人工智能在脓毒症管理中的应用进展

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[摘要] 脓毒症是一种高病死率的危重疾病，其早期识别与精准管理是临床面临的重大挑战。传统评估工具依赖静态数据，难以满足动态病情监测与个体化治疗的需求。人工智能(AI)通过整合多维度临床数据，为脓毒症的早期预警、风险分层、亚型识别及治疗决策提供了新的解决方案。然而，AI的临床转化仍受限于数据质量、模型可解释性以及伦理监管框架的缺失。本文系统综述了AI在脓毒症管理领域的最新进展：机器学习与深度学习模型能够从时序数据中识别早期风险，实现超前预警；无监督学习有助于解析脓毒症的异质性，划分具有不同预后和治疗反应的亚型；在治疗层面，AI开始为液体复苏、血管活性药物及抗生素的精准应用提供决策支持。未来的发展需聚焦于构建高质量多中心数据集、开发可解释算法，并通过前瞻性研究验证其临床效用，旨在为最终建立以医师为核心、AI为辅助的协同诊疗模式，从而改善脓毒症患者预后提供参考。

[关键词] 人工智能；脓毒症；机器学习；早期预警；决策支持

Advancements in the application of artificial intelligence for sepsis management

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[**Abstract**] Sepsis is a critical illness with a high mortality rate, and its early identification and precise management pose significant challenges in clinical practice. Traditional assessment tools rely on static data and are difficult to meet the requirements of dynamic disease monitoring and individualized treatment. Artificial intelligence (AI) offers new solutions for early warning, risk stratification, subtype identification, and treatment decision-making in sepsis by integrating multidimensional clinical data. However, the clinical translation of AI is still limited by issues such as data quality, model interpretability, and the lack of an effective regulatory framework. This paper systematically reviews the latest progress of AI in this field: Machine learning and deep learning models can identify early risks from time-series data to achieve early warning; unsupervised learning helps to analyze the heterogeneity of sepsis and classify subtypes with different prognoses and treatment responses; in terms of treatment, AI has begun to provide decision-making support for the precise application of fluid resuscitation, vasoactive drugs, and antibiotics. Future development should focus on constructing high-quality multicenter datasets, developing interpretable algorithms, and validating their clinical utility through

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prospective studies. Ultimately, a collaborative diagnosis and treatment model centered on doctors with AI as an auxiliary should be established to improve the prognosis of sepsis patients.

[**Key words**] artificial intelligence; sepsis; machine learning; early warning; decision support

脓毒症是感染导致的器官功能障碍，也是重症监护室(intensive care unit，ICU)的高发疾病。尽管临床给予抗感染治疗、血流动力学支持、免疫调控及机械通气等综合措施，但其高发病率和高病死率仍给全球医疗机构带来沉重的负担[1-2]。脓毒症具有复杂的病理生理机制，且临床表现缺乏特异性[3]。因此，早期识别的延迟、临床诊断的模糊及治疗方案的偏离会进一步加剧疾病的管理难度。目前，脓毒症的诊断和风险分层主要依赖序贯器官衰竭评估(sequential organ failure assessment，SOFA)、快速SOFA(quick SOFA，qSOFA)评分等基于指南的评估工具[4]。然而，这些传统工具常采用静态、单个时间点的截面数据，限制了临床决策的精准性。尽管研究显示整合多种工具有助于提升评估的准确性[5]，但其临床实用性仍显不足。因此，亟需探索便于临床操作、能够有效评估病情、辅助临床决策的方法，从而提升脓毒症的诊疗效率并改善患者的预后。

在此背景下，人工智能(artificial intelligence，AI)技术表现出极大的发展潜力。从机器学习(machine learning，ML)到深度学习(deep learning，DL)，再到自然语言处理(natural language processing，NLP)等算法可高效整合多维度、高通量的临床数据。这不仅有助于脓毒症的精准识别、风险评估与分型，更能为治疗策略的适时调整与优化提供可能。本文对AI在脓毒症管理中的应用现状进行整理，重点关注近3年AI在早期预警、风险分层、亚型识别及治疗决策等方面的应用；同时，本文也深入分析了当前AI面临的挑战，并对未来的创新路径进行展望，以期为脓毒症的管理提供参考。

1 AI在脓毒症预警中的应用

常规临床分析主要依据医师经验与指南标准，可能忽略了特定指标组合或特殊人群中的疾病风险动态变化。在这一背景下，AI展现出独特的优势，它不仅能识别传统统计学或人工判读难以察觉的细微关联，揭示指标与疾病间复杂的非线性关系，更能融合来自公共数据库(如重症监护信息库、阿姆斯特丹大学医学数据库等)或院内系统的多模态数据，从而实现对患者早期风险的精准识别与病情动态监测，最终有助于降低病死风险并改善患者的远期预后。

1.1 脓毒症早期预测 脓毒症传统诊断方法面临诸多挑战。AI为实现早期、精准预测提供了新的技术路径，已成为当前的研究热点。

经典ML方法如线性模型、集成学习等为脓毒症的早期预测提供了基础且多样的技术路径。ML中线性模型(可研究临床特征与结局间的线性关联；如logistic回归等是常见线性模型)结构简单和可解释性强，适用于资源有限且需快速筛查的场景，如Jiang等[6]通过logistic回归分析年龄、生命体征和症状等数据，构建用于院前和急诊的脓毒症筛查工具；此外，logistic回归在处理小规模特征集表现稳健，不易出现过拟合[7]；然而，logistic回归难以处理复杂的非线性关系，且无法直接对时间序列数据进行动态建模。相较于线性模型，集成学习[训练多个单模型，随后经平均、加权等组合而成；如轻量级梯度提升机(light gradient boosting machine，LightGBM)、核-树联合提升(kernel tree boosting，KTBoost)、随机森林等是常见的集成学习模型]具有出色的非线性关系捕捉能力，可解析不同临床指标间复杂的交互作用，如Lin等[8]利用LightGBM分析全血细胞计数及其分类差异，评估患者免疫反应状态，预测脓毒症的发生；集成学习还可通过结合不同模型以增强预测性能，如Yagin等[9]将KTBoost与沙普利加性解释(SHapley Additive exPlanations，SHAP，用于量化每个输入指标对预测结果的贡献)相结合，实现了更高的脓毒症预测精度(包括准确率、曲线下面积、敏感度和特异性)；然而，集成学习存在可解释性较低与过拟合风险较高的局限性[10]。

为进一步突破经典ML在处理时序依赖与复杂数据模态方面的限制，DL及NLP等前沿技术被引入脓毒症预测领域。DL在处理临床数据中的不规则时序依赖关系和类别不平衡等方面展现出明显的优势，如Pappada等[11]构建的多层感知器人工神经网络模型通过整合心率、血压等生命体征和SOFA评分，生成脓毒症风险指数，辅助量化脓毒症或感染性休克的风险；Apalak等[12]利用时序卷积网络模型分析心电图波形中的心率变异率特征，在脓毒症发病前6 h仍保持良好的预测性能，可为临床干预争取到关键窗口期；Kim等[13]利用全连接网络和门控循环单元开发的DeepSEPS模型通过分析生命体征等信息实时监测脓毒症风险，最早可提前24 h预警，并通过低于传统评分系统的警报频率以减轻临床负担；Gupta等[14]基于长短记忆网络开发的SepsisAI模型同样采用多参数实时预测脓毒症，还引入“警告-警报”二级机制，将误报率降至3.18%，进一步有效缓解了临床

警报疲劳；与经典ML相比，DL可从自动分析原始数据间的复杂关联及其随时间的变化趋势，无需人工特征筛选，从而更有效地识别早期异常轨迹；然而，DL依赖大量的计算资源，存在对参数高度敏感、结果不稳定及可解释性较低等局限，限制其在临床环境中的推广应用[15-16]。随着研究深入，临床非结构文本(与结构性文本相对，如病程记录、会诊意见、病理报告等是常见的非结构性文本)的重要性日益凸显。为充分挖掘此类文本的信息，NLP应运而生。NLP可借助基于Transformer架构的预训练模型[如蒸馏BERT(distilled Bidirectional Encoder Representations from Transformers，DistilBERT)[17]]进行深度文本分析，还可结合集成学习[如极端梯度提升(extreme gradient boosting，XGBoost)]对模型进行二次优化。Brann等[17]使用DistilBERT和XGBoost分析急诊分诊记录和常规临床数据，实现分诊阶段的脓毒症预测，并成功识别出多数初诊遗漏病例；然而，DistilBERT对动词替换等语义变化的敏感性不足[18]；XGBoost则无法自动学习词序信息(具有明确的词与词顺序和句法关系的文本数据，如症状变化描述、检查结果报告、用药顺序记录等是常见的词序信息)，仍依赖特征筛选与降维处理[19]。

目前，AI在脓毒症早期预测已覆盖院前[6]、预检分诊[17]、ICU[20-22]等多个诊疗环节。针对多重耐药肺炎克雷伯菌[23]、脑出血[24]、重大创伤[25]、早产儿[26]等高风险群体，研究者也开发了专用的预测模型，显示出AI在不同临床场景和患者群体中良好的适应性与应用前景，为脓毒症的精准管理提供了有力的技术支持。

1.2 脓毒症的预后预测 AI亦广泛用于脓毒症预后评估。ML模型可精准识别电子病历中与死亡风险相关的临床变量[27]，在预测脓毒症病死率方面，性能明显优于传统评分系统(如SOFA、急性生理与慢性健康评估系统)[28-29]。训练指标方面，除人口统计学、生命体征外，部分研究引入血常规(如血细胞计数[30])、组学分析(如血浆蛋白质组水平[31]、血小板基因表达水平[32]、蛋白质乳酸化修饰水平[33])，或进一步生成血压反应指数[34]、应激高血糖比值[35]等实验室指标，以提升预后分析的准确性；另有研究创新性地整合临床参数和手掌高光谱成像数据，不仅实现了对脓毒症病死率的预测，也推动了无创、快速分析技术的发展[36]。在病程预测方面，AI模型可预测入院第7、14、28、30天等时间节点的病死率，满足对不同病程阶段患者评估的需求[37-39]。在预测对象方面，AI可面向老年脓毒症[40]、脓毒症合并癌症病史[41]、脓毒症急性呼吸窘迫综合征[42]、脓毒症肾损伤[43-44]等高危人群进行特定死亡风险分析。此外，AI不限于预测脓毒症死亡风险，还可评估其他临床转归，如发展为慢性危重症[45]的风险。

2 AI在脓毒症分型中的应用

脓毒症显著的临床异质性，是制约标准集束化治疗等通用方案疗效的关键因素。利用ML可识别出具有不同生物学特征、治疗反应和预后的分型，为实现脓毒症的精准治疗奠定基础。

2.1 基于临床数据分型 临床数据的表型研究是当前较成熟的领域。在临床结局方面，Seymour等[46]通过K均值聚类识别出4种脓毒症表型(α、β、γ、δ)，α到δ呈现出从10%至40%的病死率梯度，并与特定的宿主免疫反应生物标志物谱相关。Lu等[47]使用潜在类别分析将脓毒症脑病划分为缺血-缺氧型、代谢型、混合型及未分类表型，其中混合型表型预后最差。在治疗反应方面，Zhang等[48]运用K中心点聚类识别出对液体复苏存在差异的两种脓毒症表型。与聚类1过度炎症不同的是，聚类2表现为促炎因子下调，同时可能获益于限制性液体复苏。Choudhary等[49]通过均匀流形近似与投影(uniform manifold approximation and projection，UMAP)降维，再结合K均值聚类分析，可识别出在脓毒症急性呼吸衰竭患者中对呼气末正压治疗反应各异的4种表型(A、B、C、D)。这些研究揭示脓毒症存在具有不同临床结局和治疗反应的分型，为进一步实现个体化精准治疗提供了重要依据。

2.2 基于分子特征分型 分子亚型研究为理解脓毒症的发病机制提供了新视角。在基因层面，有研究已初步识别出不同免疫代谢特点的亚型。如Ma等[50]基于糖酵解相关基因表达谱通过共识聚类分析识别出两种脓毒症亚型(C1、C2)，其中C2型表现出更高的糖酵解活性、炎症水平及免疫检查点基因表达水平，提示了潜在的干预靶点。在蛋白质层面，多项研究进一步揭示了不同分型背后的临床关联。如Antcliffe等[51]通过血浆细胞因子的分层聚类识别出脓毒症急性呼吸窘迫综合征的两种分型(高炎症型和低炎症型)，其中高炎症型与高病死率相关；Sinha等[52]通过潜在类别分析验证了类似的分型，且进一步发现活化蛋白C对不同分型的治疗反应差异。Bracht等[53]利用随机森林分类器在蛋白质组学数据中识别出4个脓毒症亚型(0、1、2、3)，其中聚类0表现为高病死率，而其他聚类则显示出免疫球蛋白水平升高或急性炎症等免疫应答特征。上述研究从基因到蛋白质，为未来开展针对特定亚型的靶向疗法奠定了科学基础。

3 AI在脓毒症治疗决策中的应用

在成功实现早期预警和分型后，AI的下一发展方向在于为脓毒症患者提供实时、个体化治疗的动态决策支持，推动临床管理模式从“反应式”向“预判式”进一步转变。

3.1 血流动力学管理的智能化 液体复苏和血管活性药物是治疗脓毒症的重要手段，然而其最优滴定策略与应用时机始终存在争议，而AI的出现为这些复杂决策的优化提供了新的途径。有研究尝试利用AI指导液体复苏，如通过DL比较林格氏液、生理盐水或白蛋白等不同液体类型对感染性休克患者病死率与肾损伤的影响[54]，或利用强化学习模型动态优化液体复苏剂量方案[55]，从而为个体化治疗提供依据。AI在血管升压药领域也展现出潜力，具有突破性意义的一项研究用强化学习模型辅助感染性休克患者血管升压素最佳起始时机的决策，初步证实AI决策在血流动力学管理中的可行性及改善患者预后的潜在价值[56]。此外，有研究还探索了AI辅助肝素治疗的决策[57]。综上，从优化治疗方案到指导临床用药，均提示AI正由理论向临床实践跨越。

3.2 抗生素应用的监测与优化 抗生素的合理应用是脓毒症救治成败的关键因素之一。在用药时机和剂量方面，Kijpaisalratana等[58]开发的实时随机森林模型可辅助脓毒症警报系统缩短从分诊到使用抗生素的时间。Marko等[59]和Ates等[60]通过随机森林模型构建的治疗药物监测系统则可进一步辅助使用β-内酰胺类药物的剂量。在用药人群方面，除成年患者外，AI模型研究也关注新生儿[61]和儿童[62]等幼龄群体的抗生素决策。此外，AI模型还可预测耐药风险和药物不良反应，为初始经验性抗生素的选择提供循证证据支持[63-64]。

3.3 表型导向的精准治疗策略 AI分型的最终目的是指导治疗决策。Boussina等[65]采用谱聚类算法发现，特定临床表型(P3)患者可能在接受大量液体复苏(>30 ml/kg)后不良预后明显增加；Lou等[66]则通过K均值聚类发现血必净注射液仅能降低部分表型(γ和δ)患者的28 d病死率。这些研究为在精准医学框架下重新评估传统疗法并筛选潜在获益人群提供了范例。

4 AI在脓毒症管理中的局限性及挑战

AI尽管在脓毒症管理中展现出一定的潜力，但仍存在数据异质性、临床解释性、隐私保护等问题，限制了相关决策模型在真实世界中的推广。

4.1 数据质量与警报疲劳 AI模型普遍面临数据质量瓶颈[67-68]。回顾性研究常存在信息缺失、记录错误和标签噪声等问题，从而影响模型的训练；因脓毒症定义更新(如从Sepsis-2到Sepsis-3)而出现的不同时期标准不一，进一步增加了建模的复杂性；各医疗机构电子病历在术语、格式等方面缺乏统一规范，导致单一机构数据上训练的模型在多中心环境中的适用性与稳定性下降。AI模型引发的警报疲劳也需引起警惕。在追求高敏感度的同时，模型不可避免地会产生假阳性结果。有研究构建的DL模型每出现一个真实警报可能伴随约1.4次虚假警报[69]。这种持续的误报会导致使用者出现警报疲劳状态，更可能掩盖真实风险预警。因此，研究者尝试引入双重警报机制[14]，但目前尚未完全解决警报疲劳，需进一步探索。

4.2 可解释性与临床信任 黑箱特性制约了AI模型的临床应用[70]。尽管可解释性技术如SHAP能够对模型特征的重要性进行量化和排序，但其本质上仍停留于统计学层面，往往缺乏对内在病理生理学机制的因果洞察，难以完全融入临床医师的认知框架。这导致医师难以将模型输出转化为可向患者解释的诊疗依据，不仅影响临床决策的透明度，也可能在实质上削弱患者的知情同意过程[71]。因此，如何在保持模型性能的同时提供直观、可信的临床解释，是实现有效人机协作的关键。

4.3 伦理规范与监督框架 AI应用涉及患者数据的保护问题[72]。联邦学习等隐私计算技术虽为数据安全与合规提供了部分创新方案，但现有模型的安全机制和数据治理仍需进一步完善。此外，AI辅助诊疗的法律依据尚不健全，导致实际责任划分存在争议。与此同时，传统的医疗器械审批流程难以适应自适应AI模型不断迭代和动态演化的特性，现有监督管理体系出现明显的滞后性与不适应性。因此，构建与AI发展相匹配的新型监管范式已成为推动智能技术安全应用的迫切需求[73]。

5 未来研究方向与创新路径

未来的研究不仅是AI预测能力的拓展，更多是临床实用性、可解释性的提升，从而推动脓毒症管理进一步智能化与规范化。

5.1 技术创新：多模态数据融合 未来AI模型将迈向多模态深度融合。理想的AI平台应无缝连接结构化电子数据、实时高频波形(如心电图)、医学影像、基因组学等[74]。即使面临部分数据缺失，AI也能构建较为全面的患者表征[75-76]。鉴于脓毒症是一个急剧演变的病理生理过程，静态模型无法满足临床决策的迫切需求。因此，AI还需基于时空网络进一步实现对病情演变的精准动态预测及实时风险分层，真正为临床干预留出时间窗。

5.2 临床转化：前瞻性验证与效用评估　AI的临床应用最终可转化为患者预后的实质性改善。当前亟需开展严谨的前瞻性、多中心随机对照试验，重点评估AI驱动的管理模式(如AI集束化治疗、表型指导的个体化方案)对临床结局指标(如28 d病死率)的影响[77]。同时，应构建标准化的临床效用评估体系，包括受试者操作特征曲线下面积、预警准确率、成本效益等临床决策相关的指标[78-80]。AI模型的医患接受度亦不可忽视。应进一步开发临床解释模块，将模型推断过程转化为医师可理解的病理生理逻辑，并为患者提供通俗、规范的解读。此外，AI应输出辅助性的决策信息，而非替代医师判断。通过直观的用户界面并提供不确定性度量，AI有望真正成为提升诊疗效率和精准度的关键工具[81-82]。

5.3 体系建设：可信赖的AI生态系统　尽管AI在脓毒症领域展现出巨大潜力(表1)，但要将其有效地临床转化，还需构建一个健全且可持续的AI生态系统。首先，应建立医疗审计规范，确保AI模型在临床验证和持续监测环节有明确的法律依据。其次，应建立通用数据框架以提升模型的泛化能力，并解决部分数据异质性问题；推动数据标准化需依赖跨部门协作，制定前瞻性的数据标注标准，并采用自动化数据清洗、结构化标签等策略以保障数据的质量[83]。再次，AI模型可通过定期更新的临床数据进行再训练和验证，主动识别并修正训练数据中的潜在偏差[84-85]；同时，设计一个分级的情境感知警报模式，依据预测风险的置信度、患者的病情发展轨迹和数据质量，触发不同级别的响应，缓解警报疲劳。AI生态系统的最终目标是实现AI与临床工作流程的深度融合，在监管下提供适时的决策支持；并通过高效的反馈机制，让临床经验能够持续指导和优化AI，最终形成人机协同的良性循环[86]。此外，脓毒症免疫生物学研究正从表型描述走向分子网络和关键机制的深入解析[87]。AI生态系统的建设不仅有望助力发现新的治疗靶点，提升临床试验的设计效率及成功率，更可能从根本上加速新药的研发进程。

表1　AI在脓毒症不同场景的应用

Tab.1　Applications of AI in different scenarios of sepsis

应用领域	用途	代表模型/技术	AI优势	文献
早期预测	常规患者识别	LR、XGBoost、LightGBM、ANN、TCN、LSTM、FCN	捕捉常规方法难以察觉的信号，从而将预警窗口前移	[6,8,11-14,20-22]
	高风险群体识别	RF、XGBoost	针对高风险人群(如创伤、脑出血)构建专用模型，实现风险精准评估	[23-26]
	院内实时监测	LSTM、TCN	多维度数据整合分析，实现实时风险监测与自动化预警	[13-14]
	新型标志物研究	KTBoost、SHAP	高效筛选出具有预测价值的核心生物标志物组合	[9]
	极早期筛查	DistilBERT、XGBoost	突破性地挖掘临床文本中蕴含的丰富语义信息(如病情变化陈述、影像结果描述等是常见的语义信息)	[17]
预后评估	死亡率/其他转归	RF、XGBoost、LightGBM、SHAP	精准预后分析，可通过SHAP等方法分析关键风险因素，增强临床可信度	[27-39,45]
	高危人群预后评估	RF、XGBoost	针对高危群体(如老年脓毒症、脓毒症呼吸窘迫综合征)的特异性预后分析	[40-44]
临床分型	亚型探索	K均值聚类、共识聚类	发现具有不同生物学特征、治疗反应及预后的分型	[46-53]
治疗决策	血流动力学优化	RL	模拟临床决策，找出个体化最优治疗策略	[54-57]
	抗生素精准使用	RF、XGBoost	权衡疗效、毒性、耐药性等多个目标，并可结合治疗药物监测数据，给出最佳用药方案	[58-64]
	表型导向精准治疗	K共识聚类、谱聚类	识别患者的不同临床表型，从而指导治疗决策	[65-66]

AI. 人工智能；LR. Logistic回归；XGBoost. 极端梯度提升；LightGBM. 轻量级梯度提升机；ANN. 人工神经网络；TCN. 时序卷积网络；LSTM. 长短记忆网络；FCN. 全连接网络；RF. 随机森林；KTBoost. 核-树联合提升；SHAP. 沙普利加性解释；DistilBERT. 蒸馏BERT；RL. 强化学习

6　总结与展望

当前，AI技术正逐步融入脓毒症的管理，在早期识别、预后预测到亚型分型和治疗决策等方面展现出超越传统评估工具的潜力，推动诊疗模式向数据驱动的范式发展。然而，AI在脓毒症领域的应用

尚处于发展与转化阶段。临床数据的可靠性、模型的透明度等诸多因素制约了AI技术从试验成果向临床获益的有效转化。

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