

Population Health Intelligence Through Claims Analytics, Automated Case Management and Digital Health Dashboards: A Framework for Value-Based Healthcare in Saudi Arabia

Abstract:

Saudi Arabia's health-sector transformation creates an opportunity to convert routinely generated claims, clinical and patient-level data into a population health intelligence system that supports measurable value rather than isolated digital activity. This review examines how claims analytics, automated case management and digital health dashboards can be combined to identify disease burden, stratify rising risk, close care gaps and monitor outcomes across a mixed public-private health system. Evidence published from 2020 to 2025 was synthesised from Saudi and international studies addressing digital transformation, value-based healthcare, claims-based risk stratification, care-management automation, dashboards, interoperability and outcome measurement. The literature indicates that claims data are valuable because they offer longitudinal visibility of utilisation, diagnoses, procedures and cost across populations, but their timeliness and clinical incompleteness limit stand-alone use. Their value rises when claims are linked with electronic health records, admission-discharge-transfer feeds, patient-reported information and structured case-management data. Automated case management can then translate risk signals into worklists, outreach, escalation and follow-up, while dashboards can connect operational activity with outcomes, equity, utilisation and cost. The review proposes a closed-loop framework in which governed data integration, risk modelling, human validation, case-management orchestration and outcome dashboards function as one learning system. For Saudi Arabia, the framework supports the Health Sector Transformation Program by linking digital maturity to measurable outcomes, coordinated care and accountable resource allocation. Implementation should therefore prioritise data quality, interoperability, clinician oversight, transparent thresholds, outcome attribution and continuous recalibration rather than treating analytics as an end in itself.

Keywords: population health intelligence; claims analytics; case management; digital health dashboards; value-based healthcare; Saudi Arabia; risk stratification; Vision 2030

1. Introduction

Saudi Arabia is moving from episodic, institution-centred care towards a more integrated health system in which digital infrastructure, financing reform and outcome measurement are expected to work together. National studies describe substantial progress in digital health maturity, electronic records, telehealth and system transformation, while also identifying persistent interoperability, governance and implementation gaps [1,2]. At the same time, value-based healthcare has become a reform direction,

with growing emphasis on patient outcomes, cost awareness and payment models that reward measurable benefit rather than service volume [3,4]. The practical challenge is not simply to generate more data. It is to convert fragmented operational, clinical and financial records into timely intelligence that identifies who needs attention, what action should be taken, and whether that action creates value.

Claims data are central to this problem because they already contain population-scale signals on diagnoses, procedures, medication use, encounters, provider utilisation and expenditure. In a national insurance and exchange environment, these records can reveal patterns that are difficult to observe inside a single hospital. Yet claims are created primarily for administrative and reimbursement purposes. They may arrive after a delay, represent coding incentives rather than clinical nuance, omit laboratory values and symptoms, and poorly capture social or behavioural risk. Evidence from care-management programmes therefore warns that claims-only risk scores can become stale, generate false positives or miss rapidly changing need [14,15]. The analytical task is consequently to preserve the breadth and longitudinal reach of claims while augmenting them with more timely and clinically meaningful sources.

The second challenge is actionability. Predictive models do not improve population health merely because they identify high-risk people. Their benefit depends on whether risk information reaches a responsible care team, triggers an appropriate intervention, and remains visible until the loop is closed. Digital case management offers a bridge between analytics and care delivery by converting risk scores and care-gap rules into prioritised worklists, outreach tasks, escalation pathways and documented follow-up. Studies of digital and adaptive case-management systems show that technology can support coordination and patient engagement, but only when workflows reflect real user needs, responsibilities and available resources [18,19].

The third challenge is accountability. Population health programmes require dashboards that show not just how many alerts were generated or cases opened, but whether preventive services were completed, avoidable utilisation changed, outcomes improved and disparities narrowed. Dashboard research consistently shows that visualisation is useful when measures are trusted, timely, interpretable and connected to decision rights; dashboards that merely display activity can increase information load without changing practice [20-25]. For Saudi Arabia, this distinction is important because Vision 2030 demands both digital transformation and demonstrable improvement in quality, access, efficiency and patient-centred care [5-7].

This review therefore develops a framework that connects claims analytics, automated case management and digital health dashboards as a single operating model for population health

intelligence. It focuses on how routinely generated data can be converted into risk stratification, coordinated preventive action and measurable value while preserving clinical oversight, privacy, fairness and auditability.

2. Aim, Objectives and Review Questions

The aim of this review is to develop an evidence-informed framework for using claims analytics, automated case management and digital health dashboards to support population-level value-based healthcare in Saudi Arabia.

Four objectives guide the review. First, it evaluates the strengths and limitations of claims and related administrative data for disease surveillance, utilisation analysis and risk stratification. Second, it examines how risk signals can be converted into coordinated actions through digital case-management workflows. Third, it identifies dashboard design principles that connect operational activity to patient outcomes, utilisation, equity and cost. Fourth, it integrates these elements into a governance and implementation model aligned with Saudi health-sector transformation.

Three review questions follow: RQ1, how should claims data be combined with clinical and patient-generated information to produce reliable population health intelligence? RQ2, what workflow and governance mechanisms are required to translate risk stratification into accountable case management? RQ3, which dashboard measures and feedback loops are needed to demonstrate value and continuously improve the system?

3. Review Methodology

A structured integrative review was adopted because the topic spans health informatics, payer analytics, case management, clinical operations, digital transformation and health-system financing. The evidence window was restricted to 2020-2025. Priority was given to peer-reviewed studies with a directly relevant contribution to one or more of six themes: Saudi digital-health transformation, value-based healthcare, claims analytics, population risk stratification, digitally enabled case management, and healthcare dashboards. International studies were retained where they described transferable mechanisms that could reasonably inform Saudi implementation.

Search concepts combined terms such as claims data, administrative data, risk stratification, population health, care management, digital case management, workflow automation, dashboard, quality improvement, value-based healthcare, Saudi Arabia and Vision 2030. Evidence was screened for methodological clarity, relevance to operational decision-making and explicit implications for

94 outcomes, utilisation, equity, cost or governance. Studies focused only on technical model performance
95 without an actionable care pathway were given less weight than work connecting analytics to clinical
96 or managerial decisions.

97 The final synthesis used 30 references published within the stated period, each with a resolvable DOI.
98 The analysis proceeded in two stages. Deductive coding grouped evidence under data foundation, risk
99 intelligence, case-management action, dashboard measurement, governance and value-based outcomes.
100 Inductive coding then identified recurring implementation mechanisms including data linkage,
101 timeliness, clinician validation, threshold design, worklist prioritisation, closed-loop referrals,
102 escalation, outcome attribution, dashboard drill-down, fairness monitoring and recalibration. No
103 primary clinical data were generated, and no causal effect estimates were invented. Where international
104 evidence is discussed, the review treats it as mechanism-level guidance rather than proof that identical
105 results would occur in Saudi Arabia.

106 **4. Claims Analytics as the Population Intelligence Foundation**

107 Claims data provide a unique system-wide view because they follow utilisation across providers and
108 over time. At population scale, diagnosis codes, procedures, pharmacy activity, place of service,
109 referral patterns, authorisations and expenditure can be organised into disease cohorts, utilisation
110 histories and cost trajectories. Such information supports surveillance of chronic disease burden,
111 identification of repeated emergency use, analysis of provider variation and detection of patients whose
112 utilisation pattern is changing. Administrative claims have also been used for quality assurance and
113 rehabilitation outcome monitoring, demonstrating that records can support population-level
114 measurement at scale when definitions and linkage rules are explicit [15-17].

115 However, the same features that make claims scalable also create analytical risk. A diagnosis code
116 indicates that a condition was billed, not necessarily its current severity. A procedure code confirms
117 service use but may not reveal whether the intervention achieved the intended clinical outcome. Claims
118 also carry a time lag that may be acceptable for retrospective burden analysis but problematic for
119 proactive case management. Research on claims-based eligibility for care-management programmes
120 found that outdated information and missing social context limited clinician confidence and forced
121 teams to manually reassess supposedly high-risk lists [14]. Similarly, combining claims with social
122 determinants, admission-discharge-transfer alerts and care-management data improved identification of
123 members likely to incur high future spending compared with traditional claims-dominant models [13].

124 For Saudi Arabia, claims intelligence should therefore be designed as a longitudinal layer rather than a
125 stand-alone decision engine. A robust population record would use claims for breadth, cost and

126 utilisation; clinical systems for laboratory results, vital signs, diagnoses and medication details; patient-
127 facing systems for reported outcomes, engagement and self-management; and near-real-time event
128 feeds for acute transitions. Interoperable records are essential because value emerges when information
129 can move across organisational boundaries and be reconciled into a consistent patient history [8-12].
130 This is particularly important in a mixed delivery environment where public, private and insurer-held
131 data may otherwise create separate versions of the same patient journey.

132 Data engineering should begin with identity resolution, terminology mapping, temporal logic and
133 provenance. Identity resolution prevents duplicated or fragmented longitudinal records. Terminology
134 mapping aligns coding systems and local vocabularies so that one disease phenotype is not split across
135 inconsistent labels. Temporal logic distinguishes active disease, historical diagnosis, suspected disease
136 and rule-out coding. Provenance records where each data element originated and when it became
137 available. These controls are not administrative extras; they determine whether a model trained on
138 historical data is valid for prospective use.

139 Population analytics should also distinguish surveillance from prediction. Surveillance asks what is
140 happening now: prevalence, service utilisation, screening gaps, complication rates and regional
141 variation. Prediction asks what is likely to happen next: disease onset, admission, readmission,
142 complication, high cost or failure to complete preventive care. The distinction affects both model
143 design and action. A prevalence dashboard may support commissioning and workforce planning,
144 whereas an individual risk score should trigger a defined care pathway. Conflating these functions can
145 result in dashboards that look sophisticated but do not identify an accountable next step.

146 Claims data can nevertheless contribute to early intervention when combined with complementary
147 information. Saudi insurance claims have already been explored for real-time risk stratification in
148 diabetes-related applications, illustrating the feasibility of extracting preventive signals from routine
149 payer data [29]. Such approaches are promising but should be viewed as an evidence-generating
150 direction rather than a substitute for clinical confirmation. The central design principle is that
151 population-scale administrative data should narrow attention and prioritise review, while clinical
152 evidence and professional judgement determine action.

153 **Table 1. Data domains, analytical signals and value-oriented uses.**

Data domain	Key signals	Primary limitation	Action enabled	Illustrative value measure
Claims &	Diagnoses,	Coding lag;	Burden analysis,	Avoidable

Data domain	Key signals	Primary limitation	Action enabled	Illustrative value measure
encounters	procedures, authorisations, utilisation, cost	limited clinical severity	cohorting, risk screening	utilisation; total cost; service variation
Clinical records	Laboratory results, vital signs, medications, diagnoses	Fragmentation; variable completeness	Clinical confirmation, disease control, care gaps	Control measures; complications; guideline adherence
Event feeds	Admissions, discharges, transfers, emergency contacts	Coverage and interface dependence	Near-real-time escalation and transition management	Time to review; 30-day acute-care use
Patient-generated data	Reported outcomes, symptoms, engagement, remote monitoring	Digital access; response bias	Self-management support and personalised follow-up	Experience; adherence; patient-reported outcomes
Case-management data	Outreach, referrals, interventions, closure, overrides	Workflow variation; documentation burden	Closed-loop coordination and accountability	Engagement; completion; unresolved cases
External/population data	Registries, geography, social and public-health signals	Linkage, consent and representativeness	Equity analysis and contextual risk adjustment	Coverage gaps; subgroup outcomes; geographic variation

155 5. From Risk Stratification to Automated Case Management

156 Risk stratification becomes valuable only when it changes care. Models can rank patients by predicted
157 admission, expenditure, complication or missed preventive opportunity, but care teams still need to
158 know what the score means, which intervention is appropriate and who owns the response. The
159 literature therefore supports a shift from “high risk” as a descriptive label to “actionable risk” as an
160 operational category. Actionable risk combines probability, expected consequence, time horizon,
161 modifiable drivers and intervention availability.

162 A practical framework uses at least three tiers. Low-risk populations receive routine preventive
163 communication and self-service support. Emerging-risk populations receive targeted screening,
164 medication review, appointment support or nurse outreach. High-complexity populations receive
165 multidisciplinary case management, care-transition support and specialist escalation. The threshold
166 between tiers should not be determined only by model probability. It should reflect service capacity and
167 expected benefit. If thousands of patients are classified as high risk but only a small case-management
168 team is available, the programme needs prioritisation logic based on preventability, urgency and
169 likelihood of engagement.

170 User-centred care-management research reinforces this point. When predictive tools are designed
171 around data availability rather than workflow, adoption is weak. By contrast, participatory approaches
172 with care managers clarify the correct prediction horizon, triggering frequency, action pathway and
173 reward function. Digital case-management programmes similarly show that implementation depends on
174 clearly specified roles, communication, shared information and follow-up processes [18,19].
175 Technology can accelerate the workflow, but it cannot compensate for ambiguity over who reviews a
176 case or what constitutes closure.

177 Automated case management should therefore be understood as orchestration rather than autonomous
178 care. Automation can create worklists, assign tasks, schedule reminders, flag overdue actions, generate
179 standard messages and escalate unresolved cases. It can also suppress low-value duplication by
180 recognising that a screening test has already been completed or that a patient is actively managed
181 elsewhere. Robotic process automation has shown substantial efficiency gains in rule-based healthcare
182 workflows, illustrating the potential to reduce repetitive administrative burden [26]. Yet human
183 confirmation remains essential where risk signals are based on incomplete billing data, where clinical
184 complexity is high, or where an intervention could cause harm.

185 A closed-loop case record should contain the original risk signal, supporting evidence, assigned owner,
186 intervention plan, contact attempts, patient response, referrals, completion status and outcome. This

187 creates an auditable chain from prediction to action. It also produces new learning data: which risk
188 signals led to engagement, which interventions were completed, which cases were overridden, and
189 which pathways produced better outcomes. Without this feedback, models remain detached from the
190 real-world effectiveness of the services they trigger.

191 Equity requires separate attention. Risk models trained primarily on utilisation may systematically
192 under-identify people who face access barriers because lower service use can appear as lower need.
193 Claims may also understate problems in groups with fragmented coverage or care outside the captured
194 network. Programmes should therefore monitor selection rates, calibration, false-negative patterns and
195 completion across relevant population groups. Human review should be permitted when clinicians
196 know about social or family circumstances not represented in the data. Evidence on socially situated
197 risk demonstrates that provider input can correct claims-based misclassification and improve
198 acceptance of algorithmic eligibility decisions [14].

199 **6. Digital Health Dashboards as the Accountability Layer**

200 Dashboards translate complex data into a form that executives, clinicians, case managers and analysts
201 can use. Their purpose in a value-based system is not decorative reporting; it is to make variation
202 visible, support prioritisation and sustain accountability. Research on clinical and quality dashboards
203 shows that useful designs enable trend analysis, comparison, drill-down, data-quality assessment and
204 navigation from summary indicators to plausible causes [20-23]. More recent work also emphasises the
205 need to co-design dashboards with users and integrate them into actual governance routines rather than
206 assuming that visibility alone changes behaviour [24,25].

207 A population health dashboard should therefore operate at multiple levels. The population view should
208 display disease prevalence, risk distribution, preventive gaps, avoidable acute-care use and geographic
209 or provider variation. The programme view should show the case-management funnel: patients
210 identified, reviewed, contacted, enrolled, intervened upon, completed and unresolved. The outcome
211 view should track screening completion, disease control, admissions, readmissions, emergency use,
212 patient-reported outcomes and cost. The equity view should stratify these measures by relevant
213 demographic, geographic and access-related groups. The governance view should show data freshness,
214 missingness, model drift, overrides and unresolved exceptions.

215 This layered structure prevents a common failure in digital health measurement: reporting process
216 activity as though it were value. A high number of alerts, dashboard views or outreach calls may
217 indicate activity, not improvement. Value-oriented dashboards should connect action to outcomes and
218 cost over an appropriate time horizon. In addition, attribution should be cautious. Changes in hospital

219 utilisation can reflect disease severity, seasonal demand, policy shifts or unrelated quality programmes.
220 Dashboards should therefore distinguish descriptive monitoring from causal evaluation.
221 Clinical leaders also need measures of variation. A dashboard designed for executive oversight can
222 highlight differences in utilisation, safety and outcomes across providers, regions or service lines,
223 focusing attention on patterns that may represent underuse, overuse or inconsistent care [21]. For Saudi
224 Arabia, such functionality could support cluster-level and national learning, but only if differences are
225 interpreted with case-mix adjustment and contextual knowledge. Raw comparisons risk penalising
226 providers that serve more complex populations.
227 Dashboard trust depends on data lineage and metric governance. Every indicator should have an owner,
228 definition, denominator, update frequency, source systems and documented limitations. Users should
229 be able to see whether a measure is based on adjudicated claims, provisional encounters or clinically
230 validated data. Where risk scores appear, the dashboard should state the prediction horizon and provide
231 interpretable drivers rather than a single unexplained number. This supports appropriate challenge and
232 reduces automation bias.

233 **7. Integrated Framework for Population Health Intelligence**

234 The proposed framework joins five layers into one operating model. The first layer is data acquisition:
235 claims, encounters, clinical records, medication data, patient-generated information and external
236 population data. The second is a trusted longitudinal data layer that performs identity matching,
237 terminology normalisation, data-quality checks, provenance capture and secure linkage. The third is
238 population analytics: surveillance, segmentation, risk prediction, care-gap detection and utilisation
239 analysis. The fourth is automated case-management orchestration. The fifth is a value dashboard that
240 measures outcomes, utilisation, equity, patient experience, cost and provider variation.

241 The architecture is deliberately closed loop. Dashboard findings should feed back to analytic teams and
242 case-management leaders. If a risk model identifies many patients who do not need intervention,
243 thresholds should be recalibrated. If one outreach pathway has poor completion, workflow design
244 should be reviewed. If preventive completion improves without reducing acute-care use, the
245 programme should investigate whether the targeted outcome or time horizon is appropriate. Learning
246 therefore occurs across model performance, workflow performance and clinical outcomes.

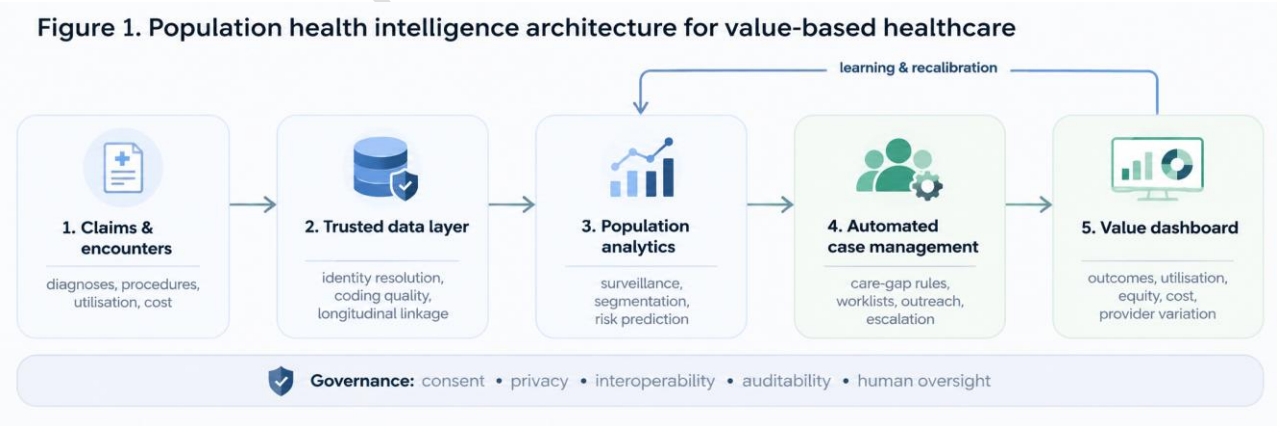
247 Governance runs across all layers. Data access should follow minimum-necessary principles and
248 purpose limitation. Sensitive data should be protected through role-based access, encryption, secure
249 exchange, audit logs and controlled secondary use. Interoperability should be treated as a governance

250 requirement rather than only a technical specification, because inconsistent data exchange directly
251 affects who is identified, which records are visible and whether case managers can coordinate across
252 organisations [8-12]. Saudi studies repeatedly identify infrastructure, integration and workforce
253 readiness as determinants of successful digital transformation [1,5,8].

254 Model governance should define intended use, validation population, performance measures, threshold
255 logic, update frequency and conditions that require revalidation. A model developed to predict high
256 cost should not automatically be used to prioritise preventable admissions; the outcome and
257 intervention logic differ. Likewise, a claims model should not silently evolve into an autonomous
258 clinical decision tool. High-consequence cases require confirmation and the possibility of override.
259 Workload effects should be monitored because poorly tuned decision-support systems can create alert
260 burden and reduce professional attention [27].

261 Case-management governance should specify role ownership, service-level expectations, escalation
262 rules and closure criteria. Automation should assign and track tasks, while accountable professionals
263 approve clinically meaningful actions. Dashboard governance should define which measures are used
264 for improvement, which are used for performance management, and which require risk adjustment
265 before comparison. These distinctions reduce the temptation to optimise visible metrics while
266 neglecting patient outcomes.

267 Figure 1 summarises the claims-to-value architecture. Figure 2 expands the model by showing how
268 multiple data domains converge on population intelligence, case-management action and dashboard
269 feedback before reaching value-based outcomes. Together, the figures emphasise that analytics,
270 workflow and measurement are inseparable components of the same system.



271
272 *Figure 1. Population health intelligence architecture linking claims, governed data, analytics, case*
273 *management and value measurement.*

Integrated framework for population health intelligence and value-based care

From claims data to automated case management and digital health dashboards in Saudi Arabia

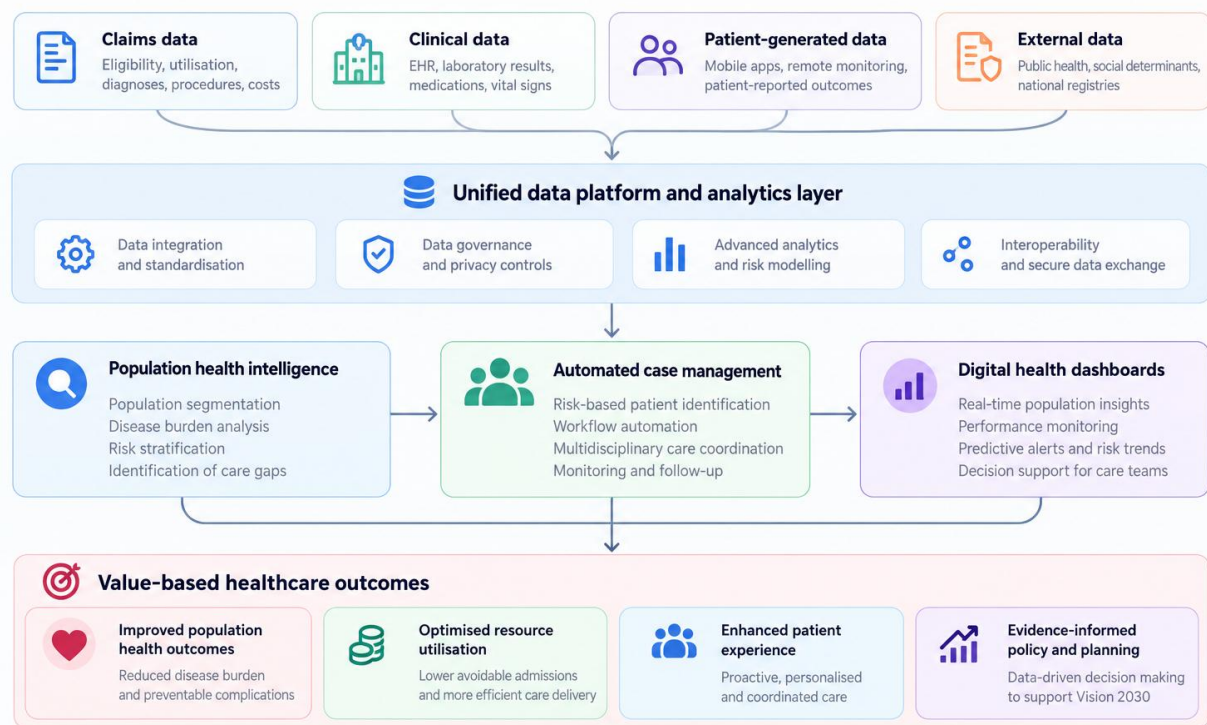


Figure 2. Integrated operating framework from multi-source data to population intelligence, automated case management, dashboards and value-based outcomes.

7.1 Measurement Logic, Attribution and Learning

The framework also requires an explicit measurement model that separates signals, actions and outcomes. Signals describe what the system detects: a rising risk score, a missed screening test, repeated emergency attendance or an unexpected cost trajectory. Actions describe what the care system does in response: clinical review, outreach, appointment booking, medication reconciliation, referral or monitoring. Outcomes describe what happens afterwards: completed prevention, improved disease control, reduced acute-care use, better experience or lower avoidable cost. Keeping these levels separate prevents organisations from claiming success merely because algorithms produced more alerts or case managers completed more tasks.

Time is equally important. Claims-based outcomes may become visible months after intervention, whereas operational measures such as contact success or appointment completion appear quickly. A dashboard should therefore combine leading and lagging indicators. Leading indicators can include time from signal to review, outreach completion, referral closure and overdue case percentage. Lagging indicators can include readmission, emergency use, total cost of care, disease-specific complications and patient-reported outcomes. Digital scheduling research demonstrates that access tools can alter no-

show patterns and utilisation, but effects vary by setting and accompanying workflow [28]. Saudi claims-based prediction work similarly shows that administrative data can support real-time risk stratification when models are clinically framed and validated [29]. Automated patient-experience collection can strengthen the feedback layer by increasing the amount and timeliness of information available for service improvement [30].

Outcome attribution should be proportionate to the decision being made. Routine programme management may rely on trend comparison, matched cohorts and risk-adjusted benchmarks. High-stakes claims about savings or clinical effectiveness require stronger quasi-experimental or prospective designs. This is especially relevant when multiple reforms occur simultaneously, as is likely during Saudi health-sector transformation. A reduction in admissions after a dashboard launch cannot automatically be attributed to the dashboard if payment reform, staffing changes or a new clinical pathway occurred at the same time.

Learning should also include negative results. If outreach fails to engage a target group, the response should not be to increase the risk threshold mechanically. Teams should examine whether contact information is incomplete, intervention timing is inappropriate, language or access barriers exist, or the risk signal identifies need that the available service cannot modify. Similarly, persistent overrides may indicate either weak model calibration or valuable clinical knowledge absent from the data. Capturing these exceptions converts operational friction into evidence for redesign.

A mature population health system therefore treats measurement as part of intervention design from the beginning. Every risk model should have a linked action, every action a measurable completion state, and every programme a defined outcome horizon. This discipline makes dashboards meaningful and creates the evidence chain needed for value-based accountability.

These linked measures should be specified before deployment, with baseline values, target direction, review cadence, owner and escalation threshold documented. Predefined measurement reduces post hoc interpretation and helps clinical, payer and management teams distinguish improvement from random fluctuation or reporting artefact.

8. Value-Based Healthcare and Vision 2030 Alignment

Value-based healthcare reframes success around outcomes relative to resources consumed. Saudi evidence indicates that the concept is becoming increasingly established, but implementation remains challenged by inconsistent outcome definitions, fragmented measurement capability and varying

322 readiness across organisations [3,4]. Population health intelligence can address part of this gap by
323 creating a common analytical chain from need identification to intervention and outcome measurement.

324 Claims are particularly useful for value measurement because they connect utilisation and expenditure
325 to longitudinal patient journeys. Clinical data are required to interpret disease control and
326 appropriateness, while patient-reported information adds outcomes that matter to individuals.
327 Automated case management then provides the operational record of what was actually done. When
328 these sources are linked, a programme can move beyond cost-only analysis and ask whether spending
329 was associated with preventive completion, fewer avoidable admissions, improved disease control or
330 better patient experience.

331 The framework also supports more disciplined resource allocation. Risk stratification can identify
332 rising-risk cohorts before they become persistently high cost, while case-management capacity can be
333 directed towards people for whom intervention is plausible. This is more consistent with value-based
334 care than retrospective hotspotting that concentrates only on historically expensive patients. Evidence
335 that claims-only risk scores may be stale further supports combining them with current clinical and
336 event data [13,14].

337 Saudi transformation also requires learning across providers. Dashboards can expose unwarranted
338 variation, but the purpose should be improvement rather than simplistic ranking. Provider comparisons
339 need transparent definitions, appropriate adjustment and opportunities to investigate context. Outcome
340 measurement studies in Saudi Arabia emphasise that the shift to value will depend on standardised,
341 trusted and usable measures rather than isolated reporting exercises [4]. Digital infrastructure can
342 accelerate this transition if it supports common definitions and routine feedback.

343 **9. Implementation Roadmap and Research Priorities**

344 Implementation should begin with a limited set of high-value use cases rather than an enterprise-wide
345 analytics programme. Suitable starting points include diabetes care gaps, hypertension follow-up,
346 frequent emergency use, potentially preventable readmission or missed screening. Each use case should
347 have a defined cohort, risk signal, accountable service, intervention menu, outcome measure and
348 evaluation period.

349 Stage one establishes the data foundation: identity linkage, code mapping, data-quality rules, event
350 timeliness and governance. Stage two creates transparent surveillance and segmentation before
351 introducing complex prediction. Stage three adds risk models only where the predicted event has a
352 plausible intervention. Stage four embeds case-management automation with clear ownership and

353 escalation. Stage five deploys dashboards that connect activity to outcomes, equity, utilisation and cost.
 354 Stage six introduces continuous monitoring, recalibration and portfolio-level governance.

355 **Table 2. Implementation stages, evidence gates and monitoring indicators.**

Stage	Priority actions	Evidence gate	Core indicators
1. Data foundation	Identity linkage; terminology mapping; data-quality rules; provenance	Trusted longitudinal record	Duplicate rate; missingness; data freshness
2. Population intelligence	Surveillance, segmentation, care-gap logic, transparent risk models	Validated signal with stated horizon	Calibration; discrimination; subgroup performance
3. Case-management action	Worklists, assignment, outreach, escalation, closure rules	Every signal has an accountable owner	Time to review; contact success; referral closure
4. Value dashboard	Outcome, utilisation, equity, experience and cost measures	Activity linked to outcome measures	Preventive completion; acute-care use; cost; PROM/PREM
5. Continuous learning	Override review, drift monitoring, workflow feedback, recalibration	Measured exceptions change the system	Drift; override yield; repeated exceptions; reconstruction time

356
 357 Research should focus on Saudi-specific external validation, prospective evaluation and comparative
 358 effectiveness. Multicentre studies are needed to test whether claims-plus-clinical models improve
 359 identification beyond claims alone, whether automated worklists increase preventive completion, and
 360 whether targeted case management changes avoidable utilisation or cost. Evaluation should report
 361 calibration and subgroup performance, not only discrimination. Qualitative research should examine
 362 clinician trust, patient acceptance and workflow burden. Economic evaluation should distinguish
 363 technology cost, workforce cost and downstream utilisation change.

364 The strongest future evidence will link prediction to intervention. A model with excellent technical
 365 performance but no effect on care is less valuable than a simpler model that consistently identifies

366 modifiable risk and triggers timely action. Saudi Arabia is well positioned to test such learning-system
367 approaches because national transformation, digital exchange and insurance reform create a setting in
368 which data, payment and delivery can increasingly be connected.

369 **10. Conclusion**

370 Population health intelligence should be understood as an operating system for coordinated care rather
371 than a collection of analytics products. Claims data provide broad longitudinal visibility of utilisation,
372 disease coding and cost, but they are most useful when combined with clinical, event and patient-
373 generated data. Risk stratification should prioritise modifiable and time-sensitive need, not simply
374 historical expense. Automated case management should translate risk into assigned, auditable actions
375 while preserving human confirmation for clinically consequential decisions. Dashboards should
376 demonstrate whether those actions improve outcomes, reduce avoidable utilisation, narrow inequities
377 and use resources efficiently.

378 For Saudi Arabia, the central opportunity is to connect existing digital transformation with the
379 measurement discipline required for value-based healthcare. The proposed closed-loop framework
380 links data integration, population analytics, case-management orchestration, dashboards and
381 governance in a continuous learning cycle. Its success depends on interoperable data, explicit
382 accountability, transparent model use, trusted outcome measures and continuous recalibration. If these
383 conditions are met, claims and digital health data can move from passive administrative records to an
384 active infrastructure for preventive, coordinated and value-oriented care under Vision 2030.

385 *Main-text word count: 4,400 (Abstract through Conclusion, including section headings and in-text*
386 *citation markers; excluding title, tables, figure captions and references).*

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