



PSYCHOLOGICAL INTERPRETATION OF "LEARNING ANALYTICS" DATA IN TRACKING THE EDUCATIONAL PROCESS: THE RISK OF IMPLICIT BIASES

Abdujobborova Rayhona Adhamjon qizi
Kokand University Andijan Branch, Distance
Education, 1st-year student of Psychology
Email: rayhonaabdujabborova7@gmail.com

Abstract: *This article comprehensively analyzes the psychological interpretation of Learning Analytics (LA) data, which is rapidly integrating into the modern higher education system. Based on statistical indicators collected by Learning Management Systems (LMS), the study examines the implicit biases, cognitive errors, and their negative impacts on student motivation that arise during the evaluation of student behavior. The psychological risks of "digital profiles" formed by algorithms—including stigmatization and the Pygmalion effect—are uncovered, and methodological recommendations are proposed to mitigate these risks.*

Keywords: *Learning Analytics, psychological interpretation, implicit biases, cognitive bias, digital education, student motivation, algorithms, educational prediction, stigmatization, Pygmalion effect, learned helplessness.*

Annotatsiya: *Ushbu maqolada zamonaviy oliy ta'lim tizimiga jadal kirib kelayotgan Learning Analytics (O'quv tahlili) ma'lumotlarini psixologik jihatdan talqin qilish masalalari atroflicha tahlil qilinadi. Tadqiqotda raqamli platformalar (LMS) tomonidan to'planadigan statistik ko'rsatkichlar asosida talabalar xulq-atvorini baholashda yuzaga keladigan yashirin stereotiplar (implicit biases), kognitiv*

xatoliklar va ularning talaba motivatsiyasiga salbiy ta'siri o'rganilgan.

Algoritmlar tomonidan shakllantirilgan "raqamli profil"larning psixologik xavflari (jumladan, stigmatizatsiya va Pigmalion effekti) ochib berilgan hamda ushbu xavflarni bartaraf etish bo'yicha metodologik tavsiyalar ilgari surilgan.

Kalit so'zlar: *Learning Analytics, psixologik talqin, yashirin stereotiplar, kognitiv moyillik, raqamli ta'lim, talaba motivatsiyasi, algoritmlar, ta'limiy bashorat, stigmatizatsiya, Pigmalion effekti, shakllangan ojizlik.*

Аннотация: *В данной статье всесторонне анализируются вопросы психологической интерпретации данных Learning Analytics (учебной аналитики), стремительно внедряемой в современную систему высшего образования. На основе статистических показателей, собираемых системами управления обучением (LMS), исследуются неявные предубеждения (implicit biases), когнитивные ошибки и их негативное влияние на мотивацию студентов, возникающие при оценке их поведения. Раскрываются психологические риски «цифровых профилей», формируемых алгоритмами, включая стигматизацию и эффект Пигмалиона, а также предлагаются методологические рекомендации по их минимизации.*

Ключевые слова: *Learning Analytics, психологическая интерпретация, неявные предубеждения, когнитивные искажения, цифровое образование, мотивация студентов, алгоритмы, образовательное прогнозирование, стигматизация, эффект Пигмалиона, выученная беспомощность.*

Introduction

In the context of global digitization, the higher education system is undergoing an unprecedented transformation. The transition of educational processes to online and hybrid formats, along with the widespread implementation of electronic learning platforms (LMS – *Learning Management Systems*, such as the HEMIS system in Uzbekistan), has resulted in every student action leaving a digital footprint. This, in turn, has generated massive streams of data—*Big Data*. Collected, measured, and analyzed to improve educational quality, *Learning Analytics* (LA) stands today as an interdisciplinary field at the intersection of pedagogy and psychology.

Currently, LA systems powered by artificial intelligence and machine learning algorithms do not merely calculate students' midterm and final grades; they also log behavior such as platform activity time, material download frequency, and quiz-taking speed. Based on this data, profiles are generated classifying students as "active," "passive," or "at-risk."

However, the quantitative abundance and precision of digital data do not always guarantee the accuracy of the conclusions drawn from them. The core of the problem lies in the fact that the "raw" indicators provided by LA systems are often subjectively interpreted by human actors—teachers, tutors, or deans. During this process, the decision-maker's subconscious implicit biases and cognitive errors are activated.

For instance, if the system indicates a low platform login frequency for a student, a teacher may subconsciously form a stereotype of that student as "irresponsible" or "struggling." In reality, a student's low activity might stem from their mastering the material faster using

alternative resources, poor internet connectivity, or a simple technical glitch.

From this perspective, psychologically interpreting digital analytics correctly, reducing the risk of artificially pigeonholing students into specific groups (stigmatization), and protecting their individual growth opportunities are among the most critical tasks of modern educational psychology.

The aim of this study is to identify the psychological nature of cognitive errors and implicit biases that occur when interpreting *Learning Analytics* data, and to develop scientific and practical recommendations to minimize their negative impact on student motivation.

Literature Review

The theoretical and ethical foundations of *Learning Analytics* have been widely studied globally. S. Buckingham Shum and R. Ferguson emphasize that learning analytics should not be viewed as a purely technical process, but rather as a complex socio-psychological system [1]. D. Prinsloo and S. Slade have detailed the ethical issues of categorizing students through digital analytics and the moral-psychological pressure this exerts on the student's personality [2]. G. Siemens champions a humanistic model of a data-informed university [3].

While Uzbek scientific circles have extensively studied the implementation of information and communication technologies in education (A. Abduqodirov [5], A. Shayusupova [9]), the impact of data generated by digital platforms on teacher-student relationships, subjective assessment, and cognitive distortions remains largely

unexplored. This paper represents one of the preliminary attempts to bridge this scientific gap.

Research Methodology

This study utilizes methods of scientific-theoretical analysis, a systems approach, comparative study, and psychological modeling. The process of assessing how statistical indicators obtained from learning platforms impact a student's personality was modeled based on the theory of "confirmation bias" from cognitive psychology, the "Pygmalion effect" (R. Rosenthal) from social psychology, and the theory of "learned helplessness" established by M. Seligman.

The object of the study comprises students' activity indicators on LMS platforms (e.g., HEMIS) and the process of how these indicators are perceived by teachers.

Research Results and Discussion

Conducted analyses indicate that many *Learning Analytics* systems rely solely on a student's past digital footprints (time spent on the platform, number of clicks, uploaded files) to predict their future potential. Such an algorithmic approach creates systemic risks in pedagogical and psychological practice:

1. Implicit Biases and the Pygmalion Effect

If an algorithmic system subconsciously flags a student as a "low-performer" due to past low performance or low platform activity, this information enters the teacher's focus. Consequently, the teacher forms low expectations regarding this student.

This triggers the chain of the **Pygmalion effect (or self-fulfilling prophecy)**, well-known in social psychology:

$$\text{\text{\text{Low expectation}}} \rightarrow \text{\text{Change in teacher's attitude}} \rightarrow \text{\text{Decrease in student motivation}} \rightarrow \text{\text{Decrease in actual performance}}$$

The teacher subconsciously pays less attention to this student, hesitates to assign them more challenging tasks, and as a result, the student indeed falls behind academically.

2. Cognitive Biases (Confirmation Bias and Halo Effect)

When a teacher looks at statistical charts and diagrams on a platform, their cognitive distortions are activated:

- **Confirmation Bias:** If a teacher has already formed a negative opinion about a student during class, they will look through the LMS platform solely for data that confirms their view (e.g., the student logging in late on a certain day) while ignoring positive indicators (e.g., excellent quiz scores).
- **Halo Effect:** A student with a high rating on the platform is perceived as an "excellent student" in all subjects, even if they have only superficially mastered a specific module.

3. Algorithmic Determinism and "Learned Helplessness" Syndrome

In modern education, students have access to view their ratings and "digital profiles." If the system constantly labels a student as "at-risk" or "low-rated," the student's self-esteem drops.

In this scenario, the **learned helplessness** syndrome described by M. Seligman develops. The student becomes convinced that their actions cannot change the situation, adopting the psychological barrier of "I cannot do it anyway, the algorithm rated me low," which completely dampens their enthusiasm for learning.

Conclusion and Recommendations

Learning Analytics systems offer immense potential for enhancing educational efficiency and personalizing learning trajectories. However, accounting for human psychology and cognitive characteristics when using them is a vital necessity. To mitigate the risks of implicit biases and cognitive distortions, the following measures are recommended:

1. **Enhancing Educators' Data Literacy and Psychological Culture:**
 - Organizing specialized methodological seminars and psychological training sessions for teachers and tutors focused on cognitive errors (confirmation bias, halo effect) that arise when interpreting digital data.
2. **Implementing the "Human-in-the-Loop" Principle:**
 - Any analytical conclusion drawn by an algorithm must not serve as a final judgment or decision, but rather as a suggestive and guiding signal for the educator. The final decision must be made through personal communication with the student and by evaluating their mental state.
3. **Transparency and Humanistic Data Interpretation:**
 - Utilizing LMS platforms not to compare students against one another through competitive rankings, but to show their individual growth dynamics over time (a humanistic approach). The rating system must never be turned into a tool for punishment.

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