The Role of EHR Data in Improving Solid Organ Transplant Outcomes: a Comprehensive Review

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Introduction

Solid organ transplantation (SOT) is a critical intervention for individuals with end-stage organ failure, but the field continues to grapple with significant challenges—namely, organ shortages, inconsistent care coordination, and persistent post-transplant complications. As of the *OPTN/SRTR 2023 Annual Data Report*, over 45,000 transplants were performed in the United States alone, with rising demands across kidney, liver, heart, and lung grafts driven by the increasing burden of chronic disease [1]. Optimizing outcomes across the transplant continuum, from waitlisting to long-term graft survival, requires coordinated, data-informed care across institutions and timeframes.

A central factor in optimizing outcomes is the ability to identify the best possible donor-recipient match. This is a complex process; finding an optimal match is essential for ensuring both graft longevity and patient well-being.

Electronic Health Record (EHR) systems have become indispensable tools in this domain. In transplantation, clinical decisions rely on the integration of complex, longitudinal data including donor-recipient compatibility, comorbidities, immunologic profiles, and treatment adherence. EHR platforms allow structured data to be captured, exchanged, and analyzed, supporting risk stratification, real-time decision support, and outcome monitoring.

Nonetheless, the field still faces notable limitations with respect to data quality, interoperability, and fragmentation of information systems. These challenges are particularly acute when EHRs operate in isolation from national transplant bases.

Without integrated EHR systems, donor-recipient matching becomes largely a guessing game, reducing the ability to reliably predict optimal outcomes.

This review examines the evolving role of EHR systems in improving outcomes in solid organ transplantation. It highlights methods in which EHRs enhance pre-transplant assessment, perioperative coordination, and post-transplant care, while identifying persistent challenges in completeness, data standardization, and integration. This review outlines next steps for leveraging EHR infrastructure to advance efficiency and outcomes in transplantation medicine by analyzing both strengths and limitations.

Pre-Transplant Applications

EHR systems play a significant role in shaping clinical decision-making, streamlining workflow, and addressing equity during the pre-transplant phase. Robust use of EHR data enables transplant centers to optimize donor-recipient matching, more accurately assess candidates, and manage waitlists in accordance with allocation policies and medical urgency, as summarized in Table 1.

Candidate Evaluation

Accurate candidate selection depends on the aggregation of longitudinal clinical data. EHRs significantly enhance the transplant evaluation process by consolidating critical clinical data—prior hospital admissions, laboratory results, imaging studies, medication histories, and comorbid conditions—into a single, accessible platform. This allows frailty, cardiovascular risk, renal function, and other contraindications to be assessed by transplant teams with greater precision. Structured documentation tools within EHR platforms can support eligibility determinations and standardize multidisciplinary evaluations. To streamline decision-making and ensure alignment with national listing criteria, integration of risk calculators and scoring systems (e.g., MELD) within the EHR is recommended.

Donor-Recipient Matching

Donor-recipient matching in the United States is overseen by the United Network for Organ Sharing (UNOS), operating under the federal OPTN system. All candidates listed in the UNOS database undergo electronic screening based on HLA factors, size, medical urgency, geographic proximity, wait-time status, and blood type compatibility. OPTN/SRTR reporting shows that as of July 2025, over 106,000 candidates (number

may be lower due to candidates waiting for multiple organs) remain on the waiting list for kidney, pancreas, liver, intestine, heart, or lung transplant. Nearly 25,000 transplants were performed in the first half of 2025 (roughly 86% from deceased donors).

Key inefficiencies have been documented in how centers manage waitlists and matching. Fragmented information and poor data integration across centers highlight delays and mismatches (e.g., manual updates [2], inconsistencies in HLA [3] or urgency scoring [4]).

Despite UNOS providing limited API access, most transplant centers do not have full real-time integration between UNet match-run data and EHR platforms like Epic. Instead, transplant teams often work in parallel systems rather than in a unified interface, meaning centers rely on bespoke middleware and manual workflows. This increases risk for error or delay and adds administrative layers.

Transplant centers suffer from duplication of effort and potential for mismatches during rapid math runs without standardized, real-time interoperability between EHR systems and UNet.

Inequities or Access Barriers

Persistent disparities in health outcomes remain deeply rooted in social and structural determinants—factors like race, geography, and socioeconomic status continue to shape who gets care and who doesn't. Marginalized populations face systemic barriers to care, including lower health literacy, reduced engagement in preventative services, and limited healthcare infrastructure [5].

Tsuang and Curtis (2024) underscore significant gaps in the data, especially around residential histories—an essential Social Determinant of Health (SDoH). The lack of granular, disaggregated data impedes policy development and targeted interventions. Healthcare systems cannot effectively address or remediate the access barriers faced by vulnerable populations without robust data systems that account for social context and intersectional factors.

Table 1.
Summarizes the main domains of EHR application during the pre-transplant phase.

Domain	Role of EHR Data	Limitations/ Challenges	Key Sources

Candidate Evaluation	Aggregates longitudinal clinical data (labs, imaging, comorbidities, hospitalizations, medication history); integrates risk calculators (MELD, frailty indices) for eligibility decisions.	Limited integration of calculators across platforms; variability in structured documentation tools across centers.	Kim et al. 2021; Boulware et al. 2025
Donor-Recipient Matching	Supports donor-recipient screening through OPTN/UNOS data (HLA, blood type, size, urgency, geography, wait time).	Restricted EHR-UNOS data exchange; reliance on manual updates; duplicate workflows increase risk of mismatches.	OPTN/SRTR 2023 Annual Data Report; UNOS technology overview
Inequities/ Access Barriers	Potential to capture SDoH (residential history, socioeconomic factors) to inform equity analyses.	Incomplete or inconsistent SDoH data; lack of disaggregated information limits equity-focused interventions.	Tsuang & Curtis 2024

Post-Transplant Management

Long-term success in organ transplantation hinges not solely on surgical proficiency, but also on meticulous post-operative care. Medication adherence, immunological monitoring, infection prevention, and psychosocial support are core components. Each domain plays a critical role in ensuring graft survival and quality of life.

Medication Adherence

Nonadherence to immunosuppressive regimens remains a principal factor behind late acute rejection and graft failure. Oudbier et al. (2025) emphasize the central role of EHR-integrated medication monitoring tools in improving adherence. Systems that include real-time pharmacy data integration, alert functions for missed doses, and

automated refill tracking offer clinicians a continuous feedback loop. These tools can identify early signs of nonadherence before clinical consequences emerge.

Leino et al. (2024) discuss the role of patient portals in reinforcing medication adherence behaviors. Portals that allow patients to receive reminders, access refill status, and view medication schedules can extend care beyond clinical visits. Despite this, such functionality is underutilized.

Predictive models developed for medication refill adherence using EHR data have shown bias toward patients with high healthcare utilization [6]. Consequently, patients with lower engagement in the healthcare system may have their nonadherence or early signs of graft dysfunction missed, increasing the risk of preventable complications. As a result, nonadherence is often discovered after preventable clinical deterioration, retrospectively. At present, EHRs function more as passive repositories of information than as active tools for supporting adherence, especially in the absence of robust interoperability and more advanced predictive algorithms.

Long-Term Monitoring

When it comes to long-term post-transplant monitoring, ongoing assessment is required—tracking trough drug levels, patient-reported symptoms, and organ function. Leino et al. (2024) proposes that EHRs can support this longitudinal oversight by incorporating brief questionnaires into appointment reminders and by tracking immunosuppression trough concentrations. However, real-world implementation is inconsistent; this creates blind spots, particularly for high-risk populations, in care trajectories.

Massoglia et al. (2021) underscore the essential role of monitoring tacrolimus (TAC) levels in transplant patients, as these values are tightly linked to patient outcomes. EHRs are already rich with TAC trough levels and corresponding dosage data [7, 8]. With adjusted configuration, systems can be used to detect and flag trends in trough level variability. In practice, most EHRs lack embedded thresholds to alert clinicians of meaningful shifts and report values passively. As a result, important changes may easily be missed.

While routine TAC monitoring offers key insights into pharmacologic management, the integration of these measurements with mobile health technologies represents a significant step forward in continuous, patient-centered care. Yet technical barriers—including siloed platforms and limited interoperability—currently restrict real-time data utilization. Mobile health (mHealth) integration could close these gaps. Home monitors,

wearables, and patient-reported outcome apps feed continuous data streams into EHRs, supporting proactive interventions. Yet integration remains siloed, superficial, or rare. Many mHealth apps are not interoperable with EHR platforms, and even where the FHIR standard is available, it is only partially implemented—most support read-only access, while write access and advanced functionality remain limited [9]. Because most EHRs only allow read-only access, clinicians cannot update records in real time across systems, preventing proactive medication adjustments or timely identification of rejection markers. The use of cloud-based architectures also raises data integrity concerns from the complete reliance on servers provided by third-party businesses [10]. Without seamless incorporation, the potential of mHealth remains restricted.

Barriers & Burdens

EHRs often generate their own burdens, even while positioned as solutions. Campagna et al. (2021) claims EHRs were embraced prematurely and are associated with clinician burnout, a major barrier to effective transplant care. Redundant documentation, excessive alerting, and nonintuitive interfaces dilute attention from critical signals [11, 12, 13]. Furthermore, significant data gaps fracture the patient narrative, especially when transitioning between care settings or providers [14]. In these cases, EHRs function more as fragmented record-keeping systems and less as cohesive continuity enablers. Figure 1 illustrates inputs, core functions, and barriers of post-transplant EHR management.
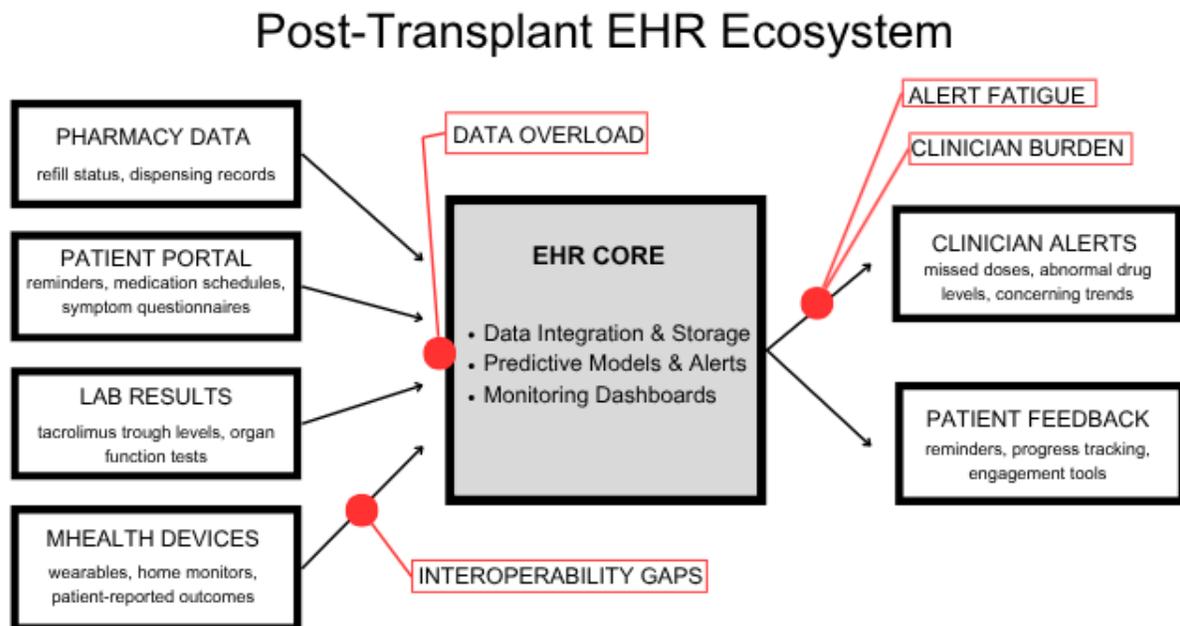

Figure 1.

Conceptual diagram of post-transplant EHR management, showing inputs, core functions, outputs, and common barriers.

Outcomes and Monitoring

EHRs have become central to monitoring post-transplant patients, providing a robust foundation for tracking outcomes and guiding clinical decisions. Their utility spans long-term survival analysis, prediction of graft rejection, and identification of high-risk patients. However, their full clinical potential is limited by systemic constraints such as data fragmentation, bias in predictive models, and underutilization of analytics tools.

Long-Term Survival Tracking

When considering long-term survival, EHRs offer a valuable dataset. In a 3-year cohort retrospective study involving 250 kidney transplant recipients, overall patient survival rates were 94.3% at 2 years, 90.0% at 5 years, and 76.6% at 10 years; graft survival rates were 89.0%, 85.1%, and 78.4%, respectively [15]. These Kaplan-Meier curves (Figure 2) illustrate how longitudinal EHR data alone, without external registry linkage, can support outcome surveillance at the institutional level.
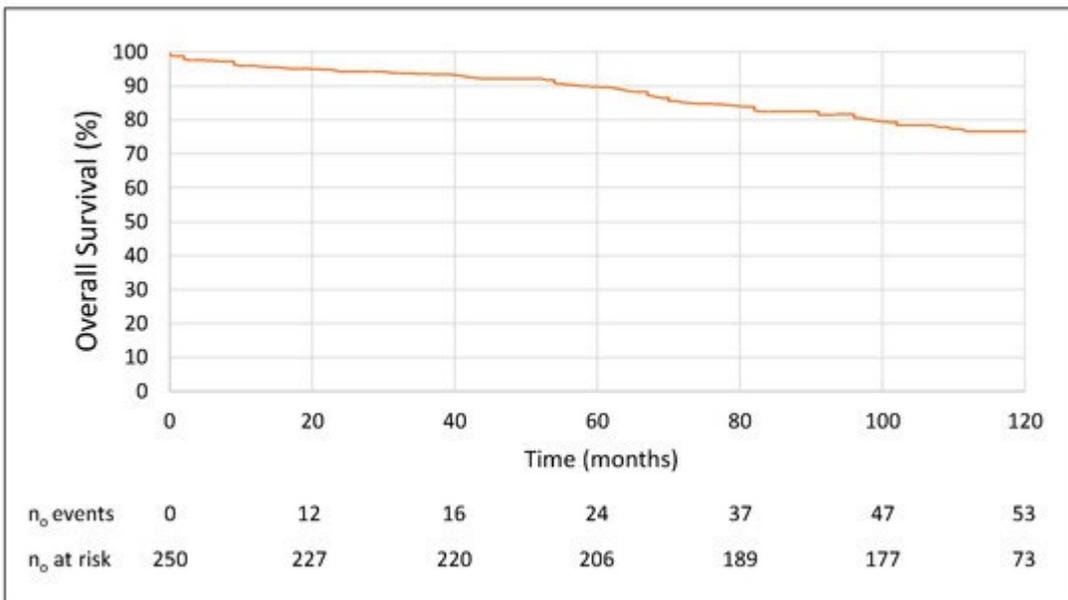

Time (months)	0	20	40	60	80	100	120
n_o events	0	12	16	24	37	47	53
n_o at risk	250	227	220	206	189	177	73

Figure 2. Kaplan-Meier survival curve for kidney transplant recipients. EHR-derived data. Beviá-Romero et al. (2023)

Furthermore, time-series data from EHRs can be leveraged to train predictive models that estimate outcomes such as five-year graft survival with greater precision than static clinical assessments [16]. These forecasts are especially useful for follow-up intensity and guiding immunosuppressive strategies.

Predicting and Managing Graft Rejection

In the context of graft rejection, EHRs consolidate varied data streams—pathology reports, clinical documentation, laboratory values—allowing earlier detection of rejection episodes through pattern recognition and trend analysis. For example, Bhasuran et al. (2025) have demonstrated that machine learning (ML) models incorporating EHR-based parameters can predict organ rejections for pediatric heart transplantations, with the highest-performing model (integrating UNOS data, EHR variables, and SDoH) achieving an AUROC of 0.798, significantly outperforming models based on registry data alone. EHR-integrated alerts can further assist clinicians by flagging concerning trends or lapses in follow-up, supporting timely intervention.

Despite ongoing advancements, the integration of predictive tools into clinical practice still faces considerable hurdles—interface complexity, skepticism among clinicians, and persistent interoperability issues often stall meaningful adoption.

Data-Driven Identification of High-Risk Patients

Modern EHR systems now facilitate continuous risk scoring, drawing on both structured data (such as vital signs, laboratory results, medications) and unstructured data (for example, clinician notes). Tools like iBox, as well as models applying NLP to unstructured clinical notes, have been used to stratify transplant recipients by risk of adverse outcomes. NLP can be applied to EHR text to classify graft loss status.

As illustrated in Figure 3, ML models embedded within EHRs can generate clinically actionable predictions through structured interfaces—potentially allowing for earlier identification of transplant patients at increased risk for complications like readmission or graft dysfunction. However, biased training data may result in misclassification of minority patients, potentially widening disparities in care.
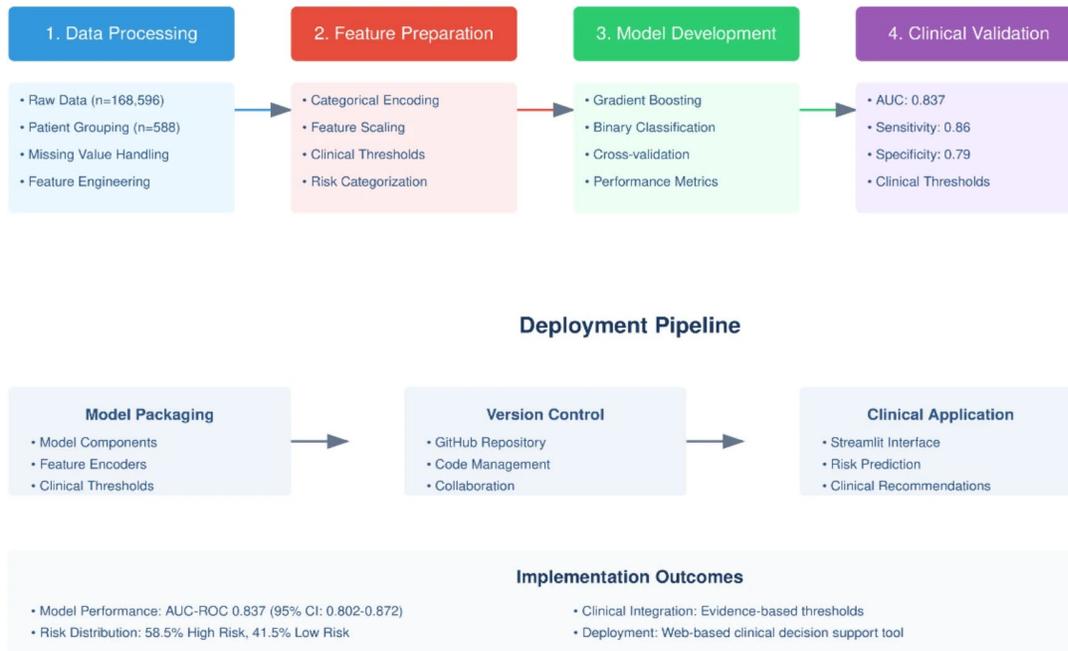
Figure 3. Four-stage ML pipeline for predicting 30-day hospital readmission in renal transplant recipients; spanning data ingestion, feature engineering, model training, and clinician-facing deployment. Based on Alnazari et al., 2025 (*BMC Nephrology).*

Limitations in Current Monitoring Approaches

EHR-based monitoring faces major limitations despite advancements. Documentation workflows and system-specific variability, including delayed or inconsistent entry of clinical data, significantly degrade the timeliness and reliability of EHR-based predictive models, as demonstrated in a comparative study across two EHR systems [17]. Additionally, lack of interoperability between EHRs at different institutions constrains the data-sharing necessary for robust modeling. Despite the growing sophistication of predictive algorithms, most transplant centers remain unable to implement these tools at scale due to persistent institutional barriers. These include insufficient technical structure, fragmented EHR systems, limited access to high-quality training data, and a lack of dedicated funding streams to support operational integration. As a result, even clinically validated models often remain siloed in research environments rather than translated into frontline transplant care, where they could inform critical decisions such as rejection surveillance and post-operative monitoring.

Although AI models can improve predictive accuracy in transplant medicine, reliance on opaque, "black box" algorithms introduces significant ethical challenges. In organ transplantation, where decisions carry life-altering consequences, lack of model

interpretability can compromise clinician accountability, hinder shared decision-making, and weaken patient trust. Without transparency, providers and patients are left without clear justification for risk predictions for treatment pathways, undermining informed consent. This reinforces the need for explainable AI frameworks, such as LIME and SHAP, that make algorithmic outputs traceable and clinically interpretable. These challenges underscore the need for better standardization, clinician education, and ethical safeguards to support responsible use of EHR-based outcome monitoring.

Systemic Limitations

Persistent systemic limitations in EHR use for SOT undermine both equity and data exchange. The primary challenge here is the fragmentation of health information systems and lack of genuine interoperability between transplant centers, referring providers, and ancillary care sites. While national registries such as OPTN/SRTR provide centralized reporting, the broader digital ecosystem remains an isolated system, with disparate EHR platforms unable to seamlessly exchange structured data. This division is further reinforced by proprietary coding systems and vendor-specific implementations, as reflected in interoperability scores; approximately 0.68 when exchanging data within the same vendor ecosystem versus only about 0.22 between different vendors, demonstrating how proprietary design choices significantly hinder effective cross-system data exchange [18]. This limited cross-vendor interoperability means that transplant centers cannot reliably access external patient records in real time, resulting in delays in donor-recipient matching, missed red flags in lab results, and potential gaps in follow-up care. This discontinuity is also compounded by inconsistent adherence to national data exchange standards and a lack of fully enforced connectivity mandates. The result is an incomplete longitudinal view of the patient, particularly for those who receive care across multiple institutions. The 2023 OPTN/SRTR Annual Data Report itself recognizes these inefficiencies, noting that since 2013, the number of organs recovered for transplantation but never actually transplanted has increased for kidneys, livers, hearts, and lungs. This trend points to clear opportunities for systemic improvement. Despite the increase in data exchange capabilities, a significant proportion of U.S. hospitals face challenges in integrating external records into their EHR systems. According to a 2023 report by the Office of the National Coordinator for Health Information Technology (ONC), while nearly all hospitals electronically send patient health information, approximately only three-quarters integrate the information they receive within their EHR systems. This indicates that a substantial number of hospitals still encounter barriers to fully utilizing external data, which may include issues

related to data format compatibility, system data exchange, and workflow integration. Table 2 compares ideal vs current interoperability metrics across vendors and hospitals.

Table 2. EHR interoperability in transplant care comparison.

Aspect	Ideal State	Current Reality	Source/Metric
Cross-vendor data exchange	Seamless interoperability (FHIR, standardized codes)	Interoperability score ~0.22 across vendors	Bernstam et al., 2022
Within-vendor exchange	Full compatibility	Interoperability score ~0.68	Bernstam et al., 2022
Registry integration	Timely, complete updates	Delayed reporting, inefficiencies	OPTN/SRTR 2023
Hospital record integration	Nearly universal	~75% of hospitals integrate received data	ONC, 2023
Rural hospital data sharing	Broadband-enabled participation	47.4% still use fax/mail	GAO, 2023

Inconsistent documentation and variable data quality further impede the utility of EHR data for transplantation. Registry and clinical datasets often suffer from irregular follow-up reporting, nonstandardized clinical variables, and incomplete demographic information. These deficiencies arise from the absence of harmonized semantic models and center-level variation in data entry practices, limiting the comparability of records across sites over time. Peer-reviewed studies emphasize that the lack of standardized data collection—whether through FHIR, SMART-on-FHIR, or equivalent architectures frameworks—compromises the integrity of research and policy evaluation. Nonetheless, as outlined in a 2022 systematic review of FHIR applications in health research, the implied benefits of scalable interoperability are still unrealized in practice. The paper details how FHIR's modular, extension-friendly architecture—while theoretically robust—has not yet achieved widespread adoption in research workflows, where multiple other frameworks (such as OMOP CDM, CDISC clinical trial models, SNOMED CT, and LOINC) are often unevenly applied, resulting in persistent lack of cohesion of data capture and analysis across healthcare and research settings [19]. In

transplantation, these inconsistencies obscure disparities, distort outcome analyses, and erode the reliability of predictive models.

These technical limitations are closely tied to broader issues of equity. Digital infrastructure disparities across the United States significantly hinder rural and resource-limited healthcare providers from fully engaging in data exchange initiatives. A 2023 report by the Government Accountability Office (GAO) indicates that smaller rural hospitals are less likely to participate in health information exchanges (HIEs) compared to their urban counterparts, primarily due to challenges such as limited IT staffing, inadequate broadband access, and the voluntary nature of programs like TEFCA. These barriers result in a reliance on outdated methods, with 47.4% of small rural hospitals frequently sending mail or fax for data exchange, compared to 30.3% of medium or large hospitals. This technological gap not only impedes efficient data sharing but also exacerbates health disparities in underserved populations [20]. Moreover, these structural barriers perpetuate inequities in data representation, as patients in marginalized regions may have their information underreported or omitted from national datasets. Without deliberate policy and technical interventions to address these disparities, EHR-based transplant research potentially risks reinforcing, rather than reducing, inequities in care delivery and clinical outcomes.

Future Directions

Coordinated action across technical, institutional, and policy levels will be required for addressing the systemic limitations in current EHR use for SOT. A foundational step would be standardizing data elements, formats, and definitions. The CHART consortium's 2025 transplant Common Data Model (CDM) is a solid example: 368 standardized data elements, meticulously structured to bridge the referral and post-transplant continuum [21]. Consistent with recent proposals advocating for transplant-specific ontologies and CDMs, adoption of CDMs developed and maintained through a dedicated consortium—augmented by privacy-preserving approaches such as federated learning and secure multiparty computation—would ensure interoperable capture of donor demographics, perioperative metrics, longitudinal graft outcomes, and social determinants across transplant centers while safeguarding patient privacy [22]. This would reduce variability, facilitate longitudinal tracking, and improve the reliability of cross-institutional analyses.

Additionally, cross-center data pooling could bust through current information silos. Establishing secure, federated data networks for transplantation could allow for large-

scale analyses without requiring full centralization of patient records, preserving privacy while enabling more robust benchmarking and research. This approach would require governance frameworks that address data sharing agreements, ethical oversight, and equitable access to pooled datasets.

Conclusion

EHRs have become foundational in modern transplant medicine, supporting both pre- and post-operative care. They streamline candidate evaluations, improve donor-recipient matching, enhance medication adherence, and facilitate continuous patient monitoring. Despite these benefits, persistent challenges—fragmented data systems, inconsistent interoperability, and underutilization of mHealth and predictive tools—limit their full clinical potential.

For tangible progress in transplant outcomes, health systems need to move beyond siloed platforms and commit to interoperable, cross-vendor EHR infrastructures that provide real-time insights and actionable clinical alerts. Policy mandates are needed to standardize data elements, reporting formats, and integration with national registries to reduce delays, errors, or inequities in access. Concurrently, research should focus on evaluating patient-level impacts of integrated mHealth solutions, AI-driven predictive models, and federated data networks, ensuring that innovations translate into measurable improvements in graft survival, follow-up adherence, and equitable care delivery. Addressing these structural, technical, and policy-level gaps will be critical to harnessing the full potential of EHRs in SOT.

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