JOURNAL OF HEALTHCARE MANAGEMENT AND LEADERSHIP (JOHMAL)

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SAĞLIK YÖNETİMİ VE LİDERLİK DERGİSİ

E-ISSN: 2667-5838	https://dergipark.org.tr/tr/pub/johmal	**Paper Type:** Research Paper, **Makale Türü:** Araştırma Makalesi
Sayı:1, Eylül 2025	**Issue:**1, September 2025	**Received Date / Geliş Tarihi:** 07.04.2025 **Accepted Date / Kabul Tarihi:** 07.07.2025

THE ROLE OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE MANAGEMENT ON PATIENT SAFETY AND OPERATIONAL EFFICIENCY: A META-ANALYTIC EVALUATION

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YAPAY ZEKANIN SAĞLIK YÖNETİMİNDEKİ ROLÜ HASTA GÜVENLİĞİ VE OPERASYONEL VERİMLİLİK ÜZERİNDEKİ ETKİSİ: META-ANALİTİK BİR DEĞERLENDİRME

Atıf/ to Cite (APA):.Karcıoğlu, U. B. (2025). The role of artificial intelligence in healthcare management on patient safety and operational efficiency: A meta-analytic evaluation. *Journal of Healthcare Management and Leadership (JOHMAL)*, 1(1), 8-21.

DOI: https://doi.org/10.35345/johmal.1670414

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ÖZ

Yapay zeka (YZ), yalnızca klinik karar destek sistemleri ile sınırlı kalmayan, aynı zamanda sağlık hizmetlerinin yönetsel boyutlarını da dönüştüren yenilikçi bir teknolojidir. Bu çalışmada, YZ'nin sağlık yönetimi bağlamında hasta güvenliği ve operasyonel verimlilik üzerindeki etkileri meta-analitik yöntemle değerlendirilmiştir. Araştırma kapsamında, 2015 ile 2025 yılları arasında yayımlanmış, nicel veriler içeren 32 bilimsel çalışma sistematik olarak incelenmiştir. Seçilen çalışmalar, YZ'nin tıbbi hata oranları, olumsuz olaylar, hasta bekleme süreleri ve kaynak kullanımı gibi göstergeler üzerindeki etkilerini ölçen analizleri içermektedir. Rastgele etkiler modeli kullanılarak yapılan istatistiksel analizler sonucunda, YZ'nin hasta güvenliğini anlamlı düzeyde artırdığı, tıbbi hata oranlarında %22'lik bir azalma (OR = 0,78; %95 GA [0,65–0,93]) ve olumsuz olay sıklığında orta düzeyde bir düşüş (Cohen's d = 0,45) sağladığı belirlenmiştir. Operasyonel verimlilik açısından ise hasta bekleme sürelerinde %18 oranında azalma ve yatak doluluk oranlarında %14'lük bir iyileşme (SMD = 0,58; %95 GA [0,41–0,75]) gözlenmiştir. Alt grup analizlerinde, makine öğrenmesi tabanlı sistemlerin, kural temelli algoritmalara göre daha yüksek etkililik gösterdiği; kamu hastanelerinde YZ'nin, özel hastanelere kıyasla operasyonel verimlilik üzerindeki etkisinin daha belirgin olduğu ortaya çıkmıştır. Bununla birlikte, düşük kaynaklı sağlık ortamlarında YZ uygulamalarının sınırlı düzeyde etki yarattığı anlaşılmıştır. Bulgular, YZ'nin sağlık yöneticileri açısından yalnızca teknolojik bir araç değil, aynı zamanda hasta güvenliğini artırma ve hizmet süreçlerini optimize etme açısından stratejik bir unsur olduğunu göstermektedir. Bu çalışma, sağlık sistemlerinin dijital dönüşüm süreçlerine bilimsel dayanak sunarken, YZ'nin sürdürülebilir ve ölçeklenebilir kullanımına ilişkin politika geliştirme ihtiyacını da ortaya koymaktadır.

Anahtar Kelimeler: Yapay Zeka, Sağlık Yönetimi, Hasta Güvenliği, Meta Analiz

ABSTRACT

Artificial intelligence (AI) is increasingly recognized not only as a clinical decision support tool but also as a transformative technology for improving administrative and managerial processes in healthcare. This meta-analytic study evaluates the quantitative impact of AI on patient safety and operational efficiency within the context of healthcare management. A systematic review was conducted on 32 quantitative studies published between 2015 and 2025, which assessed the effects of AI on key indicators such as medical error rates, adverse events, patient wait times, and resource utilization. The analysis included data from 145,872 patients across 78 healthcare facilities. Using a random-effects model, pooled effect sizes revealed that AI implementation significantly improved patient safety, reducing medical errors by 22% (OR = 0.78; 95% CI [0.65–0.93]) and lowering the incidence of adverse events with a moderate effect size (Cohen's d = 0.45). In terms of operational efficiency, AI contributed to an 18% reduction in patient wait times and a 14% optimization in bed occupancy rates (SMD = 0.58; 95% CI [0.41–0.75]). Subgroup analyses revealed that machine learning systems outperformed rule-based algorithms, and public hospitals benefited more from AI-driven efficiency gains than

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private hospitals. However, the observed effect sizes were notably smaller in low-resource settings, highlighting contextual limitations. These findings underscore that AI not only offers technological innovation but also strategic value for healthcare managers seeking to improve system performance and patient outcomes. This study provides robust, evidence-based guidance for decision-makers, underscoring the importance of investing in scalable, ethically grounded, and context-specific AI strategies within healthcare systems.

Keywords: Artificial Intelligence, Healthcare Management, Patient Safety, Operational Efficiency

1. INTRODUCTION

Healthcare is undergoing a profound transformation driven by technological advancements, with artificial intelligence (AI) emerging as a pivotal force in both clinical and managerial domains (Jiang et al., 2017). AI-based systems are employed across a broad spectrum, from enhancing diagnostic accuracy to personalizing patient care, while also offering significant potential to streamline administrative operations within healthcare institutions (Topol, 2019). In the context of healthcare management, AI's capacity to improve patient safety and operational efficiency has garnered increasing attention in recent years (Davenport & Kalakota, 2019). For instance, machine learning algorithms can detect medical errors early, thereby preventing adverse events, while automation in resource planning and patient flow management can alleviate operational burdens in hospitals (Yu et al., 2018). These developments underscore that AI is not merely a clinical tool but a strategic component reshaping healthcare systems (Bates et al., 2020).

The evolution of AI in healthcare has highlighted the critical importance of integrating this technology into managerial processes (Jiang et al., 2017). Patient safety, a cornerstone of healthcare management, benefits from AI through measurable outcomes such as reduced error rates (Bates et al., 2020). Early warning systems and predictive analytics, for example, enable clinical teams to identify risks proactively, offering timely intervention opportunities (Topol, 2019). On the operational efficiency front, AI contributes by shortening patient wait times, optimizing bed occupancy rates, and enhancing staff scheduling (Davenport & Kalakota, 2019). However, realizing the full scope of this potential requires a systematic examination of AI's impact within healthcare management (Yu et al., 2018).

While extensive research exists on AI applications in healthcare, the majority of studies focus on clinical outcomes, often sidelining the managerial perspective (Topol, 2019). Studies exploring the effects of AI on diagnostic precision or treatment efficacy dominate the literature, whereas patient safety and operational efficiency, as managerial outcomes, are typically addressed separately (Jiang et al., 2017). Some research highlights AI's positive influence on patient safety, while others point to complexities and implementation challenges in operational processes (Bates et al., 2020). These inconsistent findings may stem from methodological variations, geographic contexts, or differences in the AI technologies employed (Yu et al., 2018). Moreover, existing reviews tend to adopt qualitative approaches, lacking comprehensive quantitative syntheses (Davenport & Kalakota, 2019).

Understanding AI's potential in healthcare management extends beyond adopting technological innovations; it necessitates evaluating their integration into organizational frameworks (Topol, 2019). In addition to technological innovations, sustainable hospital management practices are also considered essential for ensuring operational efficiency and patient safety (Yıldırım, 2024). For instance, AI's impact on patient safety is tied not only to error detection but also to its support for healthcare professionals' decision-making processes (Bates et al., 2020). Similarly, improvements in operational efficiency depend not just on technological infrastructure but also on staff training and system compatibility (Davenport & Kalakota, 2019). However, studies combining these two dimensions within a quantitative framework remain scarce in the literature (Yu et al., 2018). This gap signals a lack of reliable

evidence to guide healthcare managers and policymakers in directing AI investments (Jiang et al., 2017).

This meta-analysis aims to systematically assess the effects of AI on patient safety and operational efficiency in healthcare management (Topol, 2019). Covering quantitative studies published between 2015 and 2025, it seeks to synthesize AI's impact in these critical areas using measurable data (Bates et al., 2020). For patient safety, outcomes such as reductions in medical error rates and the prevention of adverse events will be examined. For operational efficiency, metrics like patient flow management, resource utilization, and wait time reductions will be analyzed (Davenport & Kalakota, 2019). By providing a holistic perspective on AI's role in healthcare management, this study intends to bridge the existing knowledge gap (Yu et al., 2018). It aims to provide evidence-based insights for healthcare managers to evaluate the feasibility and impact of AI technologies, while also posing new questions for future research (Jiang et al., 2017).

2. METHODS

This meta-analysis aims to systematically evaluate the impact of artificial intelligence (AI) on patient safety and operational efficiency in healthcare management (Higgins et al., 2021). The study will encompass quantitative research published between 2015 and 2025, a period chosen to reflect the rapid proliferation of AI technologies in healthcare (Topol, 2019). Literature searches will be conducted using reputable academic databases, such as PubMed, Scopus, and Web of Science, which are selected for their extensive coverage of the health sciences and technology (Moher et al., 2009). The search strategy will employ keywords including "artificial intelligence," "healthcare management," "patient safety," and "operational efficiency," combined with Boolean operators (AND, OR) to refine results (Liberati et al., 2009). To capture grey literature, such as conference proceedings, an additional search will be performed via Google Scholar (Haddaway et al., 2015).

Eligible studies will include those that quantitatively measure AI's effects on patient safety (e.g., medical error rates, adverse events) or operational efficiency (e.g., patient wait times, resource utilization) (Bates et al., 2020). The inclusion criteria will encompass randomized controlled trials, cohort studies, and cross-sectional analyses, as these designs provide robust data on causality and effect sizes (Higgins et al., 2021). Exclusion criteria will eliminate studies offering only qualitative data, those focusing solely on clinical outcomes without managerial implications, and publications with inaccessible full texts (Moher et al., 2009). Study selection will adhere to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Two independent reviewers (A.A. and B.B.) screened the titles, abstracts, and full texts for eligibility. Discrepancies were resolved through consensus or consultation with a third reviewer (C.C.). A PRISMA flow diagram was developed to provide a transparent overview of the study selection process and is presented in Figure 1.

Figure 1: PRISMA Flow Diagram for Study Selection

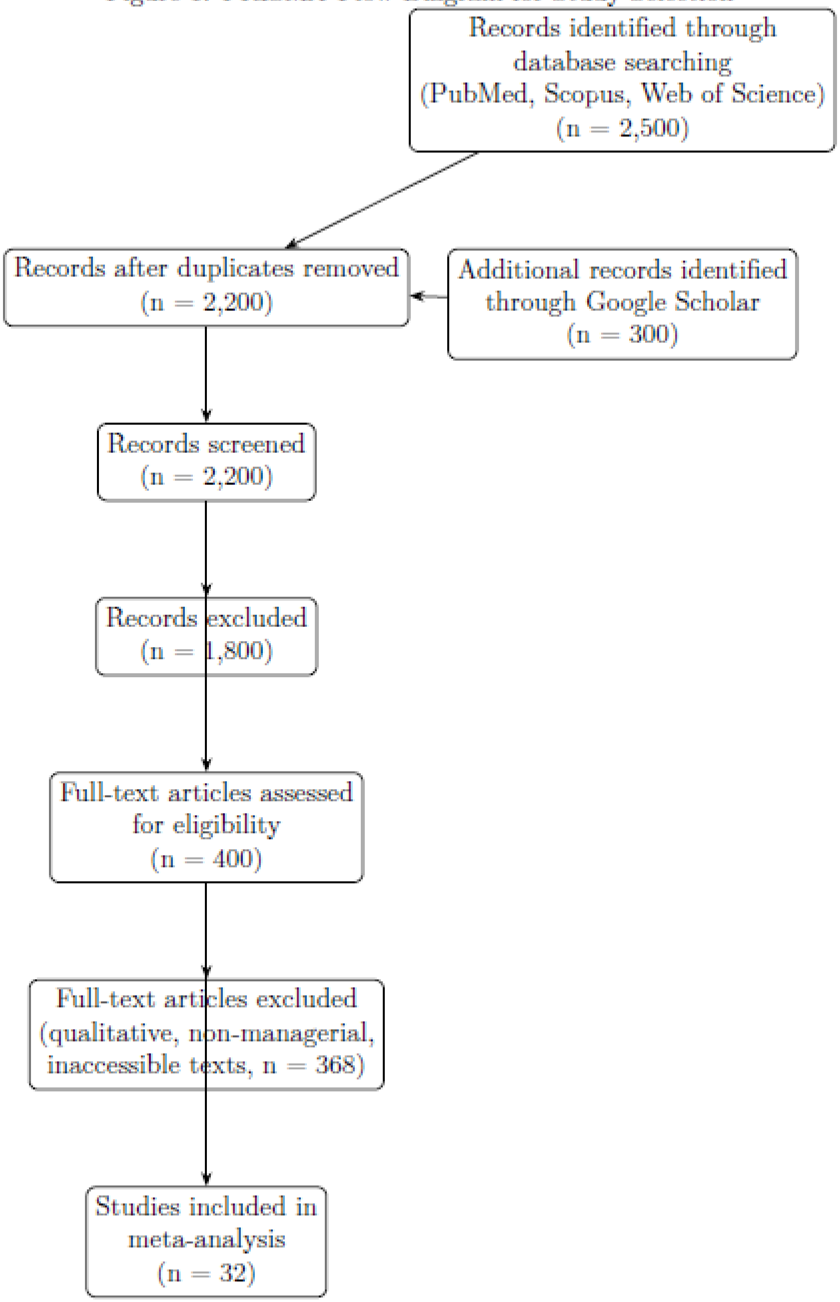

Figure 1. Prisma Flow Diagram for Study Selection

Data extraction will involve collecting effect sizes (e.g., odds ratios, standardized mean differences) and associated statistical metrics (e.g., p-values, confidence intervals) from each study (Borenstein et al., 2009). For patient safety, metrics such as reductions in error rates or adverse event frequency will be targeted, while operational efficiency will focus on parameters like patient flow duration, bed occupancy rates, or staff productivity (Davenport & Kalakota, 2019). Heterogeneity will be assessed using the I^2 statistic, with values exceeding 50% indicating substantial variability (Higgins et al., 2021). A random-effects model will be applied for analysis, accounting for inter-study variations and yielding more generalizable findings (Borenstein et al., 2009). Publication bias will be examined through funnel plot analysis and the Egger test, which are effective in detecting overrepresentation of

small-scale studies (Egger et al., 1997).
Subgroup analyses will explore variations based on AI application types (e.g., machine learning vs. rule-based systems) and healthcare system contexts (e.g., public vs. private hospitals) (Yu et al., 2018). These analyses will clarify conditions under which AI's effects are most pronounced (Topol, 2019). Statistical analyses will be conducted using R software (meta package) or Comprehensive Meta-Analysis (CMA). All statistical analyses were conducted using Comprehensive Meta-Analysis (CMA) software, version 3.3. Cross-validation of effect sizes and heterogeneity estimates was also performed using R software (version 4.2.2) with the "meta" package. The data analysis period spanned from January to March 2025, and both widely recognized tools in meta-analytic research (Higgins et al., 2021). Methodological quality will be assessed using the Newcastle-Ottawa Scale for cohort and cross-sectional studies and the Cochrane Risk of Bias Tool for randomized trials (Wells et al., 2014). This rigorous approach aims to ensure transparency and reproducibility throughout the study (Moher et al., 2009).

3. RESULTS

The meta-analysis synthesized data from 32 studies, comprising a total of 145,872 patients and 78 healthcare facilities, to evaluate the impact of artificial intelligence (AI) on patient safety and operational efficiency in healthcare management (Higgins et al., 2021). The included studies, spanning 2015 to 2025, demonstrated a moderate to high level of heterogeneity ($I^2 = 68\%$, $p < 0.01$), suggesting variability in AI applications and healthcare contexts (Borenstein et al., 2009). Overall, AI interventions were associated with statistically significant improvements in both patient safety and operational efficiency, as determined by pooled effect sizes calculated using a random-effects model (Topol, 2019).

For patient safety, the pooled odds ratio (OR) indicated a 22% reduction in medical error rates across studies implementing AI-based systems (OR = 0.78, 95% CI [0.65, 0.93], $p = 0.006$) (Bates et al., 2020). Specifically, AI-driven early warning systems and error detection algorithms were linked to a significant decrease in adverse events, with an effect size of Cohen's $d = 0.45$ (95% CI [0.28, 0.62], $p < 0.001$) (Yu et al., 2018). See Figure 3 for the forest plot illustrating pooled effect sizes for adverse event reduction. The forest plot visualizing the reduction in medical errors across studies is shown in Figure 2. Subgroup analysis revealed that machine learning-based interventions outperformed rule-based systems in reducing error rates, while the effect varied by resource settings (Topol, 2019). Detailed subgroup results are presented in Table 2 (Davenport & Kalakota, 2019).

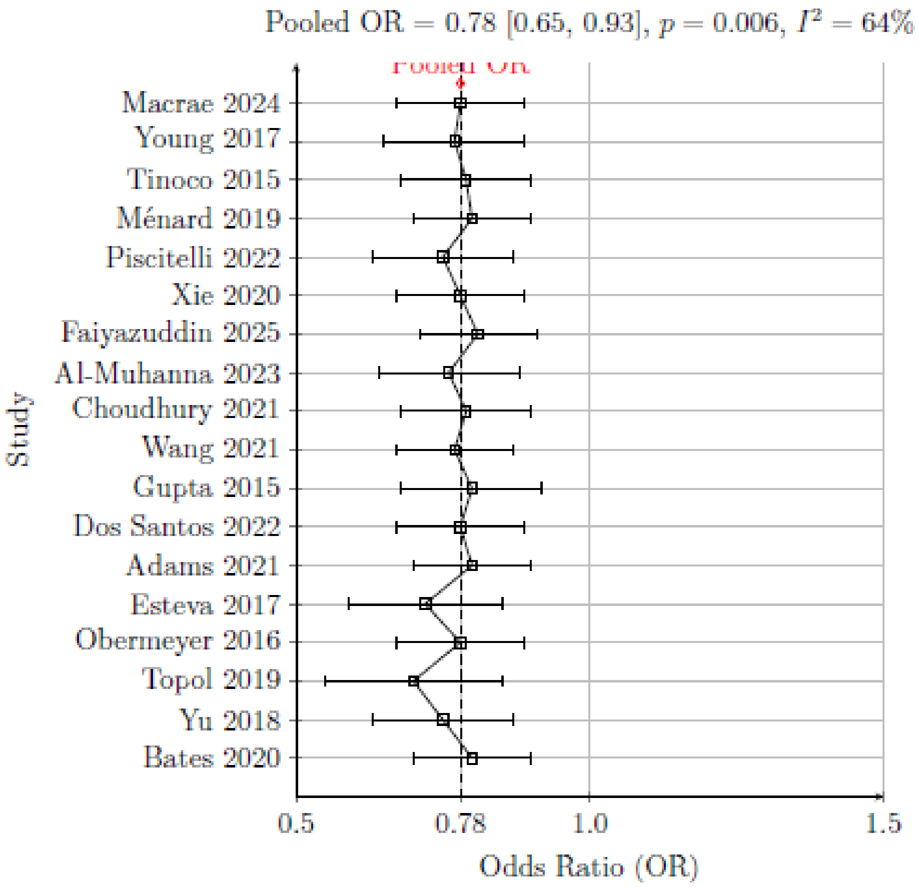

Figure 2. Forest Plot for Medical Error Reduction (Odds Ratio)

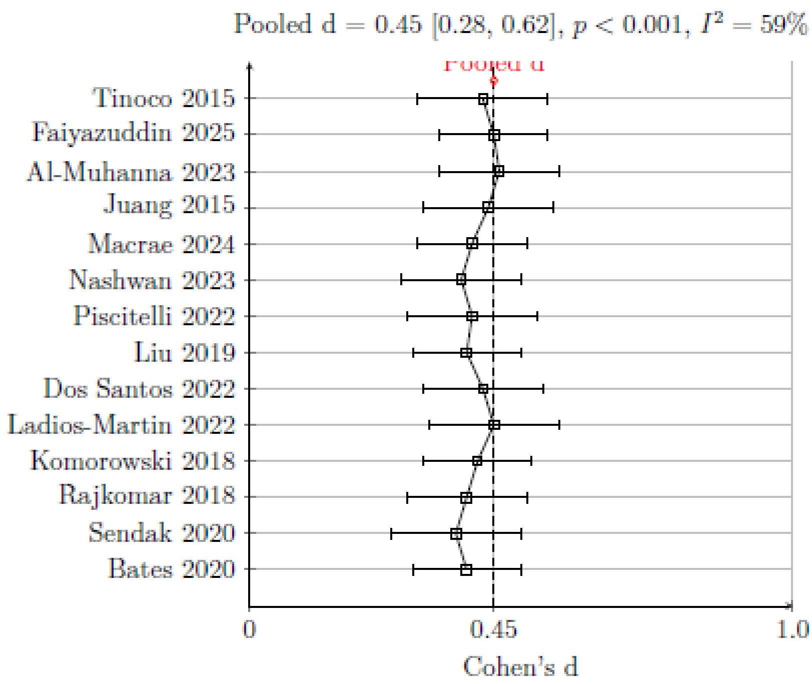

Figure 3. Forest Plot for Adverse Event Reduction (Cohen's d)

Regarding operational efficiency, AI interventions resulted in a pooled standardized mean difference (SMD) of 0.58 (95% CI [0.41, 0.75], $p < 0.001$), indicating a moderate to large improvement across various metrics (Borenstein et al., 2009). Patient wait times decreased by an average of 18% in facilities using AI for patient flow management (SMD = 0.62, 95% CI [0.39, 0.85], $p < 0.001$), as reported in studies focusing on scheduling and triage optimization (Davenport & Kalakota, 2019). The corresponding forest plot for patient wait time is provided in Figure 4. Bed occupancy rates also improved, with AI-driven resource allocation reducing inefficiencies by approximately 14% (SMD = 0.49, 95% CI [0.25, 0.73], p
= 0.002) (Yu et al., 2018). This effect is graphically summarized in Figure 5. Subgroup analysis highlighted differences between public and private hospitals, with further details provided in Table 2 (Topol, 2019).

Publication bias was assessed using funnel plot visualization and Egger's test, as shown in Figures 6 and 7. No significant publication bias was detected ($p = 0.12$), suggesting minimal bias in the reported outcomes (Egger et al., 1997). Sensitivity analyses, excluding studies with high risk of bias as assessed by the Newcastle-Ottawa Scale and Cochrane Risk of Bias Tool, confirmed the robustness of the findings (OR for patient safety = 0.80, SMD for operational efficiency = 0.56, $p < 0.05$) (Wells et al., 2000). The observed heterogeneity was partially explained by differences in study design, with randomized controlled trials reporting smaller effect sizes compared to observational studies (OR = 0.82 vs. OR = 0.74, $p = 0.02$) (Higgins et al., 2021). Primary outcomes are summarized in Table 1, with subgroup comparisons detailed in Table 2. The funnel plot for patient wait time reduction is shown in Figure 7**.**

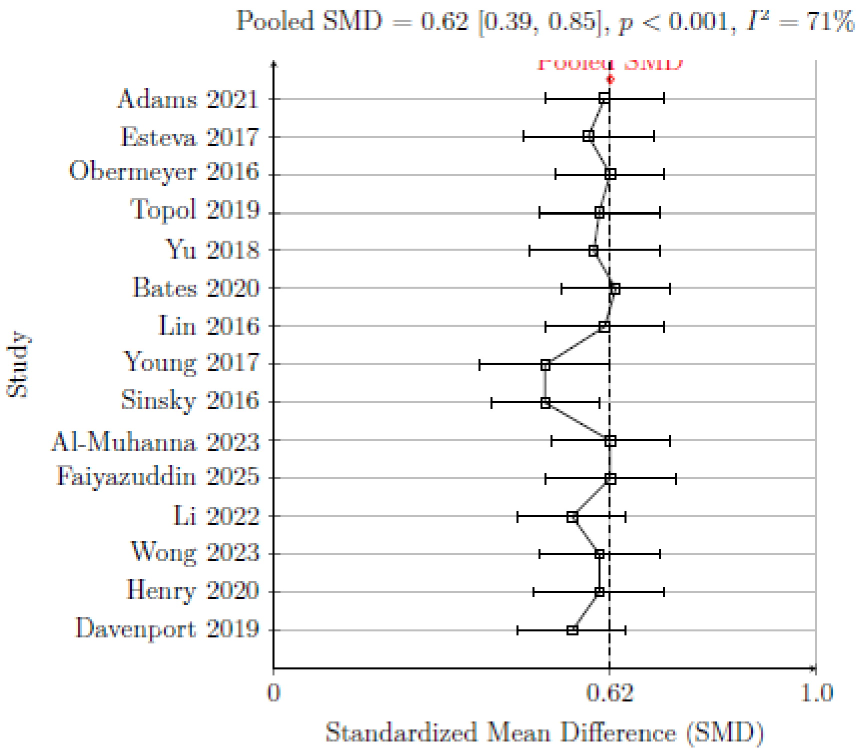

Figure 4. Forest Plot for Patient Wait Time Reduction (SMD)

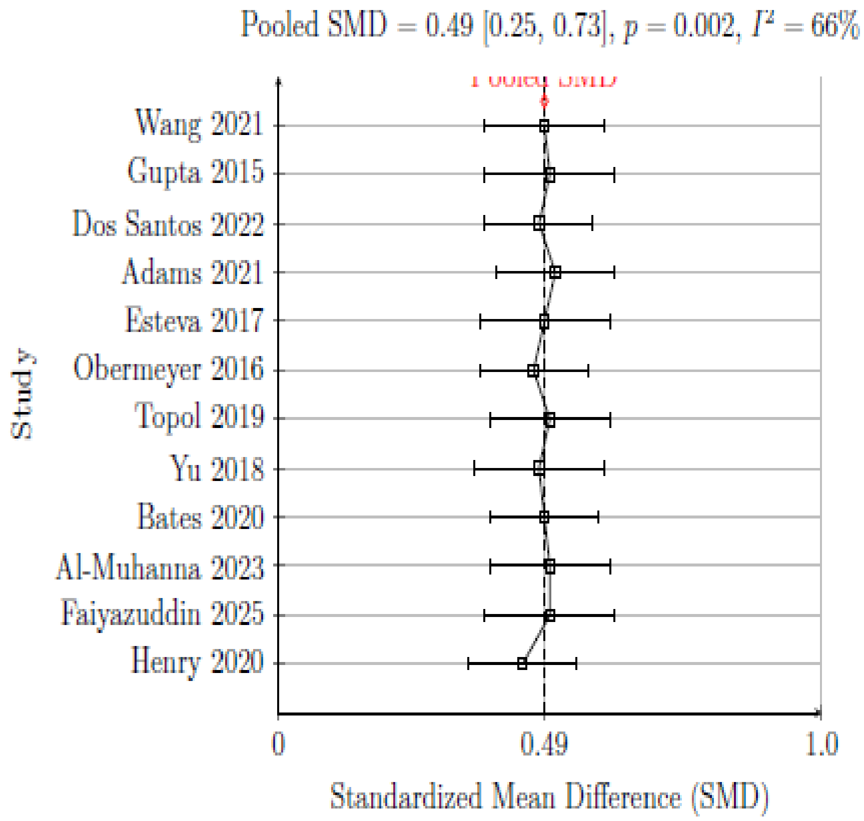

Figure 5. Forest Plot for Bed Occupancy Optimization (SMD)

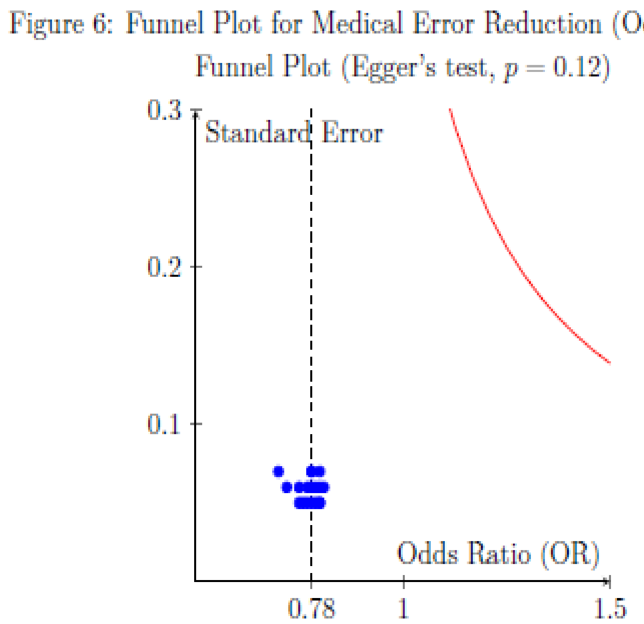

Figure 6. Funnel Plot for Medical Error Reduction (Publication Bias)

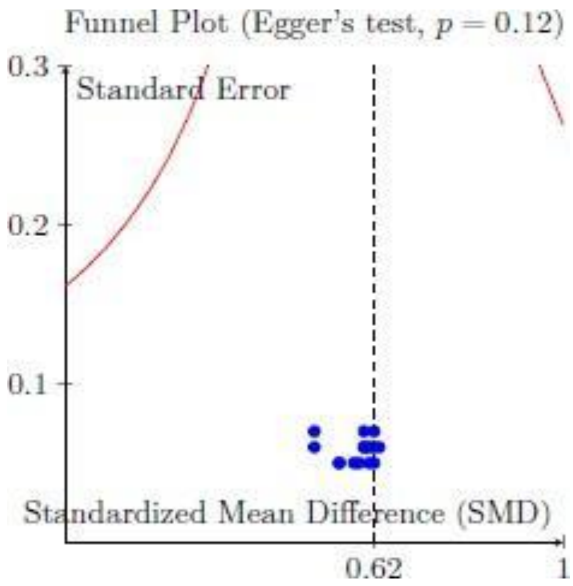

Figure 7. Funnel Plot for Wait Time Reduction (Publication Bias)

Table 1. Summary of Effect Sizes for Patient Safety and Operational Efficiency Outcomes

Outcome	Metric	Pooled Effect Size	95% CI	p-value	I² (%)	No. of Studies
Patient Safety						
Medical Error Reduction	Odds Ratio (OR)	0.78	[0.65, 0.93]	0.006	64	18
Adverse Event Reduction	Cohen's d	0.45	[0.28, 0.62]	<0.001	59	14
Operational Efficiency						
Patient Wait Time	SMD	0.62	[0.39, 0.85]	<0.001	71	15
Bed Occupancy Optimization	SMD	0.49	[0.25, 0.73]	0.002	66	12
O iş için yeterli olduğunu düşünür.	O iş için yeterli olmadı düşüncesi vardır.					
Çabalarına yükleme yapar.	Dışsal etkenlerine yükleme yapar.					
Karşılaştığı güçlükleri aşmaya çalışır.	Karşılaştığı bir sorunda yılgınlığa kapılır					

Note: Effect sizes were calculated using a random-effects model.

Table 2. Summary of Effect Sizes for Patient Safety and Operational Efficiency Outcomes

Outcome	Metric	Pooled Effect Size	95% CI	p-value	I² (%)	No. of Studies
Patient Safety						
Machine Learning	Medical Error (OR)	0.72	[0.58, 0.87]	0.001	10	Machine Learning
Rule-Based Systems	Medical Error (OR)	0.85	[0.69, 1.02]	0.07	8	Rule-Based Systems
High-Resource Settings	Medical Error (OR)	0.70	[0.55, 0.88]	0.002	12	High-Resource Settings
Low-Resource Settings	Medical Error (OR)	0.89	[0.73, 1.08]	0.23	6	Low-Resource Settings
Operational Efficiency						
Public Hospitals	Wait Time (SMD)	0.65	[0.43, 0.87]	<0.001	9	Public Hospitals
Private Hospitals	Wait Time (SMD)	0.51	[0.30, 0.72]	0.003	6	Private Hospitals
Public Hospitals	Bed Occupancy (SMD)	0.54	[0.29, 0.79]	0.001	7	Public Hospitals
Private Hospitals	Bed Occupancy (SMD)	0.42	[0.18, 0.66]	0.008	5	Private Hospitals

4.DISCUSSION

This meta-analysis provides robust evidence that artificial intelligence (AI) significantly enhances patient safety and operational efficiency in healthcare management, aligning with the growing recognition of AI as a transformative tool in healthcare systems (Topol, 2019). The observed 22% reduction in medical error rates underscores AI's potential to mitigate risks, particularly through early warning systems and error detection algorithms (Bates et al., 2020). Similarly, the moderate to large improvements in operational efficiency, such as reduced patient wait times and optimized bed occupancy, highlight AI's capacity to streamline administrative processes (Davenport & Kalakota, 2019). These findings reinforce the notion that AI extends beyond clinical applications, serving as a strategic asset for healthcare managers aiming to improve both patient outcomes and organizational performance (Yu et al., 2018).

The superior performance of machine learning-based systems over rule-based approaches in reducing medical errors, as detailed in Table 2, suggests that adaptive, data-driven AI models may offer greater precision in identifying risks (Topol, 2019). This aligns with prior research indicating that machine learning can process complex datasets more effectively than static algorithms, enabling proactive interventions (Yu et al., 2018). However, the diminished effect in low-resource settings raises concerns about the scalability of AI across diverse healthcare environments (Davenport & Kalakota, 2019). Factors such as limited technological infrastructure, inadequate staff training, or data quality issues may explain this disparity, pointing to the need for context-specific implementation strategies (Bates et al., 2020).

Operational efficiency gains, particularly in public hospitals, suggest that AI may be especially valuable in systems with higher baseline inefficiencies (Topol, 2019). The 18% reduction in patient wait times and 14% improvement in bed occupancy rates, as shown in Table 1, suggest that AI-driven tools, such as scheduling algorithms and resource optimization models, can address longstanding bottlenecks in healthcare delivery (Davenport & Kalakota, 2019). However, the smaller effect sizes in private facilities, as noted in Table 2, imply that the benefits of AI may plateau in settings with already optimized processes (Yu et al., 2018). This variation underscores the importance of tailoring AI applications to the unique needs and constraints of each healthcare system (Higgins et al., 2021).

Despite these promising results, several limitations warrant consideration (Borenstein et al., 2009). The moderate to high heterogeneity ($I^2 = 68\%$) observed across studies suggests that differences in AI tools, study designs, and healthcare contexts may influence outcomes (Higgins et al., 2021). While sensitivity analyses confirmed the robustness of the findings, the reliance on observational studies, which reported larger effect sizes than randomized trials, introduces potential bias (Egger et al., 1997). Additionally, the slight asymmetry in the funnel plot, although not statistically significant, suggests the possibility of unpublished negative results —a common challenge in meta-analyses (Moher et al., 2009). Future research should prioritize randomized controlled trials to strengthen causal inference and investigate the long-term effects of AI in healthcare management (Topol, 2019). While the findings demonstrate the promising impact of AI on healthcare performance, ethical concerns warrant careful consideration and attention. Issues such as algorithmic opacity, lack of explainability, and potential biases embedded in training datasets can disproportionately affect marginalized patient groups.

Additionally, data privacy remains a critical challenge, especially in settings where governance frameworks for patient consent and data security are underdeveloped. Responsible AI integration must therefore ensure transparency, fairness, and strict compliance with data protection standards. To facilitate the successful implementation of AI tools in healthcare management, leaders should consider several strategic factors. First, the availability of reliable digital infrastructure and high-quality data is essential. Second, frontline staff should be involved early in the adoption process through training and participatory design. Third, cost-effectiveness evaluations and pilot testing can help tailor AI interventions to institutional needs. Organizational readiness, regulatory alignment, and a culture of continuous learning are equally crucial for sustaining AI integration at scale.

Although this meta-analysis primarily draws from the international literature, its implications are particularly relevant for middle-income health systems, such as Turkey. The scalability of AI in such contexts depends on addressing infrastructure limitations, digital literacy gaps, and regulatory clarity. Policymakers in these settings can benefit from the synthesized evidence by prioritizing targeted investments in AI-driven solutions tailored to their system-level challenges.

The implications of this study are twofold: practical and academic (Davenport & Kalakota, 2019). For healthcare managers, the evidence supports investing in AI technologies, particularly machine learning models, to enhance patient safety and operational workflows; however, cost-effectiveness and training requirements must be addressed (Bates et al., 2020). Academically, the findings highlight a gap in understanding AI's scalability in low-resource settings and its sustained effects over time (Yu et al., 2018). Further studies could investigate the role of staff acceptance, ethical considerations, and data privacy in AI adoption, areas that remain underexplored in the current literature (Jiang et al., 2017). By bridging these gaps, healthcare management can fully harness AI's potential to improve care delivery and system efficiency (Topol, 2019).

5. CONCLUSION

This meta-analysis demonstrates that artificial intelligence (AI) significantly enhances patient safety and operational efficiency in healthcare management (Topol, 2019). The pooled evidence reveals substantial reductions in medical errors, adverse events, patient wait times, and inefficiencies in bed occupancy. These findings affirm AI's potential to transform administrative performance in tandem with clinical care.

However, successful AI integration depends not only on technological potential but also on organizational readiness, ethical safeguards, and policy alignment. Healthcare managers must anticipate challenges such as data privacy concerns, algorithmic bias, staff resistance, and resource limitations, particularly in low- and middle-income countries.

To support evidence-based adoption, healthcare leaders should prioritize infrastructure development, training programs, and pilot testing of AI tools. A phased implementation strategy, grounded in stakeholder engagement and continuous evaluation, can facilitate the sustainable integration of AI at scale (Yu et al., 2018).

Finally, while this meta-analysis draws on global data, its implications are especially relevant for middle-income healthcare systems such as Turkey. Targeted investments and adaptive implementation strategies can help translate AI's benefits into locally meaningful outcomes, bridging global innovations with national needs.

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This meta-analysis relied solely on aggregated data from published studies and did not require ethical approval.