Technology and Innovation in Care Transitions

Imagining the Future of Postdischarge Care

Jorge A. Rodriguez, MD[a,b,*], Anuj K. Dalal, MD[a,b]

KEYWORDS

• Care transitions • Telehealth • Wearable devices • Artificial intelligence • Readmission prevention • Digital health • Care coordination • Remote patient monitoring

KEY POINTS

- Care transitions are high-risk periods with up to 20% to 28% of patients experiencing adverse events (AEs) and readmissions in the 30 days postdischarge.
- Synchronous telehealth serves as an alternative to in-person follow-up, while remote patient monitoring addresses gaps in episodic care through detection of deterioration and proactive intervention.
- Artificial intelligence applications span predictive analytics for readmission risk stratification, generative tools for documentation and patient education, and emerging capabilities for integrating multimodal monitoring data, though all require clinician-in-the-loop frameworks that augment rather than replace clinical judgment.
- Implementation success depends on aligning technology with clinical workflows, ensuring patient engagement, and addressing equity, privacy, and reimbursement barriers.
- Key priorities include research measuring AEs rather than readmissions, implementation studies in diverse settings, and advocacy for value-based payment models that reward outcomes over volume.

INTRODUCTION

The transition from hospital to home or another care setting is a vulnerable period during which patients are at an elevated risk for clinical deterioration, readmission, and adverse events (AE). Despite advances in discharge planning and transitional care programs, patients continue to experience high AE rates: up to 20% to 28% have an AE and/or are readmitted within 30 days after discharge.[1–4] These events contribute to significant patient morbidity and health care costs. Adverse outcomes,

[a] Harvard Medical School, Boston, MA, USA; [b] Division of General Internal Medicine and Primary Care, Brigham and Women's Hospital, Boston, MA, USA
* Corresponding author.
E-mail address: jarodriguez1@mgb.org

Med Clin N Am 110 (2026) 681–693
https://doi.org/10.1016/j.mcna.2025.11.005 medical.theclinics.com

Abbreviations	
AEs	adverse events
AI	artificial intelligence
COPD	chronic obstructive pulmonary disease
HER	electronic health record
LLM	large language model
RPM	remote patient monitoring
TCM	Transitional Care Management

including hospital readmission, account for more than US$17 billion in avoidable Medicare costs.[5]

Technological innovations, including mobile and web applications (eg, patient portals), wearable sensors, and artificial intelligence (AI), are increasingly applied to bridge the gap between inpatient and outpatient care facilitated by synchronous and asynchronous telehealth delivery models.[6] Early evidence suggests that these tools can improve monitoring, facilitate timely interventions, and enhance coordination across care settings. This article reviews current evidence and innovations in 3 domains: (1) telehealth and remote patient monitoring in postdischarge care, (2) AI-driven readmission risk assessment, and (3) future digital solutions for care coordination.

DIGITAL TECHNOLOGIES IN POSTDISCHARGE CARE: TELEHEALTH AND REMOTE PATIENT MONITORING

Definitions

Understanding the landscape of digital innovations in care transitions requires distinguishing between core technologies and the care delivery models they enable (**Table 1**). Core technologies include the digital building blocks: wearable devices and sensors that collect physiologic and activity data; mobile and web applications that facilitate data collection, communication, and patient engagement; cloud infrastructure that securely stores and processes data while enabling dashboards and alerts; and AI that analyzes data to predict risk, detect patterns, or automate tasks.

These technologies are integrated into care delivery models that restructure how postdischarge care is provided. Telehealth is an umbrella term encompassing both synchronous (real-time video or phone) and asynchronous (secure messaging and remote data review) communication between patients and clinicians. Remote patient monitoring (RPM) is a specific form of asynchronous telehealth that integrates wearables, apps, cloud analytics, and often AI into structured workflows for continuous or scheduled surveillance of patient health status between traditional encounters. RPM enables longitudinal tracking of physiologic trends, medication adherence, and patient-reported symptoms during the vulnerable postdischarge period.

Synchronous Telehealth for Postdischarge Follow-up

Early postdischarge follow-up has been recognized as critical for preventing adverse outcomes. Traditional approaches include in-person visits within 7 to 14 days of discharge and proactive telephone outreach by nurses or care coordinators. Medicare's Transitional Care Management (TCM) billing codes have supported adoption of these practices by reimbursing providers for postdischarge communication (within 2 business days) and a follow-up visit (within 7 or 14 days).[7]

Telehealth has emerged as an alternative modality to deliver this early follow-up, particularly for patients facing transportation barriers, mobility limitations, or geographic distance from care. Telehealth use for postdischarge follow-up surged during the

Table 1
Technologies for care transitions

	Definition	Example
Technology		
Wearable devices and sensors	Devices worn or used by patients to passively or actively collect physiologic data, activity metrics, or patient-reported outcomes	Smartwatches (heart rate and activity), pulse oximeters, smart scales, blood pressure cuffs, continuous glucose monitors, and medication adherence sensors
Mobile and web applications	Software platforms that collect data from devices, enable patient self-reporting, facilitate communication, and deliver education	Apps for symptom tracking, medication reminders, secure messaging, video visit platforms, and patient portals
Cloud infrastructure	Secure data storage, processing, and analytical platforms that aggregate multimodal data and enable clinician dashboards	EHR-integrated data repositories, FHIR-compliant data exchange, real-time monitoring dashboards, and alert notification systems
AI and predictive analytics	Algorithms that analyze data to predict risk, detect patterns, personalize interventions, or automate tasks	Readmission risk models, early warning systems for clinical deterioration, LLMs for documentation, and chatbots for patient support
Care Delivery Models		
Synchronous telehealth	Real-time, interactive communication between patients and clinicians	Video visits for postdischarge follow-up, phone calls for symptom assessment, and virtual urgent care consultations
Remote patient monitoring (asynchronous telehealth)	An asynchronous telehealth approach that integrates wearables, apps, and cloud analytics for longitudinal surveillance of patient health status between clinical encounters	Postdischarge heart failure monitoring (daily weights, symptoms, and activity), COPD monitoring (pulse oximetry and inhaler use), and diabetes management (continuous glucose monitors)

Abbreviations: COPD, chronic obstructive pulmonary disease; EHR, electronic health record; FHIR, fast healthcare interoperability resources; LLM, large language model.

coronavirus disease 2019 pandemic with Anderson and colleagues[8] finding an increase in the proportion of TCM visits delivered via telehealth. Its use has stabilized at levels higher than prepandemic baselines, creating both opportunities and an imperative to understand its effectiveness.

Evidence for telehealth's impact on postdischarge outcomes is mixed, though support exists in specific populations. Medicare data provide encouraging evidence that telehealth performs comparably to established in-person follow-up. Among patients hospitalized for acute myocardial infarction, chronic obstructive pulmonary disease, heart failure, or pneumonia, timely follow-up within 7 days of discharge via telehealth yielded 30 day readmission rates (19.1%) comparable to in-person visits (17.2%) and substantially lower than no follow-up (23.2%).[9] Horman and colleagues[10] showed that a virtual transitions of care clinic had significantly lower readmissions rate compared to usual care (14.9% vs 20.1%) with the higher readmission reduction occurring among patients with moderate readmission risk. Similarly, Elsener and colleagues[11] found a post-discharge telehealth approach reduced 30 day readmission (9.8% vs 11%). Systematic reviews have further demonstrated that, among older adults, telehealth interventions were associated with reduced readmission rates and improved quality of life, but not reduction in emergency department visits or improvements in functional status.[12]

However, not all reported findings were favorable. A randomized controlled trial comparing video visits 2 to 5 days postdischarge to usual care did not improve adherence to discharge recommendations.[13] In a recent pragmatic trial, Masterson Creber and colleagues[14] found that adding a more intensive intervention, including a telehealth visit with an emergency medicine physician, to a standard postdischarge phone call did not reduce 30 day readmission or improve health status compared to the phone call alone. These findings suggest that telehealth intensity alone may not be sufficient without other care redesign elements.

Taken together, these findings suggest that telehealth can serve as an effective modality for postdischarge follow-up, particularly when it replaces no follow-up or facilitates earlier contact than in-person visits allow. However, telehealth alone, without accompanying care pathway redesign, risk stratification, or multidisciplinary coordination, appears insufficient to meaningfully reduce readmissions.

While effective for many patients, synchronous telehealth shares a fundamental constraint with traditional in-person care: both rely on scheduled, episodic encounters. Between these scheduled contacts several care gaps emerge. Clinical deterioration may progress undetected when patients do not recognize warning signs or know when to seek help. Episodic encounters capture only snapshots rather than trends, potentially missing gradual changes in weight, activity, or symptoms that signal decompensation. Care depends on patient-initiated contact when problems arise, which may be delayed by uncertainty or access barriers. These inherent limitations of episodic care models have driven development of remote patient monitoring as a complementary approach.

Remote Patient Monitoring

Remote patient monitoring addresses gaps in episodic care by providing continuous surveillance between scheduled encounters. Where synchronous telehealth visits capture snapshots, RPM tracks trends; where visits rely on patient recall, RPM collects data through wearable sensors and connected devices; and where traditional care waits for patient-initiated contact, RPM enables proactive outreach based on physiologic parameters, medication adherence, and symptom patterns. Tan and colleagues[15] reviewed diverse RPM modalities, including communication platforms, smartphone applications, augmented clinical devices, wearables, and standard clinical tools for intermittent monitoring. RPM was found to improve patient safety, adherence, and mobility. However, its effect on other clinical and quality of life measures was unclear. Studies suggested cost-related improvements in risk of readmission, length of stay, and number of outpatient visits. A systematic review and meta-analysis of randomized controlled trials found that electronic health record (EHR)-based interventions, most commonly involving telemonitoring following discharge, were associated with reductions in 30 and 90 day readmission compared to control.[16]

Limitations and Challenges

Several barriers limit the effectiveness and scalability of telehealth and remote patient monitoring in care transitions. Payment model misalignment represents a key challenge: fee-for-service systems reimburse episodic encounters rather than preventive monitoring. Under traditional fee-for-service, clinical teams lack financial incentives to invest in technologies that reduce billable encounters, and existing billing codes require administrative burdens that often offset financial benefits. In contrast, value-based payment models, including Accountable Care Organizations, better align incentives with preventive goals.

Workflow integration remains problematic as most technological systems operate parallel to rather than embedded within EHRs, creating information silos and requiring separate logins and data review outside clinicians' standard workflows.[17–19] Sustained patient engagement poses challenges as adherence to monitoring protocols often declines over time despite initial motivation.[20] Alert fatigue from poorly configured thresholds generates overwhelming notification volumes, many representing normal variation rather than clinically significant changes.[21,22] Finally, return on investment remains uncertain for many organizations. While some studies show reduced readmissions, the financial benefit depends on payment model and patient population.

THE ROLE OF ARTIFICIAL INTELLIGENCE IN CARE TRANSITIONS

Definitions

AI, referring to the capability of computers to perform complex tasks typically requiring human intelligence, is increasingly shaping care transitions.[23] Machine learning, a core subset of AI, leverages algorithms trained on diverse data sources, such as structured EHRs, insurance claims, and patient-reported outcomes, to predict which patients are at greatest risk for hospital readmission. These predictive capabilities support clinicians in targeting interventions and coordinating follow-up care more effectively. Recent advances in generative AI, AI designed to create new multimodal content via prompts, have further expanded the potential role of AI in care transitions. Generative AI refers to AI systems, such as large language models (LLMs), that are designed to create new content including text, images, or audio, based on patterns learned from existing data. These models can automate tasks like writing discharge summaries or patient instructions by generating human-like output from prompts.

Current applications focus primarily on text, including clinical discharge summaries and clear, patient-facing discharge instructions. Additionally, AI-powered scribe tools are now being used to capture clinical interactions and automate documentation, streamlining communication and reducing administrative burdens during the postdischarge period. Emerging video-based AI capabilities offer the potential for generating personalized patient education (eg, medication administration) and analyzing patient-recorded videos (eg, gait and inhaler technique) to detect concerning changes, though these applications remain largely investigational in care transitions. Collectively, these innovations underscore AI's growing potential in enhancing the safety, efficiency, and personalization of care transitions.

Readmission Prediction

Identifying patients at high risk for readmission to target for intervention has been a central focus in care transitions research for over a decade. Compared to traditional clinical prediction scores such as LACE and HOSPITAL, AI models often incorporate broader feature sets, capture nonlinear relationships, and can be continuously updated with new data.[24,25] Recent disease-specific and system-wide implementations have demonstrated improved predictive accuracy and clinical outcomes. In a health system implementation, a chronic obstructive pulmonary disease-specific neural network model analyzed hospitalization data to identify high-risk patients and trigger targeted interventions including intensive care management and early outpatient follow-up. This approach reduced 30 day readmissions from 15.2% to 7.9% among high-risk patients over a 1 year period.[26] Bennett and colleagues[27] tested a decision support tool, in a safety-net setting, which included a machine learning algorithm that identified patients at highest risk of readmission. This allowed population health teams to proactively contact high-risk patients, address barriers to follow-up, and coordinate outpatient care. The intervention led to a decline in readmission rates from 27.9% to 23.9% ($P < .004$) and eliminated racial disparities in readmission rates.

It is important to note that not all readmissions represent failures.[28] For example, AI-based remote monitoring programs may detect patients experiencing clinical deterioration from disease progression earlier despite optimal evidence-based treatment and management, thereby leading to more timely and appropriate intervention, including hospital readmission. While these interventions may reduce AEs like emergency department visits for ambulatory-sensitive conditions or medication errors, they might not reduce overall readmission rates. Therefore, specific outcome measures beyond all-cause readmission rates are needed as the gap between algorithmic performance and clinical utility remains a significant barrier to widespread adoption.

Generative Artificial Intelligence

Beyond predictive models, generative AI is emerging as a tool for automating documentation and communication tasks in care transitions. The primary uses of LLMs (eg, ChatGPT) in care transitions has been generating discharge summaries and postdischarge instructions for patients. The results of these studies have shown early promise in increasing the production efficiency of these important documents. When comparing LLM-generated and physician-generated discharge summaries, Williams and colleagues[29] found that there was no difference in blinded rating of quality and preference. However, LLM-generated summaries were likely to contain errors, though these were found to be of low harm. Extending to patient-facing information, Zaretsky and colleagues[30] found that LLMs generated patient-facing discharge instructions with improved readability and understandability scores compared to standard instructions. However, concerns regarding factual accuracy, completeness, and safety persisted. Together, these studies highlight the opportunity for LLMs to improve discharge communication efficiency but underscore ongoing challenges with accuracy and safety that require human oversight. Critical considerations include the risk of AI “hallucinations” (plausible-sounding but incorrect information), the need for clinician review before patient delivery, and questions about liability when AI-generated content leads to patient harm. Current best practice positions these tools as assistants within a clinician-in-the-loop framework that requires human review. This approach ensures clinical oversight while leading to improvements in clinician perceived burden.

Limitations and Challenges

Critical challenges constrain the use of AI in care transitions. Technical and data limitations include missing values, documentation inconsistencies, lack of standardization across settings, and, for LLMs, token limits that restrict how much information can be processed simultaneously. Computational costs for training and deploying models may limit their broad use. Algorithmic bias perpetuates disparities when training data reflect biased practices or differential access, requiring rigorous bias testing and mitigation strategies.[31] Clinician trust requires explainability, yet black-box models that provide predictions without reasoning undermine adoption and clinical judgment. Implementation gaps persist, including poor workflow integration, unclear action guidance, insufficient intervention resources, and alert fatigue from false positives decreases the likelihood of even accurate models from improving clinical outcomes. Regulatory frameworks remain inconsistent, with evolving questions about validation requirements, liability, and governance standards for deployment and monitoring.

IMPLEMENTATION STRATEGIES

Importantly, the potential of digital technologies in care transitions depends on effective implementation that extends beyond technical deployment to encompass workflow redesign, multidisciplinary design, and team training. These efforts should be grounded in implementation science frameworks such as RE-AIM (Reach, Effectiveness, Adoption, Implementation, Maintenance), which provides a structured approach to scaling evidence-based programs.[32]

Clinical Workflow Integration

Technologies must be embedded within existing EHR and care workflows. This requires interoperability standards, single sign-on systems, and interfaces that present actionable information at the point of care. Successful implementations often include dedicated roles (eg, remote monitoring nurses and care coordinators) who manage technology-mediated care and bridge between automated systems and clinical teams. For example, rather than requiring clinicians to log into separate portals to review monitoring data, effective systems present prioritized alerts within the EHR, summarize trends in dashboards accessible during patient chart review, and provide clear decision support (eg, “Patient meets criteria for medication adjustment”). Alert design is critical: systems should suppress low-priority notifications, escalate high-priority alerts through multiple channels, and provide context (trending data, not just single values) to support clinical judgment.

Beyond technical integration, implementation must also address data governance, including compliance with Health Insurance Portability and Accountability Act and state privacy laws, security protocols for patient-generated health data, consent processes that clearly explain data use and sharing, and policies for data retention and patient access rights. Business Associate Agreements with technology vendors, regular security audits, and staff training on privacy protection are essential infrastructure components.

Multidisciplinary Design and Operation

Technology-enabled care transitions require coordination across multiple disciplines. Care transitions require communication between clinicians, nursing, care managers, social workers, and many other health care team members. Technologies should facilitate teamwork through shared dashboards, structured communication tools, and clearly defined roles for responding to alerts and patient needs.

Effective patient onboarding is critical to program success. This includes assessing digital literacy and providing tailored device training, setting clear expectations about monitoring frequency and clinician response times, demonstrating personal value through early feedback on their data, and ensuring ongoing technical support. Programs should plan for diverse patient needs by offering phone-based alternatives for those uncomfortable with apps, providing multilingual support, and addressing cost barriers through device loan programs. Successful implementations pair technology with human connection, using initial technology-mediated interactions to build trust rather than replacing personal contact entirely.

Clinical Team Training

Successful implementation requires comprehensive training that addresses both technical skills and conceptual shifts in care delivery. Clinical teams need training not only in using monitoring platforms and interpreting dashboards but also in understanding how technology changes their role from reactive to proactive care. Training should address workflow integration (when and how to review data), clinical decision-making (what changes warrant intervention), and communication strategies (discussing monitoring data with patients). Ongoing education through case reviews, peer learning, and feedback on outcomes helps teams refine their approach. Equally important is addressing concerns by providing forums for clinical teams to voice workflow concerns and demonstrating time savings or improved outcomes.

FUTURE TRENDS IN DIGITAL SOLUTIONS FOR CARE TRANSITIONS

As technology continues to evolve, there are notable opportunities to advance care transitions through digital innovation.

Health Equity

A key gap in the current technology landscape is the inadequate focus on health equity and digital inclusion. Digital inclusion gaps persist across multiple dimensions: access (smartphone and broadband availability), affordability (data plans and device costs), and experience (digital literacy and interface design).[33] Older adults, rural residents, those with low incomes, and individuals with non-English language preference face disproportionate barriers.[34,35] For example, patients with non-English language preference report worse video visit experience compared to patients with English language preference.[36] Research should systematically examine how socioeconomic status, race and ethnicity, geographic location, and digital literacy intersect to affect both adoption and outcomes of technology-enabled care transitions. Promising approaches to enhance equity include developing low-bandwidth alternatives for areas with limited broadband infrastructure, creating adaptive interfaces that adjust to users' digital literacy levels, and providing multilingual support beyond simple translation to address cultural preferences and health literacy.[37] Critically, research must move beyond simply documenting disparities to testing interventions that actively reduce them. This includes community-based participatory research with underserved populations, economic evaluations that consider patient out-of-pocket costs, and studies examining whether technology substitutes for or supplements traditional care access.

Patient and Care Partner Engagement

While the importance of patient and care partner engagement is acknowledged in current models, this area requires further exploration and innovation. Future research should leverage behavioral economics strategies including gamification and nudges, employ codesign methodologies that involve patients in technology development, and develop personalization approaches that tailor interventions to individual preferences and needs. One promising approach involves conversational AI interfaces, including chatbots and voice assistants, that may enhance engagement by providing on-demand, personalized support. These tools can deliver real-time symptom triage, medication reminders, condition-specific education, and emotional support.

Artificial Intelligence and Remote Patient Monitoring

A frontier in care transitions involves integrating AI in the analysis of continuous RPM data streams to enable proactive, personalized care. Rather than reactive responses to thresholds, AI can detect subtle deviations from individualized baselines, recognize complex multiparameter patterns predictive of deterioration, and stratify urgency to prioritize clinician attention.[38] Wearables generate large volumes of multimodal data (eg, heart rate, activity levels, and sleep quality) that exceed clinicians' capacity to manually review and synthesize. AI-powered dashboards that integrate these data streams, identify trends, and provide actionable summaries may reduce information overload while improving clinical decision-making.[39]

Near-term innovations focus on refining these capabilities through better algorithms and expanded data sources. AI can dynamically adjust monitoring frequency and care intensity based on individual recovery trajectories, increasing surveillance when early warning signs emerge and scaling back for stable patients. This adaptive approach focuses resources on those with evolving risks while reducing burden on low-risk patients. Natural language processing of patient-reported symptoms through messaging or voice interfaces can supplement sensor data, providing richer context for clinical decision-making. Integration of social determinants data (eg, transportation barriers, food insecurity, and social isolation) with physiologic monitoring may improve risk stratification and intervention targeting. These incremental improvements build on existing infrastructure and clinical workflows, representing enhancements rather than fundamental redesigns.

Medium-term innovations may include multimodal sensing beyond traditional wearables, including voice analysis to detect dyspnea or depression, ambient sensors for home safety monitoring (eg, fall detection, activity patterns), and computer vision analysis of patient-recorded videos (eg, gait assessment, wound healing, and inhaler technique). Digital twins that simulate individual patient trajectories under different treatment scenarios could support shared decision-making and personalized care planning. Models that continuously learn from each patient's unique patterns and response to interventions, rather than relying solely on population-level training data, may improve prediction accuracy and reduce false alerts. These applications require additional validation and workflow integration but leverage maturing technologies.

Building trust in AI-enhanced care transitions requires demonstrating value through incremental, interpretable improvements before pursuing more autonomous approaches. While more speculative directions such as agentic AI systems that orchestrate workflows autonomously have been proposed, near-term focus should remain on augmenting rather than replacing clinical judgment; using AI to surface relevant information, suggest actions for clinician consideration, and reduce information overload while keeping humans firmly in decision-making roles.

SUMMARY

Digital technologies are reshaping transitional care through telehealth-enabled follow-up, wearable-based continuous surveillance, and AI-driven risk stratification. Evidence demonstrates these tools can improve outcomes when integrated into redesigned care pathways, though current studies are often small, single-center, or focused on narrow populations. Importantly, outcome measurement must distinguish between preventable AEs and appropriate readmissions reflecting timely clinical response to deterioration.

The next generation of technology-enabled transitional care must prioritize equitable design that includes underserved populations, interoperable platforms embedded within clinical workflows, transparent AI systems operating within clinician-in-the-loop frameworks, and implementation strategies addressing workflow integration, team training, and patient engagement. Most fundamentally, payment model reform is essential: fee-for-service reimbursement creates structural barriers to technologies designed for population health management, requiring transition toward value-based models that reward prevention over volume.

Achieving impact requires moving beyond technological feasibility to address organizational, financial, and equity barriers. Immediate priorities include comparative effectiveness research measuring AEs, implementation studies in diverse settings, and policy advocacy for value-based payment. Success depends on sustained partnership among technology developers, delivery systems, payers, policymakers, and patients and their care partners.

CLINICS CARE POINTS

- Telehealth and wearable devices may reduce postdischarge adverse events and readmissions when embedded in structured, responsive workflows.
- Use AI risk prediction to prioritize which patients receive intensive follow-up but maintain clinical judgment in final decisions; focus on preventing adverse events (medication errors, preventable readmissions, and falls) rather than reducing all-cause readmissions.
- Ensure that monitoring platforms integrate with the electronic health record, present actionable alerts within existing workflows, and provide clear guidance on what actions to take.
- During discharge planning, assess digital literacy and provide hands-on device training; set clear expectations about monitoring frequency and response times; ensure technical support is readily available; offer phone-based alternatives when needed.

DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this article, the authors used Gen AI. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

FUNDING

J.A. Rodriguez is supported by a grant from the National Institute on Minority Health and Health Disparities (K23MD016439). A.K. Dalal is supported by a grant from the Agency for Healthcare Research and Quality (R01HS028662).

REFERENCES

1. Forster AJ, Murff HJ, Peterson JF, et al. Adverse drug events occurring following hospital discharge. J Gen Intern Med 2005;20(4):317–23.
2. Kanaan AO, Donovan JL, Duchin NP, et al. Adverse drug events after hospital discharge in older adults: types, severity, and involvement of beers criteria medications. J Am Geriatr Soc 2013;61(11):1894–9.
3. Tsilimingras D, Schnipper J, Duke A, et al. Post-discharge adverse events among urban and rural patients of an urban community hospital: a prospective cohort study. J Gen Intern Med 2015;30(8):1164–71.

4. Forster AJ, Murff HJ, Peterson JF, et al. The incidence and severity of adverse events affecting patients after discharge from the hospital. Ann Intern Med 2003;138(3):161–7.
5. Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the medicare fee-for-service program. N Engl J Med 2009;360(14):1418–28.
6. Rodriguez JA, Rudin RS, Dalal AK. Digitally powered care transitions: a paradigm shift for hospital medicine. J Hosp Med 2024;19(8):739–43.
7. Transitional care coverage. Available at: https://www.medicare.gov/coverage/transitional-care-management-services. Accessed October 20, 2025.
8. Anderson TS, O'Donoghue AL, Dechen T, et al. Trends in telehealth and in-person transitional care management visits during the COVID-19 pandemic. J Am Geriatr Soc 2021;69(10):2745–51.
9. Data highlights | CMS. Available at: https://www.cms.gov/priorities/health-equity/minority-health/research-data/care-disparities/data-highlights. Accessed October 7, 2025.
10. Horman SF, Kviatkovsky M, Castillo E, et al. Virtual transition of care clinics and associated readmission rates: 3-year retrospective cohort study. JMIR Med Inform 2025;13(1):e73495. https://doi.org/10.2196/73495.
11. Elsener M, Santana Felipes RC, Sege J, et al. Telehealth-based transitional care management programme to improve access to care. BMJ Open Qual 2023;12(4):e002495. https://doi.org/10.1136/bmjoq-2023-002495.
12. Soh YY, Zhang H, Toh JJY, et al. The effectiveness of tele-transitions of care interventions in high-risk older adults: a systematic review and meta-analysis. Int J Nurs Stud 2023;139:104428. https://doi.org/10.1016/j.ijnurstu.2022.104428.
13. Dugani SB, Kiliaki SA, Nielsen ML, et al. Postdischarge video visits for adherence to hospital discharge recommendations: a randomized clinical trial. Mayo Clin Proc Digit Health 2023;1(3):368–78.
14. Masterson Creber R, Daniels B, Reading Turchioe M, et al. Mobile integrated health vs a transitions of care coordinator for patients discharged after heart failure: the mighty-heart randomized clinical trial. JAMA Intern Med 2025. https://doi.org/10.1001/jamainternmed.2025.4483.
15. Tan SY, Sumner J, Wang Y, et al. A systematic review of the impacts of remote patient monitoring (RPM) interventions on safety, adherence, quality-of-life and cost-related outcomes. npj Digit Med 2024;7(1):192.
16. Pattar BSB, Ackroyd A, Sevinc E, et al. Electronic health record interventions to reduce risk of hospital readmissions. JAMA Netw Open 2025;8(7):e2521785. https://doi.org/10.1001/jamanetworkopen.2025.21785.
17. Dinh-Le C, Chuang R, Chokshi S, et al. Wearable health technology and electronic health record integration: scoping review and future directions. JMIR mHealth uHealth 2019;7(9):e12861. https://doi.org/10.2196/12861.
18. Dobson R, Stowell M, Warren J, et al. Use of consumer wearables in health research: issues and considerations. J Med Internet Res 2023;25(1):e52444. https://doi.org/10.2196/52444.
19. Cresswell KM, McKinstry B, Wolters M, et al. Five key strategic priorities of integrating patient generated health data into United Kingdom electronic health records. BMJ Health Care Inform 2018;25(4). https://doi.org/10.14236/jhi.v25i4.1068.
20. van Kessel R, Ranganathan S, Anderson M, et al. Exploring potential drivers of patient engagement with their health data through digital platforms: a scoping review. Int J Med Inf 2024;189:105513. https://doi.org/10.1016/j.ijmedinf.2024.105513.

21. Liu S, McCoy AB, Sittig DF, et al. A standard-based taxonomy of features that affect user response to clinical decision support alerts. BMC Med Inform Decis Mak 2025;25(1):389.
22. Gani I, Litchfield I, Shukla D, et al. Understanding "Alert Fatigue" in primary care: qualitative systematic review of general practitioners attitudes and experiences of clinical alerts, prompts, and reminders. J Med Internet Res 2025;27(1):e62763. https://doi.org/10.2196/62763.
23. Teo ZL, Thirunavukarasu AJ, Elangovan K, et al. Generative artificial intelligence in medicine. Nat Med 2025;1–13. https://doi.org/10.1038/s41591-025-03983-2. Published online October 6.
24. Donzé J, Aujesky D, Williams D, et al. Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model. JAMA Intern Med 2013;173(8):632–8.
25. van Walraven C, Dhalla IA, Bell C, et al. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. CMAJ 2010;182(6):551–7.
26. Wang L, Li G, Ezeana CF, et al. An AI-driven clinical care pathway to reduce 30-day readmission for chronic obstructive pulmonary disease (COPD) patients. Sci Rep 2022;12(1):20633. https://doi.org/10.1038/s41598-022-22434-3.
27. Bennett DJ, Feng J, Goldman S, et al. Reducing readmissions in the safety net through AI and automation. Am J Manag Care 2025;31(3):142–8.
28. Schnipper JL, Samal L, Nolido N, et al. The effects of a multifaceted intervention to improve care transitions within an accountable care organization: results of a stepped-wedge cluster-randomized trial. J Hosp Med 2021;16(1):15–22.
29. Williams CYK, Subramanian CR, Ali SS, et al. Physician- and large language model–generated hospital discharge summaries. JAMA Intern Med 2025. https://doi.org/10.1001/jamainternmed.2025.0821.
30. Zaretsky J, Kim JM, Baskharoun S, et al. Generative artificial intelligence to transform inpatient discharge summaries to patient-friendly language and format. JAMA Netw Open 2024;7(3):e240357. https://doi.org/10.1001/jamanetworkopen.2024.0357.
31. Zack T, Lehman E, Suzgun M, et al. Assessing the potential of GPT-4 to perpetuate racial and gender biases in health care: a model evaluation study. Lancet Digit Health 2024;6(1):e12–22.
32. Glasgow RE, McKay HG, Piette JD, et al. The RE-AIM framework for evaluating interventions: what can it tell Us about approaches to chronic illness management? Patient Educ Couns 2001;44(2):119–27.
33. Richardson S, Lawrence K, Schoenthaler AM, et al. A framework for digital health equity. npj Digit Med 2022;5(1):119.
34. Rodriguez JA, Betancourt JR, Sequist TD, et al. Differences in the use of telephone and video telemedicine visits during the COVID-19 pandemic. Am J Manag Care 2021;27(1):21–6.
35. Rodriguez JA, Saadi A, Schwamm LH, et al. Disparities in telehealth use among California patients with limited English proficiency. Health Aff 2021;40(3):487–95.
36. Rodriguez JA, Khoong EC, Lipsitz SR, et al. Telehealth experience among patients with limited English proficiency. JAMA Netw Open 2024;7(5):e2410691. https://doi.org/10.1001/jamanetworkopen.2024.10691.

37. Hernandez AM, Khoong EC, Kanwar N, et al. Lessons learned from a multi-site collaborative working toward a digital health use screening tool. Front Public Health 2024;12. https://doi.org/10.3389/fpubh.2024.1421129.
38. Mahajan A, Heydari K, Powell D. Wearable AI to enhance patient safety and clinical decision-making. npj Digit Med 2025;8(1):176.
39. Tsai WC, Liu CF, Lin HJ, et al. Design and implementation of a comprehensive AI dashboard for real-time prediction of adverse prognosis of ED patients. Healthcare 2022;10(8):1498.