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Future trends of AI in precision oncology: Insights from a systematic review and evidence-based roadmap (2021–2024)

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Abstract: This systematic review investigates the advancements and challenges of artificial intelligence (AI) in precision oncology, focusing on research from 2021 to 2024, to provide an evidence-based roadmap for future implementation. Following the PRISMA guidelines, a comprehensive search was conducted across Scopus, SciELO, and Google Scholar using relevant keywords to identify studies evaluating AI applications in cancer diagnosis and treatment. Eighteen relevant articles were selected and qualitatively analyzed to identify key themes and patterns. AI models, including machine learning and deep learning, have demonstrated significant improvements in diagnostic accuracy, treatment planning, and personalized therapies. Examples include a hybrid CatBoost-MLP model that achieved 98.06% accuracy in breast tissue classification and a deep convolutional neural network with 92.08% sensitivity for early gastric cancer detection. AI also reduces radiotherapy planning times, enhancing accessibility, particularly in developing countries. The integration of AI into oncology has transformative potential, enhancing diagnostic precision, risk stratification, and personalized treatment strategies. However, challenges remain, including data standardization, the need for diverse datasets, and ethical considerations. This study highlights the need for robust AI models, international data standards, and ethical frameworks to ensure the safe, equitable, and effective clinical implementation of AI in oncology, paving the way for improved patient outcomes and healthcare accessibility.
Keywords: *Artificial intelligence, Biomarkers, Cancer treatment, Deep learning, Oncological diagnosis.*

1. Introduction

Cancer ranks among the leading causes of death globally, accounting for approximately 10 million fatalities by 2020 [1]. This disease presents substantial challenges to healthcare systems because of its clinical intricacies and diverse biological manifestations. Although traditional methods for diagnosing and treating cancer can be effective in certain instances, they often struggle with sensitivity, specificity, and customization [2, 3]. Artificial intelligence (AI) has emerged as a groundbreaking technology capable of overcoming these obstacles by enabling sophisticated analysis of complex medical images [4] and automating diagnostic and therapeutic procedures [5, 6].

Artificial intelligence, characterized by the ability of computer systems to execute tasks that typically require human intellect, has been applied across numerous domains, including healthcare [7, 8] education [9] and finance [10, 11]. This widespread adoption is driven by AI's potential to boost efficiency, precision, and decision-making, establishing it as a fundamental element of contemporary technological progress. In oncology, AI has focused on machine learning algorithms [12] and deep learning [5] which are tailored to effectively and accurately interpret medical images [4] genomic sequences, and clinical data. These technologies have shown significant value in the early detection of cancer, risk assessment, and enhancement of personalized treatment plans by facilitating precision. This approach predicts patients' reactions to specific therapies based on their distinct genetic makeup [13].

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Despite significant advancements, the incorporation of AI into clinical settings remains challenging. Key issues include ethical concerns regarding data privacy [13, 14] model interpretability [15] and ensuring fair access to these technologies [16]. For example, the World Health Organization (WHO) has stressed the need for AI systems to uphold human rights and foster equity [17]. Nonetheless, the increasing use of AI in oncology underscores its potential to revolutionize cancer treatment.

This systematic review aimed to compile recent progress in the use of AI for the diagnosis and treatment of cancer, highlighting its benefits and drawbacks. Research conducted over the past five years has examined AI algorithms in different phases of cancer management. This study offers an in-depth perspective on how these technologies are transforming contemporary oncology and explores their potential impact on the healthcare of the future.

2. Methodology

2.1. Search Strategy

This systematic review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a comprehensive and transparent approach to selecting and evaluating relevant studies [17]. The review process included searches of three electronic databases: Scopus, SciELO, and Google Scholar. Scopus is highly regarded for its controlled bibliographic data, providing reliable metrics for assessing research performance, such as publication counts, citations, and h-indices [18-20]. In contrast, Google Scholar is notable for its broad coverage of future citations, making it a key tool in this domain. It reports a greater number of citations than Scopus, which is attributed to its wider document coverage [21]. SciELO is particularly valuable for accessing scientific literature from Latin America, offering insights into regional research trends and thematic connections, such as those related to online and distance teacher training [22].

The keywords included combinations of the terms "artificial intelligence," "diagnosis," "treatment," and "cancer," alongside Boolean operators to broaden and refine the search.

2.2. Inclusion and Exclusion Criteria

The following inclusion criteria were established.

- Articles published between 2020 and 2024.
- Original studies examining the applications of AI in cancer diagnosis and treatment.
- Publications in English or Spanish.
- Full access to article text:

The exclusion criteria were as follows.

- Duplicate studies.
- Non-systematic reviews or editorials.
- The articles focused on non-clinical applications of AI.

2.3. Selection Process

Initially, a total of 452 studies were identified. After eliminating duplicates (n = 128), the titles and abstracts were reviewed, narrowing the selection to 82 articles. Ultimately, a full-text review of these studies led to 18 articles that fulfilled all criteria (Figure 1).

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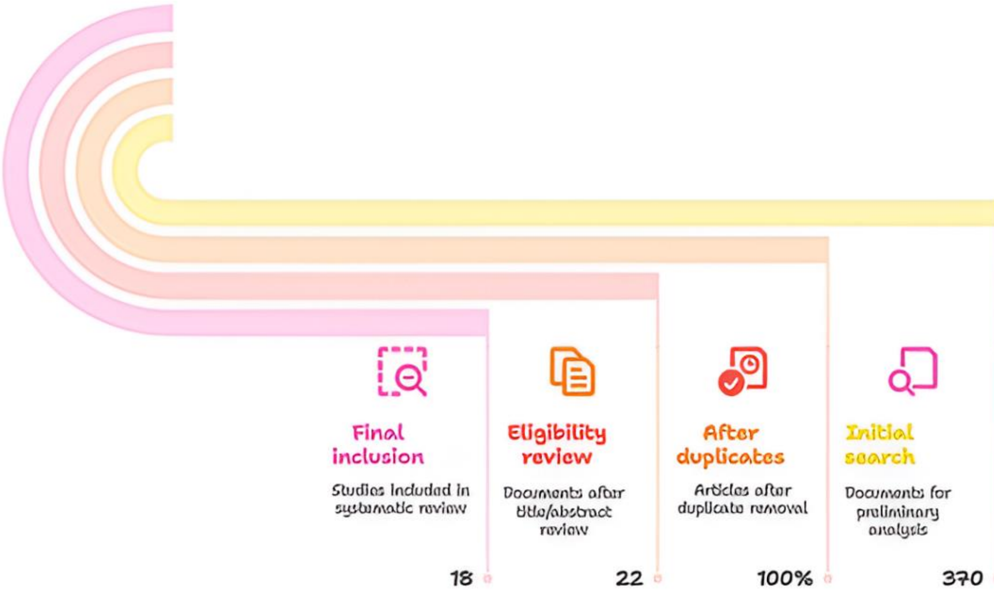

Figure 1.
Article Selection Process for Systematic Review.

2.4. Data Extraction and Analysis

From the 18 selected studies, information on the authors, year of publication, objectives, main findings, and conclusions were collected. The data were qualitatively analyzed to identify patterns and recurring themes in the use of AI in oncology.

3. Results

An examination of AI applications in cancer diagnosis and treatment revealed important insights from 18 studies. These findings highlight AI's transformative role of AI in contemporary oncology.

Xu, et al. [23] created a machine learning model to predict mismatch repair deficiency (dMMR) in colorectal cancer, enhancing presurgical detection with a decision AUC of 0.832. Similarly, Pasupuleti, et al. [24] utilized a model based on a deep neural network, achieving over 99% accuracy and proving its effectiveness for brain tumor segmentation. Furthermore, Koyama, et al. [25] demonstrated that radiomic models significantly surpassed traditional methods with a C-index of 0.841, highlighting their usefulness in selecting the best treatment.

Similarly, Yin, et al. [26] used convolutional neural networks to enhance the diagnostic precision of skin tumors by 15.6%. Additionally, Aggarwal, et al. [27] emphasized the impact of AI-driven radiotherapy planning technologies for cervical, head and neck, and prostate cancers, which significantly reduce planning durations from weeks to minutes, thereby improving accessibility in developing countries. Concurrently, a convolutional neural network optimized with a tunicate swarm algorithm achieved an accuracy rate of 98.70 % %in identifying oral cancer lesions, underscoring the potential of deep learning in rapid diagnostics [28].

In the field of biomarkers and multi-omics data, Xiao, et al. [29] discovered significant genes related to the postoperative advancement of non-muscle-invasive bladder cancer, which are associated with activated T cells and can predict postoperative outcomes. Similarly, Jia, et al. [30] created a model based on lncRNAs to forecast overall survival in patients with hepatocellular carcinoma, achieving AUC values greater than 0.785, highlighting the importance of biomarkers in personalized medicine.

In breast cancer research, a hybrid approach that integrates CatBoost with multilayer perceptron (MLP) neural networks was employed to examine electronic health records, achieving an impressive 98.06% accuracy in distinguishing between benign and malignant tissues. Explainable AI (XAI) technology enhances the interpretability of clinical decisions and boosts confidence in models [31]. This progress was furthered by Weitz, et al. [32] who used AI tools to create 3D models of breast tumors, improving surgical planning, success rates, and patient satisfaction. Additionally, Arathi and Bai [33] reached a 98.57% accuracy in predicting recurrence with a DCNN-based model, thereby optimizing therapeutic strategies.

Conversely, Zhang, et al. [34] showed that radiomic models achieved an AUC of 0.89 in predicting complications such as esophageal fistulas. Additional progress included the implementation of the U-Net architecture. Uzun, et al. [35] attained a dice score of 91.38% in segmenting brain tumors, whereas Song, et al. [36] achieved 88.8% sensitivity in identifying triple-negative breast cancer through metabolic fingerprinting and machine learning. Xing, et al. [37] highlighted a simplified proteomic panel that predicted responses to sorafenib, with an AUC of 0.988. Finally, using a random survival forest model, Liao, et al. [38] achieved AUCs of 0.92, 0.96, and 0.96 for predicting 1-, 3-, and 5-year survival rates in patients with gastric neuroendocrine neoplasms (gNENs). This model also classifies patients into high- and low-risk groups, demonstrating its potential to guide clinical decisions.

Recent advancements in artificial intelligence have significantly enhanced cancer diagnosis and treatment across various domains. In endometrial cancer, the integration of deep learning algorithms with magnetic resonance imaging results in an AUC of 0.918 for detecting high-risk cases and 0.926 for forecasting postoperative recurrence, underscoring a significant influence on clinical decision-making [39]. Likewise, for early gastric cancer diagnosis, a system utilizing deep convolutional neural networks achieved a diagnostic sensitivity of 92.08%, markedly surpassing the performance of seasoned endoscopists and demonstrating its potential in clinical environments with limited resources [40].

Recent advancements in artificial intelligence (AI) have facilitated the use of diverse models for the diagnosis, prediction of outcomes, and treatment of different cancer types. Table 1 presents an overview of the leading AI models, their performance metrics, and their primary clinical uses (Table 1). This information underscores how new technologies are revolutionizing oncology by offering precise and effective tools.

Table 1.
Summary of AI Models, Performance Metrics, and Clinical Applications.

Cancer Type	**AI Model**	**Performance Metrics**	**Clinical Application**
Breast Cancer	CatBoost + MLP Neural Network	AUC: 0.98, Sens: 98.06%	Tissue classification
Colorectal Cancer	Machine Learning (dMMR)	AUC: 0.832	Pre-surgical detection
Skin Cancer	Convolutional Neural Network	Improvement: 15.6% in accuracy	Skin tumor classification
Liver Cancer	AI-based Proteomics	AUC: 0.988	Treatment response (sorafenib)
Brain Cancer	U-Net Architecture	Dice Score: 91.38%	Brain tumor segmentation
Stomach Cancer	Deep CNN	Sens: 92.08%	Early diagnosis

Below is a summary of the most relevant clinical applications of AI models in oncology, along with key findings that demonstrate their impact on improving cancer diagnosis and treatment (see Table 2).

Table 2.
Clinical Applications and Key Outcomes of AI Models.

Cancer Type	Clinical Application	AI Model	Key Outcomes
Breast Cancer	Tissue classification	CatBoost + MLP Neural Network	98.06% accuracy in classifying malignant and benign tissues
Colorectal Cancer	Pre-surgical detection of dMMR	Machine Learning (dMMR)	AUC: 0.832, improving pre-surgical detection of mismatch repair deficiency
Skin Cancer	Skin tumor classification	Convolutional Neural Network	15.6% improvement in diagnostic accuracy
Liver Cancer	Prediction of treatment response (sorafenib)	AI-based Proteomics	AUC: 0.988, optimizing patient selection for targeted therapy
Brain Cancer	Brain tumor segmentation	U-Net Architecture	Dice Score: 91.38%, enhancing segmentation accuracy in MRI imaging
Stomach Cancer	Early diagnosis	Deep CNN	Sensitivity of 92.08%, outperforming both junior and senior endoscopists
Bladder Cancer	Identification of post-surgical biomarkers	Random Forest	AUC: 0.92–0.96 for survival prediction at 1, 3, and 5 years
Lung Cancer	Survival prediction	Radiomic Model	C-index: 0.841, facilitating personalized treatment selection

The findings indicate that AI models have not only greatly enhanced performance metrics, such as accuracy and sensitivity, but also supported essential applications in oncology, from early detection to tailored treatment planning. Additionally, it is clear that advancements in AI allow for more informed decision-making and more accurate patient care.

4. Discussion

This systematic review underscores the revolutionary role of artificial intelligence (AI) in cancer diagnosis and treatment, offering sophisticated tools that outperform traditional methods in various areas of oncology.

4.1. Application of AI Models in Oncological Diagnosis

Machine learning models have demonstrated their effectiveness in improving diagnostic accuracy across various cancer types. In colorectal cancer, the model created by Xu, et al. [23] achieved an AUC of 0.832, significantly enhancing the presurgical detection of mismatch repair deficiency (dMMR). This progress highlights AI's capability of AI to identify molecular biomarkers with greater accuracy than traditional methods, thereby optimizing personalized treatments. Furthermore, radiomic models, such as those detailed by Koyama, et al. [25] excelled in predicting survival in advanced lung cancer, achieving a C-index of 0.841, which aids in selecting more effective treatments.

In a study by Fen, et al. [40] deep convolutional neural networks were shown to detect gastric cancer with a sensitivity of 92.08%, surpassing the performance of both junior and senior endoscopists. This highlights the potential of AI in clinical settings with limited resources, where professional experience may adversely affect the results. Additionally, the U-Net architecture's effectiveness in brain tumor segmentation was demonstrated by Uzun, et al. [35] achieving a dice score of 91.38%, which illustrates its capability in processing complex medical images.

4.2. Innovations in AI-Assisted Treatment

AI has transformed cancer treatment, particularly in radiotherapy and surgical planning. According to Aggarwal, et al. [27] AI technologies have drastically reduced radiotherapy planning times from weeks to minutes for cervical, head, and neck cancer. This progress not only boosts efficiency but also enhances treatment accessibility in developing nations, thereby fostering equity in cancer care. Similarly, Weitz, et al. [32] found that AI tools for creating 3D tumor models greatly increased surgical success rates and patient satisfaction in breast cancer treatment.

Recent progress in immunotherapy and biomarker research has facilitated the discovery of crucial genetic markers linked to cancer progression. For instance, Xiao et al. [29] identified genes associated with the postoperative advancement of non-muscle-invasive bladder cancer. Jia et al. [30] created a model based on lncRNAs, achieving AUC values over 0.785 to predict overall survival in patients with hepatocellular carcinoma. These findings highlight the significance of incorporating AI into multi-omics analyses to tailor treatments and enhance prognosis.

4.3. Impact of AI on Specific Cancers

In the realm of breast cancer, hybrid models that integrate CatBoost and multilayer perceptron (MLP) neural networks, as detailed by Srinivasu, et al. [31] have achieved an accuracy of 98.06%, offering interpretability in clinical decision-making through explainable AI (XAI). This progress was furthered by Weitz, et al. [32] who enhanced surgical planning using AI tools, thereby increasing the success rates for patients with breast cancer. Moreover, Arathi and Bai [33] achieved a 98.57% accuracy in predicting recurrence using a DCNN-based model, which aids in optimizing therapeutic strategies.

In their 2022 study, Song, et al. [36] employed metabolic fingerprinting to identify triple-negative breast cancer, achieving a sensitivity of 88.8%. This underscores AI's ability of AI to discern distinct metabolic traits in specific cancer subtypes. Similarly, Xing, et al. [37] created a proteomic panel for liver cancer with an AUC of 0.988 to predict treatment responses, demonstrating AI's role of AI in enhancing pharmacological treatment strategies.

The findings indicate that AI models have not only greatly enhanced performance metrics, such as accuracy and sensitivity, but have also supported essential applications in oncology, from early detection to tailored treatment planning. Additionally, AI advancements allow for more informed decision-making and accurate patient care.

4.4. Limitations

Although the conclusions of this review are important, they are subject to some limitations. First, a significant number of studies relied on retrospective cohorts, which can lead to selection bias and limit the relevance of the findings in future clinical environments. Furthermore, most AI models assessed depend on extensive, meticulously curated datasets to perform optimally, which are not always accessible in areas with limited resources. This constraint may hinder the adoption of these technologies in regions with underdeveloped healthcare systems.

Furthermore, a significant obstacle to incorporating artificial intelligence (AI) into oncology is the diversity of existing models and variations in the datasets employed. Differences in algorithms, model structures, and evaluation standards make it difficult to compare studies directly and hinder the generalization of results. For instance, deep learning models that require large amounts of uniform data may not be suitable in situations where data are limited or inconsistent owing to variations in clinical procedures or data collection standards. In addition, resource-constrained environments face further challenges when adopting these technologies. The absence of technological infrastructure, such as specialized hardware (e.g., GPUs for model training) and high-speed Internet, impedes the implementation of these advanced models. Similarly, the lack of well-organized and annotated local datasets complicates the training and validation of models in these settings. This could exacerbate global disparities in access to advanced healthcare technologies.

To address these challenges, it is essential to create more resilient and flexible AI models that can work effectively with diverse datasets. Moreover, promoting global partnerships to exchange expertise, infrastructure, and data is vital for making technological progress accessible to countries with limited resources is vital. Employing "explainable AI" (XAI) techniques and transfer learning models could also offer practical solutions, as these methods require less domain-specific data and can be utilized in settings with less developed infrastructure.

4.5. Data Quality and Standardization as Key Challenges

Ensuring data quality and standardization is crucial for the precision and relevance of AI models in oncology. Medical data, including diagnostic images, electronic health records, and omics data, often originate from diverse sources, leading to considerable differences in collection methods, formats, and quality. This lack of consistency poses challenges in comparing studies and creating models that can be widely applied across various clinical settings. The absence of global standards for data collection and labeling creates issues related to model interoperability and reproducibility. For example, differences in the resolution of medical images, types of annotations used in imaging studies, and protocols for handling omics data can introduce biases into models, limiting their ability to generalize across diverse populations.

Errors in manual annotation and the absence of representative data from certain groups, such as those in developing countries, further compromise data quality. This not only diminishes the effectiveness of the models but also worsens disparities in access to cutting-edge healthcare technologies.

4.6. Ethical Challenges in Applying AI in Oncology

The implementation of AI in oncology raises numerous ethical challenges that must be addressed to ensure its safety, transparency, and equitable use. Key issues include:

4.6.1. Data Privacy

In the field of oncology, AI models depend on extensive patient data, which include sensitive details, such as medical images, genetic information, and clinical records. Although such data are crucial for developing precise algorithms, their collection and storage present considerable privacy challenges. If health databases are breached, personal information can be exposed, thereby eroding patient trust and willingness to engage in future research. To address these concerns, strategies such as data anonymization, use of blockchain technologies to maintain data integrity, and strict adherence to regulations such as Europe's General Data Protection Regulation (GDPR) are necessary.

4.6.2. Bias in AI Models

AI models are fundamentally shaped by the data on which they are trained. If these datasets do not accurately reflect diverse populations, the algorithms may continue or even worsen the existing disparities in healthcare. For instance, models primarily trained on data from urban areas or developed nations may not function well in rural environments or in countries with limited resources. Furthermore, variations in sex, ethnicity, and healthcare access can result in biased predictions and clinical decisions. It is essential to implement strategies to detect and reduce these biases, such as conducting regular model audits, creating more inclusive datasets, and using explainable AI (XAI) methods. These steps are vital for enabling healthcare professionals to comprehend and scrutinize algorithmic decisions.

4.7. Practical Recommendations

- Transparency: Ensure that AI models are interpretable and auditable by healthcare professionals. This not only enhances trust in predictions but also enables the real-time identification of potential errors or biases.
- International Collaboration: Promote global regulations to ensure equitable access to AI-based technologies and foster the creation of shared ethical frameworks.
- Education and Training: Equip healthcare professionals with the necessary skills to understand how AI models are developed and applied, ensuring their ethical and effective use.
- Establishment of Global Standards: Develop international standards for medical data collection, labeling, and storage to significantly improve data quality and interoperability.

- Data Curation and Validation: Implement automated curation processes and regular audits to ensure that datasets are consistent and free from annotation errors.
- Encouraging international consortia: Supports the creation of international consortia to share standardized data and protocols, enabling the development of more robust and generalizable AI models.
- Data augmentation techniques: Data augmentation and synthetic data generation techniques, such as generative adversarial networks (GANs), are used to address the lack of representative data in underrepresented populations.

5. Conclusions

While advancements in artificial intelligence (AI) within oncology hold great promise, they also bring forth substantial ethical challenges that need to be addressed to ensure responsible and fair implementation. The findings highlight critical ethical concerns, such as data privacy, biases in AI models, and algorithm transparency. Protecting data privacy is crucial for maintaining patient trust and encouraging medical institutions to share information. Conversely, biases in AI models can worsen disparities in access to effective treatment, especially among underrepresented groups.

To address these issues, it is crucial to establish strong international regulations for data management and ensure fairness in the creation and use of AI models in healthcare. Additionally, future studies should aim to create explainable artificial intelligence (XAI) tools that allow healthcare professionals to comprehend and evaluate algorithmic decisions, guaranteeing fairness and transparency. These actions would not only alleviate ethical concerns but also enhance the acceptance of these technologies among healthcare providers and patients, thereby increasing their beneficial impact on contemporary oncology.

5.1. Opportunities for Future Research

The progress of artificial intelligence (AI) in oncology presents a promising opportunity to explore its integration with new technologies, which could significantly enhance its role in cancer diagnosis and treatment. Future research should focus on the following key topics.

5.1.1. Integration with Nanotechnology

Nanotechnology enables the development of targeted drug delivery systems and molecular sensors for early tumor detection and diagnosis. Combining AI with this technology can optimize personalized treatments using algorithms that analyze real-time patient responses to nanodrugs.

5.1.2. Use of Blockchain for Data Management

Blockchain offers a secure and decentralized method for storing and exchanging clinical data, thereby ensuring both privacy and transparency. By combining AI with blockchain, it is possible to train models on extensive datasets while maintaining patient confidentiality and promoting international collaboration among healthcare institutions.

5.1.3. Combination with Advanced Oomics

Omics technologies, such as genomics, transcriptomics, proteomics, and metabolomics, produce vast quantities of data that can be examined using AI algorithms to reveal intricate biological patterns. By combining AI with these technologies, the development of predictive biomarkers can be expedited, thereby advancing the field of precision medicine.

5.1.4. Applications in Augmented Reality (AR) and Virtual Reality (VR):

In the field of surgery, integrating AI with AR and VR technologies can enhance the planning and performance of intricate operations by offering 3D visual representations of the tissues and tumors. This integration would allow surgeons to make more accurate and informed decisions during surgery.

5.1.5. Adoption of Quantum Algorithms

Quantum computing has the potential to address optimization and large-scale data analysis challenges at remarkable speed. The integration of AI with quantum computing can transform medical image analysis, treatment forecasting, and the modeling of biological interactions.

5.1.6. Development of Multimodal Models

Future studies should focus on developing models that combine various data sources, including medical imaging, omics data, and clinical records, to deliver more reliable and precise predictions for cancer treatment.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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