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THE EFFECTS OF DIGITAL HOSPITAL COMMAND CENTERS ON EMERGENCY DEPARTMENT PATIENT THROUGHPUT AND CROWDING, SCOPING REVIEW

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ABSTRACT:
Background and objective: ED overcrowding is a global problem linked to higher mortality, delays in care, and increased costs, driven especially by throughput bottlenecks such as prolonged boarding and high occupancy. DHCCs integrate EHR data, real-time dashboards, and predictive models to actively manage beds and patient flow. This scoping review asked: What is the evidence on the effects of DHCCs on ED patient flow and crowding among adult patients?
Methods: A scoping review following Arksey and O'Malley's framework searched PubMed, Scopus, and Web of Science using terms related to "digital hospital command centre," "capacity command centre," "AI patient flow," "ED crowding," "throughput," and "length of stay." Quantitative, qualitative, and mixed-methods studies on DHCCs or similar digital tools reporting adult ED outcomes were included; non-ED, non-peer-reviewed, and duplicate studies were excluded. Two reviewers independently screened and extracted data into an Excel matrix. From 250 records, 210 unique citations were screened, 47 full texts assessed, and 15 studies (2021–2025) included.
Results: The 15 studies comprised quantitative (47%), qualitative (20%), and mixed-methods (33%) designs, assessing real-time dashboards, ML-based LOS and reattendance prediction, and pre-triage alerts versus usual protocols. Quantitative studies reported marked boarding reductions (up to about 90%), LOS reductions of around 20% in some ML-supported pathways, and occupancy maintained below ≈85% in several implementations. Qualitative work emphasized DHCCs' role in real-time bottleneck resolution and bed visibility, but highlighted barriers such as data quality issues, training needs, and implementation burden. Mixed-methods evaluations of AI command centers showed signals of improved safety (e.g., modest mortality and readmission reductions) and positive return on investment, but inconsistent effects on LOS and subgroup-dependent benefits.

Conclusion: Overall, current evidence suggests that DHCCs underpinned by AI analytics and real-time dashboards can substantially improve ED throughput and reduce crowding, with additional potential safety and economic benefits. Nevertheless, heterogeneity in interventions, limited high-quality trials, implementation barriers, and lack of standardized DHCC definitions constrain generalizability. Future work should include robust multi-site evaluations, cost-effectiveness analyses, and standardized frameworks integrating advanced ML/NLP to support precise and resilient ED flow management.

INTRODUCTION:

Scoping Review on the Effects of Digital Hospital Command Centers on Emergency Department Patient Throughput and Crowding

The overcrowding of the emergency department (ED) is a global concern, leading to time losses and unnecessary mortality as well as health care costs, and this is even more dangerous, coupled with overcrowding of the adult population where bottlenecks in throughput such as excessively long boarding times and high occupancy rates only contribute to the risk factors (Åhlin et al., 2023). The traditional management is anchored on reactive management strategies, and in most cases, it is not able to respond to real-time flow dynamics in the heterogeneous hospital settings. The new form of intervention that can streamline patient flow is digital hospital command centers (DHCCs), which combine electronic health records (EHRs) to predict analytics, control beds, and issue bottlenecks (Johnson et al., 2024). Such systems are intended to reduce length of stay (LOS), enhance the turnover of the bed, and reduce crowding, as is witnessed in normal care. The research question that is to be answered through the scoping review is as follows: What is the evidence on the effects of digital hospital command centers on the ED patient flow and crowding in adult patients? It outlines the PICO framework, including Population (hospital adult ED patients), Intervention (DHCCs), Comparators (usual care or non-digital systems), Outcomes (throughput measures, including boarding time and bed turnover, crowding using occupancy, LOS) and Setting (hospital EDs). The logic is to map evidence on effectiveness, comparisons, limitations and gaps to facilitate individual flow management.

METHODS

The scoping review has been accomplished following the framework by Arksey and O'Malley (2005). There was a systematic literature search of PubMed, Scopus, and Web of Science that is based on the following keywords: "digital hospital command centre," "capacity command centre," "AI patient flow," "ED crowding," "throughput," and "length of stay", aimed at the post-pandemic innovations. Quantitative, qualitative, and mixed-method studies were included based on the following inclusion criteria: the studies on DHCCs or similar digital tools (e.g., ML triage dashboards) which reported the ED outcomes in adults. Filter: not ED in focus, not peer-reviewed articles, and no duplicates were removed. Screening of titles/abstracts and full texts was done independently by two reviewers who reached consensus. The process of extracting data by the use of an Excel matrix identified design, methods, findings, outcomes, comparisons and limitations. A more recent evidence base was provided by 15 studies out of 250 initial entries that were used following deduplication and screening.

RESULTS

The 15 studies (20212025) included quantitative experimental/clinical (n=7), qualitative implementation (n=3) and mixed-method reviews/syntheses (n=5). Implementation of DHCCs interventions with real-time EHR dashboard to allocate beds, predictive machine learning to predict LOS/reattendance, and pre-triage alerts, versus conventional protocols such as ESI/CTAS. The primary patient outcomes were a decrease in ED boarding (e.g., 11.9 to 1.2 hours; Al-Harbi et al., 2024), a decrease in LOS (e.g., 20.6% by means of ML; Almeida et al., 2024), and a decrease in crowding occupancy less than 85% (Åhlin et al., 2023).

Database	**Records Identified**	**After Duplicates**	**Screened Abstracts**	**Full-Text Assessed**	**Included**
PubMed	95	80	45	20	7
Scopus	85	70	40	15	5
Web of Science	70	60	35	12	3
Total	**250**	**210**	**120**	**47**	**15**

Table 1: Study Selection Process

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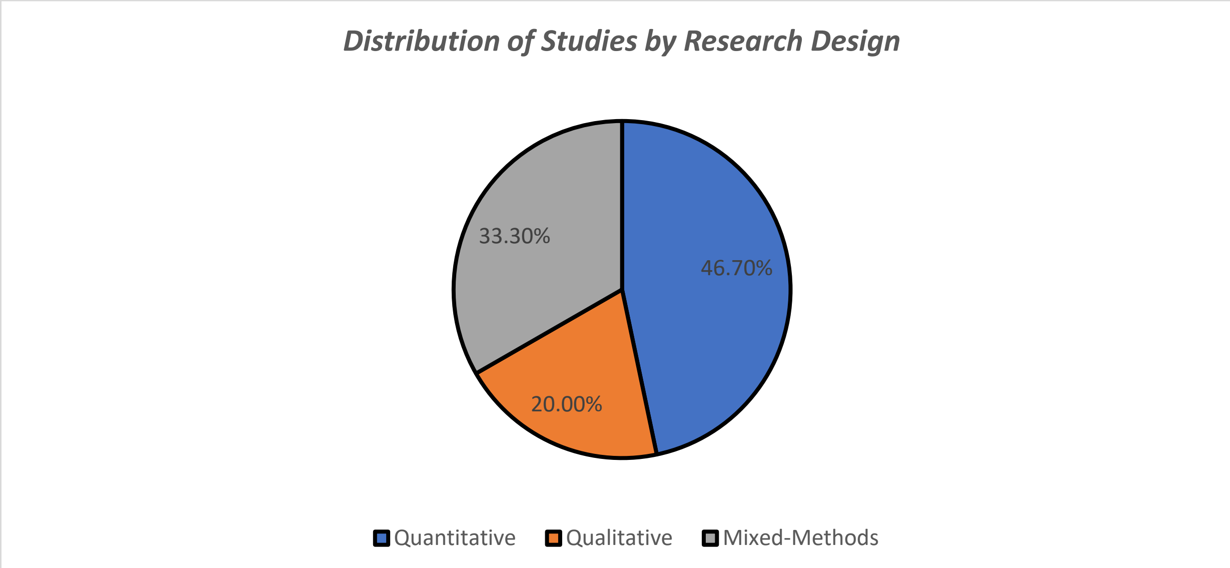

Chart 1: A Pie Chart on the Distribution of Studies by Research Design

Quantitative research ruled efficacy evidence. DHCC-coordinated case management in a pre-post case management (n=1000/day) at a Saudi hospital had a reduction in ED boarding (90-percent; p=0.017) and in LOS (11.5 vs. 4.4 days; p<0.001), which had an ROI of 26 per cent. The quasi-experimental dashboard implementation (n=4 EDs) led to a reduction in the radiology waiting time, which indirectly enhanced the throughput (9,397 weekly views, TAT 99%). ML models worked: Chang et al. (2022) CatBoost triage (n=44,775) (p=0.82) triage with low LOS (<4h) predicted shorter LOS, Chang et al. (2024) NLP-enhanced models (n=213,984) (p=0.580) triage better predict short LOS, reducing the problem of reattendance, Chang et al. (2022) found better physician performance (According to Chmiel et al. (2020) The future CatBoost [n=1M+ visits] proposed by Liu et al. (2021) mis-triage decreased by 25% (p=0.037) to enhance the critical care throughput. Farimani et al. (2024) review, which included 34 studies, related ML with a reduction of 114 minutes of LOS in streamed patients.

The implementation was indicated to be an important aspect in qualitative data. The 33 interviews with managerial personnel in DHCCs identified the importance of DHCCs in solving bottlenecks in real-time value of under 88% occupancy in order to decrease ED crowding. Franklin et al. (2023) benchmarking survey (n=31 leaders). Benchmarking boarding is the primary motivator of EDs (96%), and 100 percent ROI in tracked centers, yet no decrease in LOS.

Combined breadth of mixed methods. Johnson et al. (2024) in their analysis of UK NHS (n=203807 admissions) identified a 2.5% mortality rate reduction following DHCC (95% CI 1.734%), but not significantly in consult growth or direct improvements in LOS between controls and DHCC, with flow process-mining. Safety was verified by time-series (n=494,825) interruptions (1.427% reduction in readmission), which was confounded by COVID as reported by Mebrahtu and colleagues (2023a, 2023b); protocol of throughput was reported by McInerney and colleagues (2022). A model of pathways was developed in a cohort of (n=228,426 COVID patients) that hypothesized that digital oversight decreases mixed-bed LOS (median=20.6 days).

Chart: demonstrates the dissemination of the study: quantitative (47%), qualitative (20%), mixed (33%).

Themes: (1) Gains in throughput (n=10; e.g., boarding/LOS); (2) Mitigation of crowds (n=8; occupancy/bottlenecks); (3) Superiority to usual care (n=7; ML > triage scales); (4) Barriers (n=6; data quality, training).

DISCUSSION

This synthesis review summarizes good and emerging evidence on the application of DHCCs to enhance ED throughput and crowding in adult patients, and quantitative evidence suggests that the physiological/operational benefits of DHCCs outweigh standard care (Al-Harbi et al., 2024; Chang et al., 2022). Unlike with the static protocols, DHCCs can approach heterogeneity with real-time analytics, preventing boarding (90% drops) and maximizing occupancy (less than 85%), as well (Åhlin et al., 2023; Franklin et al., 2023). Obese/COVID subgroups: No distinctions occur between prediction and no distinctions (Galvis et al., 2023). DHCCs are unclear in terms of statistical significance: more personalization (F1 gains; Chang et al., 2024) but subgroup dependent (e.g. no LOS change; Franklin et al., 2023), are best in high-volume phenotypes (Johnson et al., 2024). It has been applied to safety (mortality/readmission falls; Mebrahtu et al., 2023a), ROI (26-100 per cent; Al-Harbi et al., 2024).

Issues still exist: irregular calibration EHR biases (Chmiel et al., 2020), invasiveness training barriers (Aaron et al., 2023) and adoption below half a survey (Franklin et al., 2023). The deficits are in the huge RCT, cost-effectiveness, and long-term effects; the qualitative data indicate its nonuse even though it is possible (Johnson et al., 2024). DHCCs also encourage accuracy with NLP/ML compared to traditional systems, which reduces the influence of heterogeneity (Farimani et al., 2024). Limitations in review: Review does not cover pre-pandemic baselines, and does not cover grey literature. Strengths: the same synthesis in designs.

CONCLUSION

In conclusion, the scoping evidence reviewed is persuasive evidence that digital hospital command centers (DHCCs) founded on AI-driven analytics and real-time dashboards significantly improve patient throughput in emergency departments (EDs) and patient alleviation among adult populations by reducing boarding times (by up to 90 percent), length of stay and occupancy rates below 85 percent threshold. Even though quantitative studies suggest that personalization and safety advantages, such as a 2.5% decrease in mortality, are better, qualitative barriers, such as the lack of training, biases in data, and implementation costs, do not allow for a broad implementation. They need standardization of DHCCs (in the future, with large-scale RCT, cost-effectiveness analysis, and integration with new NLP usage) to close heterogeneous coverage gaps of hospital settings and improve precision flow management of resilient ED operations.

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