Strategies for Successful Implementation of Digital Tools in Hospital and ICU

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Meet the Presenter

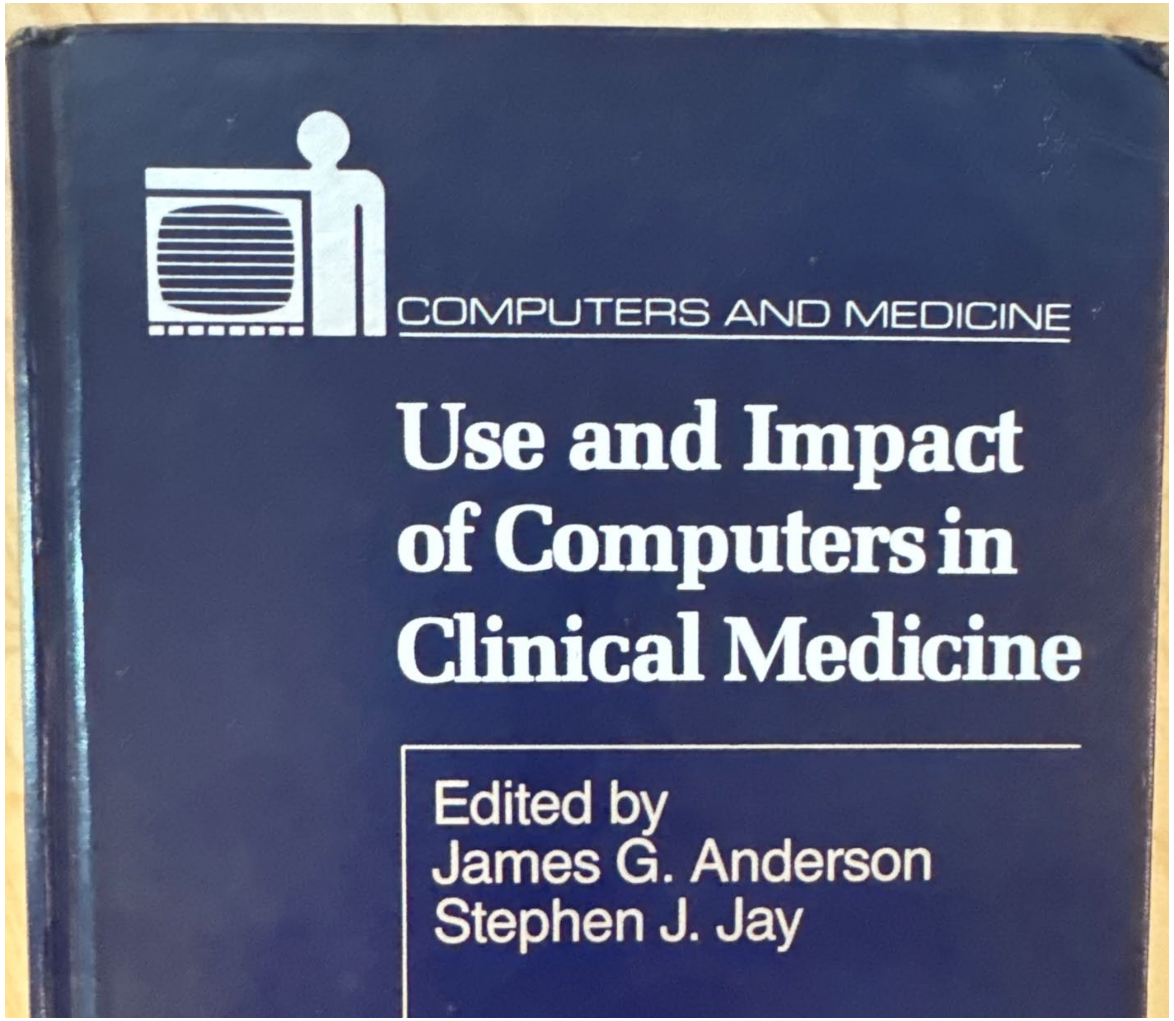
Dr. Svetlana Herasevich,

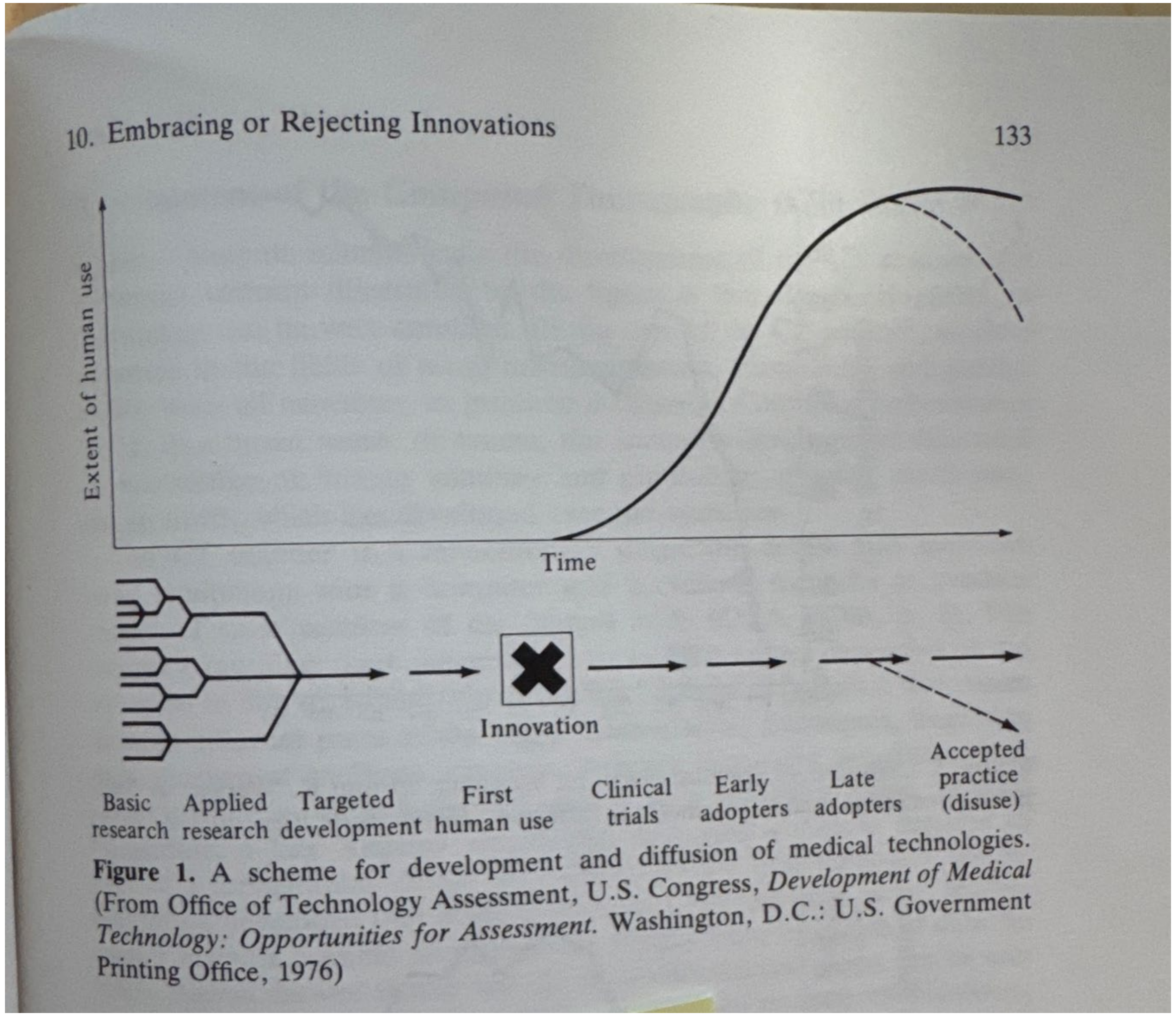
I am a physician-scientist at Mayo Clinic Rochester, USA, specializing in implementation science at the intersection of critical care and digital health.

My research focuses on developing digital solutions to enhance early detection of patient deterioration and support clinical teams in critical care.

I’m especially passionate about bring digital tools into everyday clinical practice to improve outcomes for hospitalized and critically ill patients.

Diffusion of Medical Technologies Is Not New





Why do we need Digital Tools in Healthcare?

- Improve patient outcomes
- Increase efficiency
- Support clinical decision-making

ELECTRONIC HEALTH RECORDS AND DECISION SUPPORT

CLINICAL EARLY WARNING SYSTEMS

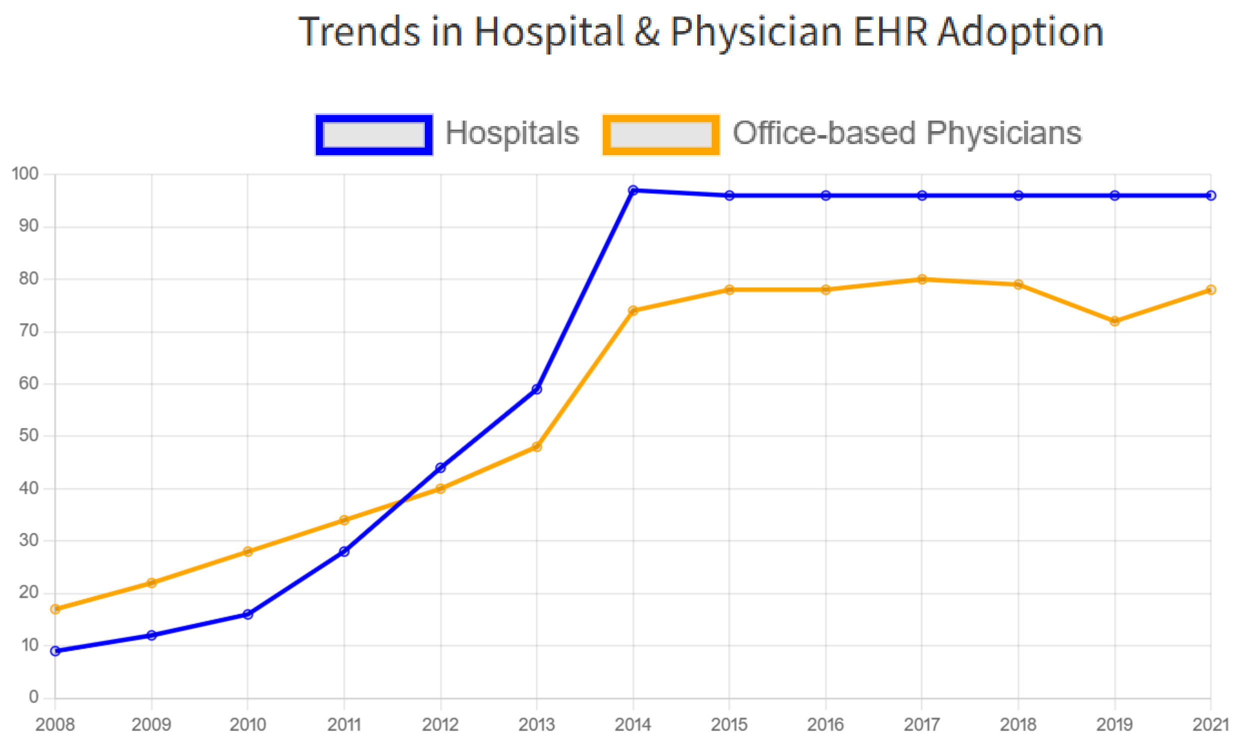
ADVANCED MONITORING PLATFORMS

ARTIFICIAL INTELLIGENCE FOR PREDICTIVE ANALYTICS

REMOTE MONITORING AND TELEHEALTH TECHNOLOGIES

Levels of Digital Tool Adoption

- **Certified EHR Systems**
  - 96% of U.S. non-federal acute care hospitals[1]
  - 78% of U.S. office-based physicians[1]
  - 90% of NHS trusts in England[2]
- **Telehealth and virtual visits**
  - Physician adoption of tele-visits increased from 14% in 2016 to 80% in 2022
- **Remote Monitoring Devices**
  - Usage among physicians increased from 12% in 2016 to 30% in 2022
- **Patient-Facing Digital Tools**
  - Over a half of surveyed U.S. hospitals and clinics implemented patient online portals



As of 2021, nearly 4 in 5 office-based physicians (78%) and nearly all non-federal acute care hospitals (96%) adopted a certified EHR. This marks substantial 10-year progress since 2011 when 28% of hospitals and 34% of physicians had adopted an EHR.

[1] *National Trends in Hospital and Physician Adoption of Electronic Health Records, 2021, HealthIT.gov*

[2] *Many NHS staff struggle to use electronic records effectively, report finds. Laura Hughes, Financial Times, 2025*

[3] *Physicians' Motivations and Key Requirements for Adopting Digital Health Adoption and attitudinal shifts from 2016 to 2022, AMA Digital Health Research*

Adoption ≠ Implementation

Adoption

Decision or **commitment** to use a new tool, practice, or innovation

Focus on psychological and organizational **readiness,** willingness, or intent to try a new tool

- Are people aware of the new tool?
- Are they willing to use it?
- Do they believe it adds value?

Example: A hospital **agrees to use** a new EHR-based early warning system after **seeing its potential**

Implementation

The **process** of putting the adopted innovative tool into **actual practice** within workflows, including training, integration, support, and adaptation

Real-world **execution**, **fidelity**, and **sustainability** of use

- Is the tool being used as intended?
- Are workflows, training, and resources aligned?
- Are barriers and facilitators identified and addressed?

Example: The hospital **integrates** the early warning system into their daily rounding, **trains staff**, **modifies alerts**, and **evaluates outcomes**

Why Implementation matters?

- **Gap between innovation and implementation**
  - **Less than 15%** of digital health tools **move beyond pilot** testing into scaled clinical use
  - Some studies suggest only **5–10% are sustainably implemented in real-world** clinical settings
  - Among **AI tools, fewer than 1%** that are published in academic literature are **deployed** in live clinical environments
- **Reasons for low implementation**
  - Lack of integration with EHR systems
  - Poor user-centered design and workflow misalignment
  - Insufficient clinical validation or generalizability
  - Regulatory, reimbursement, and liability concerns
  - Lack of clinician trust and training

Mathews SC, McShea MJ, Hanley CL, Ravitz A, Labrique AB, Cohen AB. Digital health: a path to validation. NPJ Digit Med. 2019 May 13;2:38.

Yin J, Ngiam KY, Teo HH. Role of Artificial Intelligence Applications in Real-Life Clinical Practice: Systematic Review. J Med Internet Res. 2021 Apr 22;23(4):e25759.

Cozzolino C, Mao S, Bassan F, Bilato L, Compagno L, Salvò V, Chiusaroli L, Cocchio S, Baldo V. Are AI-based surveillance systems for healthcare-associated infections ready for clinical practice? A systematic review and meta-analysis. Artif Intell Med. 2025 Jul;165:103137

Implementation: Successful or not?

Case 1 - Successful prediction model

The Stability and Workload Index for Transfer score predicts unplanned intensive care unit patient readmission: Initial development and validation*

Ognjen Gajic, MD; Michael Malinchoc, PhD; Thomas B. Comfere, MD; Marcelline R. Harris, RN, PhD; Ahmed Achouiti, MD; Murat Yilmaz, MD; Marcus J. Schultz, MD; Rolf D. Hubmayr, MD; Bekele Afessa, MD; J. Christopher Farmer, MD

Objective: Unplanned readmission of hospitalized patients to an intensive care unit (ICU) is associated with a worse outcome, but our ability to identify who is likely to deteriorate after ICU dismissal is limited. The objective of this study is to develop and validate a numerical index, named the Stability and Workload Index for Transfer, to predict ICU readmission.

Design: In this prospective cohort study, risk factors for ICU readmission were identified from a broad range of patients' admission and discharge characteristics, specific ICU interventions, and in-patient workload measurements. The prediction score was validated in two independent ICUs.

Setting: One medical and one mixed medical-surgical ICU in two tertiary centers.

Patients: Consecutive patients requiring >24 hrs of ICU care.

Interventions: None.

Measurements: Unplanned ICU readmission or unexpected death following ICU dismissal.

Results: In a derivation cohort of 1,131 medical ICU patients, 100 patients had unplanned readmissions, and five died unexpectedly in the hospital following ICU discharge. Predictors of readmission/unexpected death identified in a logistic regression analysis were ICU admission source, ICU length of stay, and day of discharge neurologic (Glasgow Coma Scale) and respiratory (hypoxemia, hypercapnia, or nursing requirements for complex respiratory care) impairment. The Stability and Workload Index for Transfer score predicted readmission more precisely (area under the curve [AUC], 0.75; 95% confidence interval [CI], 0.70–0.80) than the day of discharge Acute Physiology and Chronic Health Evaluation III score (AUC, 0.62; 95% CI, 0.56–0.68). In the two validation cohorts, the Stability and Workload Index for Transfer score predicted readmission similarly in a North American medical ICU (AUC, 0.74; 95% CI, 0.67–0.80) and a European medical-surgical ICU (AUC, 0.70; 95% CI, 0.64–0.76), but was less well calibrated in the medical-surgical ICU.

Conclusion: The Stability and Workload Index for Transfer score is derived from information readily available at the time of ICU dismissal and acceptably predicts ICU readmission. It is not known if discharge decisions based on this prediction score will decrease the number of ICU readmissions and/or improve outcome. (Crit Care Med 2008; 36:676–682)

KEY WORDS: intensive care unit; management; organization; admission; discharge; risk; prediction score; patient readmission

Prior descriptive studies have demonstrated that critical care professionals vary decision parameters regarding who is ready to leave the unit according to workload pressure and ongoing demand for intensive care unit (ICU) beds (1–5), in part because the definitions and the determination of who is "sick" are highly variable. In fact, ICU admission and discharge criteria that are employed by individual practitioners are often subjective and may not be reproducible. Many practitioners rely on intuition and subjective clinical acumen to determine who is "ready" (as opposed to "safe") to leave the ICU. Even within the same ICU, and sometimes despite consistent nurse staffing patterns, these decision parameters can fluctuate daily (6). The impact of these inconsistencies is further magnified if insufficient numbers of qualified critical care professionals (physicians, nurses, allied health professionals) are available to provide bedside care (2). These personnel shortfalls exert powerful clinical and cost pressures on individual decision-makers, who are then forced to modulate critical care resource utilization through ICU patient triage (7).

Embedded in these transfer populations are individual patients who have a higher than recognized probability of clinical deterioration in the hours to days following ICU discharge. Published data indicate that these patients, on return to the ICU, experience a higher than predicted mortality (when adjusted for the acuity of illness and comorbidities) (8). In addition, in a busy ICU, communications

*See also p. 984.

From the Department of Internal Medicine and the Mayo Epidemiology and Translational Research in Intensive Care Program (OG, TBC, MY, RDH, BA, JCF), and the Departments of Health Sciences Research (MM, MRH) and Nursing (MRH), Mayo Clinic College of Medicine, Rochester, MN; and The Department of Intensive Care Medicine, University of Amsterdam, Amsterdam, Netherlands (AA, MJS).

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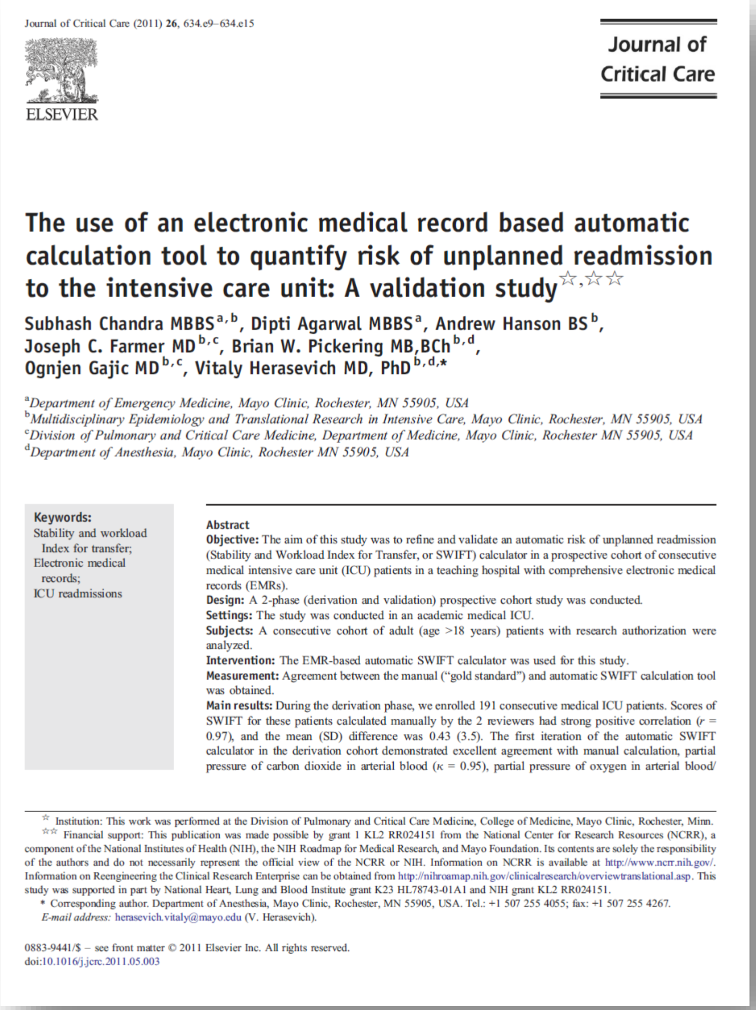
The SWIFT score predicted readmission **more precisely** (**AUC, 0.75**; 95% CI, 0.70–0.80) than the day of discharge APACHE III score (AUC, 0.62; 95% CI, 0.56–0.68).

Conclusion: The Stability and Workload Index for Transfer score is derived from information readily available at the time of ICU dismissal and **acceptably predicts ICU readmission.**

Gajic O, Malinchoc M, Comfere TB, et al. The Stability and Workload Index for Transfer score predicts unplanned intensive care unit patient readmission: initial development and validation. Crit Care Med 2008;36(3):676-82. PMID: 18431260

Implementation: Successful or not?

Case 1 - Successful Electronic Tool



Journal of Critical Care (2011) **26**, 634.e9–634.e15

ELSEVIER

Journal of Critical Care

The use of an electronic medical record based automatic calculation tool to quantify risk of unplanned readmission to the intensive care unit: A validation study☆,☆☆

Subhash Chandra MBBS[a,b], Dipti Agarwal MBBS[a], Andrew Hanson BS[b], Joseph C. Farmer MD[b,c], Brian W. Pickering MB,BCh[b,d], Ognjen Gajic MD[b,c], Vitaly Herasevich MD, PhD[b,d,*]

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Keywords:
Stability and workload Index for transfer;
Electronic medical records;
ICU readmissions

Abstract
Objective: The aim of this study was to refine and validate an automatic risk of unplanned readmission (Stability and Workload Index for Transfer, or SWIFT) calculator in a prospective cohort of consecutive medical intensive care unit (ICU) patients in a teaching hospital with comprehensive electronic medical records (EMRs).
Design: A 2-phase (derivation and validation) prospective cohort study was conducted.
Settings: The study was conducted in an academic medical ICU.
Subjects: A consecutive cohort of adult (age >18 years) patients with research authorization were analyzed.
Intervention: The EMR-based automatic SWIFT calculator was used for this study.
Measurement: Agreement between the manual ("gold standard") and automatic SWIFT calculation tool was obtained.
Main results: During the derivation phase, we enrolled 191 consecutive medical ICU patients. Scores of SWIFT for these patients calculated manually by the 2 reviewers had strong positive correlation (r = 0.97), and the mean (SD) difference was 0.43 (3.5). The first iteration of the automatic SWIFT calculator in the derivation cohort demonstrated excellent agreement with manual calculation, partial pressure of carbon dioxide in arterial blood (κ = 0.95), partial pressure of oxygen in arterial blood/

☆ Institution: This work was performed at the Division of Pulmonary and Critical Care Medicine, College of Medicine, Mayo Clinic, Rochester, Minn.
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doi:10.1016/j.jcrc.2011.05.003

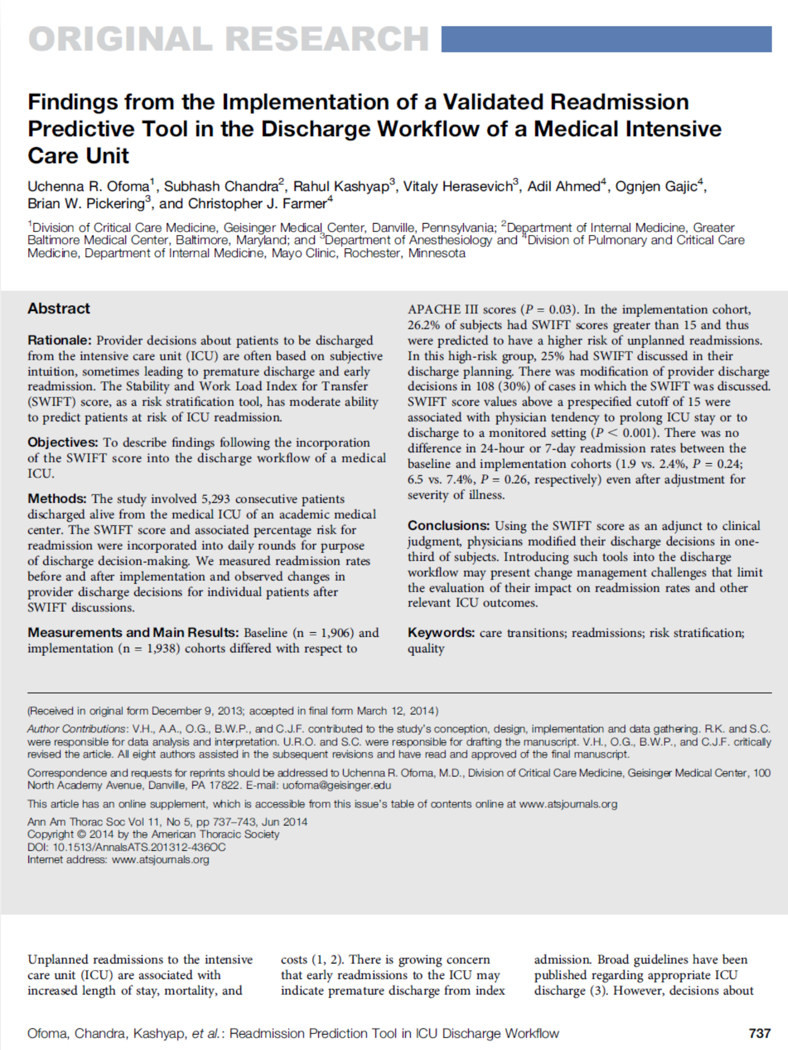
Main results: The automatic tool retained **excellent correlation with gold standard** calculation for SWIFT (r = 0.92), and the mean (SD) difference was −2.2 (5.5).

Conclusion: The EMR-based automatic tool accurately calculates SWIFT score and can facilitate ICU discharge decisions without the need for manual data collection.

Chandra S, Agarwal D, Hanson A, et al. The use of an electronic medical record based automatic calculation tool to quantify risk of unplanned readmission to the intensive care unit: A validation study. J Crit Care. 2011. PMID: 21715140

Implementation: Successful or not?

Case 1… No Impact


ORIGINAL RESEARCH

Findings from the Implementation of a Validated Readmission Predictive Tool in the Discharge Workflow of a Medical Intensive Care Unit

Uchenna R. Ofoma[1], Subhash Chandra[2], Rahul Kashyap[3], Vitaly Herasevich[3], Adil Ahmed[4], Ognjen Gajic[4], Brian W. Pickering[3], and Christopher J. Farmer[4]

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Abstract

Rationale: Provider decisions about patients to be discharged from the intensive care unit (ICU) are often based on subjective intuition, sometimes leading to premature discharge and early readmission. The Stability and Work Load Index for Transfer (SWIFT) score, as a risk stratification tool, has moderate ability to predict patients at risk of ICU readmission.

Objectives: To describe findings following the incorporation of the SWIFT score into the discharge workflow of a medical ICU.

Methods: The study involved 5,293 consecutive patients discharged alive from the medical ICU of an academic medical center. The SWIFT score and associated percentage risk for readmission were incorporated into daily rounds for purpose of discharge decision-making. We measured readmission rates before and after implementation and observed changes in provider discharge decisions for individual patients after SWIFT discussions.

Measurements and Main Results: Baseline (n = 1,906) and implementation (n = 1,938) cohorts differed with respect to APACHE III scores ($P = 0.03$). In the implementation cohort, 26.2% of subjects had SWIFT scores greater than 15 and thus were predicted to have a higher risk of unplanned readmissions. In this high-risk group, 25% had SWIFT discussed in their discharge planning. There was modification of provider discharge decisions in 108 (30%) of cases in which the SWIFT was discussed. SWIFT score values above a prespecified cutoff of 15 were associated with physician tendency to prolong ICU stay or to discharge to a monitored setting ($P < 0.001$). There was no difference in 24-hour or 7-day readmission rates between the baseline and implementation cohorts (1.9 vs. 2.4%, $P = 0.24$; 6.5 vs. 7.4%, $P = 0.26$, respectively) even after adjustment for severity of illness.

Conclusions: Using the SWIFT score as an adjunct to clinical judgment, physicians modified their discharge decisions in one-third of subjects. Introducing such tools into the discharge workflow may present change management challenges that limit the evaluation of their impact on readmission rates and other relevant ICU outcomes.

Keywords: care transitions; readmissions; risk stratification; quality

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Author Contributions: V.H., A.A., O.G., B.W.P., and C.J.F. contributed to the study's conception, design, implementation and data gathering. R.K. and S.C. were responsible for data analysis and interpretation. U.R.O. and S.C. were responsible for drafting the manuscript. V.H., O.G., B.W.P., and C.J.F. critically revised the article. All eight authors assisted in the subsequent revisions and have read and approved of the final manuscript.

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This article has an online supplement, which is accessible from this issue's table of contents online at www.atsjournals.org

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Internet address: www.atsjournals.org

Unplanned readmissions to the intensive care unit (ICU) are associated with increased length of stay, mortality, and costs (1, 2). There is growing concern that early readmissions to the ICU may indicate premature discharge from index admission. Broad guidelines have been published regarding appropriate ICU discharge (3). However, decisions about

Main results: There was no difference in 24-hour or 7-day readmission rates between the baseline and implementation cohorts (1.9 vs. 2.4%, P = 0.24; 6.5 vs. 7.4%, P = 0.26, respectively) even after adjustment for severity of illness.

Conclusions: Using the SWIFT score as an adjunct to clinical judgment, physicians <u>modified their discharge decisions in one third of subjects</u>. Introducing such tools into the discharge <u>workflow may present change management challenges</u> that limit the evaluation of their impact on readmission rates and other relevant ICU outcomes.

Ofoma UR, Chandra S, Kashyap R, et al. Findings from the Implementation of a Validated Readmission Predictive Tool in the Discharge Workflow of a Medical Intensive Care Unit. Ann Am Thorac Soc. 2014. PMID: 24724964)

Implementation: Successful or not?

Case 2 - Epic

- **Widespread Adoption**
  - > 300 healthcare organizations, >78% of the U.S. hospital market for acute care hospitals
- **Interoperability Leadership**
  - Care Everywhere - health data exchange, >600 million records shared across organizations monthly
- **Scalability**
  - Successfully deployed in large, complex healthcare systems
- **User-Centered Customization**
  - Custom configurations of Epic to match workflows, decision support tools, integration with patient portals
- **Outcomes**
  - Reported improvements in patient safety, billing accuracy, and clinician documentation consistency

Implementation: Successful or not?

Case 2 – Epic in MD Anderson Cancer Center

Epic

- **2013-2014 - Transition to Epic EHR system began**
- **Challenges**
  - Cost overruns: original $62M budget ballooned to over $450M
  - Clinical workflow disruption and user dissatisfaction
  - Revenue cycle complications due to billing and coding changes
- **Outcome**
  - Despite the setbacks, Epic was ultimately implemented, but the institution paused parts of the project in 2016 and reassessed its deployment approach
- **Lesson**
  - Even a widely successful system like Epic requires tailored planning, clinician buy-in, and organizational readiness

BECKER'S
HOSPITAL REVIEW

Financial Management

MD Anderson points to Epic implementation for 77% drop in adjusted income

Houston-based MD Anderson Cancer Center reported a 76.9 percent drop in adjusted income for the 10 months ended June 30, a downfall it largely attributes to its Epic EHR implementation project.

MD Anderson to cut about 1,000 jobs

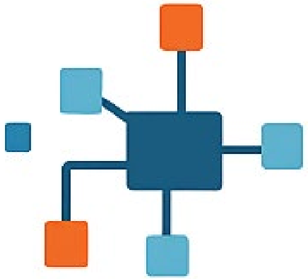
The University of Texas MD Anderson Cancer Center in Houston plans to eliminate about 1,000 jobs, or 5 percent of its 20,000-person workforce, as it tries to improve its financial health.

Rice S. "MD Anderson blames Epic EHR for $77 million revenue loss." Healthcare IT News, March 23, 2017.

Challenges in Implementation

Limited Utilization

Even when digital systems are in place, they are often used only for basic functions only



Interoperability Issues

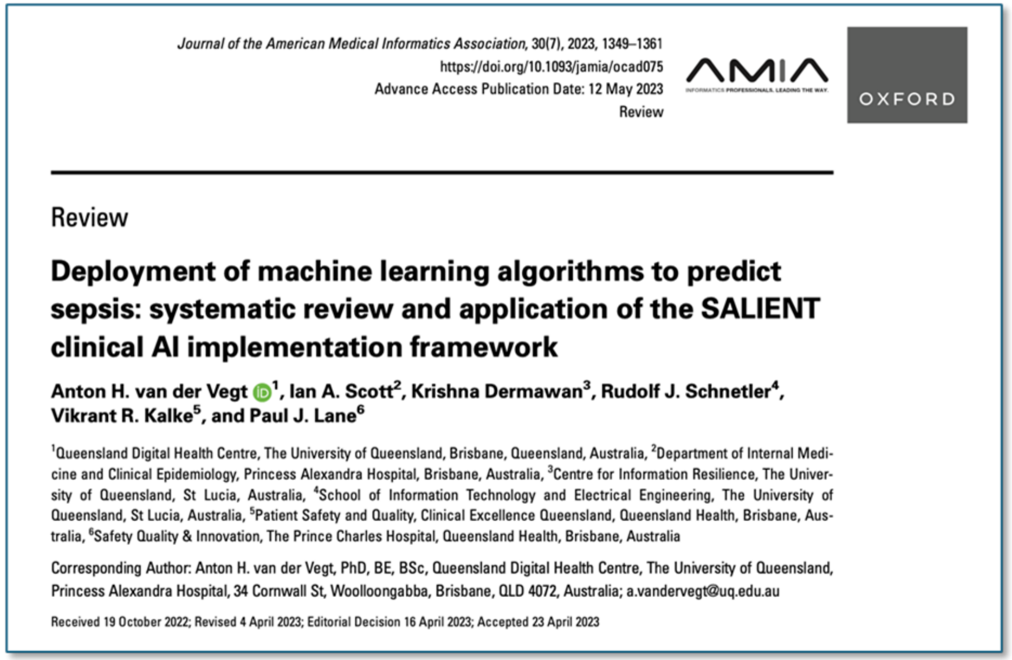
A lack of integration between different systems can lead to inefficiencies and errors

Training and Support

Insufficient staff training and support leads to underutilization and resistance to adopting new technologies.

- **Adoption** of digital health tools is **increasing**
- **Full implementation** and effective use remain **inconsistent**
- **Comprehensive strategies** that address technological, organizational, and human factors are **needed**

Systematic Review of AI Implementation in Sepsis Care


Journal of the American Medical Informatics Association, 30(7), 2023, 1349–1361
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Review

AMIA

OXFORD

Review

Deployment of machine learning algorithms to predict sepsis: systematic review and application of the SALIENT clinical AI implementation framework

Anton H. van der Vegt[1], Ian A. Scott[2], Krishna Dermawan[3], Rudolf J. Schnetler[4], Vikrant R. Kalke[5], and Paul J. Lane[6]

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Results: 30 studies of AI-based sepsis prediction algorithms applied in adult hospital settings.
Identified 14 barriers (e.g., lack of trust, workflow misfit, poor data quality),
26 enablers (e.g., clinical champions, integration into workflow), and
22 decision points which were mapped to the SALIENT framework, which outlines 5 stages of clinical AI implementation: Pre-implementation, Development, Pilot, Rollout, and Sustainment

Insights: Most successful implementations had strong governance, ongoing evaluation, and iterative feedback loops with end users.
Common pitfalls included poor clinician engagement early in development, overreliance on retrospective validation, and inadequate post-deployment monitoring

van der Vegt AH, Scott IA, Dermawan K, Schnetler RJ, Kalke VR, Lane PJ. Deployment of machine learning algorithms to predict sepsis: systematic review and application of the SALIENT clinical AI implementation framework. J Am Med Inform Assoc. 2023 Jun 20;30(7):1349-1361. PMID: 37172264

Barriers to Digital Tool Implementation

Technological Barriers

- Limited interoperability
- Legacy system incompatibility
- Performance issues

Human and Cultural Barriers

- Clinician resistance
- Lack of trust
- Privacy concerns

Organizational Barriers

- Change management
- Inadequate training and support
- Lack of leadership and governance

Financial Barriers

- Budget constraints
- Funding priorities
- Cost-benefit analysis

Steps to Successful Digital Tool Implementation

1. Define the Problem and the Goal
2. Engage Stakeholders early
3. Assess Context and Readiness
4. Select or Design the Tool
5. Pilot in a Controlled Setting
6. Train and Support
7. Integrate into Workflow
8. Monitor Use and Outcomes
9. Iterate and Improve
10. Scale and Sustain

Case Example: CEDAR Implementation into clinical practice at Mayo Clinic

- Tool: Clinical Deterioration Alert System (CEDAR)
- Phased implementation approach
- Outcome tracking: reduction in unexpected ICU transfers
- Lessons learned: importance of alert fatigue management and nurse engagement

Choose Strategic Framework for Implementation

- Utilize implementation science frameworks (e.g., SALIENT, QUERI, RE-AIM, CFIR)
- Homegrown tools must:
  - Be high quality
  - Fit clinical needs
  - Integrate with workflows
- - Measure success via:
  - Adoption, outcomes, satisfaction
  - Fe

Goodrich DE, Miake-Lye I, Braganza MZ, Wawrin N, Kilbourne AM. The QUERI Roadmap for Implementation and Quality Improvement [Internet]. Washington (DC): Department of Veterans Affairs (US); 2020

van der Vegt AH, Scott IA, Dermawan K, Schnetler RJ, Kalke VR, Lane PJ. Implementation frameworks for end-to-end clinical AI: derivation of the SALIENT framework. J Am Med Inform Assoc. 2023 Aug 18;30(9):1503-1515.

Phase 1 – Pre-Implementation / Planning

- Assess implementation context to identify barriers, facilitators, and change strategies
- Prepare multidisciplinary stakeholders to be involved in implementation
- Refine the digital tool to meet user needs and fit clinical workflows
- Determine readiness for pilot implementation

Phase 2 – Pilot Implementation

- Pilot CEDAR implementation in clinical workflows
- Support users and identify potential barriers for full implementation
- Identify units for additional testing, implement it in those units, test implementation in Plan-Do-Study-Act cycles
- Determine readiness for full implementation and scale-up
- Develop plan for large-scale implementation

Phase 3 – Sustainment and Scale-up

- Evaluate CEDAR effectiveness and implementation at scale
- Share results with key stakeholder groups
- Identify readiness for sustainability and further scale-up to new sites
- Develop CEDAR comprehensive documentation of lessons learned
- Document lessons learned to refine future CEDAR dissemination and sustainment strategies

Key Success Factors / Lessons Learned

- Stakeholder engagement must begin pre-implementation
- Co-design is critical to ensure relevance and usability
- Phased rollout allows adjustment before full-scale deployment
- Continuous monitoring and adaptation are non-negotiable
- Digital tool implementation must be aligned with institutional strategic priorities

Conclusion

- Successful digital tool implementation in hospital and ICU settings requires thoughtful planning, strong leadership, multidisciplinary collaboration, and continuous evaluation.
- Tailoring approaches to the local context and actively involving end-users are critical to ensuring adoption and impact.

Takeaway Messages

- Implementation success is not guaranteed by tool quality alone — it requires alignment with user needs, workflows, and context
- Alarm fatigue, low trust, and poor integration continue to challenge adoption
- A staged approach using frameworks like SALIENT or CFIR helps anticipate and mitigate barriers
- Low-budget or homegrown tools can succeed through co-design, adaptability, and close clinician partnership
- Monitoring and iteration are essential — implementation is not a one-time event but a continuous process

"Successful digital implementation isn't about pushing technology—it's about enabling people to do their best work."

Thank you!
Questions?

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