15 BÖLÜM

SOLUNUM YETMEZLİĞİ VE VENTİLATÖR YÖNETİMİNDE YAPAY ZEKA

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GİRİŞ

Solunum yetmezliği, acil serviste sık karşılaşılan ve hayatı tehdit edici bir acil durum olup birçok farklı nedene bağlı olarak karşımıza çıkabilmektedir.

Akut Solunum Yetmezliği' ne (ASY) bağlı ölüm oranı yıllık %3,4 oranında artmakta olup, 2014 ile 2018 yılları arasında Amerika Birleşik Devletleri'nde (ABD) 1,4 milyondan fazla ölüme neden olmuştur (1). Akut solunum yetmezliği hem yaygın hem de şiddetlidir ve 2017 yılında ABD'de 3 milyondan fazla hastaneye yatışa neden olmuş ve bu hastaların 1 milyondan fazlasının mekanik ventilasyona ihtiyacı oluşmuştur (2).

Akut solunum yetmezliği nedeniyle invaziv mekanik ventilasyon gerektiren hastalarda ise mortalite yüksek kalmaya devam etmektedir (3). Birkaç gözlem, solunum yetmezliğinin ilerlemesini tahmin etme yeteneğinin bu hastalarda sonuçları iyileştirebileceğini göstermektedir. Son veriler birkaç önemli noktayı vurgulamaktadır. İlk olarak, gecikmiş entübasyon mortalitede artışla ilişkilidir (4). İkinci olarak, uzun süreli invaziv mekanik ventilasyon daha yüksek maliyetler, morbidite ve mortalite ile ilişkilidir (5). Finansal maliyetlerin ötesinde,

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Hacim kontrollü ventilasyon (VCV) veya basınç kontrollü ventilasyon (PCV) dahil olmak üzere mevcut ventilasyon yöntemleri, yapay akciğer ventilasyonu uygulanan hastalarda ortaya çıkan temel fizyolojik sorunları tamamen ortadan kaldıramamaktadır (56). Bu sınırlamalar, yapay zekânın ventilasyon parametrelerini ayarlamak için otomatik bir araç olarak kullanılmasının klinik etkinliği sorusunu gündeme getirmektedir. Sonuç olarak, teknoloji geliştirmenin bu aşamasında yapay zekânın ventilasyon parametrelerini ayarlamak için otomatik bir araç olarak kullanılmasının klinik etkisi belirsiz olacaktır. Fizyolojik reaksiyonların daha derinlemesine anlaşılması ve entegre adaptif modellerin geliştirilmesi olmadan, bu tür çözümlerin etkinliği sorgulanmaya devam etmektedir.

Sonuç olarak solunum yetmezliğinin belirlenmesinde, ciddiyetinin değerlendirilmesinde, ARDS tahmini ve yönetiminde yapay zeka uygulamaları giderek artmaktadır. Buna paralel olarak benzer şekilde mekanik ventilasyon uygulamalarını da içeren tedavi uygulamalarının zamanlaması, etkinliği, doğru ve zamanında seçimi konusunda da giderek artan yapay zeka çalışmaları yayınlanmaktadır. Yapay zeka uygulamalarının hali hazırda kısıtlılıkların var olmasına karşın yüz güldürücü sonuçların giderek arttığı ve ilerleyen yıllarda klinik kullanım pratiğine de dahil olacağı öngörülmektedir.

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