth noting that artificial intelligence (AI) algorithms have demonstrated a notable degree of accuracy when employed to assist in the interpretation of colposcopic pictures. Specifically, these algorithms have exhibited a high level of proficiency in accurately predicting the presence of precancerous lesions during cervical cancer screening. The implementation of AI-driven cancer stratification techniques during the diagnostic phase has the potential to reduce the need for invasive treatments and unneeded surgical operations.

Objectives of the study

The aim of the proposed article is to understand the opinion of medical staff towards the AI and contribute to the existing literature.

Scope of the study

The present study will be restricted to selected leading hospitals in Odisha. It includes Apollo Hospital, Kalinga Hospital, Utkal Hospital, Aditya Care Hospital, Sparsh Hospital, SUM Hospital, Hitech- Medical College, AMRI Hospital, KIMS Hospital, AIIMS Hospital, Aswini Hospital, and Aswini Lungs Institute.

Sample size determination

The current investigation involved the calculation of the sample size within the range of 1:4 to 1:10, as suggested by previous studies conducted by Rummel (1970) and Schwab (1980). According to the aforementioned approach, it is recommended that the minimum sample size be calculated by multiplying the number of items by four, while the maximum sample size should be determined by multiplying the number of items by ten. Following the parameters of our study, a total of 13 items were selected for analysis. Consequently, the minimum sample size must be set at 52, while the maximum sample size should be established at 130. Following the removal of the prevalent outlier, a total of 92 observations were selected, adhering to the established criteria of falling within the minimum and the maximum sample size as indicated above. Based on the seminal works of Rummel (1970) and Schwab (1980), it is evident that the sample size of 97 participants chosen for our study is deemed sufficient.

Experimental

Method

The present study is based on primary data and for this purpose the junior-level house surgeons and nursing staff were considered for the data collection purpose. For the finalization of possible variables, 6 core group discussions were conducted consisting of 3 nurses and 3 house surgeons. Initially, 18 variables were considered; however, after the core group discussion, the variables were restricted to 13 only. For data, 5-point Likert type scale was followed. Accordingly, 4 points were allotted for Strongly Agree (SA), 3 points for Agree (A), 2 points for Neutral (N), 1 point for Disagree Agree (DA), and 0 for the Strongly Disagree (SDA). The weighted rank method is used for the compilation of collected data. In total, 126 questionnaires were distributed and out of that 97 questionnaires were collected in proper and complete form. This includes 53 Nursing staff and the rest House Surgeons.

TABLE 1 Computation of the Maximum Possible Score (MPS) and the Least Possible Score (LPS) for various categories of respondents

Category	Equation	MPS	Equation	LPS
NFS	(13X4X29)	1508	(13X0X29)	0
NMS	(13X4X24)	1248	(13XX24)	0
HSF	(13X4X16)	832	(13X0X16)	0
HSM	(13X4X26)	1352	(13X0X26)	0

In Table 1, the scores are being estimated with the help of :
The Maximum Possible Score = (Number of variables X Maximum possible score X Number of respondents)
The Least Possible Score= = (Number of variables X Least possible score X Number of respondents)

TABLE 2 Data analysis

Variables	NFS	NMS	HSF	HSM
AI helps in better risk assessment for cancer patients.	97	82	59	95
AI helps in patient prognosis estimation and treatment selection based on knowledge.	105	76	56	89
AI helps with early detection by analysing a patient's medical history of cancer patients.	102	83	57	94
AI helps in test results to identify patterns that may indicate the presence of cancer.	103	86	60	91
AI facilitates diagnosis with high accuracy of cancer diseases.	99	91	57	98
AI helps in predicting gene mutations from historical analysis.	99	86	62	90
AI offers immense potential for improving patient care for cancer patients.	96	87	59	97
AI assists medical professors and staff.	93	91	56	94
AI provides patient service 24x7 to cancer patients.	105	83	43	98
AI reduces human error in cancer treatment.	106	90	57	98
AI streamlines workflow in cancer treatment.	103	92	60	98
AI helps in easy information sharing for cancer patients.	109	89	58	98
AI reduces the overall cost of cancer treatment.	110	90	61	98
Total actual score	**1327**	**1126**	**745**	**1236**
Maximum possible score	**1508**	**1248**	**832**	**1352**
Least score	**0**	**0**	**0**	**0**
% of the total actual score to the maximum possible score	**87.99**	**90.22**	**89.54**	**91.42**

Source: Annexure A, B, C, and D.

In Table 2, the respondents provided answers to many questions. The resulting total scores for the variables NFS, NMS, HSF, and HSM were 1327, 1126, 745, and 1236, respectively. These scores were compared to the maximum possible scores of 1508, 1248, 832, and 1352. Under no circumstances, does the real score come close to the minimum achievable score. The significance of the factors included in the present study on the role of artificial intelligence (AI) in cancer therapy in India is shown by the percentage of the total real score concerning the highest possible score. In the current scenario, HSM exhibits the highest percentage at 91.42%, followed by NMS at 90.22%. HSF and NFS trail behind with percentages of 89.54% and 87.99%, respectively.

Conclusion

Artificial intelligence (AI) has already exerted a substantial influence on the healthcare sector and is poised to further transform the field of medicine. The potential of this technology is vast and holds significant implications in several domains such as cancer research, screening, diagnosis, therapy, and monitoring. Artificial intelligence (AI) can reduce healthcare expenditures and address inequities within the healthcare system. Numerous methods have been devised to utilize the wide range of medical data, encompassing free text, laboratory and imaging findings, radiological pictures, and omics data. In light of these objectives, more investigation is imperative to sustain and guarantee the analytical and clinical soundness, as well as the clinical usefulness.

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Conflict of Interest

The present work is contribution of authors do not have any conflict of interest as such with any other individual or institutions. No funds have been received for the present study.

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References

[1] H. Sung, J. Ferlay, R.L. Siegel, M. Laversanne, I. Soerjomataram, A. Jemal, F. Bray, Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries, *CA Cancer J. Clin.*, **2021**, *71*, 209. [Crossref], [Google Scholar], [Publisher]

[2.] L.A. Emens, P.A. Ascierto, P.K. Darcy, S. Demaria, A.M.M. Eggermont, W.L. Redmond, B. Seliger, F.M. Marincola, Science Direct Cancer immunotherapy: Opportunities and challenges in the rapidly evolving clinical landscape, *Eur. J.* Cancer., **2017**, *81*, 116-129. [Crossref], [Google Scholar], [Publisher]

[3] D.J. Ahnen, S.W. Wade, W.F. Jones, R. Sifri, J.M. Silveiras, J. Greenamyer, S. Guiffre, J. Axilbund, A. Spiegel, Y. Nancy You, The increasing incidence of young-onset colorectal cancer: a call to action, *Mayo Clin. Proc.,* **2014**, *89*, 216. [Crossref], [Google Scholar], [Publisher]

[4] V. Verma, T. Sprave, W. Haque, C.B. Simone, J.Y. Chang, J.W. Welsh, C.R. Thomas, A systematic review of the cost and cost-effectiveness studies of immune checkpoint inhibitors 11 Medical and Health Sciences 1112 Oncology and Carcinogenesis, *J. Immunother. Cancer,* **2018**, *6*, 1. [Crossref], [Google Scholar], [Publisher]

[5] J. Dong, Y. Geng, D. Lu, B. Li, L. Tian, D. Lin, Y. Zhang, Clinical trials for artificial intelligence in cancer diagnosis: a cross-sectional study of registered trials in ClinicalTrials.gov, *Front. Oncol.,* **2020**, *10*, 1-6. [Crossref], [Google Scholar], [Publisher]

[6] S. Jha, E.J. Topol, Adapting to artificial intelligence: radiologists and pathologists as information specialists, *JAMA*, **2016**, *316*, 2353. [Crossref], [Google Scholar], [Publisher]

[7] W. Linda Bi, A. Hosny, M.B. Schabath, M.L. Giger, N.J. Birkbak, A. Mehrtash, T. Allison, O. Arnaout, C. Abbosh, I.F. Dunn, R.H. Mak , R.M. Tamimi, C.M. Tempany, C. Swanton, U. Hoffmann, L.H. Schwartz, R.J. Gillies, R.Y. Huang, H.J.W.L. Aerts, Artificial intelligence in cancer imaging: clinical challenges and applications, *CA Cancer J. Clin*., **2019**, *69*, 127. [Crossref], [Google Scholar], [Publisher]

[8] A. Hosny, C. Parmar, J. Quackenbush, L.H. Schwartz, H.J.W.L. Aerts, Artificial intelligence in radiology, *Nat. Rev. Cancer,* **2018**, *18*, 500. [Crossref], [Google Scholar], [Publisher]

[9] A. Ghosh, Artificial intelligence using open source BI-RADS data exemplifying potential future use, *J. Am. Coll. Radiol.,* **2019**, *16*, 64. [Crossref], [Google Scholar], [Publisher]

[10] T. Schaffter, D.S.M. Buist, C.I. Lee, Y. Nikulin, D. Ribli, Y. Guan, W. Lotter, Z. Jie, H. Du, S. Wang, J. Feng, M. Feng, H.E. Kim, F. Albiol , A. Albiol, S. Morrell, Z. Wojna, M. Eren Ahsen, U. Asif, A. Jimeno Yepes, S. Yohanandan, S. R.Cohen, D. Yi, B. Hoff, T. Yu, E. Chaibub Neto, D. L. Rubin, P. Lindholm, L.R. Margolies, R.B. McBride, J.H. Rothstein, W. Sieh, R. Ben-Ari, S. Harrer, A. Trister, S. Friend, T. Norman, B. Sahiner, F. Strand, J. Guinney, G. Stolovitzky, L. Mackey, J. Cahoon, L. Shen, J.H. Sohn, H. Trivedi, Y. Shen, L. Buturovic, J.C. Pereira, J. S. Cardoso, E. Castro, K.T. Kalleberg, O. Pelka, I. Nedjar, K.J Geras, F. Nensa, E. Goan , S. Koitka, L. Caballero, D.D. Cox, P. Krishnaswamy, G. Pandey, C.M. Friedrich, D. Perrin, C. Fookes, B. Shi, G.C. Negrie, M. Kawczynski, K. Cho, C. Son Khoo, J.Y. Lo, A. Gregory Sorensen, H. Jung, Evaluation of combined artificial intelligence and radiologist assessment to interpret screening mammograms, *JAMA Netw. Open,* **2020**, *3*, e200265. [Crossref], [Google Scholar], [Publisher]

[11] M. Schultheiss, S.A. Schober, M. Lodde, J. Bodden, J. Aichele, C. Müller-Leisse, B. Renger, F. Pfeiffer, D. Pfeiffer, A robust convolutional neural network for lung nodule detection in the presence of foreign bodies, *Sci. Rep.,* **2020**, *10*, 12987. [Crossref], [Google Scholar], [Publisher]

[12] M. Zhang, G.S. Young, H. Chen, J. Li, L. Qin, J. Ricardo McFaline-Figueroa, D.A. Reardon, X. Cao, X. Wu, X. Xu, Deep-learning detection of cancer metastases to the brain on MRI, *J. Magn. Reason. Imaging*, **2020**, *52*, 1227-1236. [Crossref], [Google Scholar], [Publisher]

[13] X. Liu, Deep learning analysis for automatic lung nodule detection, *J. Global Oncol.*, **2019**, *5*, 27. [Crossref], [Google Scholar], [Publisher]

[14] M.M. Shaver, P.A. Kohanteb, C. Chiou, M.D. Bardis, C. Chantaduly, D. Bota, C. G. Filippi, B. Weinberg, J. Grinband, D.S. Chow, P.D. Chang, Optimizing neuro-oncology imaging: a review of deep learning approaches for glioma imaging, *Cancers (Basel)*, **2019**, *11*, 829. [Crossref], [Google Scholar], [Publisher]

[15] M. Avanzo, J. Stancanello, G. Pirrone, G. Sartor, Radiomics and deep learning in lung cancer, *Strahlenther. Onkol.*, **2020**, *196*, 879. [Crossref], [Google Scholar], [Publisher]

[16] C. Dreher, P. Linde, J. Boda-Heggemann, B. Baessler, Radiomics for liver tumors. *Strahlenther. Onkol.*, **2020**, *196*, 888. [Crossref], [Google Scholar], [Publisher]

[17] M. Kocher, M.I. Ruge, N. Galldiks, P. Lohmann, Applications of radiomics and machine learning for radiotherapy of malignant brain tumors, *Strahlenther. Onkol.*, **2020**, *196*, 856. [Crossref], [Google Scholar], [Publisher]

[18] S. Bae, C. An, S. Soo Ahn, H. Kim, K. Han, S. W. Kim, J.E. Park, H.S. Kim, S.K. Lee, Rbust performance of deep learning for distinguishing glioblastoma from single brain metastasis using radiomic features: model development and validation, *Sci. Rep.*, **2020**, *10*, 12110. [Crossref], [Google Scholar], [Publisher]

[19] J.F. Yamamoto, I.O. de Souza, L.S. Letaif, V. Cobello-Junior, Information technology challenges in a public hospital during the COVID-19 pandemic, *Clinics (Sao Paulo)*, **2021**,

76, e2648. [Crossref], [Google Scholar], [Publisher]

[20] A. Pucchio, E.A. Eisenhauer, F.Y. Moraes, Medical students need artificial intelligence and machine learning training, *Nat. Biotechnol*., **2021**, *39*, 388-389. [Crossref], [Google Scholar], [Publisher]

[21] Y. Mori, S.Ei Kudo, J. E. East, A. Rastogi, M. Bretthauer, M. Misawa, M. Sekiguchi, T. Matsuda, Y. Saito, H. Ikematsu, K. Hotta, K. Ohtsuka, T. Kudo, K. Mori, Cost savings in colonoscopy with artificial intelligence-aided polyp diagnosis: an add-on analysis of a clinical trial (with video), *Gastrointest. Endosc.*, **2020**, *92*, 905. [Crossref], [Google Scholar], [Publisher]

[22] L. Hu, D. Bell, S. Antani, Z. Xue, K. Yu, M.P. Horning, N. Gachuhi, B. Wilson, M.S. Jaiswal, B. Befano, L.R. Long, R. Herrero, M.H. Einstein, R. D. Burk, M. Demarco, J.C. Gage, A.C. Rodriguez, N. Wentzensen, M. Schiffman., An observational study of deep learning and automated evaluation of cervical images for cancer screening, *J. Natl Cancer Inst.*, **2019**, *111*, 923. [Crossref], [Google Scholar], [Publisher]

[23] K. Shaffer, Can machine learning be used to generate a model to improve the management of high-risk breast lesions? *Radiology*, **2018**, *286*, 819. [Crossref], [Google Scholar], [Publisher]

[24] L.A. Hildebrand, C.J. Pierce, M. Dennis, M. Paracha, A. Maoz, Artificial intelligence for histology-based detection of microsatellite instability and prediction of response to immunotherapy in colorectal cancer, *Cancers*, **2021**, *13*, 1. [Crossref], [Google Scholar], [Publisher]

[25] G. Liang, W. Fan, H. Luo, X. Zhu, The emerging roles of artificial intelligence in cancer drug development and precision therapy. *Biomed. Pharmacother.*, **2020**, *128*, 110255. [Crossref], [Google Scholar], [Publisher]

[26] B. Liu, H. He, H. Luo, T. Zhang, J. Jiang, Artificial intelligence and big data facilitated targeted drug discovery, *Stroke Vasc. Neurol.*, **2019**, *4*, 206. [Crossref], [Google Scholar], [Publisher]

[27] P. Liu, H. Li, S. Li, KS. Leung, Improving prediction of phenotypic drug response on cancer cell lines using deep convolutional network, *BMC Bioinformatics*, **2018**, *20*, 408. [Crossref], [Google Scholar], [Publisher]

[28] A. Artemov, E. Putin, Q. Vanhaelen, A. Aliper, I. Ozerov, A. Zhavoronkov, Integrated deep-learned transcriptomic and structure-based predictor of clinical trial outcomes, *bioRxiv.*, **2016**, 095653. [Crossref], [Google Scholar], [Publisher]

[29] H. Hassanzadeh, S. Karimi, A. Nguyen, Matching patients to clinical trials using semantically enriched document representation, *J. Biomed. Inform.*, **2020**, *105*, 103406. [Crossref], [Google Scholar], [Publisher]

[30] J. Thaddeus Beck, M. Rammage, G.P Jackson, A.M. Preininger, I. Dankwa-Mullan, M.C. Roebuck, A. Torres, H. Holtzen, S.E Coverdill, M.P. Williamson, Q. Chau, K. Rhee, M. Vinegra, Artificial intelligence tool for optimizing eligibility screening for clinical trials in a large community cancer centre, *JCO Clin. Cancer Inform.*, **2020**, *4*, 50. [Crossref], [Google Scholar], [Publisher]

[31] J.M. Unger., E. Cook, E. Tai, A. Bleyer, The role of clinical trial participation in cancer research: barriers, evidence, and strategies, *Am. Soc. Clin. Oncol. Educ. Book.*, **2016**, *36*, 185. [Crossref], [Google Scholar], [Publisher]

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