A Proposal for a Taxonomy of AI-Related Use Cases in Higher Education

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Abstract

Artificial Intelligence (AI)-based technologies are increasingly transforming higher education, leading to substantial advances in educational methodologies. Universities must document and classify existing or newly developed AI-based teaching and learning scenarios. Such classification is essential for helping instructors make informed decisions, estimate associated development and operational costs, and facilitate effective utilization. Existing literature frequently focuses classifications on either technological tool characteristics or the student's viewpoint. In contrast, this article proposes a complementary educator-centered taxonomy to make the pedagogical benefits and constraints of AI-supported educational scenarios more transparent, particularly from the educator's perspective. We propose evaluating the three core dimensions: repetition (R), data access (D), and semantic discrimination (S). By assessing these dimensions, educators gain a better understanding of which teaching scenarios benefit significantly from AI support. After reviewing existing classification literature in higher education contexts, we introduce our taxonomy and demonstrate its practical applicability in selected educational use cases.

Keywords: *Artificial Intelligence, Higher Education, Taxonomy, Educational Technology*

1. Introduction

AI use cases in higher education have commonly been classified from tool-oriented or student-oriented perspectives. Tool-oriented approaches focus primarily on technical characteristics of AI solutions, such as generation, optimization, data type (e.g., audio, video, textual), or implementation details [1]. In contrast, student-oriented classifications adopt a learner-focused viewpoint, considering factors like duration of AI usage across educational phases, class format (e.g., lectures, assignments, seminars), or student expertise levels (primary, secondary, higher education). Although the number of available AI tools grows steadily, educators still lack structured means to systematically classify, evaluate, and select suitable AI-supported educational scenarios. The literature lists various AI tools but often lacks in-depth pedagogical analysis. Keller et al. [2], for instance, provide a technology-centered classification based on AI methodologies (supervised, reinforcement learning, etc.).
The University of San Diego [3] presents an extensive list of 39 AI (and general computer) tools for education, offering limited pedagogical depth. A similar general classification of tools with student-centered criteria like temporal duration (micro, meso, and macro) has been presented by Witt et al. [4]. FernUniversität Hagen [5] similarly classifies AI use cases according to short-, medium-, and long-term usage. A widely cited reference document for AI usage in higher education produced by the Deutsche Gesellschaft für Hochschuldidaktik (DGHD) describes the educator motivations and practical uses for AI, yet lacks the educators' perspective [6]. Given this gap, we propose an educator-centered supplemental taxonomy that clearly illustrates advantages and characteristics of AI-supported teaching scenarios. We apply this novel framework explicitly on use cases described by DGHD [6] to understand, develop, and implement AI scenarios more accurately from standard Socratic dialogues to Retrieval-Augmented Generation (RAG) supported chat-bots.

2. Proposed Taxonomy Scheme

Our taxonomy comprises three essential educator-oriented dimensions:

- AI-related Repetition (R): The extent to which an AI application consistently and repeatedly performs educational tasks without degradation in quality.
- Repeat for other two dimensions for consistency.Access to Large-scale Databases (D): Effective utilization of large curated knowledge datasets or Retrieval-Augmented Generation (RAG).

- High-quality Semantic Discrimination (S): Accuracy in distinguishing subtle contextual differences among user prompts through advanced semantic methods (e.g., high-dimensional embeddings, transformers).

Each dimension is quantitatively rated from one (low/negligible) to five (high/core importance). The rating procedure includes:

- Identifying and defining AI-driven educational use cases clearly.
- Independently evaluating the R, D, and S dimensions empirically or by deliberation.
- Assigning a numerical rating to each dimension, preferably via expert deliberations, followed by averaging the scores into an RDS-score.

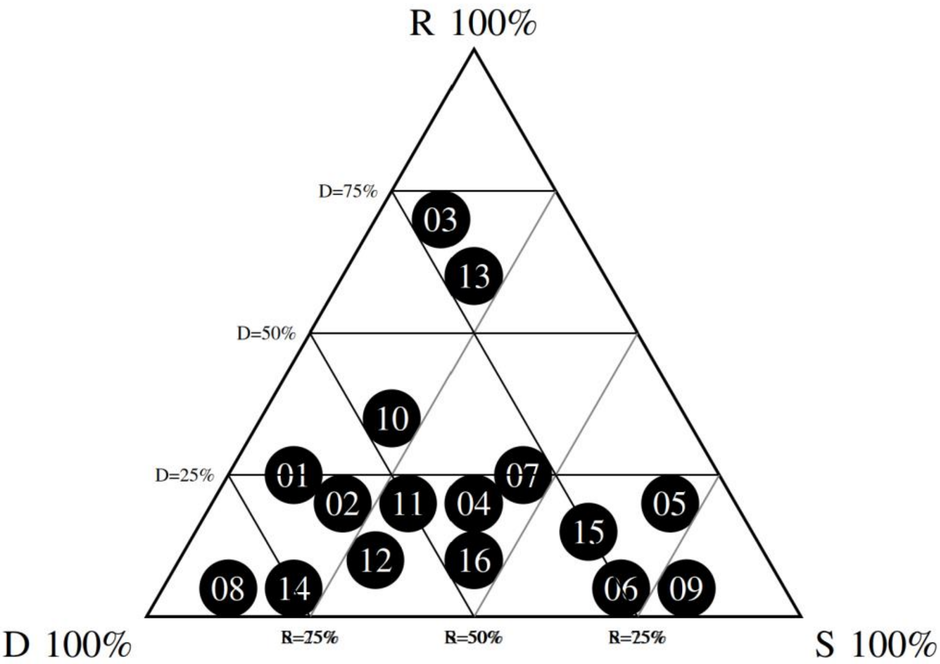

Fig. 1. AI use cases positioned in an R-D-S triangle. Percentile lines (25%, 50%, 75%) indicate distribution. IDs are described in [6] and Table 1.

Table I exemplifies the proposed classification using DGHD AI use cases ([6]):

Table 1. Estimated RDS percentages (normalized) for the AI use cases and IDs described in [6].

IDs	**AI Use-case**	**R**[%]	**D**[%]	**S**[%]
01	Brainstorming	25	65	10
02	Overcome writer’s block	20	60	20
03	Generating Tasks for Self-Tests	70	20	10
04	Explorative Workshops	20	40	40
05	Critiquing AI Output	20	10	70
06	Improve Written Scientific Expression	5	25	70
07	Socratic Dialogue	25	20	45
08	Literature Research with AI	5	85	10
09	Prompt Engineering	5	15	80
10	Tools Marketplace and Writing with AI	35	45	20
11	Stereotypes in AI Systems	20	50	30
12	Research Designs with AI	10	60	30
13	AI in Evaluation	60	20	20
14	Persona Development	5	75	20
15	Tracking AI Output	15	25	60
16	Critical Engagement	10	45	45

2.1 Repetition Type (Dimension R)

Some AI-driven educational scenarios depend on the consistently high quality of repeated AI-generated content. Tasks where human instructors may fail to consistently deliver training at the same level (due to fatigue, inconsistency, or scalability challenges), notably benefit from AI-enabled repetitive activities. Exemplary scenarios from DGHD include "Generating Tasks for Self-Tests" (ID 03) and "AI in Evaluation" (ID 13). We propose that use cases with a R-score of at least 50% are predominantly ‘repetition based’ type, i.e. that the didactic benefit of repeated use is equal or larger than the sum of the other dimensions. In these use cases, AI AI provides learning support in an untiring, consistent, and unbiased manner.

2.2 Database Access Type (Dimension D)

Access to extensive databases is essential for scenarios relying primarily on synthesized or curated materials such as literature, images, videos, or audio files. Such databases may consist of pre-existing training data or resources integrated via Retrieval-Augmented Generation (RAG). Access to internet search results or web-pages can also be considered as database access from an from an educator’s perspective. Scenario examples requiring large-scale database access include: "Literature Research" (ID 08), "Persona Development" (ID 14), "Brainstorming" (ID 01), "Overcoming Writer’s Block" (ID 02), and "Research Designs" (ID 12). We propose that use cases with a D-score of at least 50% are considered predominantly “database type”, i.e. if the didactical benefit of database access is equal or larger than the other two dimensions combined. Human instructors may fail to include comparably large data bases in their teaching- for example, recently published research papers on a specific scientific subject which is not the primary area of expertise of the teacher.

2.3 Semantic Discrimination Type (Dimension S)

Highly advanced semantic mechanisms allow AI to distinguish subtle contextual or semantic variations in user prompts, typically via high-dimensional vector embeddings. Typical educational use cases include "Prompt Engineering" (ID 09), "Improving Written Scientific Expression" (ID 06), "Critiquing AI Outputs" (ID 05), and "Tracking AI Outputs" (ID 15). We propose that all use cases with a S-score of 50% and above are considered predominantly semantic-discrimination based. In these use cases, the important contribution of AI consists in detecting subtle variation in the prompt or context entered or produced by the student. Human instructors may fail to consistently recognize slight variations, especially if presented in a foreign language. We propose that all use cases with a S-score of at least 50% are considered predominantly “semantic-discrimination type”.

2.4 Mixed Type Use Cases

Many educational AI use cases combine aspects from multiple dimensions without a clear emphasis on a single dimension. For instance, an AI-based tutor addressing student questions often merges semantic discrimination (S) with extensive database access (D). DGHD [6] mixed-use examples encompass "Stereotypes in AI Systems" (ID 11), "Tools Marketplace & Writing with AI" (ID 10), "Explorative Workshops" (ID 04), "Socratic Dialogue" (ID 07), and "Critical Engagement" (ID 16).
From an educator’s point-of-view, these use cases are of particular interest as they combine more than one advantage of AI over a human instructor. For instance, consider a class on a particular scientific theorem, material or topos covered in a few thousand dissertations written in a dozen languages: One may find one human expert on the subject and another one capable of reading the dissertations in their original language. This combination of expertise is rare, and it is unlikely such an expert would be available to answer individual questions to a larger student group.

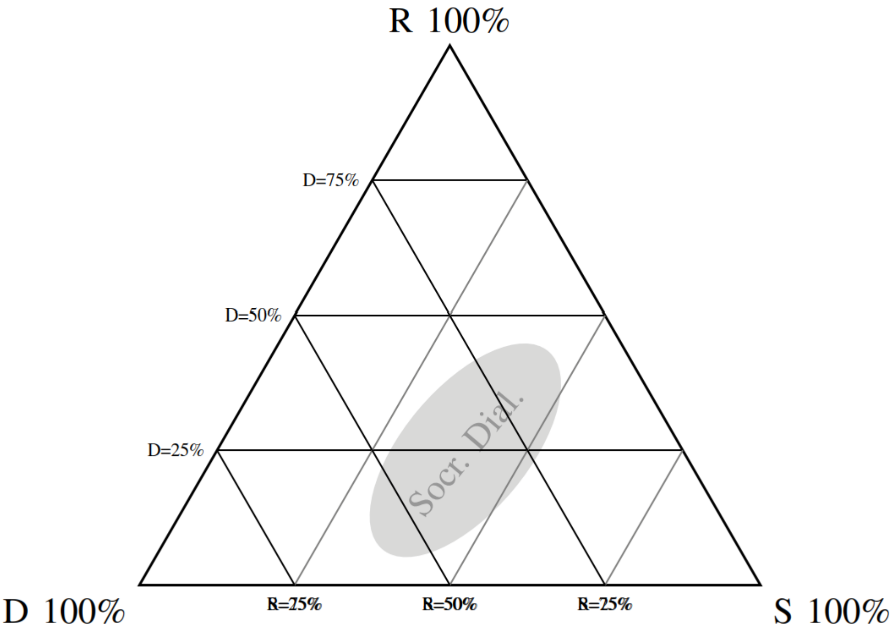

Fig. 2. RDS-score area for different AI chat-bot implementations of the Socratic Dialogue (ID 7) with more or less RAG implementation.

3. Discussion

Our proposed taxonomy distinguishes R-type, S-type, D-type, and mixed-type use cases, addressing previously unmet needs, bridging gaps between tool-centered and student-centered classification schemes. Its main value lies in supporting educators in planning and clearly communicating the benefits and characteristics of intended AI-assisted teaching methods. As a practical example, Offenburg University developed a chat-bot employing Socratic Dialogue for mathematics and statistics courses. During this development work, it became clear that Retrieval-Augmented Generation (RAG) significantly enhanced the chat-bot's performance, but implementation depended considerably on the exact subject matter and student competence level. Taxonomy visualization guided the development team to address these differences explicitly.
Educators employing our taxonomy will benefit by clarifying their educational targets and the limits or strengths of associated AI characteristics. Future work could refine evaluation methods through systematic expert consensus, extensive student and educator usability surveys, and empirical validation across different teaching contexts. For instance, details such as the scope and specificity of documents included in RAG solutions could further refine the semantic discrimination (S) dimension, which is an important practical factor potentially affecting cost and complexity. Important considerations for future discussions include:

- The interdependencies among taxonomy dimensions.
- Possible correlations between taxonomy scores and academic disciplines or specific educational topics
- The influence of external factors, such as learner preferences, teaching formats, and institutional objectives.

4. Conclusion

This paper introduces an educator-centric taxonomy designed to address the challenges educators face when selecting, classifying, and implementing AI-driven educational solutions. By explicitly including educators' perspectives through three clearly defined dimensions, our proposed taxonomy provides a structured, transparent, and interpretable framework for educators. Our proposed taxonomy provides educators with a structured, transparent, and interpretable framework. The taxonomy is also applicable outside the educational context, for determining whether AI should be used for a particular task: Is the AI helpful due to its database access, its consistently high quality in repetition, or its semantic capability? Answering these key questions provides a better indication of which AI applications may or may not be advantageous for a particular use. Subsequent research efforts should focus on empirical validation and further refinement of these taxonomy dimensions and their interactions across various educational environments and institutions.

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