IMPROVING THE MECHANISMS FOR MANAGING THE FLOW OF MEDICAL SERVICES IN THE UNIFIED DIGITAL ECOSYSTEM OF THE HEALTHCARE SYSTEM

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Abstract

The thesis examined mechanisms for managing the flow of patients and medical services in a unified digital health ecosystem. The patient pathway was treated as a chain running from primary care through referral, diagnostics and specialist or hospital care to discharge and follow-up. A set of flow indicators was proposed on the basis of Little's law, stage utilisation and Kingman's approximation. Official statistics showed that between 2021 and 2025 the number of hospitals grew by 55.1% while hospital beds grew by 10.0%. An illustrative Python simulation of a district referral pathway found that e-referral with slot booking cut the mean wait from 1.50 to 0.70 working days and raised referral completion from 91.4% to 98.0%. A digital flow map with control points and management recommendations was developed.

Keywords: patient flow, digital health, e-referral, appointment scheduling, Little's law, bottleneck analysis, Uzbekistan.

Annotatsiya

Tezisda sog‘liqni saqlashning yagona raqamli ekotizimida bemorlar va tibbiy xizmatlar oqimini boshqarish mexanizmlari o‘rganildi. Bemor yo‘li birlamchi bo‘g‘indan yo‘llanma, diagnostika, mutaxassis yoki shifoxona va chiqarilgandan keyingi kuzatuvgacha bo‘lgan zanjir sifatida ko‘rib chiqildi. Little qonuni, bosqichlar yuklamasi va Kingman formulasi asosida oqim ko‘rsatkichlari tizimi taklif etildi. Statistika qo‘mitasi ma’lumotlariga ko‘ra, 2021-2025-yillarda shifoxonalar soni 55,1 foizga, o‘rinlar soni esa 10,0 foizga oshgani hisoblandi. Tuman yo‘llanma zanjiri uchun Pythonda shartli simulyatsiya o‘tkazildi: elektron yo‘llanma va vaqt sloti bilan yozilish kutish vaqtini 1,50 ish kunidan 0,70 kunga qisqartirdi, yo‘llanmalarning bajarilish darajasini 91,4 foizdan 98,0 foizga oshirdi. Nazorat nuqtalari bilan raqamli oqim xaritasi va boshqaruv tavsiyalari ishlab chiqildi.

Kalit so‘zlar: bemorlar oqimi, raqamli sog‘liqni saqlash, elektron yo‘llanma, onlayn yozilish, Little qonuni, tor joy tahlili, O‘zbekiston.

Аннотация

В тезисе были рассмотрены механизмы управления потоками пациентов и медицинских услуг в единой цифровой экосистеме здравоохранения. Путь пациента был представлен как цепочка от первичного звена через направление, диагностику и специалиста или стационар до выписки и наблюдения. На основе закона Литтла, загрузки этапов и формулы Кингмана была предложена система показателей потока. По данным Национального комитета по статистике было рассчитано, что в 2021–2025 гг. число больниц выросло на 55,1%, а число коек на 10,0%. Для районной цепочки направлений была проведена условная симуляция на Python: электронное направление с записью на временной слот сократило ожидание с 1,50 до 0,70 рабочего дня и повысило долю выполненных направлений с 91,4% до 98,0%. Были разработаны цифровая карта потока с контрольными точками и рекомендации по управлению.

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Ключевые слова: поток пациентов, цифровое здравоохранение, электронное направление, запись на прием, закон Литтла, анализ узких мест, Узбекистан.

INTRODUCTION

Patients do not experience a health system as a list of facilities. They experience it as a path: a visit to the family doctor, a referral, a blood test or a scan, a consultation with a specialist, perhaps a hospital stay, and then follow-up at home. Each handover on this path is a point where a patient can wait, repeat a test, lose a paper slip or drop out. Hospital crowding and long waits are often caused less by a shortage of beds or doctors than by uneven, poorly coordinated flows between units [1]. Managing these flows is therefore a core task of health system governance, not a technical detail of hospital administration.

Uzbekistan offers a favourable setting for this task. Presidential Resolution No. PQ-415 of 28 December 2023 set out a programme to accelerate the digitalisation of healthcare, including the Electronic Polyclinic and Electronic Hospital systems, a FHIR-based unified digital health platform, electronic prescriptions, and a regional pilot of electronic referrals and online appointments from family doctors to specialists and hospitals [2]. By August 2026 electronic medical cards had been created for more than 38 million residents, and the DMED platform ran more than 20 modules, among them Electronic Polyclinic, Electronic Prescription and Electronic Queue [3]. The infrastructure for seeing the whole patient pathway in one place is now largely in place.

What is still developing is the management layer that turns these data into smoother flows. Digital progress is usually reported as connection counts: institutions linked, records created, computers delivered. Such counts show coverage, but they do not show whether a referral reached a specialist on time or whether a hospital bed was released without delay. The thesis addresses this gap with two research questions. RQ1: which flow indicators and control points should a unified digital health ecosystem monitor along the patient pathway? RQ2: how much can electronic referral combined with slot booking improve waiting time and referral completion in a district pathway, and under which load conditions? The contribution is a compact indicator set grounded in queueing theory, a digital patient-flow map with five control points, and a transparent, clearly labelled simulation that shows both the gains and the limits of e-referral.

LITERATURE REVIEW

Patient flow as an operations problem

Operations research gives patient flow a precise vocabulary. Little’s law states that in any stable system the average number of items present equals the arrival rate multiplied by the average time spent in the system [4]. Kingman showed that waiting in a single-server queue grows sharply as utilisation approaches one and in proportion to the variability of arrivals and service times [5]. Litvak and Fineberg argued that much of the variability in hospitals is artificial, created by how elective admissions and clinics are scheduled, and that smoothing it improves quality, safety and cost at the same time [1]. Reviews of patient flow modelling describe a wide range of queueing, simulation and lean methods applied to emergency, outpatient and inpatient units [6]. Discrete event simulation is the most common tool, yet most studies model a single department rather than the whole pathway [7].

Digital referral and appointment scheduling

Scheduling research explains why the timing of demand matters as much as its volume. Murray and Berwick showed that primary care practices can cut delays by matching daily capacity to daily demand and working down backlogs, an approach known as advanced access [8]. Gupta and Denton reviewed appointment systems across primary care, specialty clinics and surgery and identified no-shows, urgent requests and uneven demand as the main design challenges [9]. Electronic referral adds information to this picture: a referral sent electronically can be checked, triaged and booked before the patient leaves the primary care office. A scoping review of electronic referral systems reported benefits for communication between providers and for access to specialist care [10]. At a public hospital, primary care clinicians reported better access and better guidance after e-referral was introduced [11].

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Implementation studies stress that such gains depend on leadership, integration into clinical workflow and dedicated specialist time for reviewing referrals [12].

Digital health ecosystems

The WHO global strategy on digital health calls on countries to build integrated, interoperable national systems that serve patients across levels of care rather than isolated applications [13]. Earlier analysis of Uzbekistan's health system described a wide network of primary care facilities and hospitals with weak links between levels and a strong reliance on inpatient care [14]. The literature thus offers tools for flow analysis and evidence on e-referral, but few studies connect the two inside a national digital platform of a fast-reforming emerging economy. This thesis attempts that connection.

METHODOLOGY

The patient pathway was divided into five stages: primary care, referral, diagnostics, specialist or hospital care, and discharge with follow-up. For each stage the analysis defined a control point where the digital platform records a time stamp and a status. The flow indicators follow standard operations logic. Little's law links the average number of patients in a stage to the arrival rate and the time spent there [4]:

$$L=\lambda W \quad (1)$$

where L is the average number of patients waiting or being served in the stage, λ is the arrival rate (patients per working day) and W is the average time a patient spends in the stage (working days). In plain words, if 40 patients a day enter a clinic and each stays in its queue for two days, about 80 patients will be waiting at any moment. The law lets a manager check the platform's data: if the three numbers do not fit, some records are missing.

Stage utilisation identifies the bottleneck of the pathway:

$$\rho_k=\frac{\lambda_k}{c_k\mu_k} \quad (2)$$

where ρ_k is the utilisation of stage k, λ_k is its arrival rate, c_k is the number of parallel servers (doctors, scanners or beds) and μ_k is the number of patients one server can handle per day. The stage with the highest ρ_k is the bottleneck. In plain words, the busiest stage sets the pace of the whole pathway, so extra capacity added anywhere else will not shorten the wait.

Kingman's approximation shows how variability and load together drive waiting [5]:

$$W_q\approx\frac{\rho}{1-\rho}\cdot\frac{c_a^2+c_s^2}{2}\cdot t_s \quad (3)$$

where W_q is the expected waiting time before service, ρ is utilisation, c_a and c_s are the coefficients of variation of arrivals and service times, and t_s is the mean service time. In plain words, waiting depends on three things: how busy the stage is, how uneven the flow of patients is, and how long each visit takes. E-scheduling acts mainly on the second factor.

Referral completion measures whether the pathway keeps its patients:

$$RCR=\frac{N_c}{N_i}\cdot 100\% \quad (4)$$

where RCR is the referral completion rate, N_c is the number of referrals that ended in a specialist consultation and N_i is the number of referrals issued in the same period. In plain words, it shows what share of patients sent to a specialist actually got there.

Two sources of evidence were used. Real national data on hospitals, beds, outpatient institutions and doctors for 2021–2025 were taken from the National Statistics Committee [15]; [16], and growth rates and ratios were calculated by the author. The effect of e-referral was then explored with an illustrative (hypothetical) patient-level discrete-time queue simulation written in Python. It models one district referral flow from primary care to a specialist outpatient clinic with 50 consultation slots per working day and on average 45 referrals per working day, with a weekday profile of 1.30, 1.10, 1.00, 0.90 and 0.70 from Monday to Friday and 10% urgent referrals. In the paper-based scenario, 8% of referrals are never presented, patients come to the clinic 0–3 working days after referral, are seen in random walk-in order, and a patient turned away returns the next day with probability 0.85. In the

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digital scenario, every referral is booked into the earliest free slot from the next working day, 5 slots a day are reserved for urgent cases, 6% of patients miss the appointment and 70% of them rebook, and slots left free on a given day are offered to patients booked later, half of whom accept. Each scenario was run for 300 working days with a 50-day warm-up and 40 replications. These parameters are assumptions chosen to be plausible for a district setting; they are not observed data from any Uzbek facility.

ANALYSIS AND RESULTS

Expansion of the care network

Table 1 shows that the care network grew much faster in the number of facilities than in bed capacity. The number of hospitals rose by 55.1% between 2021 and 2025, while beds rose by 10.0%, so the average hospital became smaller, with about 92 beds against 129 four years earlier. Private providers accounted for most of this growth: their share of hospitals increased from 49.7% to 69.7%. Outpatient institutions grew by 33.5% and doctors by 17.6%, and bed supply per 10,000 people stayed close to 47. For flow management this means more nodes and more handovers per pathway. A patient is now more likely to be referred between providers of different size and ownership, and that is exactly where a shared digital record and electronic referral add the most value.

Table 1

Health care network of the Republic of Uzbekistan, 2021–2025[1]

Indicator	2021	2025	Change, 2021–2025
Hospitals, units	1,281	1,987	+55.1%
of which private, % of total	49.7	69.7	+20.0 p.p.
Hospital beds, thousand	165.5	182.1	+10.0%
Beds per hospital	129.2	91.6	−29.1%
Hospital beds per 10,000 population	46.9	47.6	+0.7
Outpatient and polyclinic institutions, units	6,676	8,912	+33.5%
Doctors of all specialties, thousand	95.6	112.4	+17.6%

Digital patient-flow map

[1] Source: Compiled by the author from [15]; [16]. Changes, shares and beds per hospital are the author's calculation based on these data.

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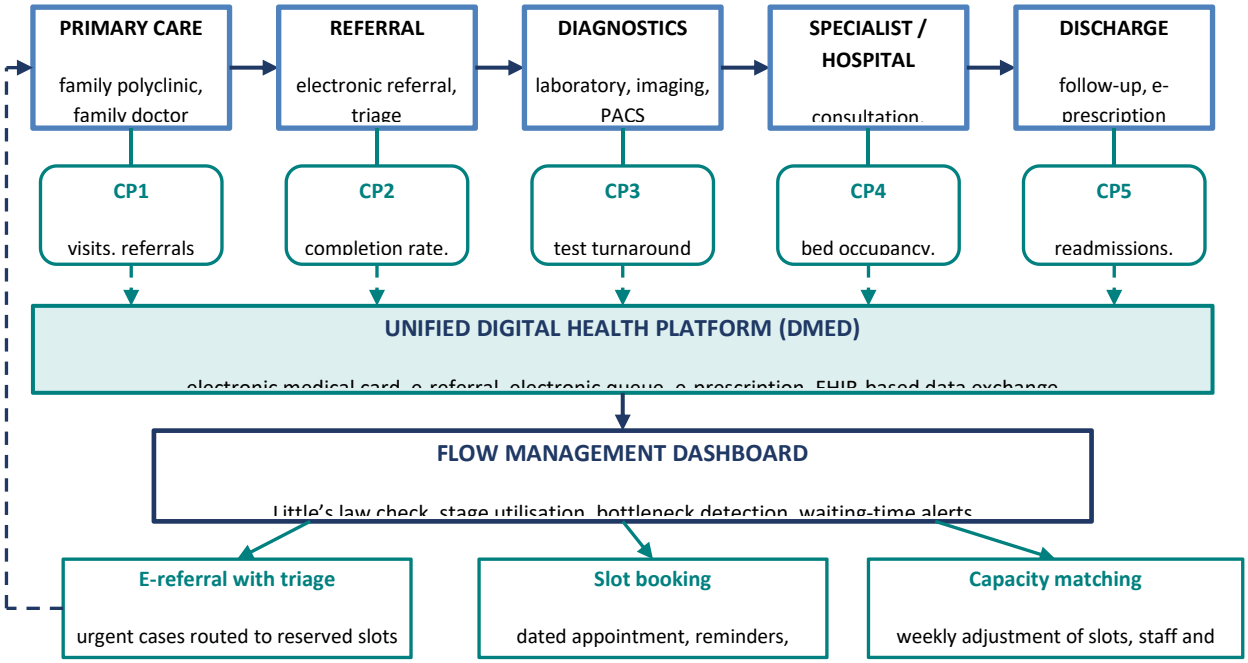


Figure 1. Digital patient-flow map with control points[2]

Figure 1 places the five stages of the pathway on top and attaches a control point to each. Every control point sends time stamps and status changes to the unified platform, where they feed a flow management dashboard. The dashboard applies equations (1)–(3) to detect the bottleneck and to flag waits that exceed a target. Three levers then act on the pathway: e-referral with triage, slot booking with a short-notice list, and weekly matching of capacity to demand. The dashed loop closes the cycle, so that what the dashboard learns this week changes slots, rosters and bed plans next week. Most components of the map already exist as DMED modules [3]; the new element is the dashboard logic that reads them as one flow.

Illustrative simulation of a district referral pathway

Table 2

Illustrative simulation results for a district referral pathway (hypothetical data)[3]

Indicator	Paper referral, walk-in queue	E-referral with slot booking
Mean wait from referral to consultation, working days	1.50	0.70
90th percentile of wait, working days	3.0	1.0
Referral completion rate (RCR), %	91.4	98.0
Patients seen per working day	41.3	44.1
Slot utilisation, %	82.6	88.2
Coefficient of variation of daily load	0.15	0.11
Urgent referrals seen within 2 working days, %	75.1	99.8
Little's law check: L vs λW, patients	62.4 vs 61.8	31.6 vs 31.0

[2] Source: Developed by the author based on [2]; [3]; [4]; [1].

[3] Source: Author's calculation; illustrative (hypothetical) patient-level simulation in Python, 40 replications of 300 working days, assumptions stated in the Methodology section. Indicators follow equations (1)–(4).

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Table 2 shows that in the illustrative setting the digital scenario improved every flow indicator. Mean waiting time fell from 1.50 to 0.70 working days and the 90th percentile from 3 to 1 day. Referral completion rose from 91.4% to 98.0%, mainly because a booked slot replaces a paper slip that can be lost and a walk-in queue that turns patients away on busy Mondays. With the same 50 slots, the clinic saw 44.1 patients a day instead of 41.3, because demand was spread evenly across the week and fewer slots stayed empty on Thursdays and Fridays. The share of urgent referrals seen within two working days rose from 75.1% to 99.8%. In both scenarios the simulated queue matched Little's law within about 2%, which confirms that the model is internally consistent.

A sensitivity run with 48 instead of 45 referrals per day showed the limits of the mechanism. Completion still rose from 91.1% to 97.0%, but because the booked clinic now served more patients, its utilisation reached 93.6% and the mean wait increased to 2.34 working days, compared with 1.52 days in the paper-based scenario. This is the effect predicted by equation (3): once utilisation is close to one, waiting grows quickly even when arrivals are smooth. In plain words, e-referral makes the queue fair and visible, but it cannot replace capacity. When the dashboard shows utilisation above about 90%, the right response is to add slots or move them from a less busy stage.

CONCLUSION AND SUGGESTIONS

The thesis showed that Uzbekistan's unified digital health ecosystem already holds the data needed to manage patient flow along the whole pathway. The network of hospitals and outpatient institutions has expanded quickly, and the DMED platform covers most residents with electronic medical cards and runs referral, queue and prescription modules. A small set of flow indicators based on Little's law, stage utilisation, Kingman's approximation and referral completion can turn these data into management decisions. The illustrative simulation suggests that e-referral with slot booking can shorten waits, keep more referred patients in the pathway and make better use of existing specialist time, provided that capacity is matched to demand.

Four recommendations follow. First, the five control points of Figure 1 can be added to the DMED dashboard as standard district indicators, published monthly together with referral completion rates. Second, every e-referral can end in a dated slot rather than an open slip, with a small daily reserve for urgent cases. Third, clinics can keep a short-notice list so that slots freed by cancellations are filled the same day. Fourth, district health managers can review stage utilisation weekly and move staff time towards the stage with the highest load. Future research can validate the simulation with anonymised DMED event logs and extend it to diagnostics and inpatient stages, where bed occupancy and length of stay can be monitored in the same way.

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