ASSESSING THE EFFECTIVENESS OF DIGITAL EDUCATION QUALITY CONTROL SYSTEMS IN HIGHER EDUCATION INSTITUTIONS BASED ON THE SPEED OF MANAGEMENT DECISION-MAKING

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Annotatsiya

Maqolada oliy ta’lim muassasalarida ta’lim sifati nazoratining raqamli tizimlari samaradorligini boshqaruv qarorlari qanchalik tez qabul qilinishi orqali baholash usuli taklif etildi. Sifat signali paydo bo‘lgan paytdan tasdiqlangan chora amalga oshgunga qadar o‘tgan vaqt uch bosqichga ajratildi: aniqlash, qaror qabul qilish va ijro. Kechikishlar Kaplan–Meier egri chiziqlari va Cox modeli bilan o‘lchandi, o‘z vaqtida qabul qilingan qarorlar ulushi va o‘tkazuvchanlik hisoblandi, ular asosida Qaror tezligi samaradorligi indeksi (DSEI) tuzildi. Usul Python dasturida yaratilgan shartli (simulyatsiya qilingan) hodisalar jurnalida sinab ko‘rildi. Raqamli rejimda qarorlar median kechikishi 32,7 kundan 17,8 kunga qisqardi, DSEI 48,7 dan 83,6 ga oshdi. Eng katta yutuq aniqlash bosqichida kuzatildi, qaror qabul qilish bosqichi esa asosiy zaxira bo‘lib qoldi. Natijalarni HEMIS ma’lumotlarida tekshirish keyingi bosqich sifatida belgilandi.

Kalit so‘zlar: ta’lim sifati nazorati, raqamli boshqaruv, HEMIS, qaror qabul qilish tezligi, Kaplan–Meier, Cox modeli, oliy ta’lim.

Аннотация

В статье был предложен метод оценки эффективности цифровых систем контроля качества образования в высших учебных заведениях по скорости принятия управленческих решений. Время от появления сигнала о качестве до выполнения утверждённой меры было разделено на три этапа: выявление, принятие решения и исполнение. Задержки были измерены с помощью кривых Каплана–Мейера и модели Кокса, были рассчитаны доля своевременных решений и пропускная способность, на их основе был построен индекс эффективности скорости решений (DSEI). Метод был апробирован на условном (симулированном) журнале событий, созданном в Python. В цифровом режиме медианная задержка сократилась с 32,7 до 17,8 дня, а DSEI вырос с 48,7 до 83,6. Наибольший выигрыш был получен на этапе выявления, тогда как этап принятия решения остался главным резервом. Проверка на данных HEMIS была определена как следующий шаг.

Ключевые слова: контроль качества образования, цифровое управление, HEMIS, скорость принятия решений, Каплан–Мейер, модель Кокса, высшее образование.

Abstract

The article proposed a method for assessing digital education quality control systems in higher education institutions by the speed of management decisions. The time from the appearance of a quality signal to the completion of an approved action was split into three stages: detection, decision and execution.

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Latencies were measured with Kaplan–Meier curves and a Cox model, the on-time decision share and throughput were calculated, and a Decision Speed Effectiveness Index (DSEI) was built from them. The method was tested on an illustrative event log simulated in Python. Under digital monitoring the median latency fell from 32.7 to 17.8 days and the DSEI rose from 48.7 to 83.6. The largest gain came from faster detection, while the decision stage remained the main reserve. Validation on HEMIS records was set as the next step.

Keywords: education quality control, digital governance, HEMIS, decision speed, Kaplan–Meier, Cox model, higher education.

INTRODUCTION

A quality problem in a university rarely announces itself as a crisis. It appears as a course where half the group failed the midterm, an attendance curve that slides for three weeks, a cluster of student complaints about one module, or a growing list of unresolved academic debts. Each of these is a signal. What separates a strong quality system from a weak one is less the number of signals it records than the time it takes to turn a signal into a decision and the decision into action. A corrective measure approved after the examination session has closed protects the next cohort, not the current one.

Uzbekistan offers a timely setting for studying this question. The Concept for developing the higher education system until 2030, approved by Presidential Decree PF-5847 of 8 October 2019, set a phased transition to the credit-module system and called for digital technologies in the educational process and effective oversight of teaching quality [1]. The sector then grew at a pace few systems have experienced: the number of higher education institutions rose from 69 in 2015 to 215 in 2025 [2], and enrolment reached 1,535.0 thousand students in the 2025/2026 academic year [3]. Earlier, the World Bank Modernizing Higher Education Project (P128516) had been approved in 2016 with the stated aim of strengthening the managerial capacity of the system [4]. Today the HEMIS platform brings student records, electronic journals, attendance, grade books, academic debt and electronic orders into one environment; the Digital Government portal lists 207 connected universities, 1,645,811 students and 121,801 professors and staff [5].

Such an infrastructure produces data continuously, yet the usual way of judging a digital quality system still rests on inputs (modules launched, users registered) or on outcomes that arrive a year later (graduate employment, rankings). Neither tells a rector whether the system helps managers act sooner. The article fills this gap by treating the quality control cycle as a sequence of timed events and by measuring effectiveness through decision speed. It asks three questions. RQ1: how can the latency between a quality signal and an implemented decision be decomposed into stages that management can influence? RQ2: which statistical tools give a fair comparison of latency before and after digitalisation when some signals are still open at the end of the observation window? RQ3: how can speed, reliability and flow be combined into one index that a quality assurance office can track each semester?

The contribution is twofold. Conceptually, the article links the literature on decision speed in organisations with quality assurance in higher education and learning analytics. Methodologically, it adapts time-to-event analysis, widely used in medicine and engineering, to the governance of academic quality and proposes the Decision Speed Effectiveness Index. Because institution-level decision logs are not yet published, the method is demonstrated on a clearly labelled simulated event log, and validation on HEMIS records is presented as the next step.

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LITERATURE REVIEW

Quality assurance as a managed cycle

L. Harvey and D. Green showed that quality in higher education has several meanings, among them fitness for purpose and transformation, and that each meaning implies a different way of checking it [6]. The European Standards and Guidelines (ESG 2015) translated this view into practice; standard 1.7 asks institutions to collect, analyse and use relevant information for the effective management of their programmes [7]. J. Newton warned that monitoring can turn into feeding the bureaucratic beast when academics see no link between reporting and improvement [8]. Two points follow for this study: information has value only when it reaches a decision, and the delay between reporting and response is part of what academics experience as quality assurance.

The evidence base for judging quality assurance itself has grown. T. Leiber, B. Stensaker and L. Harvey set out causal designs for impact evaluation and stressed the need for clear intervention logic and measurable intermediate outcomes [9]. M. Beerkens reviewed evidence-based policy in the field and argued that quality assurance agencies should rely more on systematic data and less on assumptions about what works [10]. Decision latency is a natural intermediate outcome in this sense: it sits between the introduction of a digital tool and the final change in student results.

Data use, learning analytics and decision speed

G. Siemens described learning analytics as an emerging discipline concerned with measuring and acting on data about learners and their contexts [11]. D. Ifenthaler and J. Yau found in a systematic review that analytics supports study success mainly when it triggers timely interventions [12]. Y.-S. Tsai and co-authors, surveying European universities, identified institutional readiness and unclear responsibility for action as barriers, more often than technology [13]. E. B. Mandinach framed data-driven decision making as a cycle from data to information, knowledge and action [14], and E. Brynjolfsson and K. McElheran documented how quickly data-driven decision making spread across firms [15].

Research on the timing of decisions adds a sharper lens. H. Mintzberg, D. Raisinghani and A. Théorêt split decision processes into identification, development and selection phases and showed that interruptions and delays arise at each of them [16]. K. M. Eisenhardt found that fast decision makers in high-velocity settings used more real-time information and did not sacrifice quality [17]. The stage structure used below follows this tradition: detection corresponds to identification, the decision stage to development and selection, and execution to implementation.

Two hypotheses follow. H1: digital monitoring shortens the total latency from signal to implemented action. H2: the gain is unequal across stages and is largest at detection, where automation replaces manual reporting, and smallest at the decision stage, where the procedure of approval stays the same unless decision rights are redesigned.

METHODOLOGY

The design has three steps. First, the quality control cycle was described as a chain of timed events, shown in Figure 1. Second, latency, survival, flow and composite indicators were specified. Third, the indicators were computed on an illustrative event log generated in Python and compared for a manual and a digital monitoring regime.

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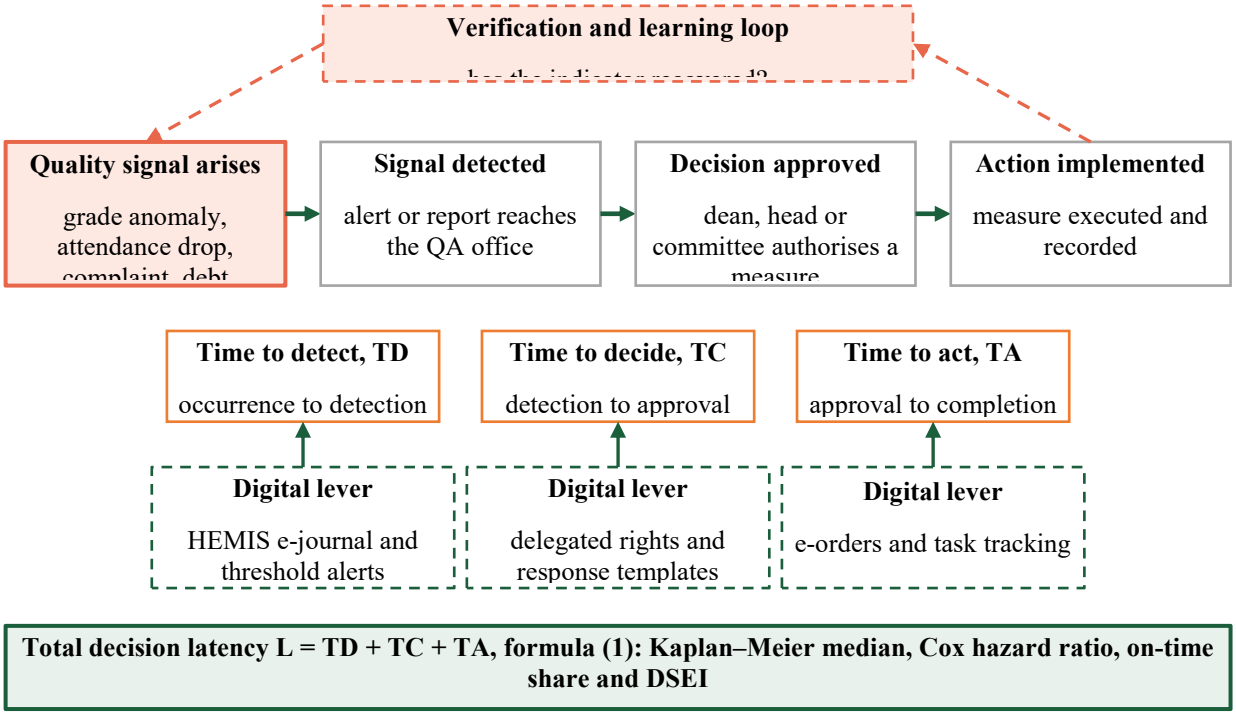


Figure 1. Quality-signal to decision cycle and its latency stages[1]

Figure 1 can be read as a relay. A signal arises in teaching or assessment, the system or a person notices it, an authorised manager approves a response, and the response is carried out and checked. The coral blocks show where time is lost, and the dashed blocks below them show which digital lever can shorten each interval. The verification loop at the top reminds the reader that an action closes the cycle only when the indicator that raised the alarm has been checked again.

Latency decomposition

For each quality signal i four time stamps are recorded: occurrence, detection, decision approval and completion of the action. The total latency and its stages are:

$$L_i = TD_i + TC_i + TA_i$$

$$TD_i = t_i^{det} - t_i^{occ};\ TC_i = t_i^{dec} - t_i^{det};\ TA_i = t_i^{act} - t_i^{dec} \quad (1)$$

where L_i is the total decision latency in days, TD_i is the time to detect, TC_i is the time to decide, TA_i is the time to act, and t_i^{occ}, t_i^{det}, t_i^{dec} and t_i^{act} are the four time stamps. In plain terms, the formula splits one long wait into three shorter ones, each owned by a different unit: monitoring, management and the executing department.

Survival analysis of latency

Some signals are still open when the observation window closes, so their full latency is unknown. Dropping them would make a slow regime look faster than it is. The Kaplan–Meier estimator handles such censored cases [18]:

$$\hat{S}(t) = \prod_{t_j \le t} \left(1 - \frac{d_j}{n_j}\right) \quad (2)$$

[1] Source: Developed by the author on the basis of [16]; [14]; [7]; [5].

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where $\hat{S}(t)$ is the estimated share of signals still without an implemented action at day t, t_j are the days on which at least one action was completed, d_j is the number of actions completed on day t_j and n_j is the number of signals still open just before that day. The median latency is the day on which $\hat{S}(t)$ first falls to 0.5, which means that half of all signals have been resolved. The two regimes are compared with the Cox proportional hazards model [19]:

$$h_i(t)=h_0(t)\cdot\exp\left(\beta D_i+\sum_k \gamma_k X_{ik}\right) \quad (3)$$

where $h_i(t)$ is the instantaneous rate at which signal i is resolved at day t, $h_0(t)$ is the baseline rate, D_i equals one under digital monitoring, X_{ik} are dummies for signal type and β and γ_k are coefficients. The hazard ratio exp(β) shows how many times faster signals are resolved under the digital regime at any given moment; a value of 2 means twice the daily chance of closure. The proportional hazards assumption was checked with the correlation between scaled Schoenfeld residuals and time [20].

Reliability, flow and the composite index

Speed on average may hide a long tail of late decisions. The on-time share measures reliability against a target T^* :

$$OT=\frac{1}{N}\sum_{i=1}^{N} I(L_i\le T^*) \quad (4)$$

where OT is the share of signals closed within T^* days, N is the number of signals and $I(\cdot)$ equals one when the condition holds and zero otherwise. Signals still open at the end of the window count as late. The flow of work is described by Little's law [21]:

$$WIP=\lambda\cdot W \quad (5)$$

where WIP is the average number of open signals, λ is the arrival rate of signals per day and W is the average time a signal stays open. The law says that, for the same flow of signals, every day cut from the waiting time removes open cases from the desk of the quality office. The three aspects are combined in the Decision Speed Effectiveness Index:

$$DSEI=100\cdot(Q_S\cdot OT\cdot Q_F)^{\frac{1}{3}} \quad (6)$$

$$Q_S=\min\left(1,\frac{T^*}{M}\right);\ Q_F=\min\left(1,\frac{\lambda_{out}}{\lambda_{in}}\right) \quad (7)$$

where DSEI ranges from 0 to 100, Q_S is the speed component based on the Kaplan–Meier median M, Q_F is the flow component equal to the ratio of the closure rate λ_{out} to the arrival rate λ_{in}, and OT comes from formula (4). The geometric mean was chosen on purpose: a regime that is fast on average but rarely on time, or that closes cases quickly but leaves a growing backlog, cannot hide one weakness behind another strength.

Illustrative data

Institution-level decision logs are not published in Uzbekistan or, to the author's knowledge, in most other systems. The indicators were therefore computed on an illustrative (hypothetical) event log generated in Python (random seed 20261106). The log describes one hypothetical university over two academic years of 300 observed days: a manual regime (paper reports and monthly committee meetings) and a digital regime (HEMIS-based threshold alerts). Four signal types were modelled, each stage duration was drawn from a lognormal distribution with shape 0.75, and the occurrence days were uniform over the window. The assumptions are given in Table 1. The target T^* was set at 21 days, roughly the time left between a midterm control and the final examination of a module. No figure in Tables 1, 3 and 4 describes a real institution.

Table 1

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Assumptions of the illustrative event log (medians of stage durations, days)[2]

Signal type	Signals, manual / digital	TD manual	TD digital	TC manual / digital	TA manual / digital
Assessment anomaly	120 / 150	12	3	10 / 7	8 / 6
Attendance decline	110 / 140	8	2	7 / 5	5 / 4
Student feedback alert	80 / 100	10	4	12 / 9	9 / 7
Academic debt build-up	90 / 110	14	3	9 / 7	7 / 6

Table 1 shows that the assumed improvement is deliberately uneven: detection medians fall to a quarter, while decision medians fall by about a third, because approval routines are assumed to be unchanged. The digital regime also records more signals, since automated thresholds catch cases that manual reports overlook.

ANALYSIS AND RESULTS

Real context of the digital transition

Before turning to the illustrative log, Table 2 places the problem in its real scale.

Table 2

Higher education institutions and students in Uzbekistan, 2021–2025[3]

Year	Higher education institutions	Students, thousand	Students per institution, thousand
2021	154	808.4	5.2
2022	191	1,042.1	5.5
2023	219	1,314.5	6.0
2024	222	1,432.8	6.5
2025	215	1,535.0	7.1

The number of students almost doubled between 2021/2022 and 2025/2026 (an increase of 89.9%), while the number of institutions grew more slowly after 2023. As a result, the average institution now serves about 7.1 thousand students, compared with 5.2 thousand four years earlier. A larger institution produces more quality signals per week, and the HEMIS coverage noted in the introduction means that the time stamps needed for formula (1) are already being created in daily operations. The constraint on faster decisions is therefore less about data availability and more about how quickly the data reach someone with the authority to act.

Latency before and after digitalisation

Table 3 reports the main results for the illustrative log.

Table 3

[2] Source: Illustrative (hypothetical) assumptions set by the author; not data of any real institution. Simulated in Python with lognormal stage durations (shape 0.75), 300 observed days per regime.

[3] Source: Compiled by the author from [2]; [3]. Students per institution are the author's calculation; the number of institutions refers to the calendar year and the number of students to the academic year beginning in that year.

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Decision latency under manual and digital monitoring (illustrative log)[4]

Indicator	Manual	Digital	Change
Signals recorded	400	500	+25.0%
Median time to detect (TD), days	10.0	2.8	−71.9%
Median time to decide (TC), days	9.9	6.7	−32.8%
Median time to act (TA), days	6.5	5.4	−17.4%
Kaplan–Meier median latency (M), days	32.7	17.8	−45.7%
Share still open at day 30, %	56.4	14.3	−42.1 p.p.
On-time share (OT, 21 days), %	20.2	62.2	+42.0 p.p.
Closures per 30 days / arrivals per 30 days	35.5 / 40.0	46.9 / 50.0	–
Average open signals (WIP)	45.41	32.05	−29.4%
Hazard ratio, digital vs manual (95% CI)	1.00 (reference)	3.32 (2.86–3.86)	–

Under the digital regime the Kaplan–Meier median latency fell from 32.7 to 17.8 days, a reduction of 45.7%. The share of signals closed within 21 days rose from 20.2% to 62.2%. The log-rank test rejected equality of the two survival curves ($\chi^2 = 223.5$, $p < 0.001$), and the Cox model gave a hazard ratio of 3.32 (95% CI 2.86–3.86), controlling for signal type. Put simply, on any given day an open signal had more than three times the chance of being resolved under digital monitoring. The Schoenfeld residual test did not reject proportional hazards ($\rho = 0.012$, $p = 0.73$), so one hazard ratio describes the whole period well. These results support H1.

The stage breakdown supports H2. The median time to detect fell by 71.9% (10.0 to 2.8 days), the time to decide by 32.8% (9.9 to 6.7 days) and the time to act by 17.4% (6.5 to 5.4 days). The decision stage accounted for 37.6% of the summed stage medians under the manual regime and 44.9% under the digital one. Digitalisation, in other words, moved the bottleneck from the monitoring office to the approval desk. Little's law held closely in both regimes (average open signals of 45.41 against $\lambda W = 45.49$, and 32.05 against 32.12), and the average number of open signals fell by 29.4% even though the digital regime received 25% more signals.

The Decision Speed Effectiveness Index by signal type

The index rose from 48.7 to 83.6 for the institution as a whole. Table 4 shows how the gain was distributed.

Attendance signals reached the highest index (91.8), because an electronic journal makes a decline visible within days and the response, such as a curator's meeting with the group, needs little approval. Student feedback alerts improved the most in relative terms, from 33.0 to 72.9, yet remained the weakest category: their median latency stayed above the 21-day target, since a complaint about teaching usually requires a hearing and a decision by the department head. Assessment anomalies and academic debt occupied the middle. The pattern suggests that the next increment of effectiveness will come from redesigning decision rights for complex signals rather than from adding new alerts.

[4] Source: Author's calculation on the simulated event log described in Table 1, using formulas (1) to (7) and [18]; [19]; [21]. Illustrative results, not empirical estimates.

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Table 4

Decision Speed Effectiveness Index by signal type (illustrative log)[5]

Signal type	Median M, manual / digital, days	OT, manual / digital, %	Flow component, manual / digital	DSEI, manual / digital
Assessment anomaly	35.9 / 19.0	15.0 / 57.3	0.85 / 0.93	42.1 / 81.2
Attendance decline	22.0 / 13.1	40.9 / 82.1	0.92 / 0.94	71.0 / 91.8
Student feedback alert	39.0 / 22.2	7.5 / 44.0	0.89 / 0.93	33.0 / 72.9
Academic debt build-up	36.5 / 17.9	13.3 / 60.0	0.90 / 0.95	41.0 / 82.8
All signals	32.7 / 17.8	20.2 / 62.2	0.89 / 0.94	48.7 / 83.6

CONCLUSION AND RECOMMENDATIONS

The article proposed and tested a way to judge digital quality control systems by what managers do with the information they receive. Three conclusions follow. First, decision latency can be split into detection, decision and execution stages, each owned by a different unit, and this split turns a vague question about effectiveness into a set of measurable delays (RQ1). Second, survival analysis gives a fair comparison when some signals are still open, and the Cox hazard ratio, the median latency and the on-time share together describe speed and reliability (RQ2). Third, the Decision Speed Effectiveness Index combines speed, reliability and flow in one figure that a quality assurance office can report each semester (RQ3).

Several recommendations follow for Uzbek universities and the Ministry. Universities can add four time stamps to every quality case in HEMIS (occurrence, detection, approval and completion), which costs little because most of these events are already recorded as electronic orders or journal entries. Quality assurance offices can publish the index and the on-time share by faculty each semester, so that progress is visible and comparable. Since the decision stage emerged as the main reserve, standard response templates for routine signals, such as an attendance drop or a missing grade, could be approved once and then applied by deans and department heads without a new committee decision. Finally, the Ministry could include median decision latency among the indicators it uses when it reviews institutional development programmes under the 2030 Concept.

The study has limitations that open directions for further research. The results come from a simulated log and show how the method works, not how large the effect is in practice. The next step is to estimate formulas (1) to (7) on anonymised HEMIS records from several universities, to test whether shorter latency is followed by better student results, and to compare institutions of different size and ownership. Faster decisions are not automatically better decisions, so future work should pair the index with a measure of action quality, such as whether the indicator recovered after the measure was taken.

[5] Source: Author's calculation on the simulated event log using formulas (4), (6) and (7). Illustrative results, not empirical estimates.

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