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A COMPARATIVE ANALYSIS OF APPROACHES TO DESIGN AND CAPITALIZE DATA INDICATORS

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Abstract: In Technology Enhanced Learning field, learning analytics cover multiple research challenges, among which tracking data analysis, data indicators design and visualization and their adoption by end-users. Part of our research effort is dedicated to changing their design and use process, in order to capitalize them. This would allow cost saving on design workflow and encourage the adoption by teachers and students throughout their implications with a better understanding of the capitalization mechanism. A study of the state of the art has been made to explore various solutions which could be exploited in the capitalization of indicators on both levels, design and use. In this paper, a proposition of capitalization is detailed through measurable and accessible functionalities. The list of those functionalities is being used as criteria in a comparative grid to analyze how existing design approaches enable data indicators capitalization process. This analysis points out the purpose of our work to reach a larger scope of users, thus helping them understand and work on data indicators capitalization. It sets a direction toward a user-centered approach, aiming at a better control of users over their own observation needs and the use of their data.

Key words: Learning analytics, data indicator capitalization, user-centered design, comparative analysis

1. INTRODUCTION

In a context where digital environments play an important role in education, practitioners use TEL (Technology Enhanced Learning) systems on a daily basis, generating at the same time a massive quantity of traces. Numerous works exploit these traces with data analysis and visualization mechanisms, transforming raw traces into data indicators as actionable knowledge (Van Leeuwen, 2019) that are much more comprehensible to users. Our research effort falls into this research area and has been carried out along with a multi-party university project *écri+* (ecriplus.fr) since 2018. The main objective of the latter is to promote students' success via a learning platform

developed to support them in improving their skills in French writing. Our research aims to study how to provide the participants in the project with a technological solution built upon trace analysis and data indicators visualization to promote their use.

Data indicators in an educational setting, according to Dimitrakopoulou (2004), are meaningful variables, related to the process and quality of learning. In a pedagogical context, using data indicators is shown to be an effective way for both teachers and students to take full possession of this digital dimension of learning, as also demonstrated by Alowayr and Badii (2014). The design process can be broken down into three steps: (i) defining the observation needs, (ii) computing data indicators and (iii) data exploitation. However, each of these steps is highly dependent on the context. For example, the environment and the target user have an important influence on the definition of data indicators and their future use (Papamitsiou & Economides 2014). The intervention of an analyst in the process is therefore necessary. This makes data indicator design resource-intensive. As a matter of fact, users' needs are to be identified and analyzed beforehand to ensure that data indicators are created to fully perform their tasks. Then comes the use of each data indicator that might no longer be satisfied, as users' needs have evolved over time. Given this complexity, it is interesting to limit the repetition of the whole process to each new need or context in order to make the design more cost-effective. There is also a limit to their adoption (Dollinger *et al.* 2019, May *et al.* 2011). A feeling of inadequacy of the proposed data indicators in relation to the requirements of the end users is sometimes noticed (Kaliisa *et al.* 2021). The complexity of identifying the observation needs of users with different profiles and the difficulty of extracting the information from a data indicator can be a deterrent (Michel *et al.*, 2017).

An approach based on the capitalization of indicators contributes in cutting down the design costs, thus enabling a better use of both technical and human resources. To achieve this, we take a closer look at a design process that simplifies not only the participation of users in each step, from defining to creating data indicators, but also assists and facilitates the capitalization of each data indicator already created in the previous steps.

At this stage of our research work, the challenges we are facing can be summarized as follows. First, what are the essential actions allowing data indicator capitalization and second, how can users participate in this process, making sure that data indicators can be reused, shared, and adapted. Understanding and collaborating are therefore the starting point of the co-design approach that will lead to further implementations of tools and platforms enabling users to perform different tasks in data indicator capitalization.

A study on the state of the art of data indicators design approaches has helped us consolidate the definition of capitalization, before isolating specific challenges to focus on. By using low level criteria to identify data indicators capitalization, we can get closer to the user's pragmatic needs. A higher level of interpretation of those requirements will, then, allow us to confront our primary conception of capitalization in a process of consolidating the definition of the notion.

This paper is structured as follows. We start by presenting a number of research efforts dedicated to data analysis and data indicators visualization. We continue by pointing out the need for data indicators capitalization and making an attempt to provide a definition of the latter. Then we specify how we established a list of criteria used to compare different approaches for data indicators design. The last section is dedicated to the description of the approaches chosen for this state of the art. The comparative study is made later in the same section.

2. RELATED WORKS

Our work is part of the Learning Analytics (LA) field, which aims at understanding and improving learning, more specifically the one carried out through TEL systems (Siemense & Long, 2011). LA life cycle is commonly divided into three phases of traces collection, analysis and visualization of learning traces (Clow 2012).

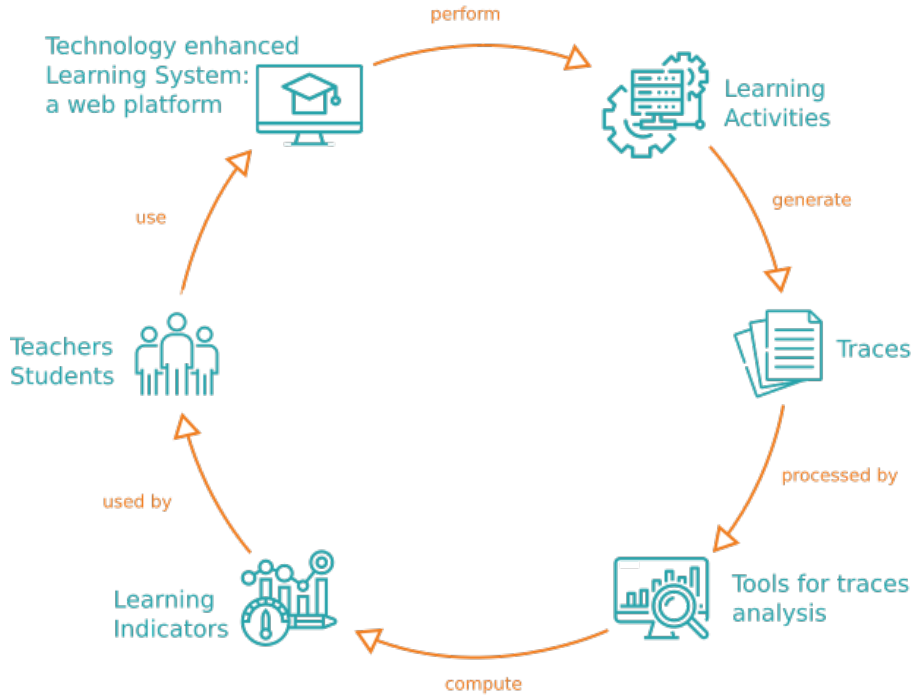


Figure 1. An example of Learning Analytics' life cycle

Figure 1 illustrates an example of a life cycle of learning traces in a TEL system. In this example, both learners and teachers use a Web platform to perform learning activities. A learner can take an academic test or view a video, a teacher can monitor learners' progress. These activities generate a large quantity but also diversity of learning traces, captured by tracking systems. This data, called traces, can include activity traces, survey's answers, logs, and so on.

The data collection phases can take many forms due to the diversity of learning activities and tools currently available. Various studies are seeking to store and structure it in a coherent way, beyond its inherent diversity. In Settouti *et al.* (2007), modeled traces (m-trace) are considered as the association between a collection of temporally situated events and an explicit model of this collection. That formalism allows transformations, requests and even computes indicators while handling heterogeneous data from multiple sources. On the other hand, in UTL (Usage Tracking Language) (Choquet & Iksal, 2007), a trace is not necessarily temporally situated, but a result of a transformation described by the language. UTL uses a model for all types of data, defining them according to three facets: The Defining (D) facet defines

the observation needs; The Getting (G) facet describes the observation means to implement the data acquisition; and the Using (U) facet defines the use of data once they are computed. Each proposal aims at offering a relevant model to support a specific type of information. It will then significantly influence the way this data can be processed and analyzed.

The collected traces are commonly processed by analysis tools. As found in Laalys (Muratet *et al.*, 2016), a statistical tool that uses a semi-automatically process to analyze learner's behavior by generating pedagogical labels in serious games. UnderTracks (Bouhineau *et al.*, 2013) assists the analysis process with its visual construction. UTL4CL (Ngoc, 2012) is based on the UTL language to generate data indicators with SQL requests on traces.

The transformation of raw data into usable information through an analysis process, thus enabling the creation of learning data indicators. These can then be displayed to users via a learning dashboard, created to suit different pedagogical practices. For example, during a course, in a synchronous way, teachers can use a dedicated dashboard to keep track of students' activities and their progress. In an asynchronous way, teachers can assess the use of a resource or adjust the structure of a course. Some work aims at creating data indicators for a specific pedagogical and digital context. For instance, Travis (May, 2011) displays data indicators for students' activities in discussion forums. Lab4CE (Broisin *et al.*, 2017) implements visualization tools in a remote laboratory for computer education intended for instructors and learners. Radar and Reflector (Phielix *et al.*, 2011) is a reflection tool for learners on group assessment.

Thus far, data indicators are seen as a tool of Learning Analytics that inherited its challenges in adoption by teachers as claimed by Kaliisa *et al.* (2021). Their work studied main challenges in teacher's adoption of LA, including the integration of technical and pedagogical expertise, the lack of connection with educational theories or pedagogies, and the failure to align with teachers' practice.

It is worth mentioning that learning indicators designate indicators focused on the study of learning, whereas data indicators designate from a general perspective the object computed throughout the analysis process of traces, which are not necessarily acquired within a learning setting. In our work, we focus on data indicators on learning, designed and used in a learning context.

The approach based on indicators capitalization is not easily highlighted among the existing comparative works in LA (Cherigny *et al.*, 2020, Croon *et al.*, 2021, Basak *et al.*, 2016, Alowayr and Badii, 2014, Corbi *et al.*, 2014, Choquet and Iksal, 2007, Dimitrakoupoulou, 2004). For that, we take a closer look at how each approach, formalism as implementation, enables users to

interact with data indicators, leading to their capitalization. Indeed, in the idea of supporting digital learning, tools were developed to provide users (student as teacher, experts as non experts) with assistance in accessing and feeding learning resources and environments. The involvement of users in all LA phases is therefore essential to the analysis outcomes and their relevance. But it is also crucial to the way indicators are used after the completion of their design and evaluation. To analyze indicators' life cycle beyond those phases, as the capitalization process suggests, a new set of requirements is needed.

3. CAPITALIZATION: DEFINITION AND CONCEPTS

3.1 Defining data indicators capitalization

The concept of capitalization is usually tied to monetary valuation. Here, the capitalization is considered as a valuation of the data and the value of the information they provide. When it comes to capitalized data indicators, their value can be determined by several factors including how relevant an indicator is, or how easy to use and reuse the existing indicators are, according to users and contexts.

For example, a teacher creates, for a particular course, an indicator for students' progression and grading based on a series of short quizzes. He can easily give it to another colleague working in the same course. But the colleague, while using a different pedagogical scenario and evaluation system, can not directly use the given data indicator. He will need to alter the core definition of the indicator's analysis process, which requires time and resources.

Capitalizing indicators would be about keeping and multiplying their value in time, contexts and users, while maintaining the reusability. Our approach considers data indicators as objects with challenges to overcome, like production cost or user validation. Indeed, they have a complex design process, highly dependent on context. Despite numerous attempts to simplify the design workflow for analysts, or the identification of observation needs for users (Laforcade *et al.*, 2009), the adoption of data indicators in learning practice for both teacher and student remains challenging (Kaliisa *et al.*, 2021). On top of that, while the usefulness of dashboards has been demonstrated in Verbert *et al.* (2013) to back up educational practitioners in any type of pedagogical scenario, many barriers remain to fully assimilate indicators as a common pedagogical resource (Basak *et al.*, 2016). The inadequacy of user's implication and expertise with the current solutions can

be considered as a design workflow issue. The commitment to create an adequate solution has led to the rise of co-design processes with users (Dollinger *et al.*, 2019). These challenges are those addressed through data indicator capitalization.

The approach of capitalization is therefore the combination of several multidisciplinary concepts, as illustrated in Figure 2. The first concept is “appropriability”, often used in human sciences (Ollagnier-Beldame, 2010) and in the field of HCI (Human-Computer Interaction). For instance, when adopting the indicators, users can apprehend and customize them without the intervention of experts. Then, comes the idea of “reusability”, that is, indicators must be designed to work with similar context. Next, “adaptability” that makes modifications possible to match other contexts or meet different needs. Finally, “shareability” must be ensured between users, thus, allowing users to access and share capitalized indicators within the system.

The association of all those concepts under the idea of data indicator capitalization aims to tackle the identified challenges and encourage a broader use of capitalized data indicators in e-learning practices. In order to verify the achievement of those four concepts, each was broken down into concrete technical properties as validation criteria, as presented hereafter.

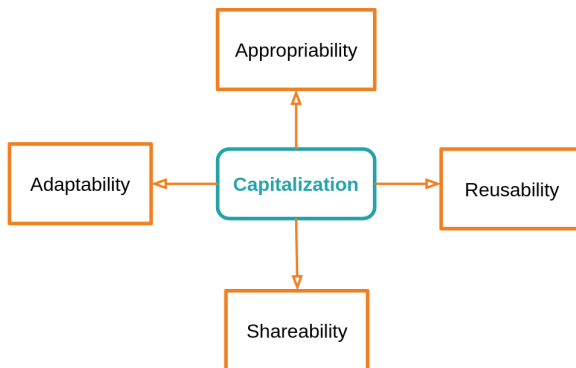


Figure 2. Pillar concepts of data indicator capitalization

3.2 Criteria to compare approaches in data indicator design

The criteria of this comparative analysis are intended to specify how an existing approach can achieve indicators capitalization. Several iterations have been made to better define each criterion.

In order to come up with a solution suitable to the platform's users, communication with the project's stakeholders has been maintained right from the start of the design process. Working groups, held primarily with teachers, allowed us to identify some of their needs and expectations. This observation work did not include any presentation of the data indicators or their capitalization process. The latter was tackled through the prism of pedagogical information, their use and challenges, creating a real involvement of the teachers, even without specific knowledge in learning analytics. This will allow us to create a relevant protocol for further experimentation on the relation between teachers or learners and data indicators. The preliminary list of needs that emerged was used as a basis to compose a series of technical properties, necessary for the verification of capitalization's concepts (Table 1). The existing criteria are meant to be fed from the experience of different users' context and profiles. The multiple iteration of user needs gathering does not affect the existing criteria, but rather help create a hierarchy among the identified needs.

The properties formulated are low level to get closer to technical functionalities and make the validation process easier. Indeed, an abstract concept is too open to interpretation to be used in a comparative approach. In the meantime, formulating a set of technical properties generic enough to apply to different kinds of approaches is no less tedious. Here after a detailed list of all currently selected technical properties classified between the four concepts:

3.2.1 2.2.1 Appropriability

Users need to regain control over the information available to them, which means that anyone can use the system, regardless of specific technical skills:

- **Granularity of entities:** the idea that each complex entity can be broken down into smaller and less complex entities. The more levels of decomposition, the better. This gives the opportunity to consider a nesting architecture to simplify the notions being handled.
- **Visualization choices:** it is an important part of data exploitation, a formalism should be able to specify how an indicator will be visualized, and an implementation should give the possibility to change it. A tool should have customizable visualization options.

- **Categorization of entities:** by classifying all entities, users will be able to access them more easily. It is even more efficient on multiple levels or with a tag system.
- **Search in existing indicators:** users can access and select existing indicators for their own use.
- **Filtering of indicators:** a variety of data indicators can be specified and narrowed down, allowing a better choice for the most relevant ones for each user's need.

3.2.2 2.2.2 Reusability

Any entity created has to be valued within the system, without losing its value through time:

- **Description of entities:** any information is useful. It can be considered as meta-data of any sort. It is important for meta-data not to be mandatory, but its availability, updatable by any user, is a plus. This co-construction raises the question of community regulations to maintain a high level of reliability.
- **Knowledge evolution:** evolution of the existing entities has to be eased. An existing indicator can be modified to create multiple new ones, without losing any previously created entities.
- **Versioning system:** the idea of keeping track of data indicator construction through the different steps, as well as its evolution as it passes from user to user. The functionality will allow "Knowledge evolution" without losing value through time.
- **Interlinking of indicators:** the possibility to create more complex indicators not only from traces but also from other indicators, all entities should be linkable and those links modifiable. It is an easier way to promote "Knowledge evolution" by using some kind of "Granularity of entities".
- **Storage of entities:** it is necessary to store the existing and created entities to ensure their future reuse. This is not necessarily handled by the tool itself, but needs to be considered when designing a system.

3.2.3 2.2.3 Shareability

To promote community and co-construction, communication between the user of the system can be achieved through different means:

- **User access management:** to create a system open to many types of user, being able to handle role and permission on data access or edition is necessary. Also, from an ethical perspective, an open system has to consider the questions of data anonymization and protection.

- **Circulation of indicators to users:** in an effort to co-build knowledge, spreading of the created and existing entities will allow different levels of user commitment and real cost saving. Ideally, any entity or set of entities can be shared to any related group of users.
- **Rating of indicators:** to promote reuse of existing entities and help newcomers navigate the potentially great quantity of entities. It can be done in many ways, including assessing different aspects of the indicators, such as their usefulness and their relevance.
- **Comments** can be made on any data indicator. Users participate through the commenting system in describing indicators and their properties.

3.2.4 2.2.4 Adaptability

The system has to provide a strong support to the expansion of indicators use:

- **List of existing entities:** an entity includes data indicators but also traces, operators, analysis processes or even users. It is required for many previous properties to have an available list of all existing entities.
- **Import of external traces:** in a new context, traces and data in general, won't necessarily be the same, adding new information has to be facilitated by design.
- **Context of the indicator:** if the context changes, the one in which an indicator has been created has to be specifically detailed in its description. That context includes the pedagogical situation and the environment setting of the TEL system.
- **Abstraction of indicators:** regardless of the context of use, each indicator can be created independently.
- **Modular data computing:** the calculation process needs to be easily adaptable to a new context, if possible automatically by the system, requiring a rigorous formalism set in “Abstraction of indicators”.

These technical properties are classified between the four pillar concepts that define the capitalization design workflow and use. However, most of this classification can be questioned. For instance, the possibility to search and filter indicators can both enable appropriation, but are related to properties classified in other concepts. In order to search among existing entities, it is necessary to have an available list of the existing ones. This related property “List of existing entities” is placed in the “Adaptability” category. In the meantime, an implementation of a formalism allowing access to existing entities does not necessarily have a “search functionality” either. Likewise, if

the filtering property is strayed forward in a tool, for a formalism it means that indicators

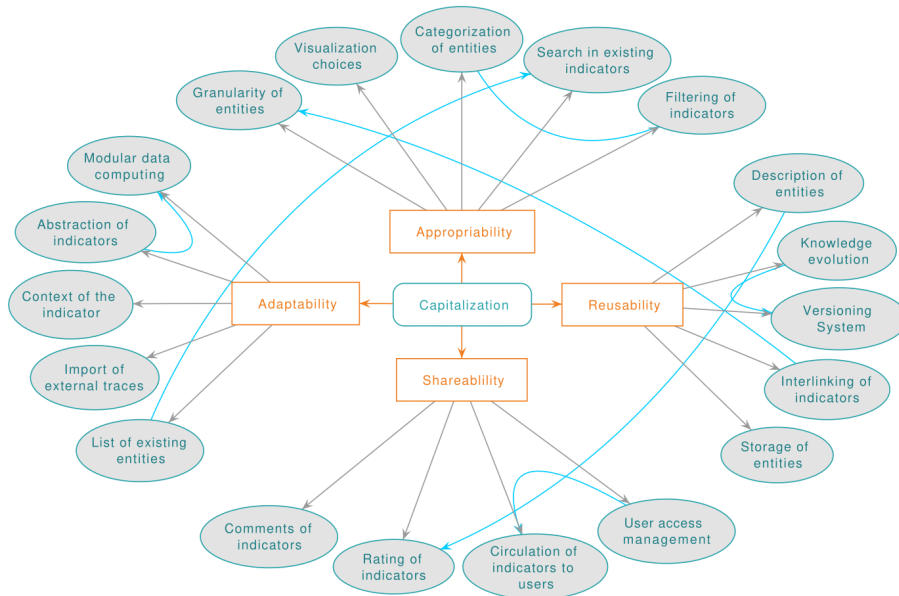


Figure 3. Related criteria for capitalization

have specifications they can be filtered on. Therefore, “Categorized entities” or “Description of entities” are considered related properties without being interdependent.

Considering the relation of some criteria (Figure. 3), their classification has been adjusted throughout multiple iterations of the literature review. The lack of information and inadequate wording was also considered to make criteria relevant to the contexts encountered.

With this list of capitalization properties, we seek to experiment how design workflow responds to the identified requirements. Comparing existing solutions through this new perspective and the present grid of criteria will allow us to consolidate the definition of data indicators capitalization within the current context.

4.COMPARING DATA INDICATOR DESIGN APPROACHES

4.1 Selection of indicators design approaches

Approaches and tools for designing indicators described in various research works have been selected. The starting point was a study of the state of the art carried out in the Thematic Groups of the Digital Education Directorate by Cherigny *et al.* (2020), completed by additional research. Once this initial list of tools had been compiled, those closest to the criteria described above were chosen, distinguishing between formalisms of various kinds and tangible implementations.

Our project's platform is meant for students' online training before a certification in accordance to their achievement and the levels they reached. It is also meant for teachers to follow the class's progress and help them through available resources. All the selected approaches are relevant in the specific context of our project. This helps us narrow down our selection on many other tools designed exclusively for interaction analyses, as well as lab sessions and practical works. Likewise, some work specialized on innovative hardware interfaces (tablets, surface tables, VR glasses, ...) were discarded as irrelevant to our work.

Each of these approaches were selected for their relevance in a capitalization of indicators design, but also for the diversity of their nature and solution provided.

Rule-based systems (Schauer, 2002) reproduce the cognitive mechanisms of an expert in a particular domain. They are based on facts and modifiable rules, which offer flexibility in data computing and the opportunity for knowledge evolution. It has been implemented in GINDIC (Generator of INDICators). Designers can use this tool to define indicators, the calculations performed on the traces and their visualization (Gendron *et al.*, 2012).

The UTL 2 language (Choquet and Iksal, 2007) is an XML-based meta-language describing the traces of a scenario. It uses the description of observation analysis methods to facilitate their capitalization. It can be used for indicators modeling with a strong attachment to pedagogical situations.

The trace-based systems, TBS, (Settouti *et al.*, 2009) consider traces as a temporal sequence of observed events along with a capitalizable model. Traces in heterogeneous formats can thus be manipulated to create different indicators abstracted from environment settings. TBS-IM (Djouad *et al.*, 2010) is a TBS implemented for indicators calculation in the Moodle learning platform. Another TBS is DDART (Michel *et al.*, 2017), a dynamic dashboard

based on activity traces and reports in the form of a Moodle plug-in. Learners can create customizable indicators related to their activities.

The Reusable Indicator Template of David *et al.* (2005) is composed of a computational function of traces and metadata explaining the reuse conditions, including the function's domain of definition, the learning situation and a description. The EM-AGIIR tool (David *et al.*, 2005) proposes an implementation of the RIT and an open multi-agent architecture to apply the indicators with new traces.

The ontological framework of Lebis (2018) is used to capitalize the analysis processes of learning traces in a so-called narrative way. It is not meant for indicator capitalization, but its originality motivated us to compare it with the rest. It is part of a larger set of tools built for analysis process capitalization.

The Academic Analytics Tool (Ross *et al.*, 2017), was developed for the Moodle Analytics project. AAT is a software allowing teachers and course managers to access and analyze student behavior data in learning systems. Course Insights is a Learning Analytics Dashboard that provides filterable and comparative visualizations of aggregated students' daily activity and learning events to teachers. The flexibility of those tools, which are not based on a studied formalism, is interesting from a user perspective.

We looked into indicators design approaches from the Learning Analytics domain, but it seems relevant to expand this research scope into other domains where context is equally important. Overall, few tools offer a solution for capitalization either from system or user standpoints. Nonetheless, each tool presents a solution or part of a solution to the issues we have pointed out above. A closer look at the existing approaches is therefore interesting for the design of our own indicator capitalization approach, while selecting the criteria that match our design choice based on the four pillar concepts, presented earlier in section 3.

4.2 Literature review grid

The findings from our study on the state of the art is synthesized in Table 1. Our proposal is based on four levels of validation of a criterion: [V] validated with respect to our work and in line with our requirements on capitalization, [PV] partially validated, [NV] not validated and [NR] not relevant, in case of inadequacy with a criterion. The number of "not relevant" criteria is due to the effort to compare objects of different nature with a common grid. The formulation of the criteria as technical properties is interpreted in a distinct way depending on whether the analyzed object is a theoretical formalism or a tangible implementation. For instance,

“Visualization options” would be the information stored for a language, the display handled for an architecture and real visualizations for implemented tools. In some cases, the property does not apply for some level of abstraction, hence the use of “not relevant”.

Validation of each criterion was done through a careful analysis of the literature. Nonetheless, the collected information for our analysis can be limited, as each tool we studied is not always meant for data indicator capitalization. The grid’s filling considers interconnection of criteria in the implementation level to fill the information gaps. It may occur that specific information contradicts the interconnection as seen in Figure 3, for instance no filtering implemented even where categorization is permitted.

		Formalisms											
		Rule - based System (Schauer 2002)	Trace-base system (Settouti et al. 2009)	TBS-IM system (Djouad and Mille 2010)	DDART (Michel et al. 2017)	Reusable Indicator Template David et al. 2005)	UTL 2 language (Iksal and Choquet 2007)	Narrative ontological framework (Lebis 2018)	Academic Analytics Tool (Ross et al. 2017)	Course Insights (Shabinejad et al. 2020)			
Appropriability	Implementations		GINDIC (Gendron et al. 2012)					EM-AGIIR (David et al. 2005)					
		Granularity of entities	NV	NV	V	PV	PV	PV	PV	V	V	V	V
	Visualization choices	NV	V	NV	NV	V	NV	PV	NV	NR	NV	PV	PV
	Categorization of entities	NV	V	PV	NV	V	V	V	V	V	V	V	NV
	Search in existing indicators	V	V	PV	NV	NV	NR	V	NR	NR	V	V	V
	Filtering of indicators	NV	PV	PV	NV	NV	NR	NV	NR	NR	V	V	V
Reusability	Description of entities	V	V	PV	PV	PV	V	V	V	V	V	V	PV
	Knowledge evolution	V	V	V	V	PV	NV	V	V	V	NV	NV	PV
	Versioning System	PV	PV	PV	NV	NV	PV	PV	V	NV	NV	NV	NV
	Interlinking of indicators	V	V	PV	NV	NV	NV	NV	V	V	V	V	V
	Storage of entities	V	V	V	V	V	NR	V	NR	NR	V	V	V
Shareability	User access management	PV	V	PV	NV	NV	NR	V	NR	NR	V	PV	PV
	Circulation of indicators to users	NR	PV	NR	NV	PV	NR	NV	NR	NR	NV	NV	NV
	Rating of indicators	NV	V	NV	NV	NV	NV	NV	NV	NR	NV	NV	NV
	Comments of indicators	PV	NV	PV	NV	NV	PV	PV	PV	PV	PV	PV	NV
Adaptability	List of existing entities	V	V	V	V	V	NR	V	NR	NR	V	V	V
	Import of external traces	V	V	V	V	V	NR	PV	NR	NR	V	V	V
	Context of indicator	V	V	NV	NV	NV	V	V	V	V	PV	PV	PV
	Abstraction of indicators	V	V	V	V	V	V	V	V	V	V	V	PV
	Modular data computing	PV	V	V	V	V	V	PV	V	V	V	V	PV

Table 1. Comparison of formalisms and implementations of data indicator capitalization

In Table 1, it can be seen that a rule-based system does not offer any specific means to categorize entities, whereas GINDIC does include the dimension and the nature of the created indicators. On its part, the Reusable Indicator Patron provides three types, Cognitive, Social and Affective, which are here considered as categorization. If we take a look at another example, “User access management” may seem a stray forward functionality for an implemented tool, therefore, it can be seen that three out of five of them have it implemented. Then for the formalisms, both rule-based system and trace-based system are considered as partially validating the criterion by suggesting a system architecture in which the property could be easily added. But this concern has not been found in the studied documentation and therefore not fully validated. For the rest of the formalisms, their nature is too disconnected from such a functionality to be considered relevant. A similar reflection has been followed for each criterion in the grid, while studying the available documentation.

Regarding the criteria suggested for the capitalization of indicators, some limits in the design solutions can be noticed. It would be interesting to look for an approach which facilitates sharing abilities of existing indicators without losing the flexibility of their design. Indeed, the criteria for appropriation and sharing of indicators are the least developed.

This involvement of the end-user is key in a successful capitalization process. But the current indicators design approach focuses mostly on the feasibility and the technical aspect of indicators, rather than the plus value and the experience the user will take from using a specific indicator. It is worth taking note that the “real use” or the “effectiveness” of the capitalized indicators is not the goal of our approach and so cannot be considered a success measure for our work. But considering the way individuals will use the created object influences how it is designed. The use of each object can evolve in time and practice behavior, thus requiring a versatile and evolving approach.

The technical usability of an approach, as an ergonomic criterion, is not directly included in this grid, but this important factor of user adoption can be partially assessed through the present criteria.

It can also be noted that an implementation does not necessarily preserve all the technical properties of the corresponding formalism. Some other properties do not seem to be related to the implemented indicators design formalism. However, the chosen formalism clearly has an impact on the implemented functionality. Thus, the conception model for an indicator design approach should not be taken lightly.

To sum up, the current grid will be used in the continuation of our work on designing an approach for capitalization, as a guideline and validation criteria. The computerization process includes consideration of the formalism as much as the implementation and the user's interactions with it. Users will find the presented functionalities to enable interesting actions in the design process but the possibility of an interaction alone, as the collection of data without an efficient indexation, will still be limited. It is therefore our main focus to enable the whole potential of users' interactions and their design activities within the idea of data indicator capitalization.

5. CONCLUSION

The democratization of data indicators in learning practices faces challenges with high design cost and limited user adoption. Capitalization as a solution to those challenges requires a closer look at the user's needs regarding data collection, transformation, computation, exploration, and visualization. The multiplicity of users' level of interaction with the TEL system, pedagogical information and data indicators make the design of a common approach more complex.

The comparative analysis developed here allows us to point out a range of concrete technical points to enhance data indicators design formalism and to support their implementations. By using this custom grid to compare a wide range of approaches, we saw how the formalism used can have an impact on the available functionalities. This initial list of criteria for a tool aiming to support capitalization is also how we choose to start building our approach. A number of specialized tools have successfully offered solutions for data analysts with highly efficient data processing and visualization, or for teachers and learners with turnkey solutions for dashboard. But the co-design of data indicators by heterogeneous users is still a challenge.

It is important for us to point out that the work presented here has some limits. First, the domain and project context in which were made the choices of design approaches remain narrow. This choice was also due to size constraints. For that reason, extending this analysis to new design solutions has already been set among our research perspectives. The lack of empirical studies to validate the grid has also been pointed out, and an analysis carried out exclusively through the literature would need to be further investigated. Finally, the criteria developed here are based on a user-centered approach that has only been initiated.

Data indicator design approach focusing on its capitalization considers the indicator's entire life cycle. Throughout this process, tools will be developed

for users to operate and specific skills are needed to effectively carry out a capitalization process. Our focus is neither on a particular tool nor a user, but on observing and studying how users interact with a tool during the capitalization process. As we have already mentioned, the capitalization is the result of a constant interaction between users and tools. The facilitation of these interactions is valuable and pertinent to help users make decisions in data indicator design and use. The provided solution needs to be modular, so each task can be, or not, achieved by using adequate formalism and implementation. The analysis we have made so far shows the necessity to accentuate the accessibility of the entities handled by the users to ensure the durability of our approach.

Capitalization also requires the active involvement of users. They need to be proactive for successful indicators' assimilation in their learning practices. This proactivity has to be supported and promoted by the process itself. With this perspective, our future work will implicate users as they will help us validate the initial conclusions. Focus groups will be organized and get involved in our design approach. Moreover, a co-design of the capitalization process has already been initiated with working groups to identify the users' actions when creating and using data indicators. This first attempt will allow us to detect the key interactions when users are involved in a capitalization process. The grid that we have presented here will serve as the base of an evolutive approach where users and their interactions will be observed and studied in each iteration of data design and capitalization.

The direction we are taking, where user involvement is continually present, leads us to acknowledge other important issues of data privacy and ethics. Their impact on users' perception and even performance is not negligible (Kaliisa *et al.* 2021, May *et al.* 2016). Thus, this consideration must be assimilated in the design process to reach a thorough user-adapted proposition.

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