USING DATA ANALYTICS METHODS TO ASSESS THE PROFESSIONAL COMPETENCIES OF MID-LEVEL MEDICAL AND PHARMACEUTICAL PERSONNEL

Nazarov Baxrom Mustafayevich
Toshkent davlat iqtisodiyot universiteti
Sun’iy intellekt kafedrasi mustaqil izlanuvchisi(PhD)
https://orcid.org/0009-0004-4073-9333

Abstract. This article examines the theoretical and methodological foundations for using Data Analytics methods to assess the professional competencies of mid-level medical and pharmaceutical personnel. It explores the possibilities of integrating electronic health records, learning management systems, certification databases, patient feedback, IoT sensors, and 360-degree assessment data within a unified analytical framework. The study employs systematic literature review, comparative analysis, content analysis, and scenario-based expert assessment. It distinguishes the roles of descriptive, diagnostic, predictive, and prescriptive analytics in competency management. The results show that, despite the growing number of data sources, their integration and conversion into management decisions remain insufficient. To overcome the condition of “data richness—knowledge poverty,” an analytical model consisting of a digital competency profile, data-quality control, and a prescriptive recommendation mechanism is proposed.

Keywords: *Data Analytics, Big Data, professional competency, mid-level medical personnel, pharmaceutical personnel, EHR, LMS, descriptive analytics, predictive analytics, prescriptive analytics, digital profile.*

Annotatsiya. Maqolada o‘rta tibbiyot va farmatsevtika xodimlarining kasbiy kompetensiyalarini baholashda Data Analytics usullaridan foydalanishning nazariy va uslubiy asoslari tadqiq etilgan. Elektron tibbiy yozuvlar, ta’limni boshqarish tizimlari, attestatsiya bazasi, bemorlar fikri, IoT sensorlari va 360 darajali baholash ma’lumotlarini yagona analitik konturda birlashtirish imkoniyatlari ko‘rib chiqilgan. Tadqiqotda tizimli adabiyotlar tahlili, qiyosiy tahlil, kontent-tahlil va ssenariyli ekspert baholash usullaridan foydalanilgan. Deskriptiv, diagnostik, prognozli va preskriptiv tahlilning kompetensiya boshqaruvidagi vazifalari ajratilgan. Natijalar ma’lumot manbalari ko‘payayotganiga qaramay, ularning o‘zaro integratsiyasi va boshqaruv qaroriga aylanishi yetarli emasligini ko‘rsatdi. “Ma’lumot boyligi –bilim qashshoqligi” holatini bartaraf etish uchun raqamli kompetensiya profili, ma’lumotlar sifati nazorati va preskriptiv tavsiya mexanizmidan iborat analitik model taklif etildi.

Kalit so‘zlar: *Data Analytics, Big Data, kasbiy kompetensiya, o‘rta tibbiyot xodimlari, farmatsevtika xodimlari, EHR, LMS, deskriptiv tahlil, prognozli tahlil, preskriptiv tahlil, raqamli profil.*

Аннотация. В статье исследованы теоретические и методические основы применения Data Analytics при оценке профессиональных компетенций средних медицинских и фармацевтических работников. Рассмотрена интеграция электронных медицинских записей, LMS, аттестационных баз, отзывов пациентов, IoT и оценки 360 градусов. На основе обзора литературы, сравнительного анализа и сценарной экспертной оценки разграничены описательная, диагностическая, прогнозная и предписывающая аналитика. Предложена модель, объединяющая цифровой профиль компетенций, контроль качества данных и механизм аналитических рекомендаций.

Ключевые слова: *аналитика данных, большие данные, профессиональная компетентность, медицинские работники, фармацевтические работники, цифровой профиль, прогнозная аналитика.*

INTRODUCTION

The digitalization of Uzbekistan’s healthcare system is changing not only clinical processes but also methods of managing human-resource capacity. Electronic health records, laboratory information systems, LMS platforms, mobile applications, and sensors generate large volumes of data. However, the use of these data to objectively assess an employee’s professional competency, identify competency gaps, and develop an appropriate training decision has not yet become systematic.

The Volume, Velocity, and Variety dimensions defined by Laney explain the scale, rate of update, and diversity of formats of modern medical data. The value of medical data lies not in their volume but in their ability to improve clinical and management decisions. From this perspective, competency assessment requires a transition from merely collecting data to producing analytical knowledge.[1]

Traditional certification systems rely on periodic and often static assessment. Data Analytics makes it possible to integrate an employee’s learning activity, clinical indicators, service quality, certifications, and peer feedback over time. This creates the conditions for interpreting competency as a dynamic profile rather than a one-time score.

The purpose of the study is to identify the functional capabilities of Data Analytics methods in assessing the competencies of mid-level medical and pharmaceutical personnel and to propose an integrated analytical model. Its objectives are to classify data sources, delimit the functions of descriptive, diagnostic, predictive, and prescriptive analytics, analyze existing scientific approaches, and develop an implementation mechanism and assessment indicators suited to the conditions of Uzbekistan.

LITERATURE REVIEW

One of the earliest theoretical foundations of the Big Data concept is Laney’s 3V model. The author explains data-management challenges through the dimensions of volume, velocity, and variety. For healthcare, the criteria of Veracity

[1]Laney D. 3D Data Management: Controlling Data Volume, Velocity, and Variety. META Group Research Note, 2001. Pages cited: 1-4.

and Value were later added to this model. Even a large volume of incomplete or erroneous data cannot support useful decisions.[2]

W. Raghupathi and V. Raghupathi describe a Big Data Analytics architecture for healthcare and the relationship among data sources, analytical platforms, and practical outcomes. They identify clinical decision support, disease detection, population health management, cost control, and operational efficiency as the principal areas of application. By adapting this approach to human-resource management, the relationship between clinical outcomes and an employee's learning history can be analyzed.[3]

Provost and Fawcett explain the analytical process through the stages of defining the problem, understanding the data, modeling, and translating results into decisions. For medical competency assessment, this approach means that the management question must be stated clearly before an algorithm is selected: whether to describe the employee's current status, identify the cause of a gap, predict a future need, or recommend a practical intervention.[4]

Siemens defines Learning Analytics as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning and the environments in which it occurs. This definition provides a methodological basis for transforming LMS data-such as test results, module-completion time, repeated attempts, and learning activity—into competency indicators.[5]

Obermeyer and Emanuel emphasize that machine learning can improve clinical prediction and risk stratification, but bias in the data and an incorrectly specified objective function can amplify erroneous decisions. Their article supports the principle that AI outputs in employee competency assessment should not be treated as absolute truth, models should be explainable and human oversight should be retained.[6]

The literature review shows that healthcare analytics is primarily focused on patient risk and clinical outcomes, whereas Learning Analytics focuses on educational activity. Integrating these two streams makes it possible to view clinical outcomes, learning activity, and professional assessment within a unified competency profile. The research gap lies precisely in the insufficient development of this integration for mid-level medical and pharmaceutical personnel.

RESEARCH METHODOLOGY

The study was conducted using a conceptual-analytical design. The primary materials comprised five core sources on Big Data, Data Science, Learning Analytics, and machine learning in medicine, together with a regulatory document on Uzbekistan's digital development. The sources were subjected to content

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[2]Laney D., 2001. The 3V model: Volume, Velocity, and Variety. Pages cited: 1-4.

[3]Raghupathi W., Raghupathi V. Big Data Analytics in Healthcare: Promise and Potential. Health Information Science and Systems, 2014, 2:3. Pages cited: 1-10.

[4]Provost F., Fawcett T. Data Science for Business. O'Reilly Media, 2013. Pages cited: 45-70.

[5]Siemens G. Learning Analytics: Envisioning a Research Discipline and a Domain of Practice. LAK'12, 2012. Pages cited: 4-8.

[6]Obermeyer Z., Emanuel E.J. Predicting the Future — Big Data, Machine Learning, and Clinical Medicine. NEJM, 2016, 375. Pages cited: 1216-1219.

analysis according to author, research object, analytical task, type of data used, and practical limitations.

The analysis was structured at four levels. Descriptive analytics answers the question “What happened?”, diagnostic analytics, “Why did it happen?”, predictive analytics, “What may happen?”, and prescriptive analytics, “What action should be taken?” For each level, the data source, method, and management outcome were specified.

The 2026 coverage indicators and implementation levels of analytics types contained in the initial source material were treated not as official statistics but as the author’s scenario-based expert estimates. They are used to demonstrate the operating logic of the conceptual model. During empirical validation, these values must be recalculated using institutional data.

The study has several limitations: there is no unified national competency database, the level of integration between EHR and LMS platforms differs across institutions, and attributing clinical outcomes solely to employee competency may create a causal error. The results were therefore interpreted at the level of conceptual development and pilot-project planning.

ANALYSIS AND RESULTS

Data Sources for Competency Assessment

Comparison of data sources shows that building a competency profile solely on certification results is insufficient. The coverage values in Table 1 represent the study’s estimates for 2026.

Data source	Data type	Update frequency	2026 coverage*	Assessment capability[7]
EHR	Clinical indicators and medical records	Real time	68%	High
LMS	Learning activity and test results	Real time	74%	High
Certification database	Qualification level and certificates	Once every five years	100%	Medium
Patient feedback	Communication and service quality	After each visit	62%	Medium
Wearables and IoT	Activity and stress indicators	Continuous	38%	Additional
360° assessment	Soft skills and team assessment	Quarterly	45%	High

Although the certification database has broad coverage, its update cycle is long. EHR and LMS platforms provide timely data, but their coverage and interoperability are limited. This condition may be described as “data richness—knowledge poverty”: information exists across different systems, but without a

[7] Author’s scenario-based expert forecast.

unified identifier, competency classifier, and analytical model, it is not converted into management knowledge.

Functional Differences Among the Levels of Data Analytics

Level of analysis	Primary question	Method for medical competency	Management outcome
Descriptive	What happened?	Mean, median, distribution, dashboard	Current competency profile
Diagnostic	Why did it happen?	Correlation, clustering, association	Causes of gaps and groups
Predictive	What may happen?	Classification, regression, time-series model	Future needs and risks
Prescriptive	What should be done?	Recommendation and optimization	Decision on module, timing, and resources

Adapted by the author to medical competency management on the basis of the research classification.[8]

Descriptive analytics presents the current state of competency but does not explain its causes or future needs. Diagnostic analytics identifies relationships among LMS activity, certification scores, and clinical indicators. It must be remembered that correlation does not imply causation.

Predictive analytics estimates which competency gap may emerge for an employee and when it may occur. Potential model features include length of service, position, specialty, certification status, test scores, learning history, and clinical indicators. Model quality should be evaluated not only by accuracy but also by precision, recall, F1 score, ROC-AUC, and fairness across groups.

Prescriptive analytics converts a forecast into a practical decision by identifying which module should be recommended, in what format, when, and for what duration. Where resources are constrained, the recommendation algorithm also accounts for instructor workload, platform capacity, budget, and continuity of service.

Integrated Analytical Model

The analysis yields a five-stage model: (1) collecting data and linking them through a unique employee identifier, (2) checking data quality, (3) building a dynamic competency profile, (4) forecasting needs and generating recommendations, and (5) monitoring results using pedagogical, clinical, and economic indicators. The model's principal distinction is that it does not directly convert clinical data into a conclusion that "the employee performed poorly", instead, it controls for working conditions, patient complexity, and team-level factors.

[8]Provost F., Fawcett T., 2013. An approach to translating analytical tasks into management decisions. Pages cited: 45-70.

DISCUSSION

The results show that the healthcare analytics architecture proposed by Raghupathi and Raghupathi can be extended to the management of personnel competencies. In this framework, the EHR reflects clinical outcomes, the LMS reflects the learning process, certification reflects formal qualifications, and patient and peer feedback reflects communicative competency. No single source provides a complete assessment, triangulation reduces the likelihood of erroneous conclusions.[9]

The benefit of Data Analytics is determined not by collecting more data but by producing timely and explainable decisions. Descriptive dashboards may become widespread, but management value increases at the predictive and prescriptive stages. At the same time, a more complex model is not always a better model: when data quality is poor, an algorithm merely automates error.

From ethical and legal perspectives, employee monitoring must not become a punitive instrument. The purpose of a digital profile should be to identify development needs and allocate resources fairly. Employees should be informed about which data are used, how recommendations are generated, and how they may challenge the outcome.

In Uzbekistan, implementation should begin with a pilot stage: a unified competency dictionary should be developed, a minimum data set for EHR and LMS systems should be established, retrospective analysis should be conducted in several institutions, and predictive recommendations should then be compared with the expert judgments of educators and managers. System-wide expansion is recommended only after validation.[10]

CONCLUSIONS AND RECOMMENDATIONS

Data Analytics enables the competency assessment of mid-level medical and pharmaceutical personnel to move from a static certification score to a dynamic, multi-source, and predictive profile. EHR, LMS, certification data, patient feedback, IoT, and 360-degree assessment complement one another, but their value depends on integration and data quality.

Descriptive analytics characterizes the current state, diagnostic analytics identifies the causes of gaps, predictive analytics estimates future needs, and prescriptive analytics produces practical training and resource decisions. System effectiveness should be assessed not only through model accuracy but also through competency growth, course completion, time savings, unit cost, and fairness.

Practical recommendations include creating a unified competency classifier, introducing a unique digital employee identifier, establishing an EHR-LMS data-exchange standard, conducting audits of data quality and algorithmic fairness, applying recommendations under human oversight, and reassessing the 2026 scenario indicators using actual institutional data.

[9] Raghupathi W., Raghupathi V., 2014. Healthcare analytics architecture. Pages cited: 1-10.

[10] Decree No. PF-60 of the President of the Republic of Uzbekistan dated 28 January 2022, Annex 1, objectives and provisions concerning healthcare digitalization. The electronic document has no stable page numbering.

The proposed model provides a theoretical and methodological basis for transforming professional development from reactive course planning into a continuous, evidence-based, and economically managed human-capital development system.

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