Proposal of Indicators for Measuring Collaborative Writing in a Digital Learning Environment

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Abstract: Collaborative Writing (CW) is a common activity in education, which is being enhanced by the use of digital learning environments, leading to a growing research field in Computer-Supported Collaborative Learning (CSCL). In order to help teachers to monitor students CW, we propose two indicators that provide measures of student contributions to a text writing, namely balance of contribution and co-writing. We also identified CW strategies that are well defined in the literature. Moreover, we conducted a questionnaire evaluation to verify the interpretation of the indicators and the strategies by teachers in higher education context, using student reports edited in a collaborative digital environment called LabNbook, during physics and chemistry courses in undergraduate level. Results showed that teachers have a good interpretation of the indicators and strategies. This work contributes to research insights in CW, and motivates future work to design meaningful learning indicators.

1 INTRODUCTION

Providing students with group work is a common activity in education. Assigning group work is largely emphasized as a method that enables students to develop collaborative skills (Sun et al., 2018). Moreover, this may be enhanced by the use of digital technologies, providing students with several tools such as collaborative writing platforms (Zhang and Chen, 2022). This led to growing research in the field of Computer-Supported Collaborative Learning (CSCL) (Chen et al., 2018). More particularly, Collaborative Writing (CW) has gained an increasing research interest in the last few years (Zhang et al., 2021). Students' interactions can be efficiently captured and stored, leading to a more fine-grained analysis of the CW process.

A large part of existing research aims at capturing student collaboration dynamics using mixed approaches: analysis of digital logs and peer student interactions such as exchanged messages or oral conversations (Zhang et al., 2021). Despite prior abundant works that characterize and assess collaboration dynamics in CW, there is a need for improved research in this field, in particular concerning measures and metrics (Zhang et al., 2021). In this work, we contribute with two new indicators that provide measures for CW, namely *Balance of Contribution* reflecting the extent to what students' contributions are equilibrated at a word level and *Co-writing* reflecting students' contributions at a sentence level in a text. We base the indicator calculations on a variance metric and explore the relationship between these indicators and typical CW strategies. The definition of these indicators is sourced from previous research that is not detailed in this paper (Hoffmann et al., 2022). Our research is anchored in a real-life context, using a web-based learning environment, called LabNbook, designed for supporting learners in the CW of scientific documents (d'Ham et al., 2019). Moreover, we evaluate the interpretation of the proposed indicators and the deduced strategies by teachers in higher education context. We use collaborative documents edited during physics and chemistry courses in un-

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dergraduate level. We address the following research questions:
RQ 1.) What are the indicator metrics that allow to measure students' CW?
RQ 2.) How can we deduce CW strategies from these indicators?
RQ 3.) To what extent these indicators and strategies are interpretable by teachers? (How close is the relationship between these measures and their interpretation).

This paper is organized as follows. Section 2 provides a state of the art of existing research on CW. Section 3 introduces the proposed indicators and the co-writing strategies. Section 4 describes our research method. Section 5 details the calculations of the proposed indicators and their relationship to the co-writing strategies. Results are discussed in Section 6, conclusion and implications are derived in Section 7.

2 COLLABORATIVE WRITING

Collaborative Writing (CW) can refer to the production of a text by two or more writers (co-authoring) (Storch, 2013). More specifically, it is defined as a process involving substantive interactions between learners sharing decision making and responsibilities for a single produced document (Zhang and Chen, 2022).

There is a long-standing interest in CW and different authors proposed early models and taxonomies of CW (Posner and Baecker, 1992; Lowry et al., 2004; Storch, 2013). With the fast-growing use of Online Learning Environments (OLE) and the ability to analyze data logs, several frameworks have been applied to examine behaviors, patterns and strategies of CW in different educational domains (Onrubia and Engel, 2009; Sundgren and Jaldemark, 2020; Olson et al., 2017). For instance, in the domain of second language (L2), a recent systematic literature review (Zhang et al., 2021) has examined more than one hundred studies revealing a strong research interest in the field of CW during the past decade.

One popular model in the literature that was proposed, is a dyadic interaction model with two constructs, namely *equality*, reflecting the learner's level of contribution and control over the task, and *mutuality*, reflecting the learner's level of engagement with each other's contribution (Storch, 2013).

These two constructs also appear in less recent literature. For example, (Dillenbourg, 1999) compares concepts from the field of Human-Computer Collaborative Learning Systems (HCCLS), where an artificial agent collaborates with the human learner, and CSCL systems, where the computer supports collaboration between two human users. He argues that collaboration implies negotiation and emphasizes on the degree of symmetry in interactions between peers. He defines *Symmetry of action* as the extent to which the same range of actions is allowed to each agent (Dillenbourg and Michael, 1996) (the agent may refer to an artificial agent or a human peer). The term symmetry is borrowed from HCCLS domain to qualify an equilibrated balance of control implied by collaboration between the system and its user (Dillenbourg and Michael, 1996).

Mutual refinement is a second main characteristic defining collaboration through negotiation (Baker, 1994). This refers to specific strategies that exist for achieving agreement in the interaction (each agent successively refines the contribution of the other) (Dillenbourg and Michael, 1996). This can be reflected in ways of editing text written by others and ways of coping with others editing one's own text (Larsen-Ledet and Korsgaard, 2019), or the degree of engaging with each other's ideas and each other's texts and providing scaffolding in producing joint writing (Li and Zhu, 2016).

This led us to say that two key indicators may help to characterize collaborative work. The first one evaluates the symmetry in contributions, while the second one measures the degree of interactions between students.

3 INDICATORS AND STRATEGIES

We define *balance of contribution* as a metric that indicates how the student contributions are equal, well balanced or imbalanced. It is aligned on the one proposed by (Olson et al., 2017), called *balance of participation* which is a team contribution measure that reflects whether individuals' contributions are *equal or imbalanced*. As a balance metric, they considered one minus the variance of team members proportions in the collaborative work. The authors argued on variance as preferable over other ways of calculation such as Gini coefficient or Blau's index, for its simplicity and ease of interpretation. We based the calculation of the *balance of contribution* indicator on a variance metric, that provides a distribution between the authors' average contributions in terms of number of words in a final document.

Balance of contribution indicator measures a student contribution at a word level, and co-writing indicator measures a student contribution at a sentence level. Indeed, balance of contribution measures only division of labor (number of words a student contribute to the text), and co-writing goes beyond that by measuring student co-construction of the text (modifying and adding words in sentences written by others in the text). The values of both indicators range between 0 and 1 (see section 5).

A possible exploitation of the indicators is the identification of CW strategies. We consider two strategies among the five proposed by (Onrubia and Engel, 2009), namely: 1) *sequential summative text construction*, *i.e.,* one group member presents a document that constitutes an initial, partial or complete, proposal for the task resolution and the rest of the participants successively add their contributions to this initial document, without modifying what has been previously written, hence, systematically accepting what is added by other co-authors; 2) *sequential integrative text construction*, *i.e.,* one group member presents a document that constitutes an initial, partial or complete task proposal, and the other group members successively contribute to this initial document, proposing justified modifications or discussing whether they agree with what has been previously written or not.

We use the term *summative* to appoint to a strategy where each student adds his text without modifying the text of the others where the result is being a juxtaposition of the individual contributions and, the term *integrative*, to appoint to a strategy where one student proposes an initial version and the other students contribute successively making modifications to the existing text (Hoffmann et al., 2022).

The first is characterized by an explicit division of work between the team members, and the second by a co-construction of the text. Students may not necessarily follow one strategy but a mix of them.

4 RESEARCH METHOD

Our objective is, on the one hand, to construct metrics of students' CW process, and on the other hand, to verify that these metrics are intelligible for teachers. To conduct our research, we choose the design based research (Wang and Hannafin, 2005) and the associated guides (Mandran et al., 2022). This method proposes to build knowledge and associated tools in an iterative way by integrating all the actors in the field. Each iteration consists of developing the tool and the knowledge on the basis of the reality in the field and the opinion of the stakeholders.

4.1 Context

We use text documents produced by students on the LabNbook platform [1], which is a digital environment for learning experimental sciences in secondary and higher education (d'Ham et al., 2019). It provides useful tools for writing collaborative scientific documents (text and equations, drawing, data processing, etc.) and allows students to interact with each other (team building, shared workspace, internal messaging and chat, etc.). LabNbook operates in a *locked co-editing mode* (Wang et al., 2017), i.e., students can work simultaneously in the shared workspace but each document, called LabDoc, composing it can be edited only by one student at a time. For instance, a collaborative report may be composed of different sections, and each section corresponds to a LabDoc.

4.2 Data Collection

We use a questionnaire to measure to what extent the strategies and indicators are interpretable by teachers (RQ3). Our objective is to verify whether the definitions make sense to them.

We selected 12 LabDocs edited on the LabNbook platform by groups of students during physics and chemistry courses (undergraduate level) in Grenoble Alpes University (France). To distinguish student contributions, we highlight in each LabDoc with a color-code the text written by each student. We choose LabDocs uniformly with different writing strategies (integrative, summative, and mixed strategies). Respondent teachers are a total of 15, situated in IMT Atlantique in Brest (France), from Computer Science discipline and in Grenoble Alpes University in Grenoble (France), from Experimental Sciences disciplines. After providing the teachers with verbatim definitions of the strategies and of the indicators, we ask them to indicate for each LabDoc:

(1) the strategy they perceive (Entirely Summative (ES), Rather Summative (RS), Between Summative and Integrative (BSI), Rather Integrative (RI), Entirely Integrative (EI) and I don't know (DN));

(2) an estimate of the level of each indicator (Low (L), Medium (M) and High (H));

(3) a numerical value for each indicator between 0 and 1.

[1] https://LabNbook.fr/

5 INDICATORS CONSTRUCTION

5.1 Text Sequences Matching Method

In order to study the evolution of a text document and compare pairs of text sequences, we use a *Sequence Matcher* method which has its origins in an algorithm published in the late 1980's by Ratcliff and Metzener under the name *Gestalt Pattern Matching* (Ratcliff and Metzener, 1988) [2].

To illustrate this method, consider a text co-written by two students *A* and *B*. Student *A* writes the first version which is then modified by student *B*. In order to qualify the evolution of the initial text to its final version, the approach consists firstly in finding the longest, in terms of number of characters, contiguous matching sequence (a set of words) that contains no useless elements, such as blank lines or white space. The same operation is then applied recursively for the sequences to the left and to the right of this longest contiguous matching sequence. Then, in order to qualify changes in the text, each sequence is tagged as follows: *Equal* (sequences are equal), *Insert* (sequence is inserted), *Delete* (sequence is deleted), *Replace* (sequence is replaced). For instance, let consider the following pair of text sequences written sequentially by two students:

- Student *A*: "*LabNbook is a digital platform used by over 3500 students*"
- Student *B*: "*LabNbook is a platform used by more than 3500 students in France*"

Student *B* contributes to the text after student *A* by inserting, deleting and modifying text. Table 1 gives the correspondent tag for each altered sequence.

Table 1: Illustration of the tagging operation.

Tag	Student *A*	Student *B*
Equal	"*LabNbook is a*"	"*LabNbook is a*"
Delete	"*digital*"	" "
Equal	"*platform used by*"	"*platform used by*"
Replace	"*over*"	"*more than*"
Equal	"*3500 students*"	"*3500 students*"
Insert	" "	"*in France*"

5.2 Contribution Matrix

To quantify and track the evolution of the text, we use a matrix that gives for each word, the level of contribution of each of the students co-writing the text. We call this matrix, a *contribution matrix*, since it gives the student levels of contributions to a text. In this matrix, rows represent contributing students and columns represent words constituting the final text.

In order to provide a formal definition of this contribution matrix, let consider a text composed of N sentences, M words and co-written by K authors. Let also $x_{i,j,l} \in [0,1]$, be the contribution level of an author i to a word l of a sentence j where $i \in [1,K]$, $j \in [1,N]$ and $l \in [1,n_j]$. Here, n_j denotes the number of words in a sentence j.

In this $K \times M$ matrix, the level of contribution of an author is expressed by a score ranged between 0 and 1. It is set to 1 when the author writes entirely a word, and to 0, when the author doesn't contribute to a word. The total authors' contributions to a word is equal to 1.

Since our scoring method is based on the sequence matching method that identifies the longest contiguous matching sequence, deleted words do not result in a score, and replaced words result in a score that returns the ratio of contributions in terms of number of characters.

In the previous example, 2 students contribute to a text which is composed of 12 words ("*LabNbook is a platform used by more than 3500 students in France*"). Consequently, the contribution matrix gives scores ranged in 2 rows and 12 columns, as follows

$$\begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 0.3 & 0.3 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.7 & 0 & 0 & 1 & 1 \end{pmatrix},$$

where the first row gives the scores corresponding to the contribution levels of the student A and the second row those of the student B.

5.3 Balance of Contribution Indicator

The balance of contribution indicator measures student's contribution at a word level. More precisely, it measures the degree to which students' contributions are equal (well-balanced) or not. The closer the value of this indicator is to 1, the more students' contributions are equal. At the opposite, the more it is closer to 0, the less the students' contributions are equal. This indicator is based on the variance in (3) of the students' average contributions, which reflects the distance between each student average contribution and the mean of all students' average contributions in (2). Note that, if the students contribute in a well-balanced way, then their scores are close to the mean and they contribute quite equally. Moreover, in order to penalize the case where the whole text is written by one student, this variance is normalized by (4). We define

[2]For implementation, we use the *Python* library *Difflib* https://github.com/python/cpython/blob/main/Lib/difflib.py

the balance of contribution indicator as follows

$$e(X) = 1 - \frac{K}{K-1}\sum_{i=1}^{K}\left(\bar{x}_{i,\bullet,\bullet} - \frac{1}{K}\right)^2 \qquad (1)$$

where, for $i = 1,\ldots,K$, $\bar{x}_{i,\bullet,\bullet}$ is the average contribution of the student i to all words of the text. Note that, $\sum_{i=1}^{K}\bar{x}_{i,\bullet,\bullet} = 1$ and the mean of all students' average contributions is

$$\bar{x}_{\bullet,\bullet,\bullet} = \frac{1}{K}\sum_{i=1}^{K}\bar{x}_{i,\bullet,\bullet} = \frac{1}{K}\,. \qquad (2)$$

Indeed, as we consider that students contribute in a balanced way if their average contributions equals $1/K$, we use in the construction of the balance of contribution indicator the variance

$$\frac{1}{K}\sum_{i=1}^{K}\left(\bar{x}_{i,\bullet,\bullet} - \frac{1}{K}\right)^2. \qquad (3)$$

However, in the case a student i writes alone the whole text, only one $\bar{x}_{i,\bullet,\bullet}$ equals 1. Then (3) becomes

$$\frac{K-1}{K^2}\,. \qquad (4)$$

Finally, as mentioned above, in order to penalize the case where one student writes the whole text, we normalize the variance (3) with (4), which gives

$$\frac{K}{K-1}\sum_{i=1}^{K}\left(\bar{x}_{i,\bullet,\bullet} - \frac{1}{K}\right)^2.$$

This dispersion reaches its minimum value 0 when all students contribute equally (or in a balanced way) to the text, that is, where the average contribution of each student $\bar{x}_{i,\bullet,\bullet}$ equals $1/K$. It reaches its maximum value 1 when a student writes alone the whole text. In this case, only the average contribution of the student i, that is $\bar{x}_{i,\bullet,\bullet}$, equals 1. Therefore, in order to make this measure easier to interpret for teachers, we compute one minus this dispersion, which gives the balance of contribution indicator in (1).

5.4 Co-writing Indicator

Similarly to the balance of contribution indicator, which measures students' contributions at a word level, the co-writing indicator measures students' contributions at a sentence level (6). Thus, this indicator requires splitting the text into sentences. To this end, we use a rule-based (heuristic) approach for sentence segmentation, for its implementation simplicity (Sadvilkar and Neumann, 2020). We use a sentence boundary detection tool based on a set of rules called *Golden Rule Set* [3], hand-designed to determine sentence boundaries, such as punctuation.

[3]https://github.com/diasks2/pragmatic_segmenter

When all sentences are written by a single student, this indicator equals 0 and it equals 1 when all sentences are co-written, in a balanced way, by all students.

The co-writing indicator is based on the balance of contribution indicator, but on a sentence level. According to the contribution matrix, we compute for each student his average contribution in all sentences. Thus, let $\bar{x}_{i,j,\bullet}$ be, the average contribution of student i to the sentence j. Then, we obtain a $K \times N$ matrix of average contributions on a sentence level. For each sentence, we compute the variance of all authors' average contributions.

$$\frac{1}{K}\sum_{i=1}^{K}\left(\bar{x}_{i,j,\bullet} - \frac{1}{K}\right)^2. \qquad (5)$$

Similarly to balance of contribution, we penalize the case where only one student writes a sentence alone, by computing the ratio between (5) and (4), and we calculate one minus the resulting quantity which gives the following dispersion measure

$$e_j(X) = 1 - \frac{K}{K-1}\sum_{i=1}^{K}\left(\bar{x}_{i,j,\bullet} - \frac{1}{K}\right)^2.$$

Therefore, the co-writing indicator is given by

$$c(X) = \sum_{j=1}^{N} p_j e_j(X) \quad \text{where} \quad p_j = \frac{n_j}{M} \qquad (6)$$

is the weight of the sentence j.

5.5 Indicators Property

The indicators present an inequality property. The co-writing indicator $c(X)$ in (6) is lower or equal than the balance of contribution indicator $e(X)$ in (1), *i.e.,*

$$c(X) - e(X) = \frac{K}{K-1}\sum_{i=1}^{K}\Bigg[\left(\bar{x}_{i,\bullet,\bullet} - \frac{1}{K}\right)^2 - \qquad (7)$$
$$\sum_{j=1}^{N} p_j\left(\bar{x}_{i,j,\bullet} - \frac{1}{K}\right)^2\Bigg] \leq 0\,.$$

Indeed, equation (7) is non-positive as soon as

$$(\bar{x}_{i,\bullet,\bullet})^2 - \sum_{l=1}^{n_j} p_j\,(\bar{x}_{i,j,\bullet})^2 \leq 0\,, \qquad (8)$$

we have

$$(\bar{x}_{i,\bullet,\bullet})^2 = \left(\sum_{j=1}^{N} p_j\bar{x}_{i,j,\bullet}\right)^2 \leq \sum_{j=1}^{N}(p_j\bar{x}_{i,j,\bullet})^2\,. \qquad (9)$$

Thanks to (9), an upper bound for (8) is given by

$$(\bar{x}_{i,\bullet,\bullet})^2 - \sum_{l=1}^{n_j} p_j\,(\bar{x}_{i,j,\bullet})^2 \leq \sum_{l=1}^{n_j} p_j(p_j-1)\,(\bar{x}_{i,j,\bullet})^2\,,$$

which is non-positive since $p_j \leq 1$.

5.6 Collaborative Writing Strategies

As values of the indicators balance of contribution and co-writing are continuous and ranged between 0 and 1, we can represent co-written text documents in a two-dimensional (2D) plane plot (x-axis for balance of contribution and y-axis for co-writing), see Figure 1. Moreover, as co-writing indicator is always lower or equal than balance of contribution ((5.5)), the 2D plane is reduced to a triangle representing the area of potential plots for documents.

It is then possible to distinguish documents which are written in summative strategies (ES, RS) or integrative strategies (EI, RI) from documents written in a mixed strategy (BSI), by considering their location in the 2D plane. When the co-writing is low the strategy is summative. Therefore, documents written in summative strategies are plotted near the x-axis. When the strategies are integrative, the documents are plotted near the 2D plane diagonal and the balance of contribution and co-writing values are close. Documents written in a mixed strategy (between summative and integrative) are plotted in between.

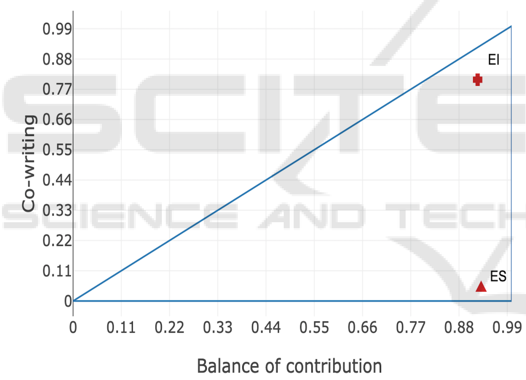

Figure 1: A 2D plane illustrating the relationship between the indicators and the CW strategies.

6 RESULTS AND DISCUSSION

After providing the mathematical demonstration of the indicators (RQ1), and the illustration of the relationship between the indicators and the strategies (RQ2), the questionnaire results allow to evaluate the teacher interpretations of the strategies and the indicators (RQ3).

We compare the indicator values and levels estimated by teachers to the values computed using formulas (1) and (6). Indicator levels are set among Low for indicator values in $]0,1/3]$, Medium for values in $[1/3,2/3[$ and High for values in $[2/3,1]$.

Teachers first indicate the perceived strategies. Table 2 compares the number of teacher responses received for each LabDoc and for each strategy. We report that $9/12$ LabDocs are well classified with a majority of good responses (8 to 14). LabDocs 1 and 6 received respectively 6 and 5 well classifications while the majority of responses are spread-out on the other strategies. This is probably due to the difficulty for teachers to perceive a mixed strategy such as in LabDoc 6. LabDoc 1 comprises mathematical formulas, and this may influence the teacher perception. For LabDoc 12, teachers answers are more spread out comparatively to LabDocs 1 and 6, but with 5 good answers and 1 answer as "I don't know". This can be explained by the fact that this LabDoc presents a very low collaboration (mainly written by a single student, a second contributor modified some words at its end) leading to a misinterpretation of the strategy by teachers.

Table 2: Teacher responses regarding the strategies they perceived. In bold, LabDocs that are misclassified by the majority of teachers. The wright strategy is ST.

LabDoc	ST	ES	RS	BSI	RI	EI	DK
1	**EI**	**0**	**2**	**4**	**3**	**6**	**0**
2	ES	11	2	1	1	0	0
3	EI	0	1	1	1	12	0
4	BSI	0	1	8	5	1	0
5	EI	2	0	0	2	11	0
6	**BSI**	**0**	**8**	**5**	**2**	**0**	**0**
7	ES	12	1	0	0	2	0
8	RI	0	0	4	7	4	0
9	RS	0	8	5	1	0	1
10	ES	14	0	1	0	0	0
11	ES	14	1	0	0	0	0
12	**EI**	**1**	**4**	**2**	**2**	**5**	**1**

Secondly, teachers estimate for each LabDoc the level and value of the two indicators. Table 3 provides for each LabDoc the number of students having contributed to its writing, the machine value and machine level of each indicator, and the number of teacher responses for each indicator level.

We also calculate the distance between the machine value (MV) of an indicator $\theta \in [0,1]$ and teachers' estimate, using the Root Mean Standard Deviation (RMSD) given by

$$RMSD = \sqrt{\frac{\sum_1^n(\hat{\theta}_i - \theta)^2}{n}}$$

where, for $i = 1,\dots,n$, $\hat{\theta}_i \in [0,1]$ is a teacher's estimate and n is the number of teachers who respond to the questionnaire.

Concerning indicator levels, $(8/12)$ of LabDocs are well classified by teachers regarding balance of contribution and $(10/12)$ regarding co-writing.

Table 3: Comparing teacher perceptions and estimations of indicator levels and values with the machine values (MV) and levels (ML). In bold, LabDocs for which a majority of answers are wrong. "NB" is the Number of Students (co-writers).

		Balance of contribution						Co-writing					
LabDoc	NB	MV	RMSD	ML	L	M	H	MV	RMSD	ML	L	M	H
1	2	0.49	0.32	M	0	7	8	**0.41**	**0.42**	**M**	**0**	**4**	**11**
2	2	0.87	0.19	H	0	6	9	0.11	0.15	L	13	1	1
3	2	0.84	0.24	H	1	2	12	0.76	0.28	H	1	0	14
4	2	0.99	0.21	H	0	1	14	0.41	0.22	M	3	9	3
5	**3**	**0.49**	**0.36**	**M**	**15**	**0**	**0**	**0.44**	**0.35**	**M**	**12**	**1**	**2**
6	2	0.99	0.19	H	0	1	14	0.50	0.2	M	7	7	1
7	2	**0.51**	**0.3**	**M**	**13**	**2**	**0**	0.07	0.09	L	14	1	0
8	2	0.99	0.3	H	0	7	8	0.74	0.21	H	0	6	9
9	**4**	**0.48**	**0.27**	**M**	**13**	**2**	**0**	0.17	0.12	L	13	2	0
10	**3**	**0.92**	**0.39**	**H**	**1**	**11**	**3**	0.09	0.1	L	13	2	0
11	2	0.29	0.19	L	15	0	0	0.04	0.04	L	15	0	0
12	2	0.14	0.07	L	15	0	0	0.09	0.09	L	14	1	0

RMSD take values in $[0.07, 0.39]$ regarding balance of contribution and in $[0.04, 0.42]$ regarding co-writing. We also report that, for both indicators, mostly all miss-classified LabDocs have a value of RMSD greater than 0.3.

This shows that when teachers succeed to perceive the correct indicator level for a LabDoc, they estimate well the indicator value. Moreover, regarding balance of contribution, most LabDocs for which the indicator levels are not correctly perceived, are those written by more than two students. Regarding co-writing, levels are not correctly perceived in LabDoc 1, this is due to mathematical formulas in this LabDoc.

From these results, and as an answer for RQ3, we can say that in some extent, the indicators and the strategies are interpretable by teachers and succeed to measure CW. Teacher misinterpretations are due to the specificity of some LabDocs, comprising mathematical formulas, or written in mixed strategies or of a very low collaboration. In fact, teachers examined manually the LabDocs, and these specific characteristics led to misconceptions.

7 CONCLUSION AND IMPLICATIONS

In this work we contribute to research in CW with new indicators that provide measures of student contributions in a text writing.

A first contribution consists in two indicators that allow to measure how student contributions are equal (balance of contribution), and how students interact with each other text contributions (co-writing).

A second contribution consists of identifying CW strategies, namely summative and integrative strategies that can be useful in pedagogical settings, for example to distinguish between cooperative (summative) and collaborative (integrative) works (Onrubia and Engel, 2009). We showed that these writing strategies can be derived from the two proposed indicators.

A third contribution is the evaluation of the interpretation of the indicators and strategies, allowing to compare teacher perceptions of the indicators with machine calculations, and to verify the perceived strategies. Results showed that teachers have a good interpretation of the indicators and the strategies. In fact, teachers were mostly able to estimate correctly the indicators based on their textual definitions, as well as the writing strategies. We conclude that the indicators may help for monitoring student CW, and characterizing the degree and strategies of collaborative work.

This work is of scholarly and practical implications. It provides interesting insights on the design of learning analytics tools that allow for a meaningful reporting of CW dynamics between peers. This may strengthen formative evaluation and provide learners with quick feedback during their collaborative work and reports co-writing.

This work is not without limitations. Our approach can produce misleading results when collaborative documents are composed of mathematical formulas. More advanced text mining methods can improve formulas detection. Moreover, it would be relevant to collect more data with teachers and students to demonstrate the value of the proposed indicators, and investigate better insights into CW and collaborative work.

Future work is motivated to measure student cognitive contributions, by considering the meaning of sentences composing the text. Our approach can be improved by considering semantic sentence detection using machine learning models. This may better inform about the collaboration process and go beyond contribution measures in terms of number of words added or modified in a text. Ultimately, it would be worthwhile to study how to enable teachers to take actions from useful visualizations of indicators and strategies, and evaluate their acceptability, usability and utility.

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