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FROM TRADITIONAL LEARNING MANAGEMENT SYSTEMS TO SMART LEARNING ECOSYSTEMS: REDEFINING DIGITAL EDUCATION THROUGH AI, ANALYTICS, AND SKILL-BASED PLATFORMS

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ABSTRACT

Digital technologies have transformed higher education, making conventional Learning Management Systems (LMS) increasingly insufficient for meeting modern educational needs. This paper examines the transition from traditional LMS platforms, primarily focused on content delivery and grade management, AI-driven smart learning ecosystems that integrate learning analytics, embedded intelligence, and skill-based profiling. The study conceptually explores this paradigm shift and analyses its practical implementation through UBEx (Uni Bridge Exchange), an Azerbaijani university-based smart learning ecosystem. Using design science research methodology, the paper presents the architectural components of UBEx, including AI-supported curriculum profiling, automated CV analysis, skill-based endorsement mechanisms, and institutional analytics dashboards.

Findings indicate that smart learning ecosystems can enhance graduate employability visibility, strengthen institutional decision-making processes, and improve alignment between graduate competencies and labour market requirements. These capabilities demonstrate the potential of data-driven educational environments to support multiple stakeholders within higher education. Despite these benefits, the implementation remains at an early stage, with stakeholder adoption still developing. Additionally, further assessment is required to evaluate the long-term impact and effectiveness of the ecosystem. The research offers a repeatable conceptual and technical framework for universities seeking to move beyond traditional grade-oriented LMS models and adopt a more comprehensive, competency-based approach to digital education.

Keywords: *Learning Management Systems, Smart Learning Ecosystems, Artificial Intelligence, Learning Analytics, Skill-Based Learning, Digital Transformation*

JEL classification codes: ***C88, I21, I23, M15, O33***

INTRODUCTION

In the last 20 years, the computerization of higher education has come a long way, with improvements in cloud computing, mobile technology and, most recently, artificial intelligence. The Learning Management System (LMS) - a type of educational software, which has been a vital backbone of universities since the early 1990s - lies at the very core of this change. Web-based learning platforms like Moodle, Canvas, Blackboard and Sakai were adopted as institutional norms, providing a centralized store for syllabi and assignments, as well as grade books. The structural weaknesses of these legacy systems have become increasingly apparent as the demands on the universities have become more complex, ranging from employability outcomes, personalised learning pathways to real time institutional analytics.

The modern-day University student is not only a consumer of content but also a growing professional whose skills and competencies and career path are directly of interest to a wide range of stakeholders, such as the academic staff, the employer and the University management. Traditional LMS platforms, which are mostly built around the idea of enrolling students in courses and keeping track of their grades, lack the structural capabilities of representing this complexity. There is limited visibility in their competency development processes, limited interfaces for the employers, and limited actionable analytic outputs to the institutional strategy level (Siemens & Long, 2011; Dyckhoff et al., 2012).

In view of these shortcomings, a new concept and technical paradigm have emerged under the umbrella of the smart learning ecosystem. Smart learning ecosystems aim to place the learner at the center of the flow of AI-driven natural language processing, learning analytics, and competency-based education frameworks and structures, bridging together academic achievement, skill acquisition, career goal, and employer need. In this paper, it is suggested that this change is not just technological, but epistemological (a change in the conception of the nature of education data and who is entitled to act upon it).

To substantiate this argument empirically the paper introduces a case study of a fully scaled smart learning ecosystem - UBEx (Uni Bridge Exchange) - which is implemented in a university in Azerbaijan. UBEx is organized for four different kinds of stakeholders, each with a specific interface, AI-driven analytical tools, and data governance procedures. In this paper, the detailed analysis of the architecture and operational logic of UBEx shows that it is technically possible and educationally fruitful to switch from traditional LMS (Learning Management System) to smart ecosystem.

The rest of the paper is organized as follows: Section 2 presents a literature review that positions the discussion under the existing body of research of LMS, AI in Education, Learning Analytics, and Skill Based Learning. The problem statement is put forward in Section 3. The research methodology is explained in Section 4. In Section 5, the system design of UBEx will be described. Results and implications are discussed in Section 6. The recommendations and directions for future research will be found in Section 7.

The Evolution and Limitations of Traditional LMS

The Learning Management Systems were developed in the 1990s as virtual extensions of the paper-based correspondence education system and have grown to become comprehensive systems that could deliver lectures, host discussion boards, and document results of assessments. Moodle had become the world's most popular open source LMS by the middle of the 2000s, followed by Blackboard, Canvas, and D2L Brightspace in the commercial arena. These platforms have been all the rage in scholarly analyses, and in every study, a central struggle has emerged: LMS platforms are great for organizing logistical elements of course delivery but inadequate tools for the learning process. (Cavus, 2010).

Watson and Watson (2007) differentiated between LMS as ‘course management' infrastructure and what they called ‘learning environments' which in essence predicted the current concept of ‘smart ecosystems. The “admin efficiency vs. pedagogy” debate, which they make, has been reiterated in the literature that followed. Coates, James and Baldwin (2005) found Australian students' experience of LMS to be primarily as a repository for documents, and not as an environment for learning, with the latter result being consistent across institutional settings. Alhazmi and Rahman (2012) recently pointed out that in the universities of the Gulf and Central Asia, the use of LMS sometimes led to the reproduction of bureaucracy structures and did not affect teaching and learning relationships between teachers and students.

The main constraint of traditional LMS in the current context is the near invisibility of LMS to the actors in the labour market. For employers who want to evaluate the skills of potential employees, there is no direct connection with the university's LMS data; they receive a standardised transcript that summarizes years of complex learning experience into a grade-point average (Brown, 2011). This is an information inequality that results in opportunities for loss of employment and loss of quality assurance in institutions.

Artificial Intelligence in Educational Settings

Since the advent of the intelligent tutoring systems in the 1980s, the use of AI in educational technology has grown immensely. In the field of education, AI can be used for various applications such as adaptive content delivery, automated essay grading, affective student analysis, prediction of student dropouts, and curriculum recommendation. Baker and Inventado (2014) offer a comprehensive taxonomy of the educational data mining techniques, the algorithmic basis of many of these applications, which include classification, clustering, regression, and relation mining.

AI's impact on education has proven to be particularly fruitful in the field of natural language processing. The ability to process free-text student submissions and recognize argumentation structures, writing quality, and semantic content has come from research prototype to deployed systems (McNamara et al., 2014). In the field of education, the introduction and evolution of large language models (LLMs) have introduced new ways of automating tasks that in the past required an expert human decision, such as mapping curriculum to CVs, competency extraction, and producing structured academic references.In the education sector, the use of large language models (LLMs) has ushered in fresh opportunities for automating tasks that traditionally necessitated expert human judgement, including tasks like curriculum mapping from CVs, competency extraction from CVs and portfolios, and the generation of structured academic references, using models like Google's Gemini or GPT-4 which are foundation models (Zawacki-Richter et al., 2019).|

Algorithmic bias and opacity have been a longstanding issue in the field of AI in education. If designed by historical inequities, AI-driven education systems can perpetuate and entrench inequity, warn Roll and Wylie (2016). In systems where machines make consequential decisions based on machines' skill assessment, e.g., recommending a person for a job position, this is a worry of particular concern. In the case of smart learning ecosystems, it is even more crucial to document the model and audit to guarantee disparate impact and human involvement at each level of the decision-making process.

Learning Analytics

Learning analytics is an emerging area of research and practice that measures, collects, analyzes and reports data about learners and their contexts to facilitate understanding and improve learning (Siemens & Long, 2011). Learning analytics is based on the simple idea that the wealth of digital data that learners leave when using learning technologies, when properly analysed, can provide insights that enhance learning and institutional strategy.

Dyckhoff et al. (2012) created an initial model for designing learning analytics dashboards to differentiate between learner-centred (for supporting SLL) and teacher-centred (for pedagogical intervention) dashboards. This typology has been expanded in subsequent work to the institutional dashboard that provides a coherent picture of analytics for programmes and cohorts, as a basis for strategic decisions (Ferguson, 2012). The visualisation of learning analytics data, using tools like D3.js, Recharts and Tableau, has captured some special scholarly interest, as interactive visualisation has been shown to significantly enhance data literacy and decision making among administrators (Verbert et al., 2014).

The problem of the heterogeneity of data sources is one of the common problems in the implementation of learning analytics. Most universities keep their academic records, library usage, attendance monitoring and career services separated, and though many of these systems might have data relevant to understanding a student's development, these data are not readily accessible or readily usable across systems. Smart learning ecosystems aiming to introduce a holistic approach to learner profiling will thus need to invest in data integration architectures that will be able to normalise and reconcile these different streams (Clow, 2013).

Competency-Based and Skill-Based Education

One of the most important curricular changes of the last 20 years is the transition to competency-based and/or skill-based education models. Competency-based education (CBE) has been associated with vocational training and professional credentialing, and it has creeping into mainstream higher education over time, as employers, accreditors, and policy makers demand that higher education institutions have the ability to prove the labour market relevance of their qualifications (Klein-Collins, 2013). The CBE approach to learning outcomes is skills and competencies rather than time in seat or course enrolment, and the focus of assessment is on evidence of performance, not norm-referenced grading.

The operationalisation of skill-based frameworks within digital systems has been facilitated by the development of competency taxonomies and ontologies, including the European Qualifications Framework, the O*NET occupational database, and sector-specific frameworks such as SFIA for information technology. These structured vocabularies provide the semantic scaffolding necessary for AI systems to extract, classify, and match competencies across CVs, job postings, and academic records (Ala-Mutka, 2011). The integration of such taxonomies into university information systems constitutes a foundational requirement for any smart learning ecosystem that aspires to mediate effectively between academic outcomes and labour market demands.

Problem statement

Although all Universities around the world invest a lot in LMS infrastructure, there is still a fundamental and persistent gap between the information that is generated by LMS and the information that stakeholders really need to make consequential decisions. There are no formal, machine-readable representations of students' emerging skills that would help them apply for jobs or plan their careers. Rich contextual knowledge about what teachers know about their students' capabilities is embedded in informal records and in their own memory - not in a manner that is systematic and takes place across the whole group. Employers face a very dilapidated information landscape when trying to determine the value of a graduate candidate, with transcripts and CVs that provide little information about how skills have been learned, demonstrated or evaluated. Academic administrators using LMS platforms have access to a lot of behavioural trace data and the ability to extract insights from them for their institutions, but they lack the analytical infrastructure.

This multiple-sided information asymmetry has real economic and social implications. The current issue of graduate unemployment and underemployment has persisted even in the face of many skilled labour shortages, indicating a persistent lack of efficiency in the matching of graduates and employers (Brown, 2011). The other side, universities are increasingly under scrutiny from accreditation agencies and government bodies to provide convincing evidence of the employability of the programmes they offer, and do not have the systems of data in place to provide such evidence. More precisely, the issue isn't one of obsolete technology, it's one of institutional design: traditional LMS were designed to support a narrow view of educational administration that is no longer fit for purpose in the context of institutions such as higher education.

The research problem in this paper can be formulated as: What does a smart learning ecosystem look like in practice and how can the architecture be designed to meet the data governance and information needs of relevant stakeholders, namely: students, teachers, employers and university administration, within an coherent and ethically responsible governance framework? The target of this question is dealt with using the empirical material of the UBEx platform, developed and deployed in an Azerbaijani university context.

Methodology/research design

To create a novel artefact (UBEx) and to provide generalisable knowledge about a class of design problems, this study follows a design science research (DSR) methodology as described by Hevner et al. (2004) which is well suited to this type of research. The position of DSR in the research landscape of information systems is unique and links between work which is purely behavioural (with the aim to explain and predict existing phenomena) and purely constructive (engineering, i.e., building working systems without necessarily theorising their design). The artefact in DSR is considered as a research product and as a theoretical contribution and measured together for usefulness and originality.

Data used in the design and evaluation of UBEx were collected from various sources. Student-side analytics were based on academic performance records, anonymised and aggregated, which were in line with the institutional data protection policies. Structured competency taxonomies were retrieved from curriculum documents, module descriptions and learning outcome statements which were processed using natural language processing pipelines.

The Student CVs uploaded on the platform were processed by an AI backend that leverages the capabilities of the Gemini API for named entity recognition, to detect the skills, work experiences, project contributions, and certifications stated by the students. Skill endorsements and structured feedback forms completed by teachers and quantitative academic data were used to create multi-dimensional student profiles and for qualitative assessment.

The system architecture of UBEx is role-based, and it is divided into four main types of actors: student, teacher, employer and administrator. There is one interface per actor type, each having a different view of the data and mode of interaction, and a common backend data layer that guarantees that data flows are consistent and correct between interfaces. The embedded analytical tools are derived from well-known libraries such as D3.js and Recharts, for data visualisation; and structured to meet the W3C Web Content Accessibility Guidelines in order to make it accessible to a wide range of users.

The UBEx system was evaluated in an iterative manner as a system was developed as well as after the first full school year of implementation. Formative assessment included systematic usability testing with representative stakeholders from each stakeholder group and expert review of the AI components by academic experts in the field of natural language processing and educational measurement. Summative assessment was based on data from platform usage logs, student, teacher and employer partner satisfaction questionnaires, and qualitative interviews with university administrators about the value of the analytics dashboards for institutional decision-making.

System Design: The UBEx Smart Learning Ecosystem

UBEx - the Uni Bridge Exchange - is conceived as a multi-stakeholder smart learning ecosystem that situates the individual student within a broader network of institutional, pedagogical, and labour market actors. Unlike traditional LMS platforms that serve primarily as content delivery and grade management tools, UBEx is architecturally designed to capture, represent, and communicate the full complexity of student development across the academic journey.

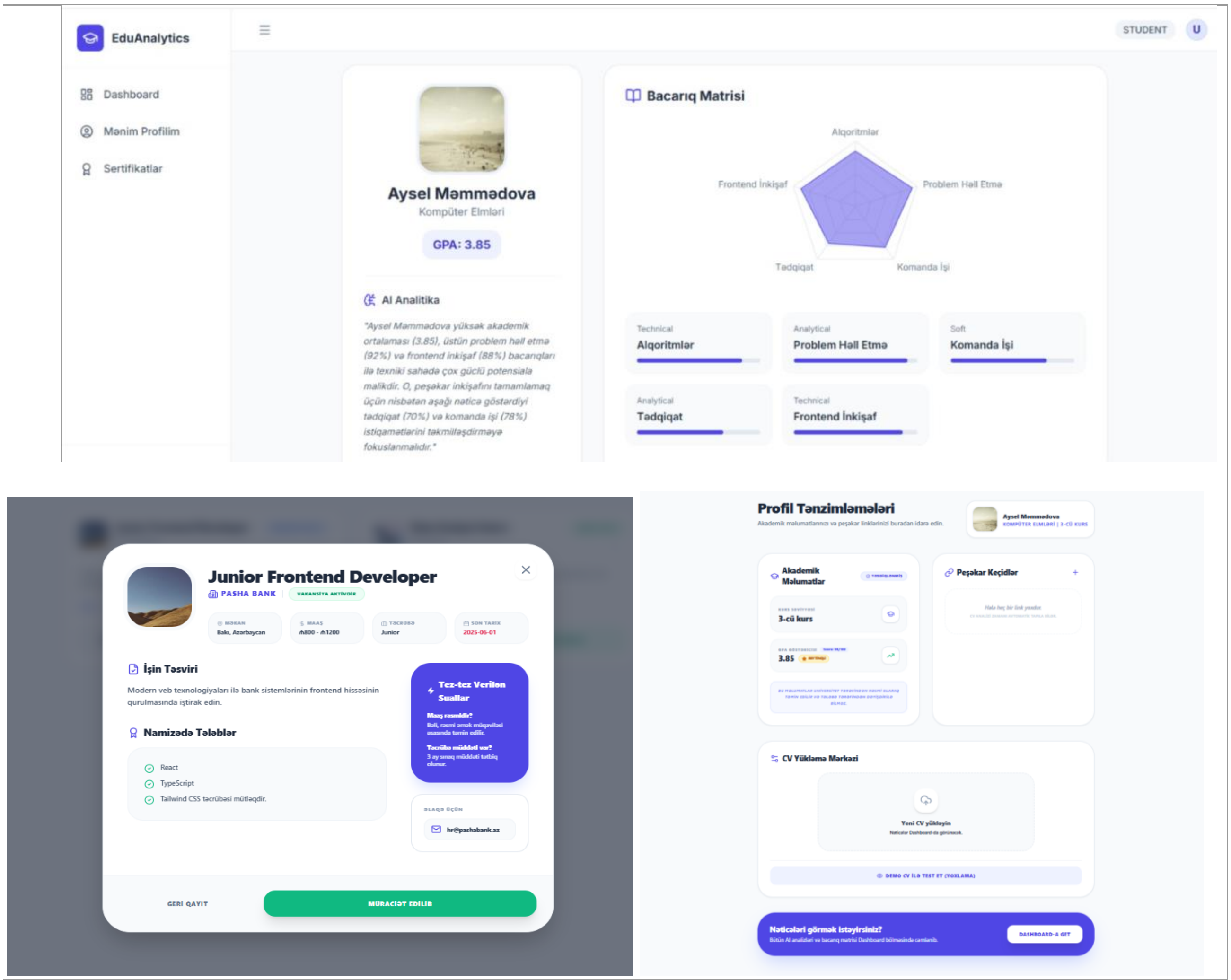
The platform is organised around four primary role-specific modules, each of which is described in detail in the following subsections.

Student Module: AI-Assisted Profiling and Skill Representation

At the front end of UBEx, an AI-based profile building system combines information from several sources to create a multi-dimensional, dynamic profile of each student's academic and professional development. Students are encouraged to submit their CV upon enrolment; this is required in PDF or DOCX. This document is analyzed using an AI analysis pipeline, developed with the Gemini API, to extract structured information, such as the presence of declared skills, work experiences, extracurricular projects, certifications, and education. The entities extracted are mapped to a standardised competency ontology, creating a machine-readable skill graph which is continuously updated as new data is available.

The academic performance data is added to the student profile, along with all the CV derived data, so that the platform can communicate the relationship between formal assessment (academic performance) and self-reported competencies. Students can also submit certificates from third-party issuers, such as professional certification providers, MOOC platforms, industry training schemes, and so on, which will go through a validation process to ensure authenticity from the issuer, if possible. Courses and extracurricular activities can be associated with project portfolios which can then be used to provide supporting evidence for skill claims made that do not have any other form of evidence.

Figure 1. Student Dashboard UI of UBEx Platform - showing AI skill graph, academic performance overlay, certificate vault, and job application tracker



A job application tracking feature in the student portal enables students to input job applications that they submit through external avenues, student notes on interview results and how their professional network grows over time. This feature is useful for personal career planning and for institutions collecting data for institutional reporting, giving a better overview of the graduate employment path that can be sent to the administrator analytics module.

Teacher Module: Structured Feedback and Skill Endorsement

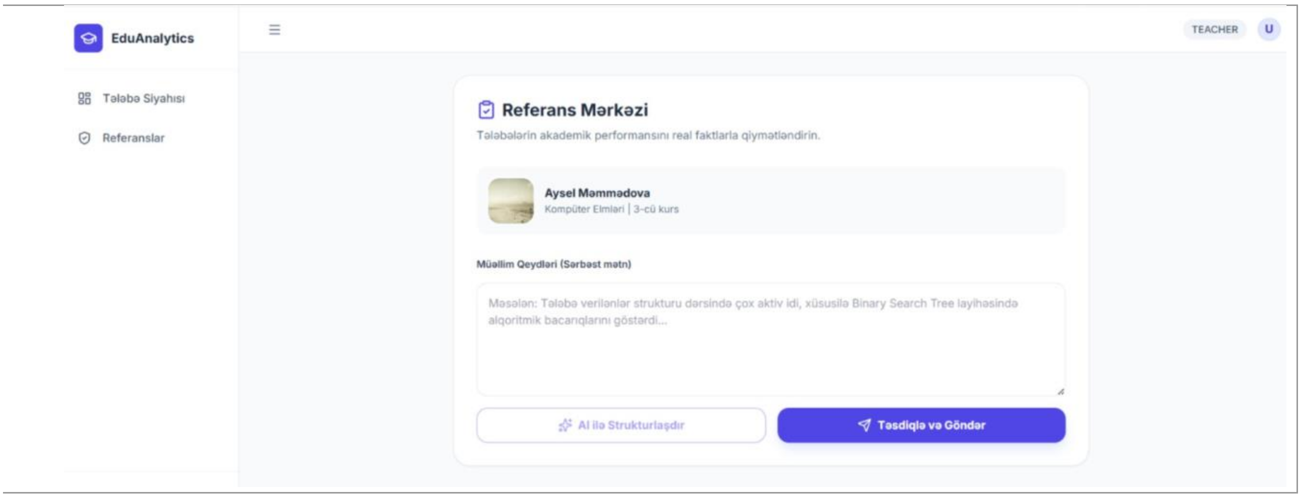
The teacher module of UBEx fills an important void in the modern educational technology world, the systematic capture of knowledge about student competencies which is held by the teacher.

Academic staff regularly produce detailed and context-appropriate evaluations of the capacity of individual students, based on long-term relationships, but much of this information is personal, informal and not shared with others. UBEx offers a framework to allow teachers to encode their implicit judgments into explicit, shareable competency evaluations.

The main tool for this knowledge capture is a skill rating and endorsement system, which displays to the teachers a student's skills profile created by the AI, asks them to rate each identified skill on a 5-point likert scale, and provides them with a space to add free-text written feedback, contextualising their judgement. These endorsements include a badge on the student profile that is verified by the teacher, as opposed to user self-reported or AI-inferred competencies, thereby making the endorsements more credible from the users' (employer) point of view.

The AI enabled reference writing module will help teachers to write structured academic/ professional references as it will pull all relevant information from the student profile such as course grades, contributions to projects, teacher's endorsement, and attendance information, and then will provide a reference narrative optimized with AI, that the teacher can review, edit, and approve. This capability eases the burden of writing a reference and ensures that the reference is written from true data, not on memory. All references created by the teacher are edited by him/her and are clearly stated as his/her own work.

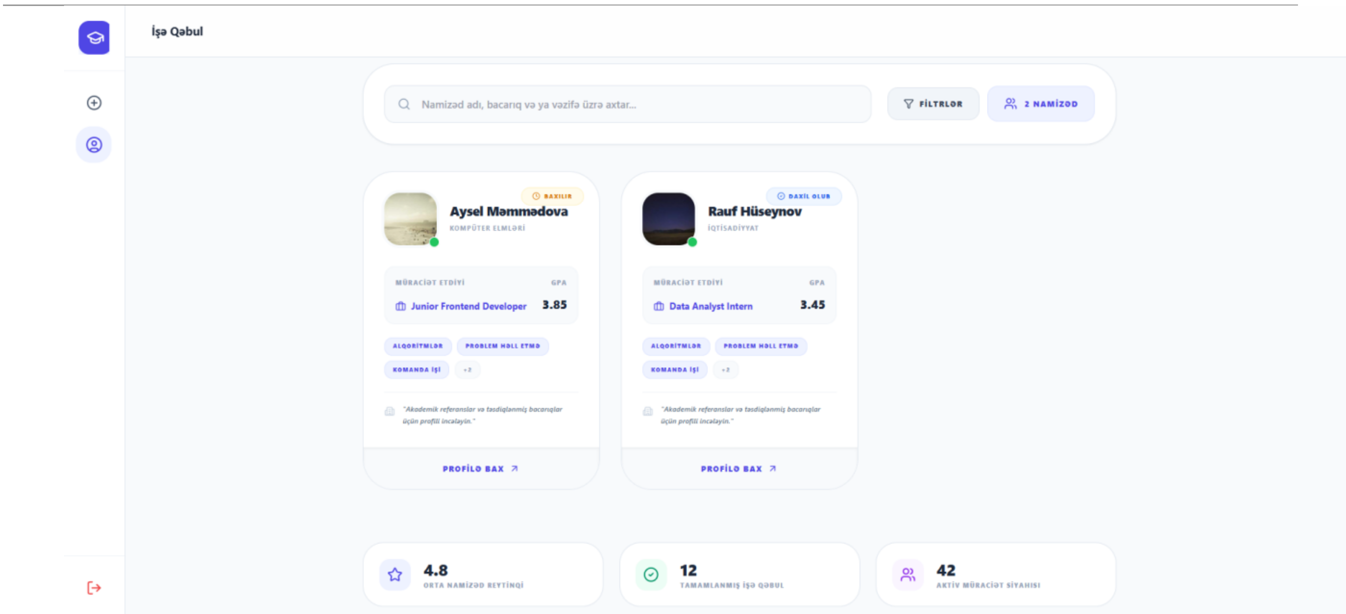
Figure 2. Teacher AI Feedback and Skill Endorsement Interface - showing skill rating panel, AI-assisted reference draft module, and endorsement history log



Employer Module: AI-Driven Recruitment Intelligence

One of the most unique products of the UBEx from the employer side of the smart learning ecosystem paradigm is the employer facing interface. UBEx enables registered employers to access student profiles in a structured and verified manner which alleviates the information-poorness currently observed in the graduate recruitment process, and also significantly lowers the search costs for employers who are looking for job candidates with particular skill sets. Employer users can search and filter on the employer recruitment dashboard for target competencies, which are a subset of the same standardised ontology that the student profiling system uses, and will get a ranked list of student users whose skill profiles are available and verified to be a match for the search criteria. The AI backend calculates a skills match score for every candidate listed in the search results and provides a summary of the teacher endorsements that align with the given competencies, with a verification status indicator to show how well a stated skills score is backed up by academic records, certificates or teacher endorsements. Employer users can also add vacancies to the platform, that AI back-end processes to be able to determine the necessary skills and build match scores with the existing students. The two-way matching feature, which involves both the student and employer providing a description in a common competency language, significantly increases the accuracy of graduate hire opportunities compared to the keyword-based matching feature typical of standard job boards. Employers are able to shortlist candidates, begin communication via the secure messaging on the platform and record the result of the recruitment, which is then added to the institutional analytics tab as proof of the employment rate per skill domain.

Figure 3. Employer Recruitment Dashboard - showing AI candidate matching panel, skill-filter search interface, verified profile viewer, and vacancy posting module

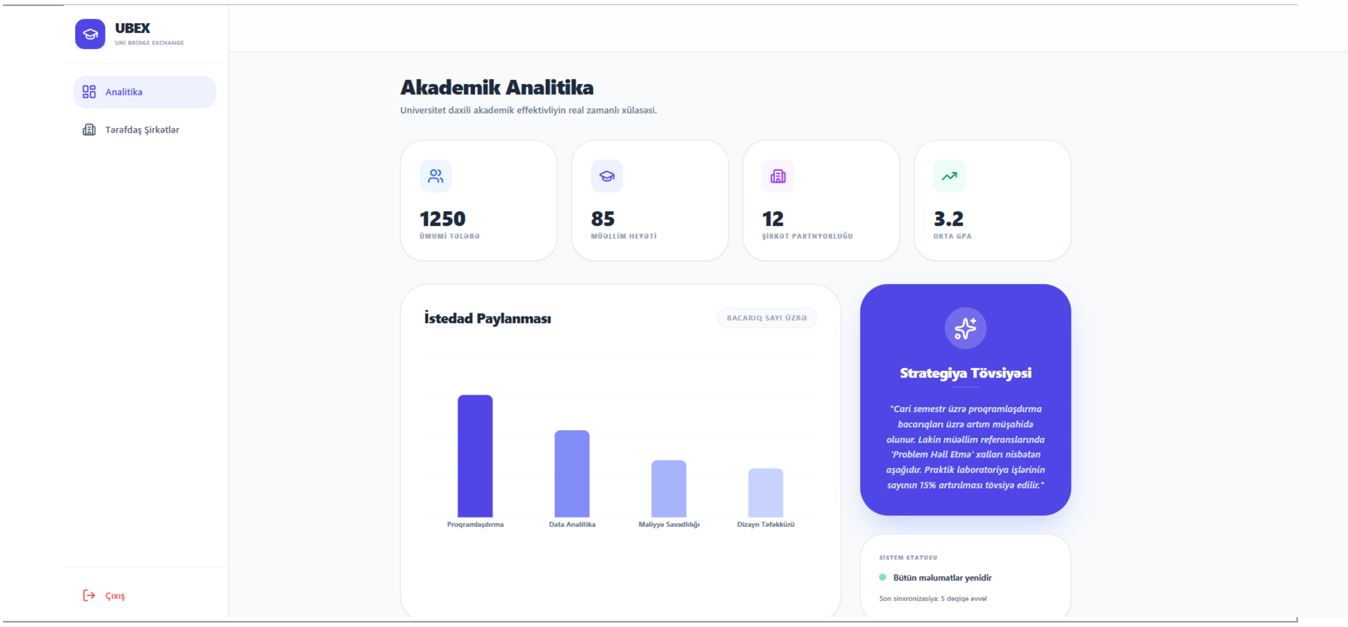


University Administrator Module: Institutional Learning Analytics

The UBEx administrator module is tailored to the strategic information needs of the university leadership, quality assurance bodies and programme management groups. It offers an analytics dashboard which pulls data from all four stakeholder modules to make analytics views at institutional level which can yield actionable insights on student development, programme outcomes and labour market relevance.

The heart of the dashboard, built with D3.js and Recharts, displays several customisable views such as Heat Maps of Skill Distribution – which show the prevalence of a particular skill in the student body – Cohort Academic Performance Trend Lines – which plot academic outcomes against time and programme variant – and Employment Outcome Trackers – which visualise the relationship between skill profile and graduate recruitment success. Each visualisation is interactive and allows administrators to explore at three different levels: programme, cohort, and individual student. A skill gap analysis module detects whether students have skills and competencies that differ from those that employers do, through the verified student profile and the skills and competencies that are listed in the employer's posting and on the assessment. This type of analysis can directly inform a curriculum review, allowing programme teams to determine the learning outcomes that require enhancement and plan specific interventions, such as extra components of a project or industry placements, or additional skill workshops. In this way, the administrator module provides the final link in the data chain started from individual student profiling and ended with the institutional curriculum strategy and is the culmination of the smart learning ecosystem vision.

Figure 4. University Analytics Dashboard - showing skill distribution heatmap, cohort performance timeline, skill gap analysis view, and employment outcome tracker (built with D3/Recharts)



RESULTS

The deployment of UBEx across one full academic year provided rich empirical material for evaluating the proposition that a smart learning ecosystem can address the informational deficiencies of traditional LMS platforms while generating new categories of value for all four stakeholder groups. The results reported here are on platform usage analytics, user satisfaction surveys, and qualitative interviews conducted during the summative evaluation phase.

Among student users, the most consistently reported benefit of the UBEx platform was the transition from passive grade reception to active competency articulation. In post-deployment surveys, students reported that the process of engaging with the AI-generated skill graph and the certificate validation workflow prompted them to reflect more deliberately on the relationship between their coursework and their professional aspirations. This finding resonates with research on e-portfolio systems suggesting that structured self-assessment activities have significant positive effects on metacognitive development (Tosh et al., 2005). The job application tracking module was also well-received, with students describing it as providing a level of career planning structure that had previously been absent from their academic experience.

Teacher users initially expressed concern about the additional time commitment associated with completing structured skill endorsements for each student. Formative evaluation revealed that this friction was substantially reduced when the AI-assisted interface pre-populated the endorsement form with inferences drawn from the student's existing profile, reducing the teacher's task from active assessment to confirmation and correction. Following this design iteration, endorsement completion rates increased markedly, with many teachers completing endorsements for all their students within the target timeframe. The AI-assisted reference writing module was rated highly by teacher users across all departments, with many noting that it substantially reduced the time required to produce high-quality references without compromising the authenticity of their professional judgement.

Employer engagement with the platform yielded perhaps the most striking results. Participating employer partners reported that the verified skill matching functionality produced candidate shortlists of substantially higher relevance than those generated through conventional recruitment channels. Several employers noted that the competency verification system - which distinguishes between AI-inferred, self-reported, certificate-backed, and teacher-endorsed skills - provided a level of candidate intelligence that was previously unavailable through any single information source. Two employers reported making graduate hires directly through the UBEx platform during the pilot year, and all participating employers indicated their intention to continue using the platform in subsequent recruitment cycles. For university administrators, the analytics dashboard provided novel insights into skill distribution patterns that had previously been invisible within the grade-centric reporting of the legacy LMS. The skill gap analysis functionality revealed several significant mismatches between the competency profiles being developed within existing programme curricula and the competency demands being expressed by employer partners - insights that have directly informed curriculum review processes currently underway. Administrators also noted that the employment outcome tracking data generated by the platform provided more granular and actionable evidence of employability outcomes than the annual graduate destination surveys that had previously constituted the institution's primary source of labour market intelligence.

The results should be viewed with due consideration for the following cautions. The deployment was conducted in one school for one academic year, reducing the generalisability of the findings. Self-selection effects may have also led to over-optimistic findings, as those students and teachers who chose to participate in the platform may have been more motivated and technologically proficient than the rest of the students or teachers. The overall performance of the platform as a whole was good, but the scores for students whose CVs and project documentation were written in Azerbaijani were lower than in English, which is a known limitation of the language model used that was built on an English training corpus. One of the key challenges recognized for future development of the platform is the multilingualism issue, which can be resolved by domain-adapted model fine-tuning on the educational texts written in Azerbaijani.

The findings presented here collectively back the core idea of this paper: the shift from a traditional LMS towards a smart learning ecosystem creates qualitatively new categories of educational and institutional value that can not be realized through the incremental development of existing LMS functionality. The UBEx platform illustrates that this shift is technically feasible within a realistic timeframe and budget for the institutions and that the benefits for all four groups of users are mutually reinforcing as well as mutually exclusive.

CONCLUSION

This paper has contended that, although popular and proven to be of administrative use, the traditional LMS is structurally unable to meet the information needs of the modern HEI. These are not "accidental" shortcomings of LMS platforms but are an expression of underlying assumptions that form the backbone of a paradigm that has been designed according to a different interpretation of the purpose of education than the one now dominant.

As outlined in this paper and demonstrated by the UBEx platform, the smart learning ecosystem paradigm is a viable and feasible solution to the aforementioned challenges. Smart ecosystems combine competency profiling with AI assistance, skill endorsement through a structured process, certificate management (verified), information for employers on recruitment intelligence, and institutional learning analytics in a single role-based architecture, which serves students, teachers, employers, and administrators at the same time and in synergy. Such a move from grade-based to skill-based representation of student achievement is the most basic epistemological reorientation that can be facilitated by this architecture, and has deep implications for employability of graduates, curriculum design, and quality assurance of institutions.

The replicable technical and conceptual framework provided by UBEx case study can be adapted by other universities, especially those in emerging and transition economies looking for the possibility of quickly and efficiently modernising their digital education space. The platform's modular design facilitates a staged rollout of functionality, so that institutions can start small with student profiling and gradually add more layers of features that are employer-facing or institution-focused analytics as they gain stakeholder buy-in and build up data quality.

Future studies should focus on the 'long-term' aspects of the smart ecosystem impact; the career paths of graduates whose learning and development were facilitated by skill-based profiling systems over the course of a few years or more, rather than a few months. In multilingual educational settings, the multilingualism of the AI components is particularly relevant, and it is crucial to create domain-specific language models for educational and professional texts in languages other than English. As the impact of these systems grows in graduate recruitment, the ethical aspects of AI-driven competency assessment, such as algorithmic fairness, consent architecture, and data minimisation, call for continuous research and study.

Finally, it is not a matter of a trendy technology shift, but of education being fit for purpose: from LMS to smart learning ecosystem. The needs of universities and their students, their employers, and the regulatory bodies are changing, and only those institutions that have focused on developing an information architecture that can capture the entirety of the educational value creation process will be best equipped to meet the challenges. One way that investment could be made is provided by UBEx.

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XÜLASƏ

Rəqəmsal texnologiyalar ali təhsili köklü şəkildə transformasiya etmiş, nəticədə ənənəvi Təlimin İdarə Edilməsi Sistemləri (Learning Management Systems - LMS) müasir təhsil tələblərini qarşılamaq baxımından getdikcə daha qeyri-kafi olmuşdur. Bu məqalə əsasən məzmunun təqdim edilməsi və qiymətlərin idarə olunmasına yönəlmiş ənənəvi LMS platformalarından öyrənmə analitikası, daxili intellekt və bacarıq əsaslı profilləşdirməni özündə birləşdirən süni intellekt əsaslı ağıllı öyrənmə ekosistemlərinə keçidi araşdırır.

Tədqiqat bu paradiqma dəyişikliyini konseptual baxımdan təhlil edir və onun praktik tətbiqini Azərbaycan universitet mühitində formalaşdırılmış UBEx (Uni Bridge Exchange) ağıllı öyrənmə ekosistemi nümunəsində qiymətləndirir. Dizayn elmi tədqiqat metodologiyasına əsaslanan araşdırmada UBEx platformasının memarlıq komponentləri, o cümlədən süni intellekt dəstəyi ilə kurikulum profilləşdirilməsi, avtomatlaşdırılmış CV təhlili, bacarıq əsaslı təsdiqləmə mexanizmləri və institusional analitika panelləri təqdim olunur.

Əldə olunan nəticələr göstərir ki, ağıllı öyrənmə ekosistemləri məzunların məşğulluq imkanlarının görünürlüğünü artırmağa, ali təhsil müəssisələrinin qərar qəbuletmə potensialını gücləndirməyə və məzun kompetensiyaları ilə əmək bazarının tələbləri arasında uyğunluğu yaxşılaşdırmağa imkan verir. Bu imkanlar məlumat əsaslı təhsil mühitlərinin ali təhsildə müxtəlif maraqlı tərəflərin ehtiyaclarını dəstəkləmək potensialını nümayiş etdirir. Bununla yanaşı, tətbiq prosesi hələ ilkin mərhələdədir və maraqlı tərəflər arasında platformanın mənimsənilmə səviyyəsi məhduddur. Eyni zamanda, ekosistemin uzunmüddətli təsirlərinin və effektivliyinin qiymətləndirilməsi üçün əlavə araşdırmalara ehtiyac vardır. Tədqiqat ənənəvi qiymət yönümlü LMS modellərindən kənara çıxaraq daha əhatəli, kompetensiya əsaslı rəqəmsal təhsil yanaşmasına keçmək istəyən universitetlər üçün təkrarlana bilən konseptual və texniki çərçivə təqdim edir.

Açar sözlər: *Təlimin idarə edilməsi sistemləri (LMS), Ağıllı öyrənmə ekosistemləri, Süni intellekt, Öyrənmə analitikası, Bacarıq əsaslı təhsil, Rəqəmsal transformasiya.*

JEL kodları: *C88, I21, I23, M15, O33*