Data Storytelling in Learning Analytics: AI-Driven Competence Assessment

Ainhoa Álvarez[a], Aitor Renobales-Irusta[b] and Mikel Villamañe[c]
Department of Computer Languages and Systems University of the Basque Country UPV/EHU, Spain

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Abstract: Learning dashboards have become very popular, but the information shown on them is often difficult to interpret by users. Different authors have worked to improve dashboards including narratives or data storytelling techniques. However, creating these narratives is a complex process. Several studies have begun to analyse the use of GenAI tools to generate these narratives in a scalable way, but this is still an area of study that is at an early stage. In this paper, we present a proposal and a study aimed at generating narratives using GenAI, extending previous work by aligning the generated narratives with the curriculum design of the course. We first present a proposal for generating the narratives and then a study to evaluate their adequacy.

1 INTRODUCTION

A learning analytic dashboard is *"a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations"* (Schwendimann et al., 2017). Dashboards have gained popularity as a tool to show analytical data regarding students (Pozdniakov et al., 2025), and thus, providing teachers with insights about the learning process of their students (Fernandez-Nieto et al., 2024). However, these dashboards are often challenging to interpret by teachers and usually provide no guidance on how to interpret them (Fernandez Nieto et al., 2022). Several authors have worked in the inclusion of explanatory features, for example, through Data Storytelling (Fernandez-Nieto et al., 2024). Those approaches are very powerful but generating the narratives is a complex process that requires much effort from creators (Li et al., 2024) and therefore, some works have begun to explore the use of Generative Artificial Intelligence (GenAI) to automate and ease their generation in a scalable way (Pinargote et al., 2024).

In a previous work (Villamañe, Mikel et al., 2025), authors have begun to explore the use of Generative AI to facilitate the comprehension of dashboards and reduce the problem of data-literacy lack that some teachers face when presented with dashboards. Authors enhanced the dashboards generated by the AdESMuS system (Alvarez et al., 2020) with GenAI capabilities. As shown in Figure 1, GenAI was introduced with three main objectives: give general explanations about the chart, provide interpretations about the data shown in the chart and provide pedagogical insights and recommendations in order to facilitate teachers taking remediation actions when needed.

Figure 1: Dashboard with GenAI capabilities.

[a] https://orcid.org/0000-0003-0735-5958
[b] https://orcid.org/0000-0002-2148-9269
[c] https://orcid.org/0000-0002-4450-1056

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We also carried out a study with 15 teachers, and one of its conclusions was that it could be useful to relate assessment items to the contents of the course in order to enhance the recommendations given by the GenAI tool. This involves aligning pedagogical intentions and course curriculum design with the narratives about the data as other authors (Pinargote et al., 2024) have also suggested.

In this paper, we address the alignment of narratives with the curriculum design of the course and present an initial approach. We present how we propose to tackle the alignment and a study aimed at answering these research questions:

- RQ1: How does providing course curriculum design information to GenAI influence the depth and utility of pedagogical insights?
- RQ2: To what extent do conclusions derived from GenAI-driven analysis align with pedagogical intentions and expectations of the teachers?

This paper first presents some previous works related to the study carried out. Next, the study design is presented followed by the obtained results, a discussion about them and finally some conclusions and future work are presented.

2 PREVIOUS WORKS

This section resumes a preliminary study conducted by the authors and that sets the basis of the work presented in this paper. It also depicts the definition of the ontology for the domain and student data used in this work.

2.1 Preliminary Study

Previous to this work, in (Villamañe, Mikel et al., 2025) we presented the use of GenAI to enhance dashboards in different aspects. One of those aspects was related to the generation of pedagogical conclusions about the data shown in the charts (see Figure 1) and providing recommendations so that the teacher could take remediation actions.

To this end, we used the prompt template shown in Table 1, along with any of the charts displayed on the dashboard showing the student's performance across different assessment items of the course (see Figure 1), and asked the GenAI to provide the teacher with conclusions about the performance of the student.

Table 1: Prompt template.

I am a university professor and I would like you to indicate in a maximum of 250 words what conclusions can be drawn from the data contained in the attached file and indicate if you consider that I should make any recommendation to the person to improve their learning process. I don't need you to describe the information, just give me the conclusions and recommendations in a general way, focusing only on those elements that are especially relevant.

This process was repeated with the charts of several students and Table 2 shows some of the sentences included in the conclusions and recommendations generated by the GenAI.

Table 2: Sentences selected from the answers generated by the GenAI.

This suggests a relatively solid knowledge in this topic
Here the student shows a deep understanding of the topic
It would be useful for him to strengthen his knowledge in analysis and design.
It is suggested to dedicate more time to studying and practicing topics related to Elem3, considering the possibility of requesting additional support or tutoring.

As can be seen in Table 2, the system introduces sentences such as *"This suggests a relatively solid knowledge in this topic"*. However, the system does not know the topics each assessment item is related to, so it can not derive more insightful conclusions. For example, what happens if there are two assessment items related to the same topic and with very different performance results?

Our thesis is that relating the curriculum design that defines the course topics or competences to the assessment items would create more comprehensive and more useful information for the teacher.

2.2 Ontology for Domain and Student Data

The objective of this paper is to analyse the comparative impact of curriculum design-enriched versus standard performance-based prompts on the effectiveness of AI-generated learning recommendations included in dashboards. We have therefore defined an ontology to formalise the domain model for the curriculum structure including its competences, learning units, learning materials, and other related elements, as well as the student model with the student-related information.

The domain model represents "the skills, knowledge and strategies of the topic being tutored" (Sottilare et al., 2016). It defines a conceptual framework to represent all the elements and relationships within a course. There are many ways to represent the domain model but it is important for the model to be general enough to be able to integrate data from different sources, such as Learning Management Systems (LMS) or Intelligent Tutoring Systems (ITS) (Samuelsen et al., 2019).

Figure 2 shows an excerpt of the domain model ontology used, which is an extension of the ontology defined in (Villamañe et al., 2018) that has been successfully used in previous studies. It is also founded on the Competence-based knowledge space theory (CbKST) (Idrissi et al., 2017) and the domain models of classical educational systems (Aleven et al., 2023). This ontology provides a framework for structuring educational content of courses with a focus on competence-based learning, establishing clear relationships between learning units, resources, activities, and the competences they help develop. It defines five core entities: Courses, Resources, LearningUnits, AssessmentItems, and Competences, connected through various relationships. This structure creates a comprehensive framework that links educational content, activities, and assessments to the skills and knowledge learners should acquire.

This structure is general enough to accommodate information coming from different educational systems such as ITSs or LMSs as Moodle, and it can incorporate data from different courses. That is, the ontology is not dependent on any specific course or educational system.

Figure 2 also shows the main elements of the student model that are used in this study. Taking into account that a key element of any student model is the student performance data (Pelánek, 2022), we have included the student general information together with the representation of its relationship to courses, assessment items, and competences.

3 STUDY DESIGN

To evaluate and validate our proposal, we conducted an initial study involving two teachers from the course *Analysis and Design of Information Systems* and the assessment data of the 60 students enrolled in the course. In this section, we present the design of the study detailing the competences defined for the course and the student data collection together with the methodology used for the study.

The process and instruments used in the study were approved by the Ethics Commission for Research and Teaching (CEID/IIEB) of the University of the Basque Country UPV/EHU with code M10-2016-181 and informed consent was obtained from all individual participants included in the study. Following the recommendations of the ethics commission, all direct identifiers and attributes that could potentially be used to identify students were supressed. Afterwards, a numerical id was randomly assigned to each student.

3.1 Competence and Student Data Definition

As mentioned before, the aim of this study is to analyse whether it would be interesting to enhance the system with course information in order to obtain more insightful conclusions and recommendations. To that end it is necessary to populate the prompt template used in the preliminary work (see Table 1), with information following the ontology shown in Figure 2.

First, the teachers defined the main competences of the course, as shown in Table 3. These competences were then linked to the assessment items that students should complete throughout the course.

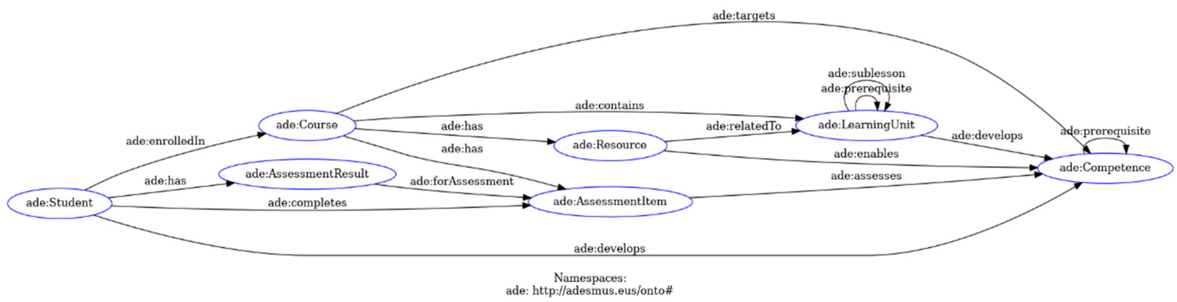

Figure 2: Extract of the defined ontology.

Table 3: Course Competences.

CODE	COMPETENCE
C1	Interact with users to gather requirements for information systems, ensuring clear understanding of stakeholder needs through effective communication techniques.
C2	Identify client requirements for software development projects, translating business needs into functional specifications using UML methodologies.
C3	Create data models that represent information structures and relationships, using UML class diagrams and entity-relationship models for database design.
C4	Analyse software specifications to determine feasibility and technical approaches, evaluating requirements against system constraints in information systems development.
C5	Create flowcharts and UML diagrams to visualize system processes, data flows, and interactions between components in software design.
C6	Plan software tests to verify functionality and validate that information systems meet requirements, developing comprehensive test cases and scenarios.
C7	Program computer systems by implementing designs into functional code, translating UML models into working software components.
C8	Write project documentation that clearly explains system architecture, design decisions, and implementation details for information system stakeholders.

Table 4 shows the relationship between the course competences and the assessment items.

Table 4: Assessment items and their relation with the course competences.

ASSESSMENT ITEM	RELATED COMPETENCES (CODE)
Use Case Exam	C1, C2
Domain Model Exam	C2, C3
Analysis and Design Exam	C4, C5
Extended Use Cases Practice	C1, C2
Domain Model Practice	C2, C3
Test Plan Practice	C6
Communication Diagrams Practice	C4, C5
Class Diagram and Relational Schema Practice	C3, C4
Sequence Diagrams Practice	C4, C5
Final Practice and Documentation	C3, C5, C8
Implementation Practice	C7
Test Implementation Practice	C6

Next, the assessment data of the 60 students enrolled in the course was collected from Moodle and formatted according to the defined ontology.

Figure 3 shows an extract of the graphical representation of some of the information related to the student with id 006.

All the structured information was then used to populate the prompt template before submitting it to the GenAI. The data was structured into JSON-LD format to assure its readability and scalability.

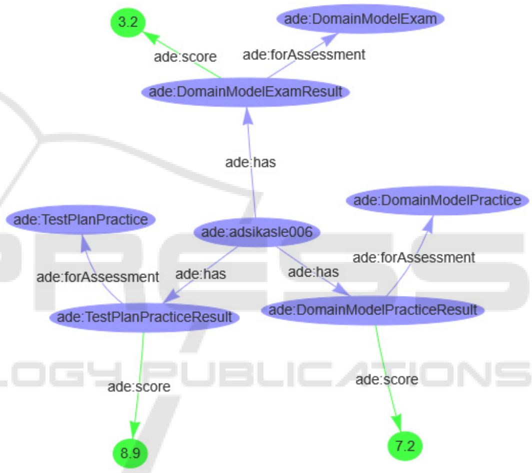

Figure 3: Extract of student 006 assessment data.

3.2 Methodology

To analyse the utility and alignment of the conclusions and recommendations provided by the GenAI with those of the educators, teachers participating in the study were invited to assess the reliability and appropriateness of the results for a sample of the group.

Since the opinions of the teachers are subjective and depend on their own perceptions, this analysis was approached as a qualitative study. Therefore, the students selected to be part of the sample were purposefully chosen based on the variety they contributed to the study, as recommended by the literature (Abrams, 2010; Shaw & Holland, 2014).

To that end, and with the collaboration of the course teachers, the different situations that could arise among the students of the course were defined.

The situations described next were identified by the teachers, who considered various potential scenarios that could occur in the course:

1. No data at all.
2. Missing some data.
3. All competences acquired.
4. Not all competences acquired

Next, students were distributed among the situations considering their assessment data. From each situation, as many students as necessary were randomly selected to maintain the percentage of representativeness of each situation in the sample, which size was decided to be of 15 students (25% of the population) aligning with recommendations in research literature for studies employing random sampling techniques (Boddy, 2016).

Table 5 shows the percentage of students that met the criteria to be assigned into each situation defined by the teachers, the number of students to be selected from those in each situation and the id of the randomly selected students.

Table 5: Distribution of students among the different situations and selected students for the sample.

Situation	Percentage of students	Number of students selected	Selected students (id)
1	1.7%	1	014
2	15%	2	038 049
3	55%	8	003 020 004 023 006 043 016 052
4	28.3%	4	013 039 035 058

4 RESULTS

With the students for the sample selected, the prompt template was used with the assessment data of each of these students. Then, the teachers participating in the study were asked to indicate on a Likert-scale of 1 to 5 their level of alignment with the narrative generated by the GenAI. With 1 being the lowest level of alignment and 5 indicating that they strongly agreed with the recommendations and conclusions obtained. They also had an open-ended question to include other comments.

When evaluating the results for the students in situation number 4 (not all competences acquired), teachers stated that the narratives generated by the GenAI were not adequate.

As shown in Table 6, the AI highlights some inconsistencies such as the student achieving significantly different results in assessment items that assess the same competence.

Table 6: First version of generated conclusions and recommendations.

Conclusions and Recommendations for Student 006

The student demonstrates a notably better performance in practical activities (average of 7.5) than in theoretical exams (average of 5.1), suggesting a greater aptitude for practical application of knowledge rather than theoretical conceptualization.

The student particularly excels in competencies related to software testing planning (8.9) and technical diagram development (8.2-8.5), showing strengths in technical and design aspects.

However, there is a significant weakness in the "create data models" competency, evidenced by the low score in the Domain Model Exam (3.2), although paradoxically the student obtains good results in the corresponding practical work (7.2).

Recommendations:

1. Strengthen theoretical understanding of domain models and their conceptualization, possibly through study techniques that better connect theory with the practical skills already mastered.
2. Work on the "identify client requirements" competency, where the student shows disparate results between exams and practical work.
3. Maintain the good performance in design and documentation competencies, which constitute the student's strengths.
4. Implement study strategies that allow transferring evident practical capability to the theoretical domain, possibly through self-assessment exercises or exam simulations.

Discussions with the teachers participating in the study revealed that this inconsistency was due to the fact that the assessment item "*Domain Model Exam*" was carried out individually, while the "*practical work*" was carried out in groups.

The distinction between whether an assessment item is conducted individually or in groups is crucial in this case. A student who scores very low on individual components but very high on group components may be benefiting from the work of their peers, indicating that competency acquisition may not be occurring adequately, despite student's average grades concealing this fact.

Following the analysis of the initial test, the ontology, and therefore, the JSON-LD were updated to include information on the categorisation of each assessment item as either individual or in-group and a new analysis was requested to the GenAI using the same prompt template as before.

Table 7 shows the main differences among the conclusions and recommendations for the same student including the new information.

Table 7: Extract from generated conclusions and recommendations.

Conclusions and recommendations for student 006

The student shows contrasting performance between individual and group assessments.

….

This difference suggests possible difficulties in applying theoretical knowledge individually or problems with exam pressure.

Recommendations:

1. Strengthen individual study ….
2. Practice more individual domain modeling exercises ....
3. Develop strategies to transfer skills demonstrated in group work to individual assessment contexts.

…

The student has demonstrated potential in practical environments but needs to consolidate their autonomy in applying theoretical concepts to improve their overall performance.

In this occasion, the GenAI suggests that the student should engage in additional individual study and practical exercises to consolidate knowledge. The GenAI also indicates the possibility that the student may experience challenges in managing the pressure of an exam.

As this GenAI generated narrative was considered more adequate by the teachers, the study was replicated and completed using the adjusted ontology and JSON-LD to populate the prompt template for all the students in the sample. Next, teachers evaluated their alignment with the new narratives.

Table 8 shows, for each situation and for each student selected, the average value of teachers' alignment with the GenAI provided narrative.

Table 8: Alignment measure for the sample.

Situation	Student (id)	Alignment score (average among teachers)	Alignment score (average for the situation)
1	014	5	5
2	038	2	2.25
	049	2.5	
3	003	5	4.38
	004	3.5	
	006	4	
	016	3.5	
	020	4.5	
	023	5	
	043	4.5	
	052	5	
4	013	5	4.38
	035	4.5	
	039	4	
	058	4	

5 DISCUSSION

The analysis of the generated narratives reveals that the information generated by the AI references specific competences such as *'create data models'* which helps in better understanding which are the student's strengths and weaknesses. This finding directly addresses our first research question (RQ1). When providing curriculum design information, the results show that GenAI provides more insightful conclusions and recommendations. This represents a significant enhancement of the generated narratives and facilitates teachers identifying the precise competences in which students need specific support.

Addressing our second research question — examining the extent to which GenAI-driven analysis aligns with teachers' pedagogical intentions and expectations— we analysed data in Table 8. The results demonstrate high alignment across most situations what positively answers RQ2. However, for situation number 2 the agreement with the GenAI generated narrative for all of its students (049 and 038) was considerably lower. This situation represents cases in which some of the data is missing because the students have not completed some of the assessment items. In these cases, the GenAI highlighted low scores in one of the exams but failed to mention that the student had not completed the other two exams, leaving out critical missing data.

As these omissions are important from an educational perspective, the prompt should be refined to include specific instructions for addressing incomplete student assessment data.

Despite this limitation, the overall high alignment suggests that, when provided with appropriate curriculum design information, GenAI tools can produce insights that closely correspond to what experienced educators would identify as pedagogically relevant. This alignment between teachers' expectations and generated narratives affirmatively answers our second research question (RQ2) whilst identifying specific areas for the improvement.

6 CONCLUSIONS

Learning analytics dashboards are very popular but present many problems to users. One of the main ones is related to the difficulties users face to interpret data shown on dashboards. To reduce this problem several authors have proposed the enhancement of those dashboards with narratives. This has shown positive results but generating the narratives is a complex process with a great workload. In this paper, we have presented a proposal that enhances dashboards with narratives automatically generated by GenAI tools. The presented proposal has been validated in a course with two participating teachers and the data of 60 students.

Populating the prompts with a context that defines the course curriculum design to align the narratives with them is very promising and significantly enhances their relevance and usefulness for educators. By incorporating course context into the prompts, the generated conclusions are more detailed and aligned with pedagogical goals, providing actionable recommendations for teachers (RQ1).

The generated narratives were evaluated by teachers and found to closely align with their own interpretations of student performance, as evidenced by a high average alignment score higher than 4 on a 1 to 5 Likert scale (RQ2).

Although the study was conducted with a relatively small sample, the results are encouraging, and the outcomes point to significant potential. This emphasizes the value of including the curriculum design of the course on the prompts. Therefore, we plan to continue the proposal validation process with a larger participant base, conducting further experiments across different courses and areas of knowledge to test its potential generalization.

The results have also shown some aspects that can be improved that we next point as future work.

Learning Management systems do not often include the option to define the curriculum design and relate assessment items to it using a systematic approach. Therefore, in the near future we plan to create a way to facilitate the definition of the curriculum design of the course and to relate it to the learning assessment items. We plan to start doing this for Moodle as it is one of the most used Learning Management System in higher education settings (García-Murillo et al., 2020).

We also plan to improve the domain and student data ontologies using educational standards and semantic web techniques in order to ensure its flexibility and applicability.

Some limitations were also identified. For example, the GenAI occasionally omitted references to assessment items not completed by students, which impacted the comprehensiveness of its conclusions. Addressing such omissions will require refining the prompts to account for incomplete data scenarios.

Finally, it is important to address the ethical concerns associated with the use of GenAI in generating educational recommendations. Our approach is designed to support, not replace, the teachers' role. The GenAI generated narratives are intended to be supplementary, providing additional insights based on the data available. To safeguard the accuracy and integrity of the educational process, we, as other authors (Chiu, 2024), propose comprehensive training for the teachers. This training will ensure teachers are aware of the limitations and ethical considerations of using GenAI, thereby maintaining their essential role in the decision-making processes.

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