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Review

The role of information systems in emergency department decision-making—a literature review

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Abstract

Objectives: Healthcare providers employ heuristic and analytical decision-making to navigate the high-stakes environment of the emergency department (ED). Despite the increasing integration of information systems (ISs), research on their efficacy is conflicting. Drawing on related fields, we investigate how timing and mode of delivery influence IS effectiveness. Our objective is to reconcile previous contradictory findings, shedding light on optimal IS design in the ED.

Materials and methods: We conducted a systematic review following PRISMA across PubMed, Scopus, and Web of Science. We coded the ISs' timing as heuristic or analytical, their mode of delivery as active for automatic alerts and passive when requiring user-initiated information retrieval, and their effect on process, economic, and clinical outcomes.

Results: Our analysis included 83 studies. During early heuristic decision-making, most active interventions were ineffective, while passive interventions generally improved outcomes. In the analytical phase, the effects were reversed. Passive interventions that facilitate information extraction consistently improved outcomes.

Discussion: Our findings suggest that the effectiveness of active interventions negatively correlates with the amount of information received during delivery. During early heuristic decision-making, when information overload is high, physicians are unresponsive to alerts and proactively consult passive resources. In the later analytical phases, physicians show increased receptivity to alerts due to decreased diagnostic uncertainty and information quantity. Interventions that limit information lead to positive outcomes, supporting our interpretation.

Conclusion: We synthesize our findings into an integrated model that reveals the underlying reasons for conflicting findings from previous reviews and can guide practitioners in designing ISs in the ED.

Key words: emergency medical services; clinical decision-making; information systems; computer-assisted decision-making; clinical decision support systems; information overload.

Background and significance

The emergency department (ED) is a critical yet volatile healthcare environment with varying patient volumes and acuity levels and a high density of decisions.[1,2] Healthcare providers start with *heuristic* decision-making through pattern recognition and memorized checklists as tools for patient assessment and care.[3,4] They then continue to a more *analytical* hypothetico-deductive approach, iterating through diagnostic hypotheses and treatment strategies[1,5] (see Figure 1). However, this dual-model approach is susceptible to errors due to limited information,[2] time pressure,[6] interruptions and distractions,[2] and multitasking.[7]

Information systems (ISs) have been posited as a potential solution to enhance clinical decision-making. ISs encompass any technical system that generates information enabling decision-makers to identify problems and needs, make evidence-based decisions, and allocate resources.[8–10] *Active* and *passive* systems represent 2 distinct approaches within ISs.[11–13] *Active* systems, such as Computerized Clinical Decision Support Systems (CCDSS), can be incorporated into electronic health record (EHR) systems or function as separate applications. These systems proactively assist physicians by offering recommendations based on patient data. *Passive* systems facilitate access to patient medical records and the latest evidence-based guidelines without *actively* interpreting the information. This category includes EHRs, which document patient interactions within a hospital, and Health Information Exchange (HIE) systems, which share patient information across healthcare facilities.[14–23]

Although ISs have shown promise to improve care quality in general clinical settings,[24–26] their impact in the ED has shown mixed results. While some studies report improved efficiency and faster, better-informed decision-making,[27,28] others indicate low adoption rates among physicians, decreased productivity, and increased burnout.[29–31] Despite the growing research body on ISs in healthcare, extant literature lacks clarity regarding the contradictory impacts of ISs in the ED. Existing reviews focus on CCDSS and evaluate the methodological study quality without addressing the underlying reasons for the observed outcomes.[32,33]

Objective

Given the critical nature of decisions in emergency care, this research analyzes the impact of ISs on decision-making and why prior results are contradictory. The established

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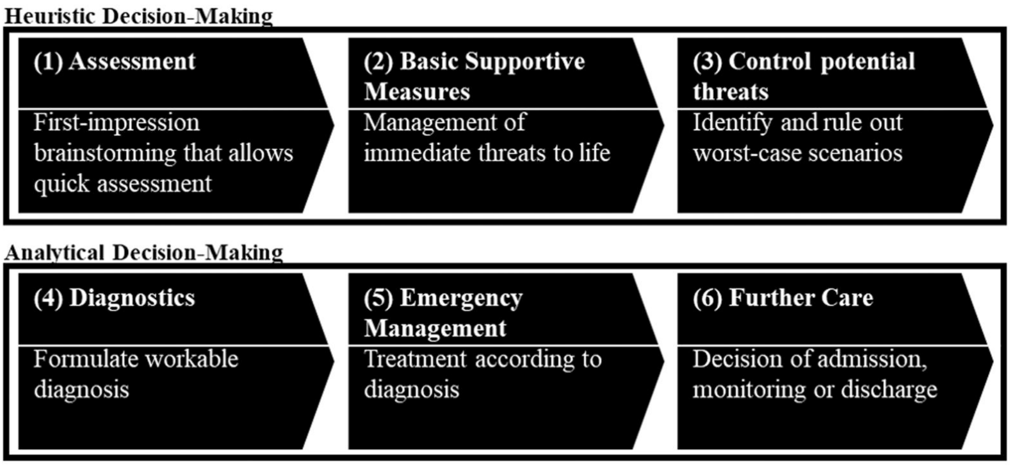

Figure 1. Dual model of decision-making in the ED (adapted from[3])

understanding of *heuristic* and *analytical* decision-making and its effect on medical reasoning[34–38] contrasts sharply with the limited exploration of its relevance to decision support systems. This gap persists despite IS research underscoring the importance of aligning the design of problem-solving aids with users' mental representation to enhance problem-solving efficiency and effectiveness.[39–41] Early evidence has identified *passive* summaries, graphics, and visual displays as advantageous for *heuristic* decision-making and *active* decision-support for *analytical* decision-making.[42,43] Our study seeks to expand on these insights by testing 2 hypotheses (see Table 1).

Table 1. Hypothesized effect matrix of technological intervention in the ED depending on their timing in the decision-making process and mode of delivery.

	Active mode of delivery	*Passive* mode of delivery
Delivered during *heuristic* phases of decision-making		H: *Passive* ISs enhance the effectiveness of *heuristic* decision-making.
Delivered during *analytical* phases of decision-making	H: *Active* ISs enhance the effectiveness of *analytical* decision-making.	

Methods

We followed the PRISMA guidelines for systematic reviews,[44] including a forward search and a backward search.

Search strategy

We conducted a literature search across PubMed, Web of Science, and Scopus on April 26, 2023. The goal was to analyze the effects of the introduction of ISs in ED decision-making. Thus, our search string combined terms in 3 domains: technological intervention, decision support, and emergency care. We based the keywords on prior literature reviews on ED CCDSS to facilitate comparison.[32,33] As the focus on CCDSS would omit established ISs like EHRs, we expanded the terms to include broader concepts, eg, "electronic" and "techn*" (see Supplementary Material S1). To ensure the robustness of our results, we focused on the most reputable medical informatics, emergency care, and IS journals in the initial search (see Supplementary Material S2).

Inclusion and exclusion criteria

We included primary research on technology implementation in the ED that compared IS-supported care with usual care. We thus excluded interventions that were (1) reviews, editorials, or perspectives, (2) nontechnological interventions, (3) outside the ED setting, or (4) did not compare outcome measures to non-IS-supported care. We refined our definition during the selection process and excluded systems (5) timed before patient assessment or after the admission/discharge decision (see Figure 1). This restriction facilitates the classification of whether physicians are in *heuristic* or *analytical* decision-making during delivery.

Study selection

Two authors independently screened titles and abstracts against the above criteria. If 1 author deemed an article relevant, we included it in the full-text screening. Two authors assessed publications for inclusion. Disagreements were resolved through discussion. One author performed forward and backward searches on the resulting publications. The eligibility of these articles was assessed similarly to the initial set, except that we did not filter on the predetermined journals.

Coding strategy

For each eligible study, we coded the intervention's timing in the decision-making process, purpose, delivery mode, and effect on outcome variables. We started this process by extracting the verbatim descriptions for each variable, which we subsequently used for categorization. We assigned interventions to the *heuristic* phase if they provided information before physicians reached a diagnosis, to the *analytical* phase if information was provided after this point, and to *both* phases if they supplied information throughout the care pathway.[3] Next, we coded the intervention's purpose within each phase to capture how the IS was used. For the mode of delivery, we categorized, eg, "alerts"[45] as *active* and "voluntary"[46] interventions as *passive*. Lastly, for the outcome variables, we drew on decision support literature[13,47] and assigned them to either "process outcomes," where the change promoted by the IS alters a behavior; "economic outcomes," where the change impacts hospital financial expenditures; or "clinical outcomes," where the change translates into an impact on patients (see Table 2). Two authors independently coded the articles, resolving conflicts through discussion.

Synthesis strategy

We first clustered similar purposes into groups by iteratively abstracting the verbatim descriptions.[65] Supplementary Material S4 provides descriptions for every purpose group and outcome variable. We compared ISs carried out at the same phase and with the same purpose and timing to reveal what outcomes they affect. We summarized these effects across interventions to assess the consistency of the results. Finally, we synthesized the interventions across purposes to test how the timing and the mode of delivery affect the efficacy of IS interventions.

Results

Our initial search (left section in Figure 2) yielded 7766 hits, with 365 studies remaining after removing duplicates and filtering for relevant outlets. We identified 39 relevant studies through abstract and full-text screening. Forward and backward searches on these yielded 2387 articles (right section). Forty-four publications met the inclusion criteria, resulting in a total of 83 included studies. The main reasons for exclusion were nontechnological interventions ($n = 388$) and studies that did not compare outcome measures with non-IS-supported care ($n = 248$).

Table 2. Coding structure.

Coded variable	Distinct values	Description	Exemplary indicators
Timing in the ED decision-making process	*Heuristic*	Intervention provides information before the healthcare providers reach a diagnosis[3], ie, phases (1) to (3) in Figure 1	"assessed the patient for the presence of sepsis,"[48] "diagnostic suggestions were displayed"[49]
	Analytical	Intervention provides information after the healthcare providers reach a diagnostic working hypothesis[3], ie, phases (4) to (6) in Figure 1	"initiation of buprenorphine,"[50] "promote take-home naloxone prescription"[51]
	Both	Intervention provides information across the care pathway[3], ie, phases (1) to (6) in Figure 1	"real time virtual patient record available at all points of care,"[52] "available [. . .] when diagnosing and admitting patients"[53]
Purpose	Verbatim descriptions	Aim of the technological intervention	"guides medication dosing for the elderly,"[54] "automatically recognizes systemic inflammatory response syndrome"[45]
Mode of delivery	*Active*	Information appears automatically[11]	"interruptive,"[55] "alert,"[45] "notification,"[56] "pop-up"[57]
	Passive	Users must proactively seek out the information they need[11]	"voluntary,"[46] "optional,"[58] "at the clinician's discretion"[58]
Type of outcome variable	Process	Variable measures a change in behavior[13,47]	Adherence to proposed Management Plan, Adherence to Medication Guidelines[13,47]
	Economic	Variable measures an impact on financial expenditures[13,47]	Cost, Cost-effectiveness[13,47]
	Clinical	Variable measures an impact on patients[13,47]	Mortality, Length of Stay[13,47]
• Effect on measured primary outcome variables	+	Intervention results in a significant increase on a certain outcome variable	"usage was increased,"[59] "significant increase was achieved"[60]
	•	Intervention has no significant effect on a certain outcome variable	"we did not observe such an effect,"[61] "there was not a statistically significant change"[62]
	—	Intervention results in a significant decrease on a certain outcome variable	"reduces the amount,"[63] "was associated with a decrease"[64]
• Desired effect on measured primary outcome variables	↑	Intervention was aimed at a significant increase	Decision Quality ↑, Adherence to Medication Guidelines ↑
	↓	Intervention was aimed at a significant decrease	Mortality ↓, Length of Stay ↓
• Alignment of effects with desired results	Black	Desired effect	Measured effect in line with expected effect
	Grey	No effect	Intervention has no significant effect (•)
	White	Undesired effect	Measured effect not in line with expected effect

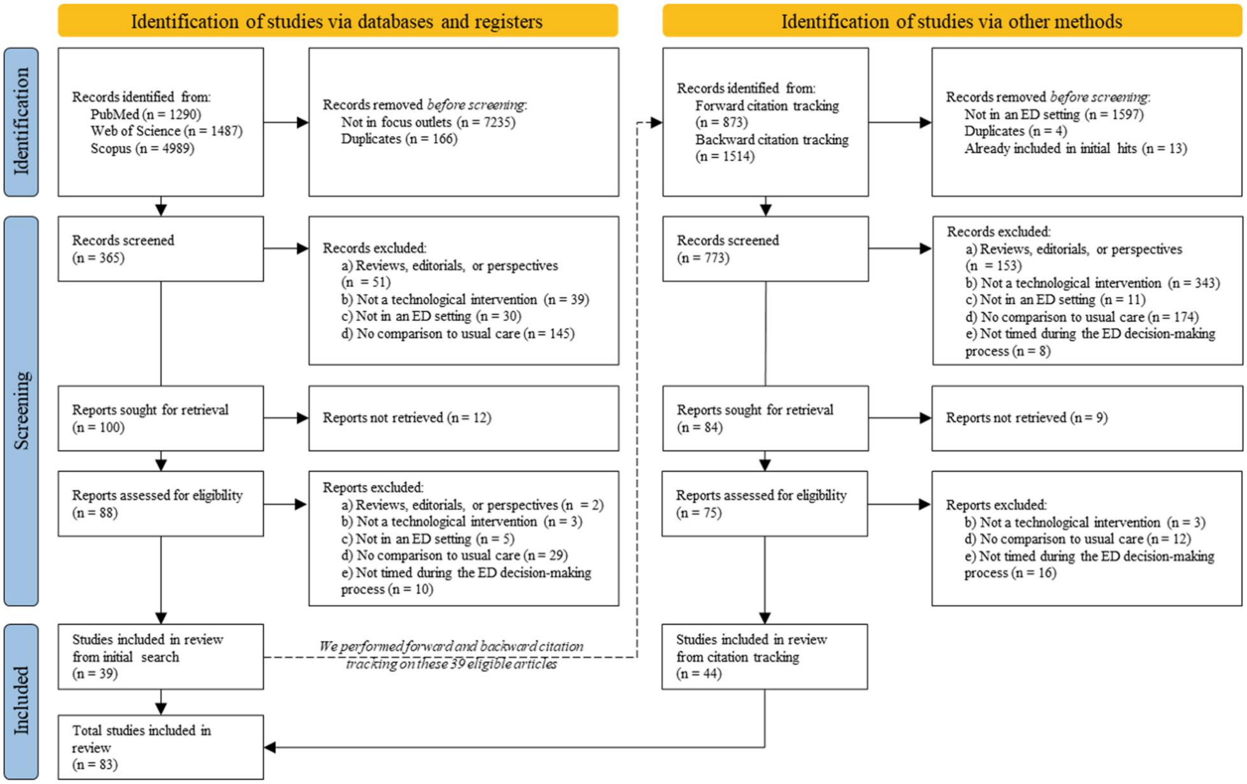

Figure 2. Study selection process.

Clustering of purposes

We assigned the 83 interventions to the *heuristic*, *analytical*, or *both* phases and detailed their purpose. We coded their delivery mode as *active* or *passive* and how the intervention affected process, economic, or clinical outcomes. Table 3 visualizes how interventions affect outcomes at the purpose level. For example, the first row documents *active* interventions identifying medical conditions and recommending actions during *heuristic* decision-making. At the intersection with the outcome measure "adherence to proposed management plan," we observe that 5 publications measure no significant impact, while 3 other ISs improve compliance. As less than 60% of the interventions have the desired effect (37.5%), we mark the cell grey. We used this granular analysis to prepare the test of our main hypotheses.

Interventions during *heuristic* decision-making

Twenty-seven interventions provided information while physicians mitigate threats to life and generate diagnostic hypotheses, ie, during *heuristic* decision-making. All aimed to support providers in (1.1) detecting a specific medical condition and recommending measures for its management.

Purpose group 1.1: detection and management recommendations for medical conditions (32.5% of identified interventions)

The 27 ISs in this group suggested diagnoses and actions based on evidence-based guidelines usually listed in order sets that include, eg, laboratory tests. These ISs provided *active* or *passive* guidance before physicians make a diagnosis.

Among the 27 articles, 18 had an *active* mode of delivery, ie, they alerted physicians to at-risk patients. Six reported positive effects. Three studies aimed to improve the timeliness of countermeasures for sepsis or acute coronary syndrome and found significant decreases in the time-to-intervention.[56,66,67] Three studies improved guideline adherence by focusing on a single countermeasure, ie, lactate testing,[45] blood culture collection,[68] and child services reporting.[69]

The remaining 12 papers with *active* guidance failed to demonstrate positive results. Seven publications did not find significant effects on LOS,[55,70–72] mortality,[48,55,73,74] and hospital admission.[73] Five studies on improving guideline adherence did not yield significant positive outcomes.[75–79] In contrast to the successful studies above, these interventions proposed multiple measures. For example, Rosenthal et al[78] demanded multiple tests, scans, and consultations.

Nine studies had a *passive* mode of delivery, ie, they provided information for physicians when experiencing diagnostic uncertainty. Eight reported positive effects. Five studies improved guideline adherence through antibiotic prescribing guidelines[46,80–82] or medical calculators.[83] Masica et al[84] embedded voluntary medical calculators and showed a decrease in hospital admissions. Ramnarayan et al[49] improve documentation quality through a diagnostic support system. Nam et al[85] decreased time-to-thrombolysis when physicians proactively notified a stroke team.

One study with a *passive* delivery mode reported no significant results. Fargo et al[58] provided a voluntary order set that did not improve time-to-antibiotics.

Interventions during *analytical* decision-making

Forty interventions provided information while physicians treat patients according to their diagnosis and decide whether to admit, monitor, or discharge patients, ie, during *analytical*

Table 3. Effects of ISs in ED.

Legend:

- ■ (dark grey) At least 60% of interventions achieve the desired effect.
- ■ (light grey) Less than 60% of interventions achieve the desired effect.
- □ The intervention leads to undesired effects.

Timing	Purpose groups	Mode	Process outcomes: Docu-men-tation: Quality of documentation ↑	Process outcomes: Clinical decision-making: Information comprehension ↑	Clinical decision-making: Decision quality ↑	Clinical decision-making: Time to decision ↓	Adherence to clinical guidelines: Adherence to proposed management plan ↑	Adherence to clinical guidelines: Adherence to medication guidelines ↑	Adherence to clinical guidelines: Time to intervention ↓	Economic outcomes: Clinical efficiency: Utilization of imaging and testing resources ↓	Clinical efficiency: Yield of imaging and testing resources ↑	Clinical efficiency: Costs ↓	Clinical outcomes: Hospital Readmission ↓	Clinical outcomes: Hospital admission ↓	Clinical outcomes: Mortality ↓	Clinical outcomes: Length of stay ↓
Heuristic	Detection and Management Recommendations for Medical Conditions	*Active*					· (5)/ + (3)[a]		− (3)					· (1)	· (4)	· (4)
		Passive	+ (1)				+ (4)		− (1)/ · (1)					− (1)	− (1)	
Analytical	Risk-Stratification for Imaging	*Active*	+ (5)							− (9)/ · (1)	· (2)/ + (4)					
		Passive								· (2)						
	Proposal of Substitute Medication or Dosage Adjustment	*Active*						+ (10)			+ (1)					
		Passive						· (1)/ + (1)			· (1)					
	Standardization of Admission and Discharge Process	*Active*	− (1)										− (2)	− (2)		− (2)/ · (1)
Both	Access to patients' medical history	*Passive*					+ (1)			− (2)	+ (1)	− (1)/ · (1)	− (3)	− (4)	· (1)	− (2)
	Emphasis Framing	*Passive*			+ (3)	+ (1)					− (1)					
	Graphical Representation	*Passive*		+ (2)	+ (1)	− (1)										

[a] Used as example in text.

decision-making. This phase is further subdivided into (2.1) risk-stratification for imaging, (2.2) proposal of substitute medication or dosage adjustment, and (2.3) standardization of the admission and discharge process.

Purpose group 2.1: risk-stratification for imaging (22.9%)

This group includes 19 studies that facilitated risk-stratification for imaging. These interventions supported clinicians *actively* or *passively* in deciding whether a patient requires imaging based on clinical guidelines.

Seventeen studies had an active mode of delivery, ie, they alerted physicians that an ordered imaging study is unnecessary. Each intervention, except one, improved outcome variables. The authors focused on head injury,[86–92] pulmonary embolism,[93–95] headache,[96] ankle[97] or wrist[63] injury, or renal colic.[98] Three studies introduced multiple guidelines.[59,64,99] All 16 studies either decreased utilization rates,[63,64,86–89,92,94,98] increased diagnostic yield,[59,92,93,99] or improved documentation quality.[89–91,95,97] Royuela et al[96] found only decreased utilization but no effect on yield. Raja et al's[94] intervention impacted neither.

The remaining 2 studies had a passive mode of delivery, ie, they provided voluntary education on risk factors, but imaging utilization rates and yield were unaffected.[61,62]

Purpose group 2.2: proposal of substitute medication or dosage adjustment (16.9%)

The second group during analytical decision-making encompasses 14 interventions that *actively* or *passively* suggested medication substitution or dosage adjustment.

Among the 14 studies, 11 had an *active* mode of delivery, ie, they alerted physicians to reconsider their order placement. All 11 interventions had a positive effect on the outcome variables. Four studies improved naloxone prescription for opioid-related overdose.[51,60,100,101] Griffey et al[54] and Terrell et al[102] reduced inappropriate medication for elderly patients. Two studies increased ketorolac prescribing[103] or decreased excessive dosing[104] in renal impairment. Dutta et al[105] alerted physicians of duplicate vaccines. Bernstein et al[106] reduced the use of proprietary antibiotics by displaying patients' insurance status. Green et al[107] demanded patient reverification and decreased wrong-patient orders.

The 3 remaining studies had a *passive* mode of delivery, ie, they provided decision support only when launched at the physician's discretion. One study demonstrated positive effects. Holland et al[50] increased the rate of buprenorphine prescription. The other 2 publications showed no or mixed effects. The authors[50] above could not replicate the results on a larger scale.[108] Horng et al's[109] study highlighted that previous prescriptions did not decrease duplicate medication orders.

Purpose group 2.3: standardization of admission and discharge process (8.4%)

Seven studies expedited the execution of the admission or discharge process by digitizing substeps. All interventions delivered content actively.

Five studies showed positive effects. Mahler et al[110] and Stoypra et al[57] computerized the HEART pathway to identify low-risk patients for discharge, reducing hospital admission. Cho et al[111] and Kim et al[112] reduced LOS by automating specialty consultations. Desai et al[113] implemented a review loop after the admission decision, decreasing admission.

Two studies measured mixed or negative effects. While Liu et al[114] confirmed the positive impact of the HEART pathway on hospital admission, they measured no difference in LOS. Driver et al[115] implemented a "hard stop"[115] when clinicians discharged patients without reviewing all lab results. However, this led to an increase in test results after discharge.

Interventions during *both heuristic* and *analytical* decision-making

The remaining 16 publications describe (3.1) accessing patients' medical history or facilitating the extraction of information from these records through (3.2) emphasis framing or (3.3) graphical representation. Although the publications did not specify the timing, usage patterns indicate that medical records are consulted during *both heuristic* and *analytical* decision-making.[28,52,53,116–119]

Purpose group 3.1: access to patients' medical history (12.0%)

This group encompasses 10 publications investigating the impact of access to medical records from previous encounters. Access to this data was either limited to visits at the designated hospital (EHRs) or extended to nearby hospitals (HIE). All interventions *passively* provided access.

Eight studies show positive effects on LOS,[120,121] hospital admission,[52,53,121,122] hospital readmission,[52,53,119] and guideline adherence.[123] Everson et al[121] additionally reported a decrease in imaging utilization. Saef et al[124] approximated a reduction in costs.

The remaining 2 studies reported mixed or no effects. Bailey et al[125] found improvements in imaging utilization and yield, but these did not translate to cost reductions. von Wedel et al[126] found no impact on mortality.

Purpose group 3.2: emphasis framing (4.2%)

Four studies focused on emphasis framing, ie, highlighting aspects of information to make it easier or more likely to be processed.[127,128]

All 4 interventions in this group had a *passive* mode delivery, ie, they highlighted certain information without alerts. Three author groups reported positive outcomes. Hwang et al[129] and Kim et al[130] highlighted radiographic abnormalities, improving their detection. Munigala et al[131] retained only 1 test in the "frequently ordered" section, decreasing urine culture utilization. One study demonstrated mixed results. Laker et al[132] emphasized the most critical information and summarized a patient's EHR. They improved decision quality, but the time-to-decision also increased.

Purpose group 3.3: graphical representation (2.1%)

Two publications described interventions that visualize textual or tabular information to enhance information comprehension, as quantified, eg, by the NASA Task Load Index.

Both interventions had a passive delivery mode and reported positive effects. Kim et al[133] converted the textual results of microbiological cultures into a visual representation, enhancing information comprehension. Thayer et al[134] developed an asthma timeline, increasing information comprehension and reducing task time.

Table 4. Effects of technological intervention in the ED on outcome measures depending on their timing in the decision-making process and mode of delivery.

	Active mode of delivery	*Passive* mode of delivery
Delivered during *heuristic* phases of decision-making	6 Desired effect (30%), 14 No effect (70%)	8 Desired effect (89%), 1 No effect (11%)
Delivered during *analytical* phases of decision-making	35 Desired effect (87%), 4 No effect (10%), 1 Undesired effect (3%)	1 Desired effect (20%), 4 No effect (80%)
Delivered during *both* phases	—	22 Desired effect (88%), 2 No effect (8%), 1 Undesired effect (4%)

Summary

Summarizing the interventions across purpose groups and outcome types, we observe that *active* interventions failed to achieve the desired effects on 70% of the outcome variables during the *heuristic* phase. In contrast, *passive* interventions achieved the desired effects on 89% of the outcome variables. During the *analytical* phase, *active* interventions achieved desired effects on 87% of outcome variables, while *passive* interventions did not affect 80%. *Passive* EHR- and HIE-related interventions achieved positive results 88% of the time in both phases (Table 4).

Discussion

This review evaluated 83 IS interventions designed to support decision-making in the ED based on their timing in the decision-making process, ie, *heuristic* or *analytical*, and their mode of delivery, ie, *active* or *passive*. In the *heuristic* phase, *active* interventions did not achieve the desired effect in 70% of the measured outcome variables, whereas *passive* interventions met 89% of intended outcomes. Conversely, *active* interventions realized 87% of desired outcomes in *analytical* decision-making, while *passive* ISs had no impact on 80%. Across *both* phases, *passive* interventions that facilitate the extraction of information achieved positive outcomes 88% of the time.

Two systematic reviews paved the way for our exploration. Bennet and Hardiker's[32] and Patterson et al's[33] reviews assessed the impact of CCDSS and the researchers' methodological rigor. Our *active* interventions have substantive overlap with the included studies. Bennet and Hardiker found that half of the studies reported positive outcomes, but their review did not categorize the interventions or examine the reasons for these results. Patterson et al highlighted positive effects in 83% of the included investigations. Their findings corroborate our own, emphasizing that improvements predominantly center around imaging and medication interventions.

Our study extends beyond CCDSS to encompass a broader spectrum of technological interventions. We explicitly included EHRs and HIEs in our search string and identified interventions that facilitate information extraction.

ISs in the *heuristic* decision-making phase

We hypothesize that information overload in the early stages of patient encounters, and the mismatch between *heuristic* thinking patterns and alerts explain the contrasting effectiveness of *active* and *passive* interventions. Decision theory suggests that increasing information quality improves decision quality. However, the relationship between information quantity and decision quality follows an inverted U-curve. Information overload occurs when the information quantity impedes decision quality more than the quality of information enhances it.[135,136]

Upon encountering a patient in the ED, physicians are met with abundant information, which they process under time pressure and high diagnostic uncertainty. To navigate this complexity and expedite care, clinicians revert to pattern recognition and algorithms, ie, *heuristic* decision-making.[34–38]

ISs add to this information in quality and quantity. However, *active* systems, eg, automatic sepsis detection,[45,48,55,58,67,74,76] represent another information stream that doctors must process alongside diagnosing and treating patients. For most *active* interventions, the adverse impact of increased information quantity overshadows the benefits of enhanced information quality, leading to mixed outcomes in process measures and no discernible effect on clinical outcomes. The few successful interventions focused on a single recommendation,[45,68,69] minimizing information quantity. In contrast, physicians consult *passive* systems, eg, databases with pneumonia treatment advice,[46,80,82] when experiencing diagnostic uncertainty, ie, information deficit. Thus, there is no information overload, and the interventions consistently improve outcomes.

Several factors inherent to the environment and tasks during *heuristic* decision-making contribute to the reduced effectiveness of *active* systems. The complexity of diagnosing patients from EHR data causes false positives, leading to alert fatigue.[55] Addressing immediate life threats requires direct interaction with patients, while alerts are generated on nearby PCs.[70,71] Alerts may be triggered after treatment has already been administered due to the reliance on outdated information.[55] These factors, ie, alert fatigue mitigation and decision support at the appropriate place and time, correlate with improved clinical practice.[137,138] The drawbacks of the difficulty of their implementation in the ED are exacerbated by the *heuristic* thinking patterns, characterized by passive responsiveness, low cognitive awareness, and high automaticity.[34–38] This can lead to notifications being viewed as noise.

ISs in the *analytical* decision-making phase

We hypothesize that the reason for the overwhelmingly positive effects of *active* interventions in *analytical* decision-making is the significant reduction in information overload. In contrast, physicians are reluctant to use *passive* resources because they do not perceive an information deficit in their tasks.

At this point in the care pathway, clinicians have managed immediate threats. They now want to confirm their diagnostic hypothesis and treat patients accordingly. The stability of patients allows providers to engage in more time-consuming but less error-prone *analytical* decision-making using the commonly employed hypothetico-deductive model.[4,5,139,140]

The identified interventions ask clinicians to reconsider their imaging, medication, or admission orders if they contradict evidence-based guidelines. We hypothesize that the reason for the consistently positive effects of *active* interventions is the significant decrease in diagnostic uncertainty and, thus, information quantity after physicians reach a working hypothesis.[4,141–144] Clinicians do not seem to experience information overload from the IS-generated information, and the studies demonstrate a significant increase in guideline adherence. In contrast, the low adoption rates[62,108] suggest physicians are reluctant to engage with *passive* resources. We attribute this reluctance to clinicians not perceiving an information deficit. They have already derived a decision, even if it diverges from the latest guidelines.

The effectiveness of *active* systems is enhanced by providing recommendations immediately after order placement based on if-then rules. This temporal and contextual immediacy ensures high accuracy and workflow integration.[137,138] The increased receptivity to alerts also indicates the shift to *analytical* thinking, characterized by active responsiveness, high cognitive awareness, and low automaticity.[34–38]

ISs in *both* decision-making phases

The overwhelmingly positive effects of providing *passive* access to patients' medical histories and *passively* facilitating information extraction support our hypotheses above. Discharge summaries and previous lab reports offer valuable information to guide diagnosis and treatment. Physicians access EHRs and HIEs from a desire to incorporate historical patient information into their decision-making, ie, from a perceived information deficit. Interventions that prepare information through emphasis framing or visual representation, eg, removing all but 1 order set from the "frequently ordered" section,[131] show favorable outcomes because they reduce information quantity or increase comprehension through visualization.[137,138,145]

Future work

Our research suggests that the under-researched concept of information overload strongly influences the effectiveness of ISs. Only 1 prior study explicitly examined its perception and impact. Most physicians surveyed agreed that information overload is a severe problem and impairs decision-making.[146] Other studies briefly mention information overload as a by-product of overcrowding.[147,148] Beyond the ED, information overload due to the electronic availability of patient information is gaining traction in the discourse. Several publications find an association between EHR use and provider burnout.[149–151] Nijor et al[152] suggest that information overload may result in more medical errors and negatively impact patient safety.

We suggest researchers tackle information overload in the ED through the lens of the systems' timing and delivery mode. In *heuristic* decision-making, physicians consult *passive* systems to reduce their diagnostic uncertainty. Researchers could identify and visualize the most contextually relevant information by timing and user group based on established guidelines and usage patterns.[28,52,53,116–119] Another angle for future research is to investigate automatic data aggregation and visualization techniques to address information quantity and comprehension in *passive* systems, building on studies outside the ED context.[153–155] An intriguing method for implementing these avenues is the *cooperative* delivery mode—an iterative "back and forth" of requesting and modifying information.[156] For example, recent studies have demonstrated the ability of large language models to generate diagnosis lists for common chief complaints.[157,158]

In the *analytical* phase, clinicians are receptive to *active* alerts issued at the time and place of the decision. Most analyzed IS are integrated into the medication or imaging ordering systems.[51,86] Future research could explore methods to maintain this workflow integration when clinicians are away from their workstations, potentially through wearables or augmented reality. Ensuring that only the most important information is relayed through these devices, future research should prevent sensory overflow and integrate rest periods away from the PC for recovery.[146] For example, the alerts' appropriateness could be derived from clinicians' physiological measures and environmental factors such as overcrowding.

Last, future research should strengthen the robustness of our results. We suggest empirically testing our hypothesis that *passive* interventions are more effective than *active* interventions during *heuristic* decision-making. We propose an RCT where EDs will be randomly assigned to implement a clinical guideline *passively* (databases), *actively* (alerting), or to control groups. A similar design is also suitable for testing the superiority of *active* over *passive* interventions in the *analytical* phase, eg, when prescribing medication.

Limitations

Our search strategy initially filtered studies based on decision support keywords and predetermined outlets, which could potentially miss relevant studies. We coded interventions as either *heuristic* or *analytical*, while physicians typically blend these strategies, with the dominant approach being influenced not only by the timing but also, eg, experience. Our analysis does not account for several factors that contribute to the effectiveness of interventions, such as the accuracy, time, and place of decision support. We did not assess the quality of the study design, considering all studies to contribute equally to the evidence base. The imbalance of delivery modes during the *heuristic* (9 *passive*/20 *active*) and *analytical* phases (5/40) affects the generalizability of our conclusions.

Conclusion

ISs have shown great promise in improving decision quality in general clinical settings,[24–26] but their impact in the ED has shown mixed results. We assessed 83 studies from 2 angles: their timing during *heuristic* or *analytical* decision-making and their *active* or *passive* mode of delivery. We synthesize the findings into an integrated model (Tables 3 and 4), which we provide as a printable tool (Supplementary Material S5). It reveals underlying reasons for the mixed results of prior reviews and can serve as a reference tool for practitioners involved in designing ISs in the ED (see Supplementary Material S6 for practical implications).

Author contributions

Cornelius Born, Timo Böttcher, and Andreas Hein designed the review. Cornelius Born and Romy Schwarz performed the

study selection and coding process. Cornelius Born synthesized and interpreted the findings, and drafted and revised the manuscript. Timo Böttcher, Andreas Hein, and Helmut Krcmar reviewed the drafts and provided feedback.

Supplementary material

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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Conflicts of interest

None declared.

Data availability

The list of all articles identified by our search strategy with their inclusion/exclusion criteria and the detailed coding of all studies (summarized in Supplementary Material S3), including the verbatim descriptions for each variable and the rationale for their categorization, will be provided upon request.

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