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

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Abstract: In a Computer-Supported Collaborative Learning environment (CSCL), teachers are brought to monitor students during their Collaborative Writing (CW) process for academic purposes. This paper proposes two quantitative indicators, based on text mining, to support teachers in their monitoring tasks. Combining these indicators leads to detect the strategies adopted during the CW process. These strategies are the sequential summative construction and the sequential integrating construction. A perception of these indicators and strategies is also investigated through questionnaire.

1 INTRODUCTION

Providing students with group work is a common activity in education, enabled by various digital technologies. Assigning group work is largely emphasized as a method that enables students to develop collaborative skills (Dede, 2010; Sun et al., 2018), and impacts their academic success (Kooloos et al., 2011; Vaughan, 2002). Moreover, it is recognized that collaborative learning may be enhanced by the use of digital technologies, providing students with several tools such as discussion forums (Biasutti, 2017), wikis (Forte and Bruckman, 2007; Kimmerle et al., 2011) and collaborative writing platforms (Wang et al., 2015; Liu et al., 2018; Zhang and Chen, 2022). This led to a 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 aim to capture 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 of prior abundant work that qualitatively and quantitatively 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 based the indicator calculations on a variance metric and exploited a numerical inequality property between the two indicators, leading to deducing CW strategies. The definition of these indicators is sourced from a previous research based on focus groups and interviews with teachers, 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 collaborative writing of scientific documents (d'Ham et al., 2019). Moreover, we evaluate the interpretation of the proposed indicators and the deduced strategies by teachers that are not expert users of LabNbook. We address the following research questions:

RQ 1: What are the indicators (metrics) allowing to measure collaborative writing?

RQ 2: What are the collaborative writing strategies that can be deduced from these indicators?

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RQ 3: To what extent these indicators and strategies are interpretable? (How close is the relationship between these measures and their interpretation).

The present paper is organized as follows. In Section 2, we briefly review works related to the Collaborative Writing. Section 3 provides an overview of the proposed indicators and the resulting strategies. Section 4 describes the methodology and the experimental framework used in this research. Section 5 gives details on the approach used to derive ours indicators and strategies. Section 6 discusses the interpretation of these indicators and strategies through a numerical analysis of a questionnaire results given in Section 4. Finally, Section 7 presents our conclusions and gives some limitations and perspectives of this research.

2 RELATED WORK

2.1 Collaborative Writing, a Growing Research Field in CSCL

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 (Ede and Lunsford, 1992; Lowry et al., 2004; Storch, 2013; 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, suggested 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; Abrams, 2016; Cho, 2017; Li and Kim, 2016; Zhang and Chen, 2022). 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.

2.2 Characterizing Collaboration in Collaborative Writing

One popular model in the literature that was proposed to examine the learners' CW strategies, is a diadic 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 appear also in less recent other works. For example, (Dillenbourg, 1999) compares concepts from the field of Human-Computer Collaborative Learning Systems (HCCLS), where an artificial agent collaborate 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. *Symmetry of action* is defined 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 the user of the system (Dillenbourg and Michael, 1996). For instance, in HCCLS domain, in the 'assistant' or 'slave' metaphors, the balance of control is on the user's side (Dillenbourg and Michael, 1996).

Mutual refinement is a second main defining characteristic of 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).

3 NEW INDICATORS AND DERIVED STRATEGIES FOR COLLABORATIVE WRITING

3.1 Balance of Contribution and Co-writing Indicators

We define *balance of contribution* as a metric that indicates how the students' 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 reflect 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. If four team members contribute exactly equally (exact same number of characters), the contribution of each will be 25%, and the variance is 0.0, thus the balance of participation for the team will be 1.0. If only one person wrote the whole document, the balance will be 0.75. 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. While the balance of contribution indicator measures a student contribution at a world level, the co-writing indicator measures a student contribution at a sentence level. Indeed, we consider that a sentence carries an idea, and supervising the sentence construction process informs us about the way that students construct ideas.

3.2 Derived Strategies

The strategies we deduced from the proposed indicators are derived from the ones proposed by (Onrubia and Engel, 2009). Since LabNbook allows for an asynchronous CW, (i.e students edit a shared written text not at a same time), we retained two strategies among the five proposed by (Onrubia and Engel, 2009), namely *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, and a *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, the result 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 on the existing text (Hoffmann et al., 2022).

The first is characterized by an explicit division of work between the team members, i.e. each student writes a part of the text, the second by a co-construction of the text, i.e. all team members take responsibility of the whole text aligning their viewpoints. Students may not necessarily follow one strategy but a mix of them.

4 RESEARCH METHOD

Our research objective is, on the one hand, to construct metrics of students' collaboration level, based on the analysis of their CW process when producing scientific text documents, and on the other hand, to verify that these metrics are intelligible for teachers.

To conduct our research we adopt the method of epistemological posture of Pragmatic Constructivism (PC) (Avenier and Thomas, 2015), whose construction of scientific knowledge assumptions are based on the consideration of reality and the human in this reality. In PC, the aim of scientific construction is "to develop intelligible models of human experience, offering suitable and viable reference points". Observed facts can change the research question and the proposed tools. Regarding the validity of results, PC recommends the use of multiple methods of data production to bring out known and unknown phenomena. We choose the PC method since in this research we need field data produced by teachers' opinions to evaluate the proposed metrics. We also chose the design based research (Wang and Hannafin, 2005) and the associated guides (Mandran et al., 2022) to conduct our research. This method proposes, among others, 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. Our research is conducted according to theses epistemological principles.

4.1 Context

To construct our indicators, we use scientific 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, experimental protocols and data processing and modeling) and allows students to interact with each other (team building, shared workspace, internal messaging and chat, etc). Moreover, teachers can pre-configure the students' workspace by structuring it into subsections or by in-

[1] https://labnbook.fr/

serting content within it. Students can produce various documents, such as laboratory notebooks, practical work reports, project or problem-based learning reports.

It is worth to noticing that, in LabNbook, students edit asynchronously a shared text document, which means that a text document cannot be edited simultaneously by multiple authors.

4.2 Data Collection

We used a questionnaire to measure to what extent the indicators are interpretable by teachers who are not expert users of Labnbook (RQ3). Our objective is to verify whether the definitions of the indicators make sense. In the LabNbook plateform, reports written by students are called *Labdocs*. We selected 12 LabDoc from the LabNbook database, which are co-written by 2 to 4 students in real conditions (classroom activities). The writing contributions of different students were highlighted. These Labdocs are chosen with different writing strategies: 4 Labdocs written with an integrative strategy (Entirely Integrative - EI), 4 Labdocs with a summative strategy (Entirely Summative - ES), and 4 Labdocs with intermediate strategies: part of the text was written with a summative strategy and part with an integrative strategy. For the latter, the text of 2 LabDocs is roughly written half/half (Between summative and integrative - BSI)), for one mostly summatively (Rather summative - RS), and the last is mostly integrative (Rather integrative - RI). Respondent teachers are 15, they are asked to read the 12 LabDocs. In addition, for each Labdoc, we ask the teachers to indicate:

(1) the writing strategy between 6 choices: EI, RI, BSI, RS, ES or I don't know;

(2) a rough estimate for the indicators, among 3 levels: Low (L), Medium (M) or High (H);

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

5 INDICATORS CONSTRUCTION

In this section, we detail the approach used to construct our indicators. First, we explain how we qualify, through tags, the evolution of an initial text to its final version in a CW process (5.1). Secondly, thanks to these tags, we explain how we quantify and represent this evolution (5.2). Next, we show how this representation is used to derive our indicators (5.3) and (5.4). Finally, we illustrate how we combine these indicators in order to get the CW strategies mentioned above (5.6).

5.1 Text Sequences Matching Method

In order to study the evolution of a text document and compare pairs of text sequences, we employ 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 in Table 1.

Table 1: Description of sequence tags.

Tag	Description
Equal	the sequences are equal
Insert	the sequence is inserted
Delete	the sequence is deleted
Replace	the sequence is replaced

For instance, let consider the following pair of text sequences written sequentially by two students *A* and *B*.

- 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*"

In this example, student *B* contributes to the text after student *A* by adding, deleting and inserting text. Table 2 gives the tags for each sequence that is altered in the text.

5.2 Contribution Matrix

In order to quantify and keep track of the evolution of a text, we use a matrix that gives for each word of a final text, the level of contribution of each of the students co-writing the text. We call this matrix, a *contribution matrix*, since it gives the students' levels of

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

$$\begin{pmatrix} x_{1,1,1}\dots x_{1,1,l}\dots x_{1,1,n_1} & \dots\dots & x_{1,j,1}\dots x_{1,j,l}\dots x_{1,j,n_j} & \dots\dots & x_{1,N,1}\dots x_{1,N,l}\dots x_{1,N,n_N} \\ \vdots & & \vdots & & \vdots \\ x_{i,1,1}\dots x_{i,1,l}\dots x_{i,1,n_1} & \dots\dots & x_{i,j,1}\dots x_{i,j,l}\dots x_{i,j,n_j} & \dots\dots & x_{i,N,1}\dots x_{i,N,l}\dots x_{i,N,n_N} \\ \vdots & & \vdots & & \vdots \\ x_{K,1,1}\dots x_{K,1,l}\dots x_{i,1,n_1} & \dots\dots & x_{K,j,1}\dots x_{K,j,l}\dots x_{i,j,n_j} & \dots\dots & x_{K,N,1}\dots x_{K,N,l}\dots x_{K,N,n_N} \end{pmatrix} \quad (1)$$

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*"

Table 2: Illustration of the tagging operation.

contribution to a co-written text. In this matrix rows represent contributing students and columns represent words constituting the final text sequence.

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 the sentence j, such that

$$\sum_{j=1}^{N} n_j = M.$$

Then, the $K \times M$ contribution matrix is given in (1).

In this 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 world, and to 0, when the author doesn't contribute to a world. It is worth to noticing that the contribution matrix does not take into account the deleted words. The total authors' contributions to a word is therefore equal to 1,

$$\sum_{i=1}^{K} x_{i,j,l} = 1\,.$$

In the previous example, there are 2 contributing students, and the final text comprises 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 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 (5) of the students' average contributions, which reflects the distance between each student average contribution in (3) and the mean of all students' average contributions in (4). 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 (6). We define the balance of contribution indicator as follows

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

where, for $i = 1, \dots, K$,

$$\bar{x}_{i,\bullet,\bullet} = \frac{1}{M} \sum_{j=1}^{N} \sum_{l=1}^{n_j} x_{i,j,l} \quad (3)$$

which 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

$$\bar{x}_{\bullet,\bullet,\bullet} = \frac{1}{K} \sum_{i=1}^{K} \bar{x}_{i,\bullet,\bullet} = \frac{1}{K}\,. \quad (4)$$

Indeed, as we consider that students contribute in a balanced way to the writing of the text if there average contributions in (3) equals $1/K$, we use in the construction of the balance of contribution indicator the variance

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

However, in the case where the student i writes alone the whole text, only one $\bar{x}_{i,\bullet,\bullet}$ equals 1 . In that case, (5) becomes

$$\frac{K-1}{K^2}\,. \tag{6}$$

Then, as mentioned above, in order to penalize the case where one student writes the whole text, we normalize the variance (5) with (6), 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 (2).

5.4 Co-writing Indicator

Similarly to the balance of contribution indicator, which measures students' contributions at a world level, the co-writing indicator measures students' contributions at a sentence level (9). In our knowledge, there are three approaches for sentence segmentation: *i*) Supervised machine learning (*c.f.* (Palmer and Hearst, 1997)), requiring annotated datasets, *ii*) Unsupervised machine learning (*c.f.* (Kiss and Strunk, 2006)), requiring distributional statistics derived from raw text and *iii*) rules-based, requiring hand crafted rules/heuristics (*c.f.* (Sadvilkar and Neumann, 2020)). We chose the rules-based approach for its implementation simplicity. We use a *Golden Rule Set* [3] to enumerate edge cases observed in sentence boundaries. The *Golden Rule Set* contains hand-constructed rules designed to determine sentence boundaries, such as punctuation at the end of a sentence. It is worth to noticing that, 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. As it is shown in Sub-section 5.6, the co-writing indicator is always lower than the balance of contribution indicator which is a useful property to deduce the CW strategies mentioned above.

The co-writing indicator is based on the balance of contribution indicator, but on a sentence level. According to the contribution matrix in (1), we compute for each student his average contribution in all sentences. Thus, let a

$$\bar{x}_{i,j,\bullet}=\frac{1}{n_j}\sum_{l=1}^{n_j}x_{i,j,l} \tag{7}$$

be the average contribution of student i to the sentence j. Then, we obtain a matrix of average contributions on a sentence level, as follows

$$\begin{pmatrix} \bar{x}_{1,1,\bullet} & \dots & \bar{x}_{1,j,\bullet} & \dots & \bar{x}_{1,N\bullet} \\ \vdots & \ddots & \vdots & & \vdots \\ \bar{x}_{i,1,\bullet} & \dots & \bar{x}_{i,j,\bullet} & \dots & \bar{x}_{i,N,\bullet} \\ \vdots & \dots & \vdots & \ddots & \vdots \\ \bar{x}_{K,1,\bullet} & \dots & \bar{x}_{K,j,\bullet} & \dots & \bar{x}_{K,N,\bullet} \end{pmatrix}.$$

For each sentence, we compute the variance of all authors' average contributions (8). Since $\sum_{i=1}^{K}\bar{x}_{i,j,\bullet}=1$, we have, for a sentence j,

$$\bar{x}_{\bullet,j,\bullet}=\frac{1}{K}\sum_{i=1}^{K}\bar{x}_{i,j,\bullet}=\frac{1}{K}$$

and then, this variance is given by

$$\frac{1}{K}\sum_{i=1}^{K}\left(\bar{x}_{i,j,\bullet}-\frac{1}{K}\right)^2\,. \tag{8}$$

Similarly to the balance of contribution indicator, we penalize the case where only one student writes a sentence alone. This leads to compute the ratio between (8) and (6) which gives the 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

$$c(X)=\sum_{j=1}^{N}p_je_j(X)\quad\text{where}\quad p_j=\frac{n_j}{M} \tag{9}$$

is the weight of the sentence j.

5.5 Indicators Property

A useful property of our indicators, for deducting the used strategy in a CW process, is that the co-writing indicator $c(X)$ in (9) is lower or equal than the balance of contribution indicator $e(X)$ in (2), *i.e.*

$$c(X)-e(X)=\frac{K}{K-1}\sum_{i=1}^{K}\Big[\big(\bar{x}_{i,\bullet,\bullet}-\frac{1}{K}\big)^2- \sum_{j=1}^{N}p_j\big(\bar{x}_{i,j,\bullet}-\frac{1}{K}\big)^2\Big]\leq 0\,. \tag{10}$$

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

Indeed, equation (10) is non-positive as soon as, for $i = 1, \ldots, K$,

$$\left(\bar{x}_{i,\bullet,\bullet} - \frac{1}{K}\right)^2 - \sum_{j=1}^{N} p_j \left(\bar{x}_{i,j,\bullet} - \frac{1}{K}\right)^2 \leq 0 . \qquad (11)$$

Thus, the left hand side of (11) can be rewritten as

$$(\bar{x}_{i,\bullet,\bullet})^2 - \sum_{l=1}^{n_j} p_j \, (\bar{x}_{i,j,\bullet})^2 . \qquad (12)$$

Using the fact that

$$\bar{x}_{i,\bullet,\bullet} = \sum_{j=1}^{N} \frac{n_j}{M} \frac{1}{n_j} \sum_{l=1}^{n_j} x_{i,j,l} = \sum_{j=1}^{N} p_j \bar{x}_{i,j,\bullet} \, ,$$

we have

$$(\bar{x}_{i,\bullet,\bullet})^2 = \left(\sum_{j=1}^{N} p_j \bar{x}_{i,j,\bullet}\right)^2 \leq \sum_{j=1}^{N} (p_j \bar{x}_{i,j,\bullet})^2 . \qquad (13)$$

Then, according to (13), an upper bound for (12) 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 $p_j \leq 1$.

This property allows to represent LabDocs in a triangle, as in Figure 1, designed in a two dimensional plane where x-axis and y-axis represent respectively the range of values of the balances of contribution and the co-writing indicators.

5.6 Collaborative Writing strategies Deduction

Combining these two indicators, and using property (10), we are able to distinguish the CW strategies *i.e.* the sequential summative construction and the sequential integrative construction defined above and, also, three other intermediary strategies.

In the case of a text written entirely with a summative strategy, the co-writing indicator is low. As shown in Figure 1, LabDocs from a summative construction are thus located near the x-axis. *A contrario*, LabDocs written in an integrative manner, are located near the diagonal. In this case, the balance of contribution values are close to the co-writing values. LabDocs written with intermediary strategies fall between these two borderline cases. For instance, we illustrate in Figure 1 two examples: a LabDoc written with an integrative strategy, having a balance of contribution and a co-writing score equal to 0.92 and 0.78 respectively. A second LabDoc written summatively with coordinates (0.99, 0.03).

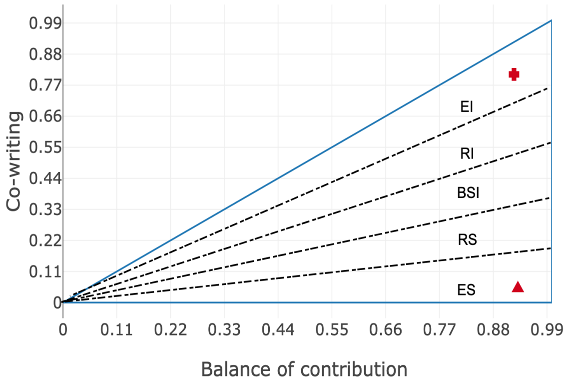

Figure 1: A representation of CW strategies. Acronyms ES, RS, BSI, RI and EI stand respectively for: Entirely Summative, Rather Summative, Between Summative and Integrative, Rather Integrative and Entirely Integrative.

It is worth to noticing that, in order to distinguish between the strategies represented by sub-triangles in Figure 1, it is necessary to set thresholds. This has been done in an equivalent way in the sens that the areas of all sub-triangles are equals.

6 RESULTS AND DISCUSSION

We investigate in this section teachers' interpretation of the proposed indicators and strategies through the questionnaire results introduced in Section 4. To this end, we compare these questionnaire results on indicators values, levels and strategies with, respectively, the values computed thanks formulas (5) and (9), the levels obtained by splitting the indicators interval of values $[0,1]$ on three levels: Low for values in $]0,1/3]$, Medium for values in $[1/3,2/3[$ and High for values in $[2/3,1]$, and the strategies obtained by the position of each LabDoc in the Figure 1.

Table 3 resumes the questionnaire results of question (1) about the CW strategy perceived by teachers for each LabDoc. According to the strategies column (ST), where bold type applies when the LabDoc is misclassified, we report that $9/12\,(75\%)$ of LabDocs are well classified with a majority of good responses varying from 8 (57%) to 14 (93%). For the misclassifed LabDocs 1, 6 and 12, we notice that there are respectively 6 (40%), 5 (33.3%) and 1 (0.08%) well classifications and that teachers' responses are spread-out on the other strategies. We think that this is probably due to the fact that some teachers don't take into account the amount of students contributions on integrative strategies. Indeed, these teachers consider that a few modifications of a student in the text written by others make the strategy summative. However it is really summative if the amount of theses modification is higher.

LD	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	[illegible]	14	1	0	0	0	0
12	**ES**	**1**	**4**	**2**	**2**	**5**	**1**

Table 3: Questionnaire results of question 1. Acronyms ST, ES, RS, BSI, RI, EI and DK stand, respectively, for: Strategies, Entirely Summative, Rather Summative, Between Summative and Integrative, Rather Integrative, Entirely Integrative and I Don't Know. Bold type holds when the Machine Strategy (MS) is significantly different from the majority of responses.

Table 4 resume the questionnaire results of question 2 and 3 concerning, respectively, the level (Low, Medium and High) and the value of each indicator. The distance between the machine value (MV) of an indicator $\theta \in [0,1]$ and teachers' estimate is measured by 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 the level of each indicator (low, medium, high), results show that 66% (8/12) of LabDocs are well classified regarding the balance of contribution and 83% (10/12) regarding the co-writing indicator. We report that the RMSD take values in the interval $[0.07, 0.39]$ regarding the balance of contribution and in the interval $[0.04, 0.42]$ regarding the co-writing indicator. We also report that, for both indicators, all miss-classified LabDocs have a value of RMSD greater than 0.3 except for the balance of contribution computed on the LabDoc 9 which equals to 0.27. This shows that teachers who succeed to well classify LabDocs, estimate well the indicators' values. Also, for both indicators, Labdocs with misclassified indicators are written by more than two students except for the co-writing indicator computed on LabDoc 1. This fact suggests that the visual interpretation of both indicators becomes difficult when there is more than two students in the CW process.

From the results on indicators levels and RMSD, we can conclude that teachers have a good comprehensive understanding of these two indicators.

7 CONCLUSION

Regarding research questions, we give in Section 4 details about the construction of our indicators (RQ1). We proposed the balance of contribution indicator in order to have an appreciation of the amount distribution of the student's contribution in terms of words. In order to measure how ideas are constructed,we proposed the co-writing indicator which measures the balance of contribution in terms of sentence. Combining these two indicators allows mainly deduce the CW summative and integrative strategies (RQ2). We conducted a questionnaire in order to investigate how teachers interpret these indicators and strategies (RQ3). Overall, the questionnaire results showed that teachers have a good interpretation of the proposed indicators and strategies. However, we noticed that it is much easier for teachers to give a rough estimation for the indicators (Low, Medium and High) than numerical values since for the majority of LabDocs the RMSD is relatively high. We conclude from this research that the balance of contribution and the co-writing indicators are a good candidate for monitoring students collaboration as they characterize well the degree and type (strategies) of collaboration.

This work is not without limitations. The small number of teachers who participated to the questionnaire is probably the main weakness of our results. Also, ours indicators behave poorly when there are mathematical formulas on the text. A possible approach to deal with weakness is to extract mathematical formulas by training a machine learning model, based on Hidden Markov Chain, and to process them in a different way than the text. Another limitation is the non-semantic sentence detection that we use. A possible improvement is to consider a semantic sentence detection thanks to a supervised machine learning model (*c.f.* (Palmer and Hearst, 1997)) or an unsupervised machine learning model (*c.f.* (Kiss and Strunk, 2006)).

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LD	NBS	Balance of contribution						Co-writing					
		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

Table 4: Questionnaire results (questions 2 and 3). Bold type holds when the Machine Level (ML) is significantly different from the majority of responses. Letters “L”, “M” and “H” stand, respectively, for “Low”, “Medium” and “High”. The acronyms “NBS” and“MV” stand respectively for the Machine Value and Number of Students.

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