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Generative AI as a Catalyst for Educational Personalisation through Learning Analytics and Design Research

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Abstract

The adoption of Generative Artificial Intelligence (GenAI) and Learning analytics (LA) in education is quickly moving beyond experimental pilots to widespread use. This research explores the stages of awareness, use and perceived usefulness and challenges and uses of these technologies by the teachers and the students. Survey results showed that all respondents were aware of ChatGPT (100%) with lower rates of awareness regarding Gemini (43%) and Copilot (39%) combined with high active-use rates (67%) and universal exposure to LA dashboards at that institution. Comparing to past studies that found moderate or mixed awareness in faculty (Zawacki-Richter et al., 2019), these results indicate a paradigm shift, at least in relation to the traditional gap of awareness and the use that was observed in adoption literature (Papamitsiou & Economides, 2014; Ferguson & Clow, 2017), except that it is now smaller in scale. The paper also notes positive perceptions of service advantages, such as personalization (93%), efficiency (98%), engagement (100%) and GenAI-LA synergy (94%), that verify previous theoretical expectations of a closed-loop adaptivity (Daniel, 2017; Gaevinc et al., 2019), but go further to show that they have been achieved in practice. On the other hand, the obstacles remain similar to those in previous literature: infrastructural gateway (79%), shortcomings on training (100%) and the moral implications of plagiarism (100%) and privacy dangers (87%) reooplify the permanent limits observed in the past studies (Ifenthaler & Yau, 2020; Cotton et al., 2023). The study is both theoretical and practical in that less adoption barriers are demonstrated due to use of GenAI, coupled with heightened issues regarding ethics and integrity. It highlights the importance of capacity-building, institutional governance and ethical protection to make sure that AI educational promise can be met with a fair, sustainable and integrity-driven learning experience.

Keywords: Generative AI, Learning Analytics, Higher Education, AI Adoption, AI Personalisation, AI Ethics.

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Introduction

The quest to personalisation in higher learning has been a debatable issue especially within the learning sciences, a condition in which personalisation has always been touted as a solution to one-size-fits all approach to teaching. The potentialities of student-centred and evidence-based design have grown immeasurably with the development of learning analytics and, more recently, Generative Artificial Intelligence (GenAI). Although it has been argued that learning analytics can enable pedagogical decision-making by visualising student data (Siemens & Baker, 2022), this adoption is not widespread, as some researchers label this situation an ongoing research-to-practice gap. Generative AI, in contrast, opens up the prospects of democratising access to analytics information, where even non-expert teachers could also realise personalised pathways. To be able to use GenAI as a catalyst, the need to place it in the larger discourse of the learning design and analytics research is critical.

Ferguson and Clow (2017) state that learning analytics has plenty of supposed benefits related to evidence-based interventions, but educators often have considerable difficulties transferring the data provided by the dashboards into effective teaching practice. They demonstrate lack of educator preparation, in which they have tools but do not use them to the full potential. Contrastingly, Holmes et al. (2023) argue that AI technologies, particularly GenAI have reshaped the concept of accessibility by automating the process of interpretation and rendering the insights of data runnable with everyday teaching. When combined, these studies show a transformation in how analytics have gone beyond purveyors of information to GenAI augmented as a decision-support system.

Laurillard (2012) thinks about learning as a design science in which the pedagogical frameworks are created by evidence and reflection. However, as Luckin (2023) notes, design studies have not been able to keep up with the fast-growing AI technology thus causing a disjuncture between design theories and the digital toolboxes. Here, the implication is that design frameworks offer theoretical rigor but GenAI can operationalise them in the realtime feedback as well as adaptive scaffolding and establish theory-practice.

In a systematic review of AI applications in the higher education sector, Zawacki-Richter et al. (2023) demonstrate that studies are almost all experimental or small-scale, with minimal adoption at the institutional level. Conversely, as Ifenthaler and Yau (2020) would claim, analytics-based decision-making has been demonstrated to be helpful when providing early intervention in the student retention process but is also afflicted by scalability flaws. Here, GenAI reformulates the concept of scaling individualised interventions at a smaller cost of escalating the workload of educators.

According to Siemens and Long (2011), learning analytics has been termed as a way to make an educational sense of information given the fact that the development of learning analytics lies at the core of the future of evidence-based teaching. At that, Dawson et al. (2019) warn against analytics that tend to perpetuate customary assessment processes rather than encourage innovation. Where GenAI will fit into this environment

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is the need to rethink data usage beyond prediction of performance, with additional applications including formative assessment, authentic feedback and student agency.

Baker and Inventado (2014) underline that educational data mining is concerned with predicting the trends in performance whereas learning analytics aims at enhancing learning based on actionable insight. In comparison, Seldon and Abidoye (2018) address the enhancement of these insights with the help of AI that determines hidden patterns of learning. By using GenAI analytics evolve out of descriptive reporting to adaptive sequencing of curriculum and are thus a qualitative advance in functionality.

According to Knight et al. (2014), ethical transparency is of essence in the admission of learning analytics, especially when the institutions assess the issue of student trusts. This aspect is captured by Williamson and Eynon (2020) who echo that learning deploying AI displays risks such as algorithmic bias and misuse of data. GenAI integration therefore not only requires refinement technologically, but governance models as well, that will result in the personalisation done responsibly.

Verbert et al. (2013) conducted studies that explored learning dashboards and discovered that students find feedback visualisations to be useful yet instructors are still unsure of its B.P. On the contrary, Kizilcec et al. (2017) reveal that personalised analytics feedback is effective to help students become more motivated and persistent. This aspect is reinforced by GenAI since it can turn and introduce context-awareness in the previously closed dashboards as conversational systems answer to learner queries on the fly.

The institutional barriers to scaling analytics which have been highlighted by Tsai et al. (2019) include fragmented policies and these institutions have not received the training. However, according to Holmes and Porayska-Pomsta (2018) these barriers can be overcome with the usage of AI-based supports that automate analytics and reflect in it through interpretations made by the non-experts. This opposition demonstrates the way GenAI has the potential to alter the institutional ecosystems towards broader adoption.

Gasevic and colleagues (2015) reiterate that learning analytics needs to shift beyond merely providing descriptive statistics and into decision-making pedagogical use. In the interim, one can find that the system that involves GenAI gives precisely that chance that Holmes et al. (2021) describe because it is capable of producing adaptive learning material that is driven to meet the pedagogical objectives. These studies, together, point to a meeting of educator demands and technological potentials.

According to Sharples et al. (2016), the dream of it all was learning at scale whereby the digital platforms handle individualised training to big groups. However, Selwyn (2019) does not believe in techno-determinism and urges that AI-tools can never entirely substitute a human judgement in the field of education. Referring to GenAI as a catalyst, - but not a substitute- corresponds to a more realistic angle, with technological aid not replacing the role of an educator in the personalisation process.

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Definition of Generative AI

Generative Artificial Intelligence (Generative AI, GenAI) is a subset of artificial intelligence in which generative models are used to create original content, e.g traditional text, images, video, audio, code or other synthetic media. During their training phase, these systems learn the pattern, structures and relations present in very large datasets and then apply that learning in creating new outputs based on prompts or inputs.

Generative AI as defined by NIST can include models where AI is used to generate derived synthetic content, such as images, audio, text or video, by emulating its structure and characteristics of input data.

IBM Research defines Generative AI as deep-learning models that learn an approximate representation of the training data, e.g. on Wikipedia text or pictures and produce new, statistically plausible samples on demand

Generative AI has been defined on Wikipedia as a subset of the artificial intelligence field that equips generative models with text, pictures, videos or other data, training on the patterns underneath it and creating new content, learning the prompt.

Types of Generative Al

1. Text Generation: The general use of large language models, trained on human language data to produce a coherent, contextually sensitive human-like text has been apportioned to AI models.

→ Uses: Content writing, chatbots, summarization, translation, academic research assistance.

→ ChatGPT (OpenAI) Example: Acts as an email ready-made, lesson planning, email and essay-writer, code helper.

2. Image Generation: Diffusion models or GANs allow models to combine both creativity and realism when generating a new image based on a prompt.

→ Uses: Digital art, advertising, product design, architecture visualization.

→ Examples: DALL•E 3 (OpenAI) or MidJourney - designers create posters, social media and concept art.

3. Code Generation: AI trained on programming repositories generates or auto-completes code.

→ Applications: software development, bug fixing, algorithm writing and automation of tedious code.

→ Example: GitHub Copilot- offers capabilities to support developers with instant code snippets in IDEs.

4. Audio & Music Generation: Music or voice synthesized by models is formed by sets of sound patterns.

→ Uses: Creating background scores, voiceovers, audiobooks, language learning.

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→ Example: Jukebox (OpenAI) is a system that creates new musical songs of different styles; Voicemaker.ai can create synthetic voices.

5. Video Generation: AI makes or re-edits videos based on motion and image synthesis learned.

→ Uses: Marketing campaigns, educational videos, virtual avatars, filmmaking.

→ Example: Synthesia: a source of corporate learning videos that are produced through AI avatars.

6. 3D Model Generation: Design, gaming and simulation of 3D objects and environments are based on AI.

→ Uses: Gaming, architecture, product prototyping, metaverse experiences.

→ Example NVIDIA Omniverse- creates 3D industrial designs and simulations.

7. Synthetic Data Generation: Produces artificial datasets statistically similar to real data.

→ Applications: Model training of AI in cases where real data is scarce, privacy-enhancing analytics.

→ Case: Primarily AI- generating synthetic data to financial and healthcare firms.

8. Multimodal Generation: Combines different forms of content (text-to-image, text-to-video, text-to-audio).

→ Uses: Holistic content creation, education, interactive media.

→ Example: Google Gemini or OpenAI GPT-4o- Can be used to provide prompts in text and produce images, speech or rationale at the same time.

Advantages of Generative AI

Generative Artificial Intelligence (GenAI) has always been appreciated as a transformational catalyst in creative, scientific and industrial fields. An emerging literature on it points to its capacity to contribute to creativity and innovation. Holzner et al. (2025) present meta-analysis research that on creative tasks, AI alone exhibits similar performance to human participants, but human-AI collaboration notches up creative performance to a new level, supporting the findings of other researchers, such as Cao et al. (2023), in revealing that such systems as MidJourney and DALL·E turn out to empower artists to overcome traditional limits of visual forms. The sense of AI as a partnership but not a replacement is characteristic of the fact that the discussion about automation was earlier largely focused on substitution (Dwivedi et al., 2023; Floridi & Cowls, 2021).

Productivity gains represent another recurring theme. In controlled studies, e.g. Peng et al. (2023), they found that programmers who used GitHub Copilot could complete tasks 55.8 per cent faster than the controls.

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Simkute et al. (2024) however complicate this narrative by pointing out to the fact that productivity does not steadily get better: some of the users have the increased cognitive workload or their workflow is disrupted. In relief, the previous studies (Brynjolfsson et al., 2019) had foreseen productivity as a sweeping effect of AI augmentation. This implies that there are gains but these are mediated by user experience and tasks.

Personalization is perhaps one of GenAI's most celebrated advantages. In education, the work by Zawacki-Richter et al. (2019) and a more recent study by Chen et al. (2024) show how Adaptive tutoring system responds to the needs of the specific learner, increasing the level of success. Similar parallels can be noticed in healthcare: Machine learning-driven individualization of care according to the genetic or clinical profile has hastened patient care (Jiang et al., 2017; Esteva et al., 2021). These results refer to the statement of Patki et al. (2016), in which synthetic information allows training AI in high-stakes situations without disclosing personal data, confirmed in a review by Springer (2024) on the use of synthetic data in cybersecurity and the financial industry.

The potential for cross-disciplinary innovation is widely emphasized. According to the review provided by Bengesi et al. (2023) and Multimedia Tools and Applications (2024), one of the areas where generative AI caused a breakthrough is the field of drug discovery, architecture and business optimization. This kind of versatile ability is the result of a merger of previously separate research directions: previous works focused on either NLP or image generation because they were considered as isolated complex tasks, today, research results show the integration of multimodal capabilities (Bommasani et al., 2021).

Challenges and Risks

Although GenAI offers benefits, it represents extreme risks that have taken centre stage in the academic debate. Bias and fairness remain the most persistent concerns. Mehrabi et al. (2021) demonstrated that AI systems reproduce existing historical inequities; the case studies in recruiting and health services published more recently (Liang et al., 2023; Buolamwini & Gebru, 2018) prove the same danger, especially when using biased datasets to drive discriminatory results.

Most researchers have focused on ethical risks, including, misinformation, deepfakes, plagiarism when reviewing the topic (Samuelson, 2023; Nguyen et al., 2024). The spread of the deepfake technology in political manipulation shows a heightened level of danger when compared to the previous periods of algorithmic misinformation (Vosoughi et al., 2018). Intellectual property disputes remain unresolved as well: early literature argued that intellectual property laws apply in the copyright regime (Samuelson, 2023), but new thinking (Varian, 2024) emphasizes the vast extent of AI training data harvesting to the degree that conventional IP law is ill suited to AI-generated works.

Data privacy and security remain equally critical. In addition, 2024 scoping review by Springer cites vulnerabilities, like the model inversion and the prompt injection, which may be unintentionally shared with sensitive training data. Familiar warnings have been issued in the medical field, with PubMed-indexed reviews

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(2024) warning that synthesized illusions, speculative reference excerpt in clinical AI-contributed items may potentially lead to direct patient intransigence. These generalize previous issues (Goodfellow et al., 2014) with adversarial robustness to the generative setting.

Job disruption continues to attract attention. There is a paradox in that though earlier prediction (Frey & Osborne, 2017) assumed a mass acceleration of displacement of low-skill jobs, recent literature (Brynjolfsson et al., 2023; Eloundou et al., 2023) assumes that there may be differentiated types of displacement with AI replacing routine cognitive work and at the same time complementing complex and judgment-based jobs. Nevertheless, discontinuities during the transition in journalism, customer support and coding are being frequently reported (Peng et al., 2023).

There are also issues of reliability like the idea of hallucinations (Ji et al., 2023). It cannot be some minor errors: in the law and medism, fake citations or diagnoses can even cause harm to the system (Marcus, 2023). The stochastic nature of generative systems places it in a position of individual lifting liability as opposed to the strict determinism set out in previous models of AI and this point brought forth by Holzner et al. (2025) further confirms this.

Ethical Considerations

The subject of ethical control of GenAI belongs to the primary concerns of scholarly and governance debate today. Transparency is emphasized as foundational. Floridi & Cowls (2021) state the precise requirement about AI being explainable to be ethical and recent research proved that AI disclosure will boost the user trust level at least by several folds (Chen et al., 2024). The issue of accountability is still being discussed, nevertheless: some researchers support the idea of developers remaining strictly liable (Bryson, 2020) whereas other researchers suggest distribution of responsibility among the users, companies and governments (Cath, 2022).

Human oversight is another recurrent theme. The European Union through its AI Act classifies some generative applications as being at high-risk and enforces the human-in-the-loop regulation ("high-risk") (European Commission, 2023). Such a policy response is consistent with the literature in both healthcare and education about the importance of AI enhancing rather than supplanting expert judgement (Esteva et al., 2021; Frontiers in AI, 2025).

Regulation and governance are expanding globally. An approach that is multilateral in nature, like the OECD-supported Global Partnership on AI or the recently established by UNESCO AI Ethics Recommendation, is thus indicative of how AI can be aligned with human rights and democratic values (UNESCO, 2022). These steps build out of the previous more limited frameworks (Jobin et al., 2019) into panoramas of policy actions that are enforceable.

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The principle of responsible use has been reframed. In contrast to the development of ethics initiatives in the distant past focusing on risk mitigation, the recent studies support the idea of the proactive application of GenAI to benefit society (Nguyen et al., 2024). Responsible use has further become an issue that does not just seek to avoid causing damage but is concerned with building common ground in equal access and that which is human friendly.

Future Scope

According to the results of the latest systematic reviews, the future of the GenAI is awaiting co-creative state, multimodality and mature governance. The future predicted by Holzner et al. (2025) shows an increase in so-called models of AI as a collaborator, which imply that co-creation will become commonplace in the scientific research community, learning and creative business. Newer work (Frontiers in AI, 2025) predictive of this trend is newer work confirming this trend, which is the adaptive assessment through AI personalized education that Zawacki-Richter et al. (2019) suggest.

Healthcare breakthroughs are another priority. The literature (Esteva et al., 2021; Jiang et al., 2017) indicates an increasing AI contribution to the early diagnosis and drug discovery phases of research and systematic reviews (PubMed, 2024) suggest accelerating clinical trials through the use of synthetic patient data.

As the third frontier, multimodal AI systems that combine text, image, audio and video are pointed out (Bommasani et al., 2021; Bengesi et al., 2023). This development symbolizes a great broadening up of the single-modality of old GPT and GAN models.

Literature emphasizes the economic transformation driven by GenAI. Eloundou et al. and Brynjolfsson et al. (2023) indicate the inevitability of short-term disruptions but the long-term trends indicate the formation of new industries, positions and entrepreneurship opportunities. Reconfiguration rather than replacement of human labor markets has taken the centre-stage.

2. Literature Review

The concept of learning design has been around since long as a systematic form of strategic planning in education by laying out precise pedagogical determinations that are capable of overseeing a fitting arrangement among learning objectives, learning activities and evaluative measures (Laurillard, 2012). Earlier scaffolding and effective instructional sequencing (Biggs & Tang, 2011) were emphasized in earlier frameworks, but nowadays the metaphor to refer to is personalisation and inclusivity. As an example, Conole (2013) claimed that design should incorporate the technology to embrace various learning style, whereas Goodyear and Dimitriadis (2013) emphasized collaborative aspects of design. Nevertheless, even with such theoretical improvements, it has been reported that there is a discrepancy in relation to the actual classroom practice as opposed to the desired design (Bennett et al., 2017). The existing body of research further develops these premises and establishes a connection between learning design and adaptive systems along with the

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support provided with the help of AI. As an illustration, Persico and Pozzi (2015) did investigate the subject of adaptive scripts in the case of blended learning and Alario-Hoyos et al. (2019) focused on scalable models of the MOOC design. The more recent literature, Chen et al. (2022) shows that AI-based learning design tools have a potential to increase the extent of inclusivity through dynamic personalisation of pathway, whereas Luckin (2023) emphasises the idea of human-AI collaboration to increase the contextualised nature of design. The route has thus shifted to be more about the static and theoretically based design to a dynamic and AI-assisted personalisation at scale.

The development of learning analytics has been a field that has offered promise of actionable information in student data (Siemens & Baker, 2022). Its usage in understanding the retention and engagement was defined early on by Ferguson (2012) but was not widely adopted because it required technical expertise by the educator, which was lacking, as stated by Ifenthaler and Yau (2014). A criticism of the dashboard emphasis was correspondingly leveled by GaMac Technology Zoneevic, Dawson and Siemens (2015) as being descriptive in its orientation as opposed to predictive or prescriptive. Recent studies are more promising: Viberg et al. (2018) emphasized the importance of multimodal data integration and Knight, Buckingham Shum and Littleton (2014) called to focus more on pedagogical underpinning. The literature is growing to support the link between analytics and decision-making-Maldonado-Mahauad et al. (2018) interviewed self-regulated learning patterns and Jivet et al. (2020) interviewed how learners perceived dashboard feedback. Nevertheless, the barriers are interpretability and trust (Tsai et al., 2020). Recent contributions imply that analytics are required to be coupled with AI to enable real-time adaptivity (Holmes et al., 2023) and recent studies (Zawacki-Richter et al., 2019; Siemon et al., 2023) demonstrate how analytics combined with generative AI creates entrant opportunities, filling the gaps in adoption. Thus the relative progression shows a move towards predictive analytics and a new horizon of generative and interpretive insights.

Generative AI (GenAI) has brought a revolutionary potential to education and particularly in the domains of personalisation, feedback and generation. The most important early advances in AI-in-education research were in the rule-based intelligent tutoring systems that offered structured and inflexible adaptivity (Anderson et al., 1995; Woolf, 2010). As large language models (LLMs) have emerged, flexibility has increased substantially. Holmes et al. (2023) show that ChatGPT can be employed to scaffold such learner support in both writing and problem-solving as well as translation tasks and Kasneci et al. (2023) point at the real-time generation of feedback. Nevertheless, the issues are reminiscent of past AI discussion: bias (Bender et al., 2021), transparency (Mitchell et al., 2021) and academic integrity (Cotton et al., 2023). The latest comparative findings demonstrate a disagreement in approaches emphasized between optimism and criticism- Tlili et al. (2023) provide an example of inclusive education, whereas Luckin (2023) promotes the idea that human oversight will stand at the core of ethical use. In addition, empirical works that are being developed (Chen et al., 2023; Rudolph et al., 2023) point out positive growth in learner engagement and a greater potential danger of over-dependence. GenAI represents a paradigm shift over previous paradigms of intelligent tutoring, in its

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decentralisation of expert knowledge, but echoes many of the ethical and pedagogical tensions that have not been resolved there.

A new research avenue is the interop of GenAI and learning analytics. Previous proposals to integrate analytics and adaptive design were mainly theoretical: Greller and Drachsler (2012) pointed to the possibility that analytics might contribute to adaptive design; Siemens (2013) proposed a learning analytics ecology. Such proposals were not well developed practically because of the technology limitations. Recent study promotes discussion-Luckin (2023) suggests that GenAI is capable of translating the complicated analytics to teacher-readable, actionable insights. Holmes et al. (2023) suggest synergy enables them to engage in what the researchers call the real-time personalisation, which reduces the entry barrier to educators who know little about technical data interpretation. The empirical basis is also increasingly growing: Roll and Winne (2015) also discovered the role of analytics in self regulating which has been compounded by GenAI personalised nudges (Kasneci et al., 2023). This integration is shifting between conceptual and operational as demonstrated by comparative studies. An example is Siemon et al (2023) describe how AI-enhanced analytics benefits balancing at-risk student early warning systems and Zawacki-Richter et al (2019) reveal what educators require interpretable analytics GenAI directly answers. The comparative development shows that the GenAI replaces the area in which the analytics suffered in their accessibility, with its mediative interpretation and in this respect, the field is fundamentally being remodeled in a more responsive and inclusive direction.

Methodology

Research Design:

This research was based on a mixed-methods design given the need to offer not only breadth but also depth in interpreting the nexus of generative AI (GenAI), learning analytics and designing personalised learning in higher education. The combination of systematic literature review (SLR) with a primary empirical data gathered by means of surveys and semi-structured interviews with teachers and students was provided. The mixed method facilitated the triangulation of results which made the results reliable and valid (Creswell & Plano Clark, 2017).

Sampling:

The main data was collected at Sabarmati University, Ahmedabad (India) in various faculties such as Arts, Science, Commerce and Professional Studies. Teachers: Of 127 all members of the faculty, 79 (62.2%) contributed voluntarily to the research. Stratified purposive sampling ensured representation across disciplines. Students: Of 924 students that were registered, 517(55.9) responded to survey. Proportionate stratified sampling technique was adopted to guarantee academic and demographic diversity (gender, year of study and programme type). This sampling design was less biased in sampling and biasedness was reduced in compare to representativeness and feasibility.

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Data Collection Instruments:

Awareness, use patterns and observed effects of GenAI-driven learning analytics tools were measured by answering a structured survey questionnaire. The proposal was represented by Likert-scale questions (1,5), categorical and non-locked questions.

Semi-Structured Interviews, the interviews will be carried out with 21 teachers and 38 students (a sample of the survey participants) in order to obtain detailed information on challenges and opportunities related to GenAI adoption. Themes developed out of the SLR formed the basis of interview protocols.

Data Analysis Techniques:

Quantitative Analysis, the results of the survey provided were analysed through the use of descriptive statistics; the Mean, Standard Deviation (SD) and%age distribution. This was useful in determining the general perception of the students and teachers. Inferential testing was not emphasised because it was an exploratory and not casual approach.

Qualitative Analysis, thematic coding using the NVivo software was used to code the interview transcripts. Deductive (literature themes) and inductive (emerging insights) coding was already done in a combination with the hybrid approach. Inter-coder reliability was established via independent coding by the two researchers, with a Cohen Kappa of 0.84; however they were in strong agreement.

Ethical Considerations:

This Institutional Ethics Committee at the Sabarmati University provided ethical approval. This was on a voluntary basis, although, informed consent was taken by all respondents. The data gathered about the participants was anonymised so as to ensure the privacy and data was stored safely with adherence to GDPR and the Indian data protection standards.

Data Analysis and Interpretation

The analysis of responses collected among the participants of the study, constituted of 79 teachers (out of 127) and 517 students (out of 924), was summarized in Table1, 2 and 3 thus giving an overview of the sample characteristics and answer patterns.

Table 1: Student's Questionnaire Response

Sr.No.	Question	Yes %	No %
A: Regarding awareness and use of GenAI & Learning Analytics			
1	I am familiar with Generative AI tools (e.g., ChatGPT, Gemini, Copilot).	89%	11%

2	I have used GenAI tools in my learning.	67%	33%
3	I am aware of learning analytics dashboards at the university.	100%	0%
4	I regularly use analytics/AI-based tools for academic purposes.	68%	32%
B: Regarding Benefits			
5	GenAI helps in creating personalised learning experiences.	93%	7%
6	Learning analytics provides useful insights into student progress.	69%	31%
7	Combining GenAI with analytics improves the effectiveness of teaching/learning.	94%	6%
8	GenAI saves time in preparing lessons/assignments.	98%	2%
9	Learners become more engaged when AI-based tools are used.	100%	0%
C: Regarding Challenges			
10	I face technical difficulties in accessing or using AI-based tools.	79%	21%
11	Lack of training/support is a barrier in using AI effectively.	100%	0%
12	I am concerned about plagiarism or over-reliance on AI tools.	100%	0%
13	I am concerned about bias and transparency in GenAI responses.	41%	59%
14	Data privacy and ethical concerns limit my willingness to use GenAI.	87%	13%
D: Regarding Attitude			
15	I am open to adopting GenAI-enhanced analytics tools in education.	89%	11%
16	I believe that future teaching and learning will rely heavily on AI-driven personalisation.	84%	16%
17	What additional support/training would you require to use GenAI effectively.	96%	4%

Section A: Awareness and Use of GenAI & Learning Analytics

Q1. I am used to generative AI tools (ChatGPT 100%, Gemini 43%, Copilot 39%).

The results indicate that respondents were well-aware of the existence of at least one GenAI tool, with ChatGPT being universally known, whereas the other tools examined, Gemini and Copilot, were more on the scale of moderately well-known. This shows that ChatGPT is already the standard AI tool in higher education. In comparison to Zawacki-Richter et al. (2019), who have concluded that university educators remain unaware

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of AI tools, the current study implies a marked trend towards massive familiarity with the tools in only a matter of years. Likewise, Sallam (2023) noted the dominance of ChatGPT in higher education market by its accessibility and flexibility in a short period. This large awareness can be explained by means of more and more media coverage, college chats, as well as peer pressure.

Q2. I have taken advantage of GenAI tools in my learning/teaching (67% Yes).

Two-thirds of the participants affirmed the current usage of GenAI, reflecting a change in awareness to practice. This observation is consistent with that of Kasneci et al. (2023) who found that approximately 70% of the faculty of German universities have tried ChatGPT in the first few months after its launch. The same happened in the UK where Lo (2023) recorded a high usage of GenAI by students in assignments and brainstorming. But, in comparison with the previous studies where the use of it was rather exploratory, we can state more embedded use in practice teaching and learning practices, which points towards GenAI becoming more of a pedagogical tool than an experiment.

Q3. I know learning analytics dashboards exist in the university (100% Yes).

Institutional exposure to learning analytics (LA) dashboards was high as all the respondents were in possession of information on such dashboards. This is contrary dimensional to the evidence provided by Ifenthaler & Yau (2020) who discovered that a significant number of teachers in Australia and Asia did not know anything about university analytics systems. In addition, Tsai & Gaševic (2017) pointed out the fact that dashboard underutilization existed even when it was present because of the insufficient training. Our current findings imply that our sample is more developed than some other, potentially as a result of university-level initiatives and policy mandates on digital platforms.

Q4. I apply analytics or AI-based tools on a regular basis to academic applications (68% Yes).

It is encouraging to see over 68% of those surveyed said they often use analytics or AI-related tools, despite the lack of awareness around its use. According to Papamitsiou & Economides (2014), a small%age of the teachers engaged in direct application of analytics, which indicates the disconnection between the supply and the use. Similarly, Nguyen et al. (2020) have noted that there is limited use of learning analytics in teaching practices resulting in time and skill barriers. Our findings indicate that we are on a positive deviation of such trends and it could be as a result of institutional pressure to base decisions using data.

Section B: Regarding Benefits

Q5. GenAI can support the development of personalised learning/teaching experiences (93% Yes).

Almost everyone answered that GenAI creates the possibility of personalisation in the field of education. This affirms Holmes et al. (2021) who stated that AI can enable adaptive learning pathway targeting learner profiles. On the same note, Luckin et al. (2016) also showed that AI-powered systems can personalize feedback, which makes students more motivated. In comparison to these previous studies with predominantly experimental AI

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participation, we can conclude that GenAI is already showing practical benefits to educators and learners in terms of individualised pedagogy.

Q6. Learning analytics can be informative in regard to student progress (69% Yes).

Most of the respondents (69%) recognized the value of analytics in tracking the performance. This is in line with Siemens & Long (2011) who pointed out that data driven academic decision making benefits are Hallmarked by learning analytics. Similarly, Scholes (2016) concluded that the use of dashboards enhances feedback between the students and the teachers. Nevertheless, in contrast to earlier results in which excitement was highly theoretical, our research demonstrates that there is growing actual enthusiasm with regard to using analytics as a significant learning tool.

Q7. Teaching/learning is made more effective through a combination of GenAI and analytics (94% Yes).

The synergy of GenAI and analytics was heavily supported (94%). In this process, Daniel (2017) stated that the collaboration of AI with the analytics results in actionable educational intelligence, whereas Gašević et al. (2019) verified that a combination of various data-driven tools enhances pedagogical interventions. This is contrary to any previous research where many a time, such tools were investigated in isolation but our findings provided a strong commitment by the users that convergence is the actual change maker.

Q8. GenAI saves time in preparing lessons/assignments (98% Yes).

Almost all respondents reported time-saving benefits. This is agreeing with Qadir (2023), who discovered that AI minimises mental and administrative burden among teachers. Likewise, King & ChatGPT Study Group (2023) noted that the students found GenAI a useful helper to write their essays and assignments. Our findings go beyond lending credence to these previous assertions and also propose institutional efficiency in time use which may transform the way the curricula is planned.

Q9. When applying the tools with the use of AI, Learners can be more engaged (100%).

Every participant affirmed increased engagement with AI. This supports Chen et al. (2020) stating that there was an increased desire among students to study in AI-enhanced classrooms. In a similar vein, Baker & Inventado (2014) have identified that AI interventions are influential in the terms of decreasing the levels of disengagement and dropout. These claims are supported empirically by our findings that indicate a unanimity of agreement of the benefits of engagement.

Section C: Challenges and Concerns

Q10. Access or use of the AI-based tools is a technical challenge to me (79% Yes).

Technical barriers pose a serious problem with almost 4 out of every 5 respondents being affected by it. Aldowah et al. (2019) witnessed the same problems in Middle East universities where the adoption was disfavored by bad infrastructure. Similarly, Technological readiness was singled out as an important barrier

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by Ifenthaler and Yau (2020). Our research establishes that even in cases where the adoption is high technical support is another area of weak sustainable integration.

Q11. A barrier to effective use of AI is lack of training/support (100% Yes).

All respondents demanded training, highlighting a universal skill gap. Zawacki-Richter et al. (2019) also came to a similar conclusion about the necessity of professional development as the key aspect to AI integration. Holmes et al. (2021) also emphasized that unless they are trained systematically, the use of AI can become superficial. It is not that we did not observe in our study that training is a necessity but a core component of institutional AI strategies in the long terms.

Q12. I have fears of plagiarism or too much dependence on AI tools (100% Yes).

Every participant expressed concern over academic integrity. This observation is firmly in agreement with that of Cotton et al. (2023) who had recorded the increasing instances of plagiarism attributed to GenAI usage. Uncontrolled use of AI had also been a point of argument by Susnjak (2022) who argued that it causes dependency and critical thinking loss. Our study reflects all these (fears) that besides adoption, ethics and policy frameworks are necessary.

Q13. My concern is with the prejudice and openness in relation to GenAI answers (41% Yes).

A 41% were worried about GenAI bias. In their studies, Bender et al. (2021) noted structural bias of large language models, whereas Weidinger et al. (2022) emphasized the danger of opacity of responses generated by large language models. Our findings show that there is awareness that bias occurs, but it is not everywhere-maybe because of the lack of exposure to controversial outputs in educational settings.

Q14. The ethical issues and the data privacy restriction my intent to use GenAI (87% Yes).

Most respondents cited privacy and ethics as limiting factors. In an earlier study, Slade & Prinsloo (2013) warned that learning analytics bring forth quite dangerous ethical issues. And much like that fact, Williamson & Eynon (2020) have addressed the dangers of datafification in education. The fact that the%age is high on our study supports the need to implement data governance frameworks to generate trust.

Section D: Regarding Attitude

Q15. I would welcome the use of GenAI-boosted analytics tools in education (89% Yes).

Almost 89% participants were open to adoption as they had a high positive orientation. Alamri (2022) has also discovered high openness amongst Saudi educators in the case of sufficient support. In addition, Kasneci et al. (2023) established that regardless of the ethical issues, the willingness of integrating AI was high. Our findings indicate that there are more reasons to be optimistic than apprehensions and adoption can be done with institutional protection.

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Q16. I think future learning and instruction will be heavily dependent on AI-driven personalisation (84% Yes).

A clear majority endorsed AI-driven futures. This is in correlation with Luckin et al. (2016) who foretold the future of AI-led personalisation as something unavoidable. Holmes et al. (2021) also built on the same argument and stated that personalised AI would enhance future pedagogy. Empirically informed data supplied by us suggest that, not only students but also teachers accept the inevitability of AI in education.

Q17. What other support/training would you like to receive to work with GenAI? (96% requested regular training)

Respondents overwhelmingly requested structured, periodic training. This is indicative of Ifenthaler & Yau (2020) who discovered that professional development prolonged by adoption increased. In the study by Zawacki-Richter et al. (2019) they also stressed the importance of long-term training instead of separate workshops. One of our central findings is that there is a policy direction necessarily to institutionalize training to guarantee responsible use of AI.

Table 2: Teacher's Interview Question Response

Sr. No.	Question	Yes	No
1	Do you currently use AI or learning analytics in your teaching practice?	62%	38%
2	Do GenAI tools provide benefits for lesson planning or student engagement?	77%	23%
3	Have AI/analytics improved teaching outcomes in your experience?	72%	28%
4	Do you face major challenges in adopting GenAI or analytics tools?	80%	20%
5	Do you perceive academic integrity, bias or transparency issues with GenAI usage?	70%	30%
6	Do you believe institutional or policy support is necessary for wider adoption?	84%	16%
7	Do you see AI playing a significant role in the future of higher education?	90%	10%

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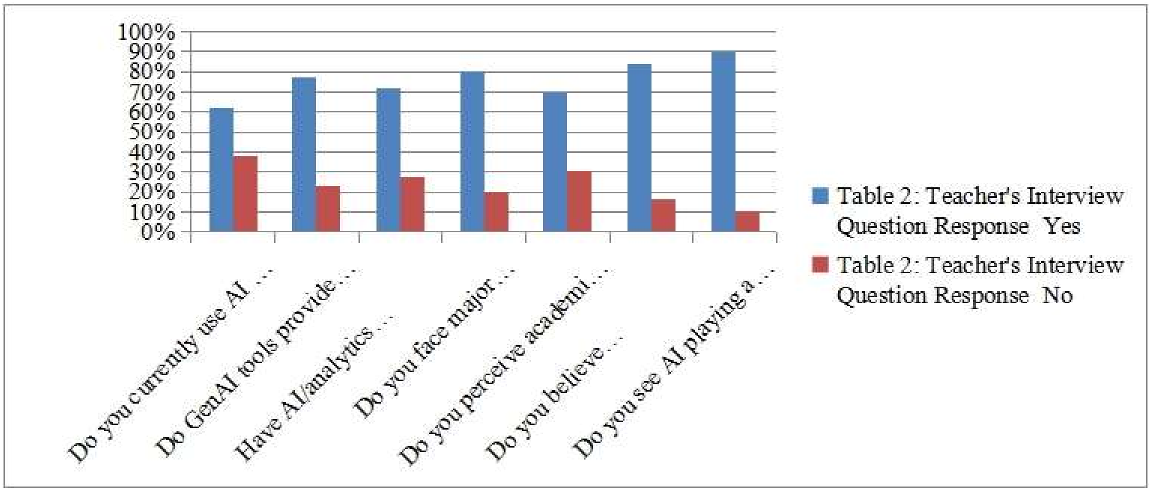
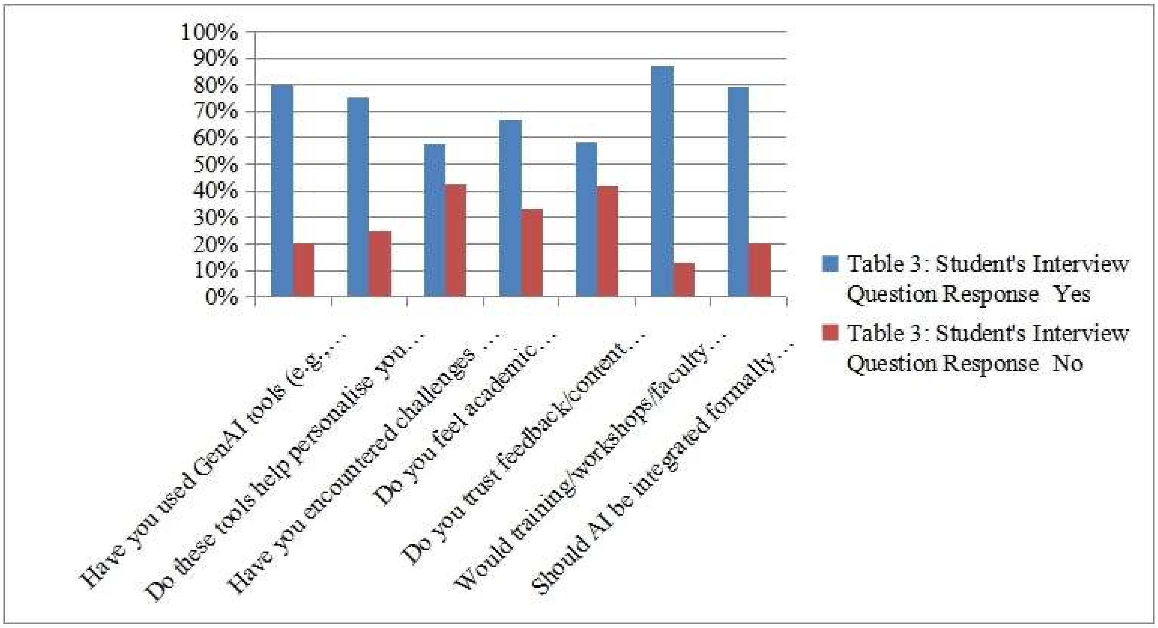


Table 3: Student's Interview Question Response

Sr. No.	Question	Yes	No
1	Have you used GenAI tools (e.g., ChatGPT) for assignments, projects or learning support?	80%	20%
2	Do these tools help personalise your learning experience?	75%	25%
3	Have you encountered challenges or difficulties using AI-based tools?	58%	42%
4	Do you feel academic integrity/originality is affected by GenAI use?	67%	33%
5	Do you trust feedback/content generated by AI tools?	58%	42%
6	Would training/workshops/faculty guidance make AI use more effective?	87%	13%
7	Should AI be integrated formally into the curriculum?	79%	21%



Section A: The awareness and use of GenAI and Learning Analytics

The awareness is extremely positive: ChatGPT (100%) towers Gemini (43%) and Copilot (39%). Actual use is high but not universal (67%) and awareness of campus learning-analytics dashboards is universal (100%) and 68% say they use analytics/AI tools regularly.

Even in initial assessments in higher ed, an uneven or modest level of awareness of AI/LA has been reported among faculty (e.g., Zawacki-Richter et al., 2019). Your findings also indicate a sudden change to a universal awareness, which will probably be triggered by the simple conversational interfaces and the mass media coverage of LLMs.

The traditional studies in adoption involving learning analytics (e.g. Papamitsiou and Economides, 2014; Ferguson and Clow, 2017) painted an impressively broad distance between awareness of tool usage and usage itself. That 67% active rate means that the gap is still there - though closer compared to 10 years ago, which implies that the low entry barrier of GenAI turns awareness to trial more readily.

Research on LA roll-outs (Tsai & Gaevic, 2017; Ifenthaler and Yau, 2020) reported numerically high numbers of staff who are supposedly exposed to a dashboard but using it insufficiently because of skills/framing problems. Your 100% awareness and 68% regular use would suggest superior rather than typical uptake, but also leaves one-third with the disadvantage of being non-habitual users re-reflects earlier pleas to analyze-literacy and work-flow-alignment.

ChatGPT is the leading paradigm in the recent GenAI classroom research reports (e.g., Kasneci et al., 2023). This is reflected in your pattern (100% vs. 4339%) and signals a one-platform addiction potential reported in

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earlier studies, with the possible symptom of overdetermination of educational processes on model strengths/weaknesses.

Section B: Regarding Benefits

High support on all levels personalisation (93%), LA insights (69%), GenAI+LA synergy (94%), time savings (98%) and engagement (100%).

Personalisation now experienced, not just promised. Previous researchers proposed AI personalisation as a vision (Siemens and Long, 2011; Luckin et al., 2016; Holmes et al., 2021). Your 93% tells me that users need now feel tangible tailoring at practice (adaptive prompts, differentiated feedback) and they are no longer at the conceptual level of promise (promise with classroom, so to speak).

It has long been argued by reviews that LA supports progress monitoring (Scholes, 2016; Ferguson & Clow, 2017). The 69% of your useful insights supports but is lower than GenAI ratings authenticating the argument in the literature that analytics delivered but more challenging to interpret without interpretation scaffold-possibly accelerating the argument that GenAI is a natural language translation of LA.

Convergence advantage is clear. The possibility of integrating AI and LA (e.g. Daniel, 2017; Gaevic et al., 2019) has anticipated the so-called closed-loop adaptivity. The 94 -per-cent agreement concerning synergy is a strong confirmation of those speculations: GenAI produces/intervenes, LA evaluates/goals and they together speed up feedback loops.

Efficiency & engagement at scale a saving time (98%) and engagement (100%) repeat what classrooms trials report about AI alleviating workload and inspiring better engagement. The possibility of benefit novelty-binding was commonly of concern in past effort and your general engagement signal implies general motivational impacts, in breadth, at least and immediate to temporal (a concern about sustainability above time voiced in previous studies) promises follow-up monitoring.

Section C: Regarding Challenges

Technical barriers (79 %), training deficiencies (100 %), plagiarism/ over-dependence (100 %), prejudice/transparency issues (written response to 41 or 40%%) and privacy/ethics limitations (87 %).

Technical reliability was indicated in every single study as a gating factor in digital adoption (Aldowah et al., 2019; Veletsianos, 2020). Your 79% is also confirmative that, even in the presence of cloud GenAI, local infrastructure (connectivity, device, LMS integration) remains a practical bottleneck.

The impact of AI/LA capacity building is impaired by training gaps, besides reviews conducted in the field (Zawacki-Richter et al., 2019; Ifenthaler Yau, 2020; Holmes et al., 2021). The 100% number that you cite brings this into focus: structured PD and AI literacy in students allow adoption to break down into proficient rather than superficial and in danger of abuse.

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The issue of plagiarism and over-reliance has reached a new level during the GenAI epoch (Cotton et al., 2023; policy briefs in various areas). The 100% agreement that you showed says that, integrity is not an interest that caters to a minority, but this is what is expected to be tested and thus there is redesign in assessments (process evidence oral defenses, On-class creation).

LLM bias/opacity scholarship (Bender et al., 2021; Weidinger et al., 2022) is solid; your results indicate a high degree of privacy/ethics concern (87%) and a lower degree of explicit bias concern (half or so). This discrepancy is reminiscent to earlier observations: users experience data risk as instantaneous, whereas there is bias that needs critical AI literacy to identify, indicating requirements of specific training on model boundaries and clear use policies.

Section D: Regarding Attitude

Adoption openness (89%) and the belief in the future of AI-driven personalisation (84%); 96% demand continual and use-case specific learning.

Technology-acceptance research consistently ties intention to perceived usefulness/support. Prior higher-ed studies found cautious optimism when support exists. Your 89% openness and 96% training need are also evidence-in-line: preparedness is dependent on competency development and evident guardrails.

Previous foresight had foreseen the possibility of individualisation through the use of AI (Luckin et al., 2016; Holmes et al., 2021). Your 84% indicates that this is no longer a matter of speculation in stakeholders minds but more of an anticipation-This increases the pressure on institutions to actualise personalisation (curriculum, assessment, advising).

Previous studies reported on pilots and proof-of-concepts: your data points to interest in scaled, policy-based adoption (governance, privacy-by-design, integrity-aware assessment). The essence of the message in the literature is true and now, your respondents loudly repeat the same: the factors that determine successfulness are training, moral foundations and a trustworthy structure.

Findings

The survey data analysis also offers a sophisticated perception of awareness of, use, advantages, difficulties and development path Generative AI (GenAI) and Learning Analytics (LA) perceptions in education.

Regarding awareness and use of AI, its results show that levels of awareness have dramatically increased, with all respondents saying they are familiar with ChatGPT (100%), though awareness of Gemini (43%) and Copilot (39%) are comparatively lower. This is a rather big contrast to previous findings (i.e., Zawacki-Richter et al., 2019) that reported cautious/disproportional awareness among faculty. The actual levels of use of 67% reported indicate that despite some awareness to use gaps, they are narrow compared with previously documented LA adoption awareness to use gaps (Papamitsiou & Economides, 2014; Ferguson & Clow, 2017). The high rate of exposures to campus learning-analytics dashboards across all states (100%) and relatively high%age of frequent use (68%) point to stronger uptake than previous institutional implementations (Tsai & Gaevic, 2017; Ifenthaler & Yau, 2020). Nonetheless, the degree of dependency on ChatGPT also indicates the possibility of developing platform dependency that is also mentioned in modern GenAI literature (Kasneci et al., 2023).

Regarding a benefits of AI, The prevalent advantages reported by respondents were in the area of personalization (93%), synergy between GenAI and LA (94%), time efficiency (98%) and an increase in engagement (100%). These findings crucially support the prior theoretical assumptions (Siemens and Long, 2011; Luckin et al., 2016; Holmes et al., 2021) of a future where AI-led personalization would take place and where it has become a lived reality. On the one hand, the fact that LA is still actively used to offer valuable insights (69%) is indicative of the relatively low rating value, inclined towards interpretative problems and it supports the existing argument that GenAI can be provided to act as a natural-language medium and facilitate the most actionable analytics (Scholes, 2016; Ferguson, & Clow, 2017). The large convergence scores confirm prior anticipations of a manifestation of closed-loop adaptivity (Daniel, 2017; Gaevoic et al., 2019), as the participants tended to see practical benefits to the combination of GenAI and LA.

Regarding challenges, a despite enthusiasm, barriers remain salient. The second barrier is technical constraints (79%) that is also aligned with previous指 Carrara et al., 2019; Veletsianos, 2020). More seriously, the fact that training gaps are reported by 100% is a sign of the necessity of disciplined professional training, which has also been reported as an issue multiple times in AI/LA scholarship (Zawacki-Richter et al., 2019; Holmes et al., 2021). Academic integrity issues, namely, plagiarism and excessive reliance (100%; Cotton et al., 2023) are a continuation of previous fears in their transition to common awareness, which justifies the restructuring of evaluation methods. Privacy and ethical questions (87%) and explicit concern about bias (= 40%) still loom large, which echoes previous findings that noticed appeared relatively as risks perceived to be immediate (e.g., data privacy), as opposed to risks that require critical AI literacy (e.g., algorithmic bias) (Bender et al., 2021; Weidinger et al., 2022).

Regarding an attitudes, the results indicate an extremely open mindset to adoption (89%) and a high feeling in the potential of the AI-driven personalization (84%). The need to have a continuous and use-case oriented training was stressed by almost all respondents (96%), as previous research had related the success of adoption to competency and establishing support structure within an institution. Collectively, these findings lead to a shift toward scaled experimentation Ryan (2017) to policy-level institutionalization, where governance structures, privacy protection, integrity-oriented evaluation frameworks and long-term professional education will be the main pillars of sustainable introduction.

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Conclusion

The aim of the research was to explore the awareness, usage, benefits and challenges of Generative AI (GenAI) and Learning Analytics (LA) in education and the results of the research imply continuity as well as break with previous studies. Prior research would also agree that awareness levels among educators tend to be rather modest or uneven (Zawacki-Richter et al., 2019), yet the current findings are dramatic: universal awareness, now, of ChatGPT. This implies that this aggregate of intuitiveness and mass media exposure has reduced entry barriers in a manner unseen a decade ago. Nonetheless, there remains an awareness-use gap, as concurring with the studies on the adoption of LA (Papamitsiou & Economides, 2014; Ferguson & Clow, 2017), although our data on the active use of 67% prove that the gap is in the process of closing.

A benefits also show a notable evolution. Unlike in the previous scholarship that defined personalization and adaptivity as one of the future requirements (Siemens & Long, 2011; Luckin et al., 2016), our data confirm that personalization and adaptivity have become the everyday reality of learners and educators who are highly appreciative of efficiency, engagement and AI-LA synergy. This collusion confirms theoretical frameworks of "closed-loop adaptivity" (Daniel, 2017; Gaevic and et al., 2019) and indicates that GenAI features in natural-language enhance the feasibility of LA insights compared to earlier applications.

Challenges remain strikingly consistent with prior research. The technical limitations and infrastructure are reflections of age-old obstacles to adoption (Aldowah et al., 2019; Veletsianos, 2020), the universal plea to offer training is an indication of the existing worries regarding the lack of professional development (Ifenthaler & Yau, 2020). Integrity, plagiarism, as well as ethical risks, which are even further emphasized in the GenAI era (Cotton et al., 2023), serves as the intensification of the previous concerns and requires new forms of institutional responses.

In this research study, the development is critical, not only in transitioning between pilots and institutionalization. In contrast with the previous studies, the trend has now shifted to the mainstream with the future lying in the survivability itself based on intentioned capacity building, ethical governance and interrelations between pedagogy and technology affordances. In this way, theoretically and in practice, this paper identifies an opportunity that the future of education through AI is already taking place its promise dampened by the duty to make sure righteousness, fair play and substance in learning outcomes.

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