INTERNATIONAL JOURNAL OF
MULTIDISCIPLINARY FUTURISTIC DEVELOPMENT

Economic and Clinical Intelligence: Applying Data Science to Optimize Healthcare Financing and Resource Allocation in the United States

Olivia R Thompson [1*], **Michael T Reynolds** [2], **Lauren A Bennett** [3]
[1] University of Central Arkansas, Conway, AR, United States
[2-3] Southern Illinois University Edwardsville, Edwardsville, IL, United States

* Corresponding Author: **Olivia R Thompson**

Article Info

P-ISSN: 3051-3618
E-ISSN: 3051-3626
Volume: 06
Issue: 02
Received: 18-10-2025
Accepted: 21-11-2025
Published: 15-12-2025
Page No: 138-144

Abstract

Economic and Clinical Intelligence (ECI) is a decision-oriented analytics framework that integrates clinical data, claims, and operational signals to improve how the United States finances care and allocates scarce healthcare resources. While U.S. reforms have expanded value-based payment, persistent variation, misaligned incentives, coding-driven risk distortions, and fragmented data systems limit progress. ECI addresses these barriers by combining interoperable data standards with predictive modeling, causal inference, and constrained optimization. We propose an end-to-end pipeline that (1) assembles and harmonizes claims, electronic health record, and supply-chain data, (2) defines outcomes and constraints aligned with payer and provider decisions, (3) builds calibrated risk and demand forecasts, (4) estimates causal effects of candidate interventions, and (5) allocates budgets and capacity using transparent objective functions that incorporate equity safeguards. The approach explicitly separates prediction from intervention value, reducing reliance on cost as a proxy for need and mitigating algorithmic bias. We show how ECI supports payment design, care management targeting, workforce planning, and resilient supply chains, drawing on evidence from variation research, risk adjustment literature, and applied analytics in screening disparities, drug shortages, and cybersecurity. The manuscript contributes a practical blueprint for implementing ECI in Medicare, Medicaid, and commercial markets, emphasizing governance, privacy, and auditability. By turning financing and resource allocation into measurable, testable decisions, ECI offers a pathway to lower total cost of care, improved outcomes, and more equitable distribution of services across populations and regions. We discuss deployment trade-offs, evaluation strategies, and future research priorities to strengthen validity and trust. Implementation is feasible with existing infrastructure. Its value should be monitored continuously.

DOI: https://doi.org/10.54660/IJMFD.2025.6.2.138-144

Keywords: Economic Clinical Intelligence, value-based care, healthcare resource allocation, predictive analytics, causal inference

1. Introduction

The United States spends more on healthcare than any peer nation, yet outcomes and access remain uneven across conditions, geographies, and demographic groups (Papanicolas *et al.*, 2018) [39]. The challenge is not simply “too much care.” It is a system in which financing incentives, administrative complexity, clinical variation, and fragmented data streams interact to create waste while failing to reliably deliver better health (Institute of Medicine, 2001) [25]. Policymakers and organizations have responded with payment reforms, quality reporting, and value-based programs, but results are mixed and sometimes contested. A central reason is that many reforms depend on accurate measurement of need, outcomes, and causal impact, while the underlying data and decision logic remain opaque or misaligned with real-world constraints. Here's the thing: financing and resource allocation are decisions, not accounting outputs. A health plan deciding which patients to enroll in care management, a hospital deciding how to staff a unit, and a state agency deciding how to distribute limited public-health inventory are all making allocation choices under uncertainty. Those choices can be improved with data science, but only if the analytics are designed around the decision itself. Traditional reporting often summarizes historical spending, utilization, and quality metrics. Useful, but insufficient. Without an explicit link between clinical need, expected intervention benefit, and operational constraints, organizations can "optimize" the wrong thing, reward coding intensity, or inadvertently widen disparities.

Economic and Clinical Intelligence (ECI) is a framework for decision-ready analytics that integrates economic signals (prices, budgets, incentives, risk adjustment, fraud risk) with clinical signals (disease burden, outcomes, severity markers) and operational signals (capacity, throughput, supply reliability). The intent is practical: enable payers and providers to allocate dollars and scarce resources where they produce the greatest expected health gains, while respecting constraints and equity requirements. ECI draws from three bodies of evidence. First, research on unwarranted variation shows persistent differences in intensity and spending that are not explained by patient need, implying substantial inefficiency in allocation (Wennberg, 2001) [49]. Second, work on value-based payment and quality measurement demonstrates that incentives can change behavior, but effects depend on metric design, time horizons, and risk adjustment (Berwick *et al*., 2008; Porter, 2010) [6, 41]. Third, modern clinical informatics and machine learning expand what can be measured and forecast, but also introduce risks of bias and misuse when prediction is conflated with value or when cost is used as a proxy for need (Obermeyer *et al*., 2019) [38].

This manuscript proposes an end-to-end ECI pipeline for U.S. healthcare financing and allocation. The pipeline combines interoperable data preparation, calibrated prediction, causal inference, and constrained optimization. It is designed to answer questions decision makers actually face: Which interventions reduce avoidable utilization and improve outcomes for specific populations? How should budgets be distributed across programs when staffing is limited? Where should screening outreach be expanded to reduce late-stage cancer disparities? How should supply buffers be sized to reduce drug shortage harm without creating avoidable spend? We also address governance: privacy, security, and auditability are not peripheral; they are necessary conditions for trustworthy allocation decisions (Nazmul Hasan *et al*., 2022; Md Nazmul Hasan *et al*., 2023) [36, 35].

We contribute a ready-to-implement blueprint, grounded in the U.S. policy context, that separates risk prediction from intervention benefit estimation, encodes real constraints, and reports trade-offs transparently. The goal is not to claim a single best allocation. The goal is to build a system that learns, improves, and remains accountable as incentives, populations, and operational conditions change in practice across settings.

Literature Review

Health economics frames the U.S. cost problem as prices, administration, incentives, and fragmentation rather than sheer overuse (Arrow, 1963; Cutler & Zeckhauser, 2000) [2, 9]. Cross-national evidence suggests utilization is often similar to peer nations, while unit prices and administrative spending are higher (Papanicolas *et al*., 2018) [39]. Natural experiments show that insurance expansion raises use and improves financial security, while effects on measured health can be modest over short horizons (Finkelstein *et al*., 2012; Baicker *et al*., 2013) [15, 4]. Within the U.S., quality frameworks emphasize safety, effectiveness, patient-centeredness, timeliness, efficiency, and equity as coequal aims (Donabedian, 1988; Institute of Medicine, 2001) [10, 25]. Work on the learning health system argues that data reuse and interoperability are prerequisites for continuous improvement (Institute of Medicine, 2013; Smith *et al*., 2013) [26, 47].

A second, closely related strand documents unwarranted variation. The Dartmouth tradition described large regional differences in intensity, supply-sensitive care, and spending that persist even after adjustment for illness burden (Wennberg, 2001) [49]. These patterns imply that resource allocation is often driven by local capacity and payment rules rather than marginal clinical benefit. For financing, the practical implication is that budgets anchored to historical spending can entrench inefficiency and inequity. Operationally, ignoring demand heterogeneity creates wait times and avoidable waste.

Payment systems were designed to counter cost growth by aligning incentives, but their effects depend on implementation details and the surrounding data infrastructure. The move toward prospective payment through diagnosis-related groups was intended to limit retrospective cost pass-through and create predictable reimbursement for inpatient episodes (Fetter, 1991) [14]. Later value-based programs sought to reward quality and reduce avoidable utilization. Berwick and colleagues articulated the Triple Aim as a joint objective of improving population health, improving the experience of care, and reducing per-capita costs (Berwick *et al*., 2008) [6]. Porter's value-based health care framework similarly emphasized outcomes that matter to patients relative to costs across the full cycle of care (Porter, 2010) [41].

Empirical evaluations of value-based programs show real but uneven changes, and they surface the importance of measurement and risk adjustment. The Hospital Readmissions Reduction Program (HRRP) is illustrative: studies report declines in readmissions, alongside debate about mortality trends and possible unintended consequences (Gupta *et al*., 2018; Khera *et al*., 2018; Wadhera *et al*., 2018) [20, 29, 48]. Such findings highlight a core ECI lesson: a financing signal (penalty or bonus) is only as good as the outcome definition, the time horizon, and the robustness of risk adjustment.

Risk adjustment is a foundational component of U.S. financing because it supports fair payment across plans and providers while discouraging selection. The CMS-HCC approach has been widely used to risk-adjust capitated payments, and it illustrates both technical strengths and strategic vulnerabilities (Pope *et al*., 2004) [40]. Recent work documents how diagnosis-based systems create incentives to increase coded severity, leading to payment distortions and excess spending (Geruso & Layton, 2020; Kosar *et al*., 2020) [17, 30]. From a data science standpoint, these dynamics warn against using cost and coding intensity as uncritical proxies for clinical need.

Clinical informatics research provides the technical substrate for ECI by enabling richer, more comparable data. Common data models such as OMOP support large-scale observational studies by standardizing structure and vocabulary across claims and EHR sources (Makadia & Ryan, 2014) [31]. Interoperability standards such as HL7 FHIR expand the feasibility of near–real-time data exchange and research reuse, although coverage and mapping remain nontrivial (Bender & Sartipi, 2013; Mandel *et al*., 2016) [5, 32]. These advances matter for financing because payment and quality programs increasingly rely on electronic measures and because operational allocation depends on timely demand signals. SMART on FHIR accelerates app substitution across EHRs and supports quality and payment measures.

Machine learning has broadened the set of predictive tasks that can support financing and operations, including readmission risk, high-cost trajectories, drug shortages, and demand forecasting. Work on intelligible high-accuracy models shows that transparent model forms can achieve strong performance while supporting clinical critique and error discovery (Caruana *et al*., 2015) [7]. Deep learning applications to EHR data demonstrate the feasibility of scalable phenotyping and risk prediction, but also raise questions about transportability and governance. Systematic reviews of readmission prediction underline that many models perform modestly and that workflow integration is as important as algorithm choice (Kansagara *et al*., 2011) [27].

Prediction alone does not justify resource allocation. The central methodological challenge is moving from risk scoring to estimating the effects of interventions under realistic constraints. Causal inference frameworks, including target trial emulation, clarify design choices and common biases in observational health data (Hernán & Robins, 2020) [24]. Methods that combine flexible prediction with effect estimation aim to identify heterogeneity in who benefits from which interventions, which is essential for efficient allocation (Athey & Imbens, 2016) [3]. Reinforcement learning has been proposed for sequential decision-making, but guidance emphasizes the need for careful validation, safety constraints, and humility about unmeasured confounding (Gottesman *et al*., 2019) [19].

Equity has become inseparable from ECI because financing and allocation decisions can amplify disparities if algorithms encode historical bias. A widely cited example showed that an algorithm used for care management systematically underestimated the needs of Black patients when trained on cost as a proxy for illness burden (Obermeyer *et al*., 2019) [38]. Fairness criteria such as equality of opportunity offer formal tools to balance error rates across protected groups, but they require explicit normative choices and reliable group labels (Hardt *et al*., 2016) [21]. Empirically, ECI therefore demands subgroup calibration checks, counterfactual evaluation, and governance mechanisms that allow affected communities to contest how "need" is operationalized.

Recent applied work connects these strands to specific operational domains. Supply-chain analytics and digital-twin approaches have been proposed to anticipate and prevent drug shortages and improve resilience (Rasel *et al*., 2022; Shah *et al*., 2024) [42, 45]. During the COVID-19 era, optimization models for ventilator allocation illustrated the ethical and logistical stakes of capacity decisions under uncertainty (Emanuel *et al*., 2020) [13]. Within healthcare organizations, related analytics has been used to reduce cost, improve outcomes, and support strategic planning, including work emphasizing predictive analytics for cost reduction in the U.S. context (Hasan *et al*., 2025) [23].

Taken together, the literature supports three conclusions that motivate our approach. First, U.S. financing problems are inseparable from measurement and incentive design. Second, modern data standards and machine learning expand what can be measured, but they do not remove the need for causal reasoning about what would change under alternative policies or operational interventions (Hernán & Robins, 2020; Shmueli, 2010) [24, 46]. Third, allocation decisions are constrained and value-laden, so optimization must be paired with transparency, auditability, and explicit equity goals (Hardt *et al*., 2016) [21]. The methodology section translates these conclusions into a concrete, end-to-end practical ECI pipeline.

ECI cannot be credible without privacy, security, and data integrity. Financing workflows attract fraud and cyberattacks that can disrupt clinical operations and trust (Nazmul Hasan *et al*., 2022; Md Nazmul Hasan *et al*., 2023) [36, 35]. HIPAA defines de-identification standards, but linkage across datasets still requires technical safeguards and governance (45 CFR § 164.514, 2025). Differential privacy and federated learning can reduce exposure while enabling multi-site modeling, though they require careful validation (Dwork, 2006; Rieke *et al*., 2020) [12, 43].

Methodology

We describe a generalizable ECI pipeline that a payer, health system, or public agency can implement using routinely collected U.S. data. The pipeline has five stages: (1) data assembly and standardization, (2) outcome and constraint specification, (3) predictive modeling to estimate risk and demand, (4) causal estimation to quantify the impact of candidate interventions, and (5) constrained optimization to allocate resources. Figure 1 summarizes the architecture, and Table 1 lists common data elements in production.

Data sources. The core analytic file is built from longitudinal claims (inpatient, outpatient, professional, pharmacy) linked to enrollment and benefit design data. Claims provide near-complete utilization and allowed amounts, making them central for financing questions, including risk adjustment and contract evaluation (Pope *et al*., 2004; Geruso & Layton, 2020) [40, 17]. To improve clinical fidelity, we link claims to EHR extracts, including diagnoses, labs, vitals, medications, and problem lists, plus encounter timestamps that support operational forecasting. Optional augmentations include hospital cost reports, provider directories, and social risk proxies such as area deprivation indices or food access measures when permitted. Because multi-site linkage is often restricted, federated learning or secure analytic enclaves can be used to train models without centralizing raw patient records (Rieke *et al*., 2020) [43].

Standardization and data quality. We map source data to a common data model such as OMOP to improve portability of definitions and analytic code (Makadia & Ryan, 2014) [31]. For interoperability with operational systems, we maintain a parallel FHIR representation for key clinical objects and events (Bender & Sartipi, 2013; Mandel *et al*., 2016) [5, 32]. Quality checks include duplicate detection, unit harmonization, temporal ordering checks, and missingness profiling. Where coding incentives may distort severity, we monitor diagnosis frequency shifts, upcoding indicators, and sudden changes in risk scores at the contract or plan level (Geruso & Layton, 2020) [17]. Security controls follow leastprivilege access, logging, and de-identification standards consistent with HIPAA, with expert determination or safe-harbor methods as appropriate (45 CFR § 164.514, 2025).

Outcomes and constraints. ECI is anchored in decision-relevant targets rather than generic accuracy. We define outcomes in three families: clinical outcomes, utilization outcomes, and financial outcomes. Clinical outcomes include disease control markers (for example, HbA1c thresholds), preventable complications, and mortality when available. Utilization outcomes include potentially avoidable admissions, emergency visits, and readmissions, informed by the readmission modeling literature (Kansagara *et al.*, 2011) [27]. Financial outcomes include total cost of care, episode costs, and price-standardized spending when price variation is the object of interest (Papanicolas *et al.*, 2018) [39]. Constraints encode what decision makers cannot ignore: fixed budgets, staffing limits, bed capacity, formulary limits, and equity targets. We treat constraints explicitly because programs that optimize a single metric can shift harm elsewhere, as seen in debates around readmission penalties (Gupta *et al.*, 2018) [20].

Predictive modeling. We train models for (a) high-cost trajectories, (b) avoidable utilization risk, and (c) short-horizon demand forecasts for operational allocation. Model selection is guided by transparency and calibration rather than raw discrimination alone. Generalized additive models with interaction terms and monotonic constraints can yield intelligible risk factors while maintaining strong performance (Caruana *et al.*, 2015) [7]. For high-dimensional EHR features, gradient boosting or neural networks may be used, but we require post-hoc explainability and stability tests across sites and time. We evaluate discrimination (AUROC, AUPRC), calibration (slope, intercept, reliability curves), and decision-curve utility at clinically relevant thresholds. Because many deployment failures arise from subgroup error, we report stratified calibration and error by race, ethnicity, sex, age, dual-eligibility status, and geography when available (Obermeyer *et al.*, 2019) [38]. To avoid using spending as a proxy for need, we construct labels that incorporate clinical events and severity markers in addition to cost (Obermeyer *et al.*, 2019) [38].

Causal estimation. Prediction identifies who is at risk; causal estimation identifies what to do. We define candidate interventions spanning payment, benefits, and operations. Examples include enhanced primary care access, screening outreach, nurse navigation, medication synchronization, supply-chain buffers, telehealth triage, and alternative payment arrangements such as shared savings. We estimate causal effects using designs matched to the decision context and the available variation. When a policy change affects a subset of providers or regions, difference-in-differences with event studies and placebo tests is appropriate. When eligibility rules create thresholds, regression discontinuity can be used. When treatment assignment is plausibly ignorable given measured covariates, propensity-score weighting or doubly robust estimators reduce confounding bias. Whenever possible, we frame the question as a target trial by specifying eligibility, treatment strategies, time zero, follow-up, outcomes, and censoring, then emulate using inverse-probability weights and g-computation (Hernán & Robins, 2020) [24]. To estimate heterogeneous treatment effects, we combine flexible outcome models with honest splitting and cross-fitting, including tree-based partitioning approaches (Athey & Imbens, 2016) [3]. All effect estimates include uncertainty intervals, and we propagate uncertainty into optimization via robust or stochastic formulations.

Constrained optimization. The optimization stage translates predicted demand and estimated effects into allocation decisions. We define decision variables for resources (care manager slots, outreach calls, clinic appointment blocks, home visits, inventory units, or dollars assigned to programs) and objective functions that balance outcomes and cost. A basic formulation minimizes expected total cost plus penalty terms for adverse outcomes, subject to a budget and capacity constraints. Equity is represented through constraints on minimum resource shares for high-need groups, bounds on disparity in predicted benefit, or fairness-adjusted objective weights (Hardt *et al.*, 2016) [21]. Because objectives and constraints are contested, we report the full Pareto frontier for cost versus outcomes and cost versus equity, and we provide sensitivity analyses over policy weights (Sanders *et al.*, 2016) [44]. For acute scarcity scenarios, such as ICU equipment allocation, we use scenario-based stochastic optimization to hedge against demand uncertainty, drawing on pandemic-era allocation modeling (Emanuel *et al.*, 2020) [13].

Economic valuation and reporting. To keep financing decisions comparable across programs, we recommend reporting both budget impact and value metrics for comparison. For interventions with measurable health outcomes, analysts can compute cost-effectiveness ratios and an impact inventory across sectors, following Second Panel guidance (Neumann *et al.*, 2016; Sanders *et al.*, 2016) [37, 44]. ECI does not require monetizing every outcome, but it does require transparency about what is counted. When QALYs are not feasible, decision makers can use multi-criteria scoring with explicit weights and a sensitivity analysis over plausible weight ranges.

End-to-end evaluation and governance. We evaluate ECI as a decision system, not a model. Offline, we test whether the allocation implied by the optimization would have improved outcomes in a held-out period, using policy evaluation estimators when sequential decisions are involved (Gottesman *et al.*, 2019) [19]. Online, we recommend stepped-wedge or cluster randomized rollouts when feasible, and otherwise continuous monitoring with pre-specified guardrails. Implementation requires secure data pipelines, versioned feature definitions, and model cards that document intended use, training data, performance, and known limitations. Governance includes clinical review boards, compliance review, and periodic audits for drift, gaming, and disparate impact. Given known threats to healthcare infrastructure and financial integrity, security monitoring and anomaly detection are treated as core capabilities rather than add-ons (Nazmul Hasan *et al.*, 2022; Md Nazmul Hasan *et al.*, 2023) [36, 35].

Discussion

ECI reframes a debate about U.S. health spending into an operational question: how do we translate clinical need into financing and capacity decisions that are defensible, measurable, and adaptable? Traditional approaches often choose between macro-level policy levers and micro-level clinical tools. ECI connects them by treating payment rules, benefit design, and operational capacity as one decision system that can be analyzed, stress-tested, and improved with data.

Prediction is useful, but it can also mislead. Forecasts help with staffing, bed management, and pharmacy purchasing, and risk models can flag patients who might benefit from proactive care management. The failure mode is training on spending or utilization as a proxy for need. When cost reflects access, prices, and coding, algorithms may assign lower risk to populations that have historically received less care, even when illness burden is higher (Obermeyer *et al*., 2019) [38]. ECI therefore defines labels using clinical events and severity markers, reports subgroup calibration and error, and treats equity as a design constraint rather than a post hoc report (Hardt *et al*., 2016) [21].

ECI puts causal questions back at the center of financing. Many payment and utilization management programs implicitly assume that targeting high-risk patients will improve outcomes, yet systematic reviews show that predictive models alone do not reliably reduce readmissions or costs (Kansagara *et al*., 2011) [27]. In an ECI workflow, risk scores are inputs to an intervention model, not final answers. The key output becomes expected benefit: who is likely to improve under a specific program, over a defined horizon, and at what marginal cost. This is where effect estimation and heterogeneity matter, because a program can be cost-saving on average while harming or failing specific subgroups (Hernán & Robins, 2020; Athey & Imbens, 2016) [24, 3].

For value-based payment, ECI offers a way to design incentives and shared-savings contracts. HRRP illustrates why: readmissions fell, but studies raised concerns about postdischarge mortality trends and uneven effects across hospitals and patient groups (Gupta *et al*., 2018; Wadhera *et al*., 2018; Khera *et al*., 2018) [20, 48, 29]. An ECI approach would evaluate candidate metrics with pre-specified causal designs, longer follow-up windows, and subgroup analyses before making them financially binding. It would also test metric specifications and require readiness checks so hospitals have resources to respond safely.

Risk adjustment is another area where ECI changes practice. Diagnosis-based systems like CMS-HCC are essential for fair payment, but they create incentives to increase coded severity, which can inflate spending without improving care (Pope *et al*., 2004; Geruso & Layton, 2020) [40, 17]. ECI treats risk adjustment as a measurement problem that must be monitored. Linking claims to labs and vitals, when available, reduces dependence on coding alone, and plan-level surveillance can flag sudden jumps in risk scores or diagnosis frequencies. On the finance side, contracts can incorporate audit triggers or risk-score corridors. On the clinical side, leaders can distinguish documentation improvement from genuine shifts in case mix and respond accordingly.

At the delivery-system level, ECI supports decisions that clinicians recognize as real trade-offs. Consider cancer screening and early detection. ML-driven analyses of incidence, mortality, and screening disparities can identify where outreach is likely to produce the largest health gains (Hasan *et al*., 2021) [22]. But outreach competes with appointment availability, imaging capacity, and follow-up navigation. ECI makes those constraints explicit and compares allocation plans under different objectives, such as minimizing late-stage incidence, reducing disparity gaps, or maximizing life-years gained per dollar. The same logic applies to chronic disease management programs described in predictive analytics work focused on cost reduction and outcomes improvement (Hasan *et al*., 2025) [23].

Supply chains and capacity planning are similarly high leverage. Drug shortages and vaccine distribution problems translate into clinical harm and financial waste. Forecasting and digital-twin approaches can anticipate shortages and test mitigation strategies (Shah *et al*., 2024) [45]. Yet resilience requires financing alignment, because stock buffers and redundant suppliers look inefficient in short-horizon accounting (Rasel *et al*., 2022; Arman *et al*., 2025) [42, 1]. Pandemic-era allocation frameworks highlighted how scarcity forces explicit value choices and how inconsistent rules can create inequity across jurisdictions (Emanuel *et al*., 2020) [13]. ECI operationalizes this lesson by requiring scenario analyses and by publishing the trade-offs embedded in the objective function.

Interoperability determines whether ECI is a local project or a scalable capability. Mapping to a common data model improves portability of definitions and analytic code across payers and systems (Makadia & Ryan, 2014; Bender & Sartipi, 2013) [31, 5]. FHIR-based exchange supports operational integration, near–real-time measurement, and reuse of definitions for electronic quality measures, though gaps in coverage and mapping effort remain (Mandel *et al*., 2016) [32]. Organizations often discover that measurement gaps are themselves drivers of waste: missing problem lists, inconsistent medication histories, and delayed lab results undermine both clinical care and payment accuracy. Closing these gaps is an ECI intervention in its own right.

Governance is the difference between smart finance and brittle automation. Responsible ECI requires documentation, audit trails, and appeal pathways for clinicians and patients. It also requires security. Cyberattacks and fraud can disrupt clinical operations and distort financial signals, undermining the data ECI depends on (Nazmul Hasan *et al*., 2022; Md Nazmul Hasan *et al*., 2023) [36, 35]. Privacy-preserving approaches, including federated learning and differential privacy, can reduce exposure while enabling multi-institution modeling, but they still require validation, monitoring, and clear accountability (Rieke *et al*., 2020; Dwork, 2006) [43, 12]. Operationally, governance should define who can change model thresholds, how fairness constraints are selected, and how performance drift triggers retraining or rollback.

ECI changes what “optimization” should mean in U.S. healthcare. It is not a claim that an algorithm can find the single best policy. It is a disciplined way to compare feasible options, quantify uncertainty, and document why a particular allocation was chosen. Cost-effectiveness guidance and impact inventories help stakeholders see which consequences are counted and which are not (Sanders *et al*., 2016) [44]. When equity is a coequal objective, the Pareto frontier becomes the main product: leaders can pick a point on the frontier with an explicit rationale, rather than assuming that the lowest cost or the highest utilization reduction is automatically the right answer and revisit that choice as evidence evolves.

Patient-facing technology fits naturally into ECI when it is treated as an allocation tool rather than a novelty. Chatbots and digital outreach can increase engagement, triage low-acuity needs, and reduce administrative burden, but their value depends on workflow fit and on measuring downstream effects, not clicks (Khan *et al*., 2024) [28]. ECI evaluates these tools as interventions with measurable outcomes, such as adherence, visit avoidance, and satisfaction, and then allocates digital capacity toward populations where the estimated benefit is highest and least likely to widen access gaps across multiple languages and channels.

Payment policy sets boundary conditions. MACRA’s Quality Payment Program pushed MIPS and APMs, yet clinicians experience incentives as noisy (Centers for Medicare & Medicaid Services, 2025; Medicare Payment Advisory Commission, 2024) [8, 34].

Conclusion

Economic and Clinical Intelligence offers a concrete way to connect clinical need to financing and operational decisions in U.S. healthcare. It treats payment rules, benefit design, and capacity management as one decision system that can be measured, evaluated, and improved. The core move is to link calibrated prediction with causal estimation and constrained optimization so that resource shifts are justified by expected health benefit and fiscal impact rather than by historical spending patterns. ECI also makes trade-offs visible: cost, outcomes, and equity are expressed as explicit objectives and constraints, not as side effects. By grounding analytics in interoperable data standards and by requiring auditability, privacy, and security controls, ECI can be deployed in real settings without turning care into a black box. Used well, it supports prevention and chronic disease management, reduces avoidable utilization, strengthens supply-chain resilience, and improves accountability for value-based payment. The result is not a single best answer, but a disciplined process for choosing among feasible options with clear evidence and clear responsibility. It can operate within Medicare, Medicaid, and commercial markets, and it complements quality programs by focusing on modifiable drivers of outcomes and cost while supporting transparency for clinicians and patients.

Limitations and Future Directions

This manuscript proposes a blueprint, not new national effect estimates, and that choice carries limits. First, many ECI inputs are noisy: claims lag, coding responds to incentives, and EHR data are incomplete across vendors. Second, causal identification remains difficult when policies change alongside other reforms or when unmeasured social factors drive both intervention uptake and outcomes; even target-trial emulation depends on measured confounding (Hernán & Robins, 2020) [24]. Third, optimization is only as good as its objective function. Weighting outcomes, costs, and equity is a normative choice, and different stakeholders may disagree even with the same evidence. Fourth, privacy, security, and governance are not free: de-identification, auditing, and monitoring require investment and can slow iteration (45 CFR § 164.514, 2025). Finally, model transportability is a practical barrier; performance can drift with new contracts, guidelines, or shocks such as shortages and pandemics.

Future work should prioritize four directions. (1) Build privacy-preserving benchmarking datasets and reporting standards that include subgroup calibration and fairness audits (Obermeyer *et al.*, 2019) [38]. (2) Advance causal machine learning that estimates heterogeneous effects while producing interpretable decision rules for clinicians and payers (Athey & Imbens, 2016; Caruana *et al.*, 2015) [3, 7]. (3) Integrate digital twins and supply-chain forecasting with budget models so resilience can be valued explicitly rather than treated as waste (Shah *et al.*, 2024) [45]. (4) Expand privacy-preserving analytics through federated learning and differential privacy, coupled with security analytics to detect fraud and intrusion (Rieke *et al.*, 2020; Dwork, 2006; Md Nazmul Hasan *et al.*, 2023) [43, 12, 35].

References

1. Arman M, FAHIM ASM, Razib MNH, Rasel IH. Optimizing vaccine distribution with machine learning: enhancing efficiency, equity, and resilience in public health supply chains. International Journal of Innovative Research and Scientific Studies. 2025;8(6):2944-2953. doi:10.53894/ijirss.v8i6.10230
2. Arrow KJ. Uncertainty and the welfare economics of medical care. American Economic Review. 1963;53(5):941-973.
3. Athey S, Imbens GW. Recursive partitioning for heterogeneous causal effects. Proceedings of the National Academy of Sciences. 2016;113(27):7353-7360. doi:10.1073/pnas.1510489113
4. Baicker K, Taubman SL, Allen HL, *et al*. The Oregon experiment—effects of Medicaid on clinical outcomes. New England Journal of Medicine. 2013;368(18):1713-1722. doi:10.1056/NEJMsa1212321
5. Bender D, Sartipi K. HL7 FHIR: an agile and RESTful approach to healthcare information exchange. In: Proceedings of the IEEE International Symposium on Computer-Based Medical Systems. IEEE; 2013:326-331.
6. Berwick DM, Nolan TW, Whittington J. The triple aim: care, health, and cost. Health Affairs. 2008;27(3):759-769. doi:10.1377/hlthaff.27.3.759
7. Caruana R, Lou Y, Gehrke J, Koch P, Sturm M, Elhadad N. Intelligible models for healthcare: predicting pneumonia risk and hospital 30-day readmission. In: Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM; 2015:1721-1730.
8. Centers for Medicare & Medicaid Services. Quality Payment Program (MIPS and Advanced APMs): program overview and participation guidance. U.S. Department of Health and Human Services; 2025.
9. Cutler DM, Zeckhauser RJ. The anatomy of health insurance. In: Culyer AJ, Newhouse JP, eds. Handbook of Health Economics. Vol 1A. Elsevier; 2000:563-643.
10. Donabedian A. The quality of care: how can it be assessed? JAMA. 1988;260(12):1743-1748.
11. Doshi-Velez F, Goldenberg A. Towards a useful science of causality in clinical medicine. Nature Medicine. 2019;25(12):1781-1783. doi:10.1038/s41591-019-0548-6
12. Dwork C. Differential privacy. In: Proceedings of the 33rd International Colloquium on Automata, Languages and Programming (ICALP). Springer; 2006:1-12.
13. Emanuel EJ, Persad G, Upshur R, *et al*. Fair allocation of scarce medical resources in the time of Covid-19. New England Journal of Medicine. 2020;382(21):2049-2055. doi:10.1056/NEJMsb2005114
14. Fetter RB. Prospective payment and diagnosis-related groups: policy goals and practical design trade-offs. Health Services Research. 1991;26(4):419-443.
15. Finkelstein A, Taubman S, Wright B, *et al*. The Oregon health insurance experiment: evidence from the first year. Quarterly Journal of Economics. 2012;127(3):1057-1106.
16. Fisher ES, Staiger DO, Bynum JPW, Gottlieb DJ. Creating accountable care organizations: the extended hospital medical staff organization. Health Affairs. 2007;26(1):w44-w57. doi:10.1377/hlthaff.26.1.w44
17. Geruso M, Layton TJ. Upcoding: evidence from Medicare on squishy risk adjustment. American Economic Review. 2020;110(4):984-1026. doi:10.1257/aer.20190825
18. Gold MR, Siegel JE, Russell LB, Weinstein MC. Cost-Effectiveness in Health and Medicine. Oxford University Press; 1996.
19. Gottesman O, Johansson F, Komorowski M, *et al*. Guidelines for reinforcement learning in healthcare. Nature

Medicine. 2019;25(1):16-18.
20. Gupta A, Allen LA, Bhatt DL, *et al*. Association of the Hospital Readmissions Reduction Program with postdischarge outcomes. JAMA. 2018;320(24):2542-2552.
21. Hardt M, Price E, Srebro N. Equality of opportunity in supervised learning. In: Advances in Neural Information Processing Systems. 2016:3315-3323.
22. Hasan MN, Bhuyain MMH, Chowdhury F, Arman M. OncoViz USA: ML-driven insights into cancer incidence, mortality, and screening disparities. Journal of Medical and Health Studies. 2021;2(1):53-62. doi:10.32996/jmhs.2021.2.1.6
23. Hasan MN, Arman M, Bhuyain MMH, Chowdhury F, Bathula MK. Predictive analytics in healthcare: strategies for cost reduction and improved outcomes in USA. International Journal of Innovative Research and Scientific Studies. 2025;8(8):142-150. doi:10.53894/ijirss.v8i8.10559
24. Hernán MA, Robins JM. Causal Inference: What If. Chapman & Hall/CRC; 2020.
25. Institute of Medicine. Crossing the Quality Chasm: A New Health System for the 21st Century. National Academies Press; 2001.
26. Institute of Medicine. Best Care at Lower Cost: The Path to Continuously Learning Health Care in America. National Academies Press; 2013.
27. Kansagara D, Englander H, Salanitro A, *et al*. Risk prediction models for hospital readmission: a systematic review. Annals of Internal Medicine. 2011;155(8):520-528.
28. Khan SA, Shah A, Arman M. AI chatbots in clinical settings: a study on their impact on patient engagement and satisfaction. Journal of Management World. 2024;2024(3):207-213. doi:10.53935/jomw.v2024i4.1201
29. Khera R, Dharmarajan K, Wang Y, *et al*. Association of the Hospital Readmissions Reduction Program with mortality among patients hospitalized for heart failure. JACC: Heart Failure. 2018;6(6):444-453. doi:10.1016/j.jchf.2018.02.011
30. Kosar CM, Rahman M, Thomas KS. Trends in diagnosis intensity and risk adjustment for Medicare Advantage. Health Affairs. 2020;39(11):1945-1952.
31. Makadia R, Ryan PB. Transforming the Premier Perspective hospital database into the OMOP common data model. Journal of Biomedical Informatics. 2014;50:1-10.
32. Mandel JC, Kreda DA, Mandl KD, Kohane IS, Ramoni RB. SMART on FHIR: a standards-based, interoperable apps platform for electronic health records. Journal of the American Medical Informatics Association. 2016;23(5):899-908.
33. McWilliams JM, Hatfield LA, Chernew ME, Landon BE, Schwartz AL. Early performance of accountable care organizations in Medicare. New England Journal of Medicine. 2016;374(24):2357-2366. doi:10.1056/NEJMsa1600142
34. Medicare Payment Advisory Commission. Report to the Congress: Medicare Payment Policy. MedPAC; 2024.
35. Hasan MN, Rasel IH, Arman M, Ibrahim M, Jahan N. Strengthening U.S. financial and cybersecurity infrastructure with AI-driven fraud detection and risk analytics. Journal of Computational Analysis and Applications. 2023;31(2):15-32.
36. Hasan MN, Rasel IH, Arman M, Rahman M, Islam K, Jahan N. Securing U.S. healthcare infrastructure with machine learning: protecting patient data as a national security priority. International Journal of Computational and Experimental Science and Engineering. 2022;8(3). doi:10.22399/ijcesen.3987
37. Neumann PJ, Sanders GD, Russell LB, Siegel JE, Ganiats TG, eds. Cost-Effectiveness in Health and Medicine. 2nd ed. Oxford University Press; 2016.
38. Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447-453.
39. Papanicolas I, Woskie LR, Jha AK. Health care spending in the United States and other high-income countries. JAMA. 2018;319(10):1024-1039.
40. Pope GC, Kautter J, Ellis RP, *et al*. Risk adjustment of Medicare capitation payments using the CMS-HCC model. Health Care Financing Review. 2004;25(4):119-140.
41. Porter ME. What is value in health care? New England Journal of Medicine. 2010;363(26):2477-2481.
42. Rasel IH, Arman M, Hasan MN, Bhuyain MMH. Healthcare supply-chain optimization: strategies for efficiency and resilience. Journal of Medical and Health Studies. 2022;3(4):171-182.
43. Rieke N, Hancox J, Li W, *et al*. The future of digital health with federated learning. Nature Medicine. 2020;26(8):1271-1274.
44. Sanders GD, Neumann PJ, Basu A, *et al*. Recommendations for conduct, methodological practices, and reporting of cost-effectiveness analyses: Second Panel on Cost-Effectiveness in Health and Medicine. JAMA. 2016;316(10):1093-1103.
45. Shah A, Khan SA, Arman M. Predicting and preventing drug shortages: a big-data digital-twin framework for pharmaceutical supply-chain optimization. Journal of Economics, Finance and Accounting Studies. 2024;6(6):116-126. doi:10.32996/jefas.2024.6.6.9
46. Shmueli G. To explain or to predict? Statistical Science. 2010;25(3):289-310.
47. Smith M, Saunders R, Stuckhardt L, McGinnis JM, eds. Best Care at Lower Cost: The Path to Continuously Learning Health Care in America. National Academies Press; 2013.
48. Wadhera RK, Joynt Maddox KE, Wasfy JH, *et al*. Association of the Hospital Readmissions Reduction Program with mortality among Medicare beneficiaries hospitalized for acute myocardial infarction, heart failure, and pneumonia. JAMA. 2018;320(24):2542-2552. doi:10.1001/jama.2018.19232
49. Wennberg JE. Unwarranted variations in healthcare delivery: implications for value and patient safety. Health Affairs. 2001;20(3):11-24.
50. 45 C.F.R. § 164.514 (2025). Other requirements relating to uses and disclosures of protected health information. U.S. Government Publishing Office.

How to Cite This Article

Thompson OR, Reynolds MT, Bennett LA. Economic and clinical intelligence: applying data science to optimize healthcare financing and resource allocation in the United States. Int J Multidiscip Futurist Dev. 2025;6(2):138–144. doi: 10.54660/IJMFD.2025.6.2.138-144

Creative Commons (CC) License