Automatic Identification of Knowledge Transforming Content in Argument Essays Developed from Multiple Sources

by

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Abstract

Developing skills to transform information mined from multiple sources for argumentative writing may help students to articulate convincing evidence for their claims and increase domain knowledge. To successfully engage in knowledge transforming, writers need to strategically select and combine multiple cognitive and metacognitive processes.

Many post-secondary students, especially novice writers, struggle to transform knowledge when drawing on multiple sources for essays. External support is needed. As a first step toward developing software that scaffolds knowledge transforming in writing, this study investigated how to identify sentences representing knowledge transformation in argumentative essays.

A synthesis of cognitive theories of writing and Bloom’s typology identified 22 linguistic features to model cognitive processes in knowledge transforming, a methodological contribution to research on multi-source based writing. These features were used as independent variables in a predictive algorithm trained to predict a sentence’s writing mode as knowledge-telling or knowledge-transforming. A corpus of 38 undergraduates’ essays was examined using this algorithm and a coefficient of knowledge transforming was computed for each essay.

Two thirds of all evidential sentences were knowledge-telling indicating undergraduates mostly paraphrase or copy information from sources rather than deeply engage with the source material. Eight linguistic features were important predictors of whether an evidential sentence tells or transforms source knowledge: relative position of an evidential sentence in a paragraph, absolute distance between an evidential sentence and the most recent argument, incidence of low- and high-accessibility anaphoric devices, incidence of rhetorical connectives that indicate reasoning, content-word overlap between the evidential sentence and source text, semantic overlap between evidential sentence and preceding/succeeding argument, and semantic overlap between evidential sentence and source text. The machine learning algorithm accurately classified nearly 3 of 4 evidential sentences as knowledge-telling or knowledge-transforming, offering potential for use in future research. The coefficient of knowledge transforming positively but weakly correlated with essay scores assigned by the course instructor. This contrasts with a view that knowledge-telling texts often fail to fulfill writing task requirements.
Keywords: Knowledge transforming; knowledge telling; argumentative writing; evidence; machine learning
Посвећено Марији, Максиму и Лани

Dedicated to Marija, Maksim and Lana
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Table of Contents

Approval .......................................................................................................................... ii
Ethics Statement .............................................................................................................. iii
Abstract ............................................................................................................................ iv
Dedication ........................................................................................................................ vi
Acknowledgements ......................................................................................................... vii
Table of Contents .......................................................................................................... viii
List of Tables .................................................................................................................. x
List of Figures ................................................................................................................ xi

Chapter 1. Introduction .................................................................................................... 1
1.1. Argumentative writing as a learning tool ............................................................... 1
1.2. Thesis purpose and structure ............................................................................... 3

Chapter 2. Literature Review ........................................................................................ 4
2.1. Knowledge-transforming model ........................................................................... 4
2.2. Knowledge-telling model ..................................................................................... 5
2.3. Epistemic potential of knowledge transforming .................................................. 6
2.4. Anatomy of knowledge transforming – cognitive processes and strategies ....... 7
2.5. Post-secondary students struggle to engage in knowledge transforming .......... 10
2.6. Computer-based scaffolding to foster knowledge transforming ....................... 13
2.7. The four stages in this study and research questions ......................................... 14

Chapter 3. Method .......................................................................................................... 16
3.1. Population and writing sample ............................................................................ 16
3.2. Writing task .......................................................................................................... 17
3.3. Theoretical framework for coding evidential sentences ..................................... 18
3.4. Hand coding – codebook .................................................................................... 19
3.5. Hand coding – inter-rater reliability .................................................................... 21
3.6. Linguistic features ............................................................................................... 23
3.7. Linguistic features in rhetorical space ................................................................. 24
3.8. Linguistic features in content space .................................................................... 26
3.9. Technical implementation ................................................................................... 28

Chapter 4. Results .......................................................................................................... 29
4.1. Essay macrostructure ........................................................................................... 29
4.2. Argumentation ....................................................................................................... 29
4.3. RQ1: To what extent do undergraduate students engage in knowledge transforming while writing argumentative essays from multiple sources? ............... 32
4.4. RQ2: To what degree does engaging in knowledge telling and transforming correlate with essay scores? ................................................................. 33
   4.4.1. Coefficient of knowledge transforming ....................................................... 33
   4.4.2. Correlation analysis ..................................................................................... 34
4.5. RQ3: How accurately does the supervised learning algorithm classify evidential sentences as knowledge telling vs. knowledge transforming? .............................................. 35
  4.5.1. Multicollinearity check .......................................................... 35
  4.5.2. Random forest classification .................................................. 36
  4.5.3. Model selection and testing ................................................... 38
4.6. RQ4: What linguistic features predict whether an evidential sentence tells or transforms source knowledge? ........................................................................ 40
  4.6.1. Random forest feature importance ........................................... 40
  4.6.2. Feature importance results ..................................................... 41

Chapter 5. Discussion ............................................................................. 47
5.1. Two thirds of all the evidential sentences were knowledge-telling .... 47
5.2. The correlation between the coefficient of knowledge transforming and essay score is positive and weak ............................................................ 48
5.3. The machine learning algorithm accurately classifies nearly 3 out of 4 evidential sentences as either knowledge-telling or knowledge-transforming .............................................. 49
5.4. The eight linguistic features are important predictors of whether an evidential sentence tells or transforms source knowledge .................................. 51
  5.4.1. Linguistic features in a rhetoric space ..................................... 51
  5.4.2. Linguistic features in a content space ..................................... 53
5.5. Instructional and research implications ........................................ 54
5.6. Limitations ..................................................................................... 55

References .............................................................................................. 56

Appendix A. List of source text titles and modules ................................ 62

Appendix B. Corpus statistics ................................................................. 71
List of Tables

Table 3.1. Framework for classifying evidential sentences in argumentative writing 19
Table 3.2. Round 1 inter-rater agreement .................................................................. 21
Table 3.3. Round 2 inter-rater agreement .................................................................. 22
Table 3.4. Round 3 inter-rater agreement .................................................................. 22
Table 3.5. Example of evidential sentences coded for the writing mode ............... 23
Table 4.1. Feature importance measured by Mean Decrease Gini ....................... 41
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Figure Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 3.1</td>
<td>Low- and high-scoring essays</td>
<td>17</td>
</tr>
<tr>
<td>Figure 3.2</td>
<td>Hand-coding process</td>
<td>20</td>
</tr>
<tr>
<td>Figure 4.1</td>
<td>Frequency of argumentation categories in corpus</td>
<td>30</td>
</tr>
<tr>
<td>Figure 4.2</td>
<td>Frequency of argumentation categories (claim vs evidence vs not applicable)</td>
<td>31</td>
</tr>
<tr>
<td>Figure 4.3</td>
<td>Frequency of writing mode categories</td>
<td>33</td>
</tr>
<tr>
<td>Figure 4.4</td>
<td>Correlation between essay score and coefficient of knowledge transforming</td>
<td>35</td>
</tr>
<tr>
<td>Figure 4.5</td>
<td>Correlational matrix of predictors</td>
<td>36</td>
</tr>
<tr>
<td>Figure 4.6</td>
<td>The decision tree model that uses 2 features from the dataset (Pos_P_norm and Sol_S) and two conditions on which the tree splits into branches; the final branch that does not split anymore is the class prediction</td>
<td>37</td>
</tr>
<tr>
<td>Figure 4.7</td>
<td>OOB error stabilizes when 3500 trees are used</td>
<td>39</td>
</tr>
<tr>
<td>Figure 4.8</td>
<td>Tuning number of features (mtry) for the random forest model</td>
<td>40</td>
</tr>
<tr>
<td>Figure 4.9</td>
<td>Mean Decrease Gini for 19 features; higher value marks higher importance</td>
<td>43</td>
</tr>
<tr>
<td>Figure 4.10</td>
<td>Partial dependence on 8 most important features</td>
<td>46</td>
</tr>
<tr>
<td>Figure 5.1</td>
<td>Writer’s response to the tool’s decision</td>
<td>49</td>
</tr>
<tr>
<td>Figure 5.2</td>
<td>Guiding writer towards knowledge transforming</td>
<td>50</td>
</tr>
<tr>
<td>Figure 5.3</td>
<td>Writer marks a sentence as knowledge-telling to get a revision prompt</td>
<td>51</td>
</tr>
</tbody>
</table>
Chapter 1. Introduction

1.1. Argumentative writing as a learning tool

Argumentation is a skill post-secondary students need to form informed and well-structured arguments, the “logical or quasi-logical sequence[s] of ideas that [are] supported by evidence” (Andrews, 2009, p. 16). It is also a cognitive tool that encourages deep processing of knowledge and closer engagement with disciplinary content (Langer & Applebee, 1987). By applying cognitive processes to research and forge arguments supported by evidence, students also acquire and develop wider and deeper understanding of content (Van Drie, Van Boxtel, & Braaksma, 2014). In the literature, two theoretical perspectives are commonly taken to examine and implement argumentation in teaching and in research: learning to argue and arguing to learn (Hemberger, Kuhn, Matos, & Shi, 2017).

In educational contexts, argumentation can be promoted by organizing a classroom debate, posing a contestable topic for online discussion, and assigning an argumentative essay requiring a thesis statement (also called the main claim) plus a set of sub-claims related to the thesis statement. Claims need to be substantiated by credible evidence mined from academic and other well-regarded sources (Newell, Beach, Smith, & VanDerHeide, 2011). This requires students to navigate between the rhetorical problem space and the content problem space (Bereiter & Scardamalia, 1987).

In the rhetorical problem space, students work on designing, structuring, and precisely and coherently communicating claims and their supporting evidence. Solving rhetorical problems accomplishes the argumentative goals of the essay. Simultaneously, in the content problem space, students process information they identify and mine from sources. In comparing and contrasting facts and reasons, generalizing findings, and establishing semantic relationships among key terms, they have opportunity to transform evidence relating to claims positioned in the rhetorical space.

In this process, students actively rework their thoughts according to parameters of the writing task and its goals. Bereiter and Scardamalia (1987) modeled such interactions among discourse processing, information processing and metacognitive
monitoring as an integrated process they called knowledge transforming. They explained
difficulties that are encountered in the rhetorical space, in making a
statement clear or convincing, may be translated into subgoals of
generating examples of a concept, reasons for belief, intermediate steps in
a chain of reasoning, arguments against a competing belief (Bereiter &

Because this process triggers reflective thinking while writing, the authors argued
knowledge transforming promotes learning.

Not all writers successfully transform knowledge they gain from sources into
writing. Bereiter and Scardamalia’s research (1987) showed students rarely succeed in
knowledge transforming when writing grounded in multiple sources. Subsequent
research following Bereiter and Scardamalia’s (1987) research showed post-secondary
students often failed to: paraphrase, interpret, and evaluate content in sources; establish
novel associations across multiple sources; and integrate multiply-sourced information
into coherent form (Stein, 1989; Dong, 1996; Petrić, 2007; Boscolo, Ariasi, Favero, &
Ballarin, 2011; Aull, 2015). As a result, novice post-secondary writers often engage in
relatively limited knowledge telling rather than knowledge transforming. Writers who
generate text by the knowledge-telling process typically underuse monitoring and
planning needed to develop text coherence. Rather, knowledge telling writers focus
overly on how to generate basic text, e.g., staying on topic.

Many post-secondary students, especially novice writers, find it difficult to
strategically combine reading and writing in learning tasks (Stein, 1989; Spivey, 1996).
These students tend to tell knowledge from sources they consult rather than transform
knowledge they borrow. For example, in the rhetorical problem space, many such writers
fail to elaborate ideas mined from source texts, and list rather than structure propositions
to form convincing arguments. In the content problem space, they struggle to decide
which source material is best to include in the essay, don’t recognize appropriate
applications of prior knowledge about the essay topic, and overlook useful linking of
information across multiple sources. To help post-secondary writers move from
knowledge telling to knowledge transforming, scaffolding is needed to mark specific
writing issues so writers become more aware of opportunities to engage in knowledge-
transforming processes, and practice writing, reading, and arguing strategies that help
them navigate between and jointly solve problems in the rhetorical and content spaces.
1.2. Thesis purpose and structure

This study investigates knowledge transforming in evidential sentences in post-secondary argumentative essays, i.e., ways students transform source information to create evidence and thus promote claims in the essay. The long-term goal of my research is developing a computational tool to analyze linguistic properties of evidential sentences in a draft essay relative to information available in sources, and to generate writing analytics to scaffold writers towards knowledge transforming as they bring evidence to bear in supporting claims. The development of this complex tool will build on findings from this study.

The dissertation consists of four more chapters. Knowledge-telling and knowledge-transforming models of writing are detailed in Chapter 2. Cognitive processes underlying knowledge transforming and challenges students face to engage in this writing mode also are elaborated in Chapter 2. A novel methodology for classifying evidential sentences and modelling linguistic properties of knowledge-telling and knowledge-transforming sentences is detailed in Chapter 3. Results are presented in Chapter 4. In Chapter 5, I discuss the study outcomes.
Chapter 2. Literature Review

2.1. Knowledge-transforming model

Bereiter and Scardamalia’s (1987) knowledge-transforming model of writing builds on a theory of human problem solving in information processing tasks (Newell & Simon, 1972; Klein, 1999). In general, this theory models the task environment as a problem space. In the problem space, a human problem solver works out the task specific problem. The characteristics of the task determine the structure of problem space. Finally, the structure of problem space determines possible ways to work through givens and constraints to solve the problem.

The knowledge-transforming model consists of two problem spaces, rhetorical and content. In the rhetorical space, the rhetorical problems of accomplishing goals of the written composition are worked out. Simultaneously, in the content problem space, writers deal with problems of processing content knowledge. Following, I elaborate characteristics of the two problem spaces in the context of evidence-based argumentative essay writing, the focal writing task examined in this study.

Rhetorical goals in argumentative essay writing relate to designing, composing and communicating arguments supported by evidence to convince the reader of a particular claim (thesis statement). Content goals, on the other hand, deal with processing information from source articles to identify evidence for claims the writers provide in the rhetorical space. Klein (1999) explains that functioning according to knowledge-transforming model “…writers set rhetorical goals … [t]hen set sub goals in content space that subserve these rhetorical goals” (p. 244). For example, if a writer composes an essay arguing against the use of plastic bags, they may set a goal in the rhetorical space to convince the reader of a claim that plastic materials have harmful impact on people’s health. This goal then is translated into a subgoal in the content space, e.g., find and synthesize information in the source articles that support this claim. Then the writer goes back to the rhetorical space and works on properly expressing evidential information. This includes revising expression of written text to make the argument more convincing to a reader. In this way, striving to accomplish rhetorical goals of the argumentative essay, the writer transforms information to create new content knowledge.
2.2. Knowledge-telling model

Bereiter and Scardamalia (1987) modelled knowledge telling, another mental process that occurs in writing. Knowledge telling is a component of the knowledge transforming process. It determines how the text is generated using three sources of cues for composing: topical information, a discourse schema (e.g., an argument) and text already produced. The interactions between the content problem space and the rhetorical problem space in the knowledge-telling model are few and unproductive.

Topical cues are usually conveyed by instructions setting out the assignment. For example, the assignment might ask an author to write an argumentative essay about harmful effects of plastic bags on the environment. To form a topical foundation for the essay, the writer generates topical identifiers inspired by the assignment instructions, e.g., plastic, toxic materials, and pollution. Another set of cues is defined by the discourse schema, again determined by the assignment. Since the assignment is to take form as an argumentative essay, the author constructs cues from knowledge about the genre and from additional specifications for the essay, if provided by the assignment instructions. For instance, the writer may think about an argumentative essay as discourse that provides relevant background information and a thesis statement in the introductory paragraph, a set of arguments and counterarguments backed-up by evidence in body paragraphs, and a summary of the essay in a closing paragraph.

Finally, the text already produced might provide cues for further selection of content. With these characteristics in mind, Bereiter and Scardamalia (1987) posited the quality of a written composition using this model depends on the author’s knowledge of the topic, sophistication in the literary genre and language abilities.

However, writers engaged in the knowledge-telling mode of writing neglect to apply cognitive and metacognitive strategies of knowledge-transforming. The texts produced using this model tend to stay on topic and realize an organizational structure appropriate to the genre. However, even though knowledge-telling compositions manage to tell relevant knowledge within the domain outlined by keywords of the assignment, most of the time these essays fail to fulfill what the writing task has demanded, i.e., convincing readers why plastic materials are harmful. Bereiter and Scardamalia (1987) posited that the knowledge-telling model ignores making the connections among elements of content. This reflects inert knowledge, i.e., knowledge that learners could express but not use for other purposes. The authors warned “... knowledge telling is
educationally faulty because it specifically avoids the forming of connections between previously separated knowledge sites” (p. 187).

2.3. **Epistemic potential of knowledge transforming**

According to the knowledge-transforming model, when writers compose essays they reinterpret and reorganize some parts of their knowledge (Bereiter & Scardamalia, 1987) to pursue rhetorical goals for composition. Writers thus comprehend, evaluate and select relevant source information, and make novel connections among disconnected pieces of knowledge. These cognitive activities appear to promote knowledge acquisition in the domain.

For example, while composing argumentative text, the writer relates source content to information within multiple sources and/or to prior knowledge, and brings this new structure together as evidence for arguments in the written composition (Wiley & Voss, 1999). In this way, the writer actively constructs a situation model of source content which results in fuller understanding of subject matter. This process has been documented in Wiley and Voss (1999) and Rouet (2006), in the context of post-secondary education.

Furthermore, while constructing inter-text situation models (i.e., situation models that span and integrate multiple sources), writers make decisions about which content to include in their composition. Studies by Bråten, Strømsø, Britt (2009), Willey, Goldman et al. (2009), and Goldman, Braasch, Wiley, Graesser, and Brodowinska (2012) demonstrated that evaluating source knowledge is not only a basis for creating articulated evidence, it also helps post-secondary students improve their comprehension of subject matter.

Accordingly, developing knowledge-transforming skills in writing may help students improve their learning gains by actively building their knowledge, regardless of the domain (Bereiter & Scardamalia, 1987). In light of this, the authors of the model stated that “develop[ing] a knowledge-transforming model of composing is itself a major intellectual achievement” (p. 362).
2.4. Anatomy of knowledge transforming – cognitive processes and strategies

To accomplish knowledge transforming and fulfill the goals of writing tasks while navigating between text comprehension and production, it is critical for writers to possess a set of relevant strategies, sequences of cognitive operations selected and performed with regard to writing goals (Klein & Boscolo, 2016). In this section, I detail cognitive processes and strategies embedded into knowledge transforming.

In their seminal work Stein (1990) identified four major groups of cognitive processes that occur in reading and writing from multiple sources: planning, monitoring, elaborating, and structuring. Planning and monitoring are cognitive processes that focus on procedural aspects of cognition in a problem-based learning environment and, thus, are commonly considered metacognitive processes. I extend Stein’s (1990) list with another group of metacognitive processes, metacognitive control, following Son and Schwartz’s (2002) stance that metacognitive control operations often accompany monitoring.

In the process of planning, the writer sets goals for the composition. Goals could be both content- and rhetoric-related goals (Updike, 1994). In this way, writers plan their responses negotiating between available content knowledge and rhetorical constraints the writing task imposes on discourse. Flower, Schiver, Carey, Haas, and Hayes (1989) distinguished between schema-driven, knowledge-driven and constructive planning strategies in writing. The standard for schema-driven planning is a framework implied by the writing task. An example of a schema is this task instruction: Develop an argumentative essay that conveys a main claim, and provides three supporting sub claims and one counterclaim, all backed-up with empirical evidence. Consequently, the writer who employs schema-driven planning “could concentrate on filling in the slots with appropriate information” (Flower et al., 1989, p.4). Knowledge-driven planning strategies, on the other hand, draw upon the writer’s initial representation of content knowledge. For example, a writer may decide to organize the essay in a way that reflects the integrated structure of their own knowledge. Flower et al. (1989) warn that using only schema- and knowledge-driven planning strategies hardly support knowledge-transforming and could often lead to producing ineffective texts given the rhetorical goals of the task, such as convincing a reader to pursue an argument. This is in line with Bereiter and Scardamaila’s (1987) position that goal-setting that does not go beyond a specification
of genre and topic is characteristic of the knowledge-telling writing model. To meaningfully engage in knowledge-transforming processing, writers should engage constructive planning (Flower et al., 1989). Constructive-planning strategies subsume schema- and knowledge-driven planning, and include generating interconnected goals, organizing goals hierarchically, monitoring progress toward goals, instantiating goals in the written product, and identifying and resolving conflicts between goals.

Further, while engaged in act of writing from multiple sources, the authors monitor if the meaning they produce is in agreement with the goals they set for the composition (Hacker, Keener, & Kircher, 2010). For example, the author engaged in monitoring might reflect: “After reviewing my goals for the essay and re-reading this paragraph, I am not sure if this paragraph effectively supports my main claim.” Metacognitive monitoring can also be performed in relation to schema-driven goals, so the author may wish to monitor for the task requirements, e.g., “According to the assignment instructions, I think I yet to provide a counterargument in my essay.”, or “Is the evidence I have created empirical?”. According to Hacker et al. (2010), the goal-oriented monitoring strategies that authors use to ensure their writing meets goals are: reading, re-reading, reflecting and reviewing.

Writers also monitor for comprehension (Stein, 1990) making sure they handled content information properly, e.g., “Have I paraphrased this paragraph from the source article correctly?”; and embedded this new knowledge into the draft in a way that meets the rhetorical goals for the composition, e.g., “Is this idea really relevant for my argument?” Metacognitive monitoring often leads writers to re-evaluate and modify their written product and/or even goals they previously set for the essay. In this way, the writer engages in metacognitive control, a set of parallel cognitive operations that include evaluative reading, problem-solving and text production aimed at improving text quality (Hayes, 2000). According to Hacker et al. (2010), there are six metacognitive control strategies in writing: editing, drafting, idea generation, word production, translation, and revision.

Metacognitive monitoring and control strategies interweave during knowledge-transformative writing. For example, while engaged in knowledge transforming, the writer reads over source texts and generates potentially appropriate ideas. These ideas then are evaluated against goals for writing and some of them have been translated into the essay. Monitoring continues as other ideas are being shaped into rhetorical form in the
essay draft. If the meaning produced in the draft is not in agreement with the author’s goals for writing, the writer may choose to rewrite the text to conform better to writing goals. According to Bereiter and Scardamalia (1987), due to multiple revisions performed in the writing process, knowledge-transforming writers tend to filter more ideas before deciding what to include in composition. Further, Klein (1999) posits that text coherence improves through re-reading and reviewing ideas incorporated into the essay, which reduces discrepancies among sentences in knowledge-transforming texts.

Elaborating is another group of cognitive processes typical in learning contexts where reading and writing co-occur. While elaborating, writers use their prior knowledge to construct and enhance meaning from source texts (Stein, 1989). This assumes structural transformations in the content problem space to meet rhetorical goals of the composition. According to Spivey (1990), three cognitive operations are central to this process: organizing, selecting and connecting. While organizing, writers reorder or recombine multi-source material and group pieces of information together into chunks (e.g., descriptions of plastic materials; claims against plastic materials; empirical evidence tied to each of these claims,…). Writers then select chunks of content they deem relevant for inclusion in their essays and connect selected chunks of information to each other and/or to prior knowledge.

Stein (1989) highlights the potential that elaboration brings to knowledge transforming. By integrating their prior knowledge with source material writers may: produce examples and counterexamples of the ideas introduced in sources, instantiate source ideas in their essays, make inferences, criticize/evaluate ideas, and generate new ideas/proposals. For example, to make an argument against using plastic bags more convincing, a writer may link empirical evidence from source articles to an appropriate real-world example. Or they may clash empirical findings that support the idea of using plastic materials with a study that invalidated those findings, and dispute a counterargument in this way.

Last, through structuring activities, writers manipulate multiple connected (or partially connected) source text propositions harvested during elaboration. In this process, writers want to ensure that the content material was reshaped properly in the written composition. Stein (1990) distinguished the following structuring activities:

looking for instances of agreement and disagreement between propositions in source texts or between a proposition in the source text and the student’s prior topic knowledge, looking for superordinate categories
under which to subsume items in the source text, arranging text into high-level and low-level propositions, and discovering relations between ideas in the text that may not have been apparent. (p. 122)

It is important to note that cognitive processes described in this section are not mutually exclusive. For example, suppose after outlining an essay (planning) by creating an empty 2x2 grid to be populated with information about pros and cons of using plastic materials in two domains (e.g., economy and health), a writer re-reads source texts to find out if the available information can support the plan (monitoring for goals). While reading source texts, the writer monitors whether they processed the source information to build comprehension (monitoring for comprehension). At the same time, writer groups the source information into smaller topical units (elaborating-organizing), establishes links between some of these chunks (elaborating-connecting) and compares text to the superordinate categories from the essay grid, e.g., cons in health (monitoring for goals) under which some of topical units may be subsumed (structuring). As they work, the author may notice some categories in the essay plan are not sufficiently elaborated in the source corpus (monitoring for goals) and decide to modify the plan, e.g., by crossing out the cons for the economy cell in the grid (planning, metacognitive control).

Knowledge transforming is considered a highly demanding and challenging task where multiple cognitive and metacognitive processes interweave. To be able to successfully navigate such a complex cognitive landscape and accomplish goals of the task, writers need to strategically select and combine cognitive processes. They should know how each process works and when to invoke it in the context of evolving, immediate subgoals for the composition. These demands appear to prevent most post-secondary students from successfully engaging in knowledge transforming.

2.5. Post-secondary students struggle to engage in knowledge transforming

This section reviews research investigating challenges post-secondary students face in knowledge-transforming processing. The reviewed studies agree that, across different levels of higher education, students appear to struggle applying cognitive and self-regulatory strategies that underlie this writing model.

Investigating types of papers that undergraduate and master students produce while engaged in ill-defined, multisource based writing tasks, Stein (1989) asked
students to read the source texts, identify, use and interpret relevant data, synthesize information, write their own statements and be comprehensive. The analysis of 36 papers that participants created revealed that 28 papers were summaries which Stein (1990) operationalized as products of knowledge-telling, and only 8 papers were interpretations or syntheses which Stein (1990) operationalized as products of knowledge-transforming processes. In most papers writers preserved global organizational patterns from the sources (Spivey, 1990) rather than transforming source information. The author explained this outcome in two ways. First, a writer’s tendency was to switch to knowledge telling in the context of vague task requirements and thus avoid additional cognitive challenges, which resonates with findings from Weinstock’s (2010) research. Second, writers lacked command of strategies needed to produce a synthesis paper. However, as other studies reveal, even in contexts where the task requirements were unambiguous, such as an argumentative writing task investigated in this study, post-secondary students still tend to engage in knowledge telling, having hard times to strategically use cognitive processes embedded into knowledge transforming.

The 52 undergraduate participants in Boscolo, Arfé and Quarisa’s (2007) experiment conceived academic writing as a means of transforming knowledge from other sources through elaboration and continuous revision, rather than through restating knowledge and providing personal points of view. Even though the students seemed clear about the function of academic writing and they were assigned a clearly specified experimental task (synthesize the main points from the three source texts), the students produced low-quality syntheses during the pre-interventional round of the experiment. The essays were assessed as moderately informative and cohesive, and also poorly integrated and organized. Students seemed to have issues elaborating source materials, and structuring and revising written composition.

Aull and Lancaster (2014) and Aull (2015) explored linguistic features of 4,032 evidence-based argumentative papers written by incoming first-year university students responding to specific writing tasks. As a gold standard in the analysis, the authors used 615 A-level papers written by advanced undergraduate and graduate students. Although focused on only rhetoric of the compositions, this large-scale study revealed first-year undergraduates struggled to delimit and logically articulate arguments based on source information. The argumentative papers they produced were less convincing to readers than those produced by the advanced writers. These findings indicate first year
undergraduates lack text structuring strategies. For instance, students insufficiently used rhetoric devices such as reformulation markers (e.g., *in other words, in particular, …*) and transition phrases (e.g., *in addition to, therefore, …*). Their production of ineffective arguments could be further explained by a lack of metacognitive monitoring (e.g., for writing task and goals) and control (e.g., editing and revising the draft).

In Hyytinen, Löfström, and Lindblom-Ylänne’s (2017) experiment, participants from different levels of higher-education were prompted to write arguments and counterarguments related to a particular issue using multiple sources. Only 19 of 138 participants managed to thoroughly process source texts by identifying and connecting main ideas, evaluating different positions presented in sources, and selecting relevant information to be included in arguments. The authors linked this problem to students’ negligence in reflecting on the writing process, explaining that although “the texts improved as the students went along […] the students did not return to their starting sentences to revise them to the same standard” (p. 425). This led to the production of unclear and unconvincing arguments that poorly used source information.

Researching source and citation use in master students’ writing, Petrić (2007) developed a coding scheme consisting of nine rhetorical functions: attribution, exemplification, further reference, statement of use, application, evaluation, establishing links between sources, comparison of one’s own findings or interpretation with other sources, and other. Analyzing almost 2,000 instances of citation use in written texts, Petrić identified overall students’ tendency towards attribution, a descriptive rhetorical function that “…can be realised as a summary/paraphrase or quotation” (p. 243). Petrić linked attribution to the knowledge-telling mode of writing and pointed out that, by engaging in attribution, students are just re-telling what is stated in the sources instead of building novel associations and elaborating sources using prior knowledge.

Challenges in knowledge transforming in graduate school are also documented by two case studies by Dong (1996) and Tardy (2005). Dong (1996) followed three doctoral students for six months as they were developing their dissertations. The researcher noted students’ problems to paraphrase, interpret, synthesize, evaluate and integrate content from reading materials, noting these skills present difficulties both for native and non-native English writers. The initial master thesis and research paper drafts written by two graduate students participating in Tardy’s (2005) study revealed
challenges writers faced with structuring composition and evaluating source information to promote their claims in the draft.

These research findings reveal many students tend to tell knowledge from sources they consult rather than transform knowledge they borrow. When the task is argumentative writing, this leads to poorly articulated evidence resulting in essays that lack persuasiveness. Moreover, the acquisition of the domain knowledge might not be accomplished to its greatest extent when students limit their engagement to knowledge telling (Bereiter & Scardamalia, 1987). To help post-secondary writers move from knowledge telling to knowledge transforming, external support is needed to mark specific writing issues so writers become more aware of opportunities to engage in knowledge transforming processes and to practice cognitive strategies that help them navigate between and solve problems jointly in the content and rhetorical spaces.

2.6. Computer-based scaffolding to foster knowledge transforming

To develop cognitive and self-regulatory processes that characterize knowledge transforming, writers need to be engaged in effortful and scaffolded (i.e., externally supported) writing practice within an authentic learning environment (Proske, Narciss, & McNamara, 2012). Scaffolds take the form of external feedback about the writer’s performance plus opportunity to re-engage with the writing activity acting on the feedback. In this way, novice writers can gradually hone task-relevant cognitive processes and increase their ability to monitor and control those processes to a point where feedback is no longer needed (Ericsson, 2006).

Scaffolding can be provided to learners by humans (e.g., instructors, more experienced peers… (Vygotsky, 1978)) or by a software tool. The idea that a computer can offer scaffolding emerged from research on interactive learning environments (see Reiser, 2004). In a computer-based scaffolding (CBS) environment, the learner interacts with the software and receives formative feedback from the software. In a context of academic writing, computer-generated formative feedback relates to specific writing issues and aims to help students acquire and control cognitive processes involved in writing. The present research explores this promising approach to writing instruction.
Several instructional writing tools for university students have been developed. Escribo (Proske et al., 2012) scaffolds students by providing informational hints (Roscoe, Varner, Crossley, & McNamara, 2013) on how to collect source information, plan, write and revise essays. In the Web-Based Tutor (Wolfe, Britt, Petrovic, Albrecht, & Kopp, 2009) students practice identifying elements of an argument (main claim, reason, counterargument, and response to the counterargument) using predefined formative feedback. The Open Essayist (Whitelock, Twiner, Richardson, Field & Pulman, 2015) analyzes the essay draft using natural language processing (NLP) algorithms and generates feedback about rhetoric (e.g., most prominent words, representative sentences, essay’s internal structure) and provides prompts that encourage the student’s reflections on the draft. The XIP Dashboard (Simsek, Buckingham Shum, Sandor, De Liddo, & Ferguson, 2013) supports post-secondary writers in searching for relevant source content, classifies sentences according to their rhetorical functions (summarizing, background knowledge, contrasting ideas, novelty, significance, surprise, open question and generalization), and provides learning analytics to instructors.

Aiming to support particular cognitive processes in learning contexts where reading and writing co-occur, the aforementioned tools have demonstrated empirical benefits. The tools designed so far only focus on rhetorical aspects of a composition. The novel approach in this study addresses both rhetorical and content aspects of writing from multiple sources. I orient my research agenda towards developing a tool that will analyze the degree to which students drafting arguments transform knowledge borrowed from source texts. Therefore, the tool to be developed will examine writing with regard to source texts.

To this purpose, I explore the idea of providing computer-based scaffolding to promote knowledge transforming to realize the promises of this writing mode in improving argumentative writing and domain knowledge acquisition. The ultimate goal of this research is developing a computational tool to scaffold writers towards knowledge transforming as they bring evidence to bear in supporting claims. My study is a first step toward developing of such a computational tool.

2.7. The four stages in this study and research questions

The computational tool will use linguistic features of evidential sentences in the essay draft as a set of standards for generating writing analytics (Buckingham Shum,
Sandor et al., 2016) to writers about how to revise sentences to be “transformative” in successive drafts. To model linguistic properties of knowledge-telling and knowledge-transforming discourses, it is important to understand cognitive processes writers use when developing text (Sanders & Spooren, 2007). Accordingly, my method employs an ensemble of techniques from computational and cognitive linguistics to model linguistic features of evidential sentences and map them to cognitive processes of knowledge transforming, detailed in the Method chapter. This study comprises four stages.

The first stage in this study seeks to confirm earlier findings that post-secondary students appear to struggle to engage in knowledge transforming when writing from multiple sources. In the second stage, I model and compute a coefficient of knowledge transforming in written composition and use this metric to determine the extent to what knowledge transforming correlate with the essay score. The third stage includes developing, training, validating and testing the supervised learning algorithm as the tool’s text processing engine. In the fourth stage, I use statistical analysis to identify linguistic features that predict knowledge-telling and knowledge-transforming sentences. Accordingly, the following four research questions guide this study:

RQ1: To what extent do undergraduate students engage in knowledge transforming while writing argumentative essays from multiple sources?

RQ2: To what degree does engaging in knowledge telling and transforming correlate with essay scores?

RQ3: How accurately does the supervised learning algorithm classify evidential sentences as knowledge-telling vs. knowledge-transforming?

RQ4: What linguistic features predict whether an evidential sentence tells or transforms source knowledge?

The development and empirical validation of the writing analytics tool in authentic learning settings is planned to be a part of future research projects.
Chapter 3. Method

3.1. Population and writing sample

The corpus for this study comprised of 40 argumentative essays produced by undergraduate writers enrolled in various disciplinary majors and registered in an introductory educational psychology course in a Western Canadian university. The corpus of 40 essays was created by selecting the 20 lowest- and 20 highest-scoring essays from a pool of 72.

Three graduate teaching assistants (TA) experienced in supporting this course marked the essays, 24 per TA. Each essay was scored out of 30 points. Before marking, the TAs had a meeting with the course instructor to go over marking criteria. I conducted a between-groups analysis to check if there was a statistically detectable difference in the essay scores of the three teaching assistants. The assumption of scores normality in the 3 TA groups has been violated. Visual judgment of scores distribution shows: TA 1: skewness = -1.945, kurtosis = 3.618; TA 2: skewness = -1.018, kurtosis = 1.063; TA 3: skewness = -0.779, kurtosis = -0.570). Shapiro-Wilk’s method for test of normality confirms the results of visual inspection: TA 1: $W = 0.755, p < 0.001$; TA 2: $W = 0.924; p = 0.072$, TA 3: $W = 0.880, p = 0.008$. The Kruskal-Wallis (Kruskal & Wallis, 1952) non-parametric test was performed. The test revealed the central tendency of essay scores was not statistically different across the TAs, $H(2) = 5.183, p = 0.075$.

The median score in the low-scoring group was 17.5 points (58.33 %) with $SD = 3.22$ points. The median score in the high-scoring group was 27.5 (91.66 %) with $SD = 1.12$ (Figure 3.1).
3.2. Writing task

Students were assigned to write an argumentative essay of 1500-2000 words on a specific issue or topic under the theme of teaching and learning. Information about the chosen topic was sourced from a corpus of 207 summary articles, ranging from 500-1000 words, of primary academic journal articles about topics in teaching, learning and educational psychology. The summaries were created by the editors of the ScienceDaily web portal and published at the sciencedaily.com. The corpus had also included two primary articles (14109 and 13125 words long). The instructor of the course grouped the source texts into 13 topical modules, such as cognitive development, learner differences and learning needs, behavioral views of learning, cognitive views of learning, etc. The complete list of source text titles and modules is provided in Appendix A. Students were instructed to use five to seven sources to develop an argumentative essay addressing a specific thesis. Students were allowed to use a course textbook as an additional source.

Further, students were instructed to present in the essay body a minimum of three arguments supported with evidence from the sources, at least one counterargument with evidence, and a rebuttal to the counterargument(s). Students were also instructed to include meaningful headings (e.g., “Advantages of Bilingualism” instead of “Body”), an introduction and a conclusion. In the introduction, students were required to provide background to the problem of interest and declare a thesis statement. The conclusion was supposed to summarize main points of the essay. A 6-
A part grading rubric was defined for the essay: writing mechanics, macrostructure, thesis statement, arguments, counterargument(s) and rebuttal, and evidence. Points assigned to each part were 5, 5, 5, 7, 3 and 5, respectively.

3.3. Theoretical framework for coding evidential sentences

Discourse analysis was applied to evidential sentences to identify their linguistic properties. Relationships among those properties and the knowledge telling/transforming writing modes were explored. To model the linguistic properties of knowledge telling and knowledge transforming in evidential sentences, cognitive processes writers use when developing a text should be taken into account (Sanders & Spooren, 2007).

With this in mind, the multilevel analysis of the essay text was performed in several steps. First, three coders manually coded essays to classify: (a) sentences as belonging to one of four macrostructural blocks of text, as defined by the instructions for the assignment: introduction (containing background information and thesis statement), heading (marking sub-section of the essay), body (containing claims and supporting evidence) or conclusion (providing summary of the essay); (b) argumentative functions of sentences in body paragraphs as argument, counterargument, rebuttal, evidence or not applicable; and (c) evidential sentences as knowledge-telling or knowledge-transforming based on 6 categories in Bloom’s taxonomy (Sadker & Sadker, 2006, as cited in Woolfolk, Winne & Perry, 2016) (see Table 3.1).

I elaborated Bereiter and Scardamalia’s (1987) model contrasting knowledge telling and knowledge transforming by categorizing evidential sentences in argumentative writing in terms of Bloom’s taxonomy of the cognitive domain (Table 3.1). The taxonomy describes a progression of thinking processes across knowledge, comprehension, application, analysis, synthesis and evaluation. While not without criticism (e.g., see Darwazeh, 2017) it has potential to supply an underlying framework for developing informative, specific and useful learning analytics to guide learners in advancing from knowledge telling to knowledge transforming.

According to Bereiter and Scardamalia’s (1987) writing model, students engaged in knowledge telling neglect cognitive and metacognitive operations that transform knowledge. Using Bloom’s taxonomy to classify writers’ evidential sentences could reflect underlying cognitive and metacognitive processes writers engage in. Bloom’s
knowledge classification aligns with Bereiter and Scardamalia’s knowledge-telling model where writers focus on generating basic text. Bloom’s comprehension, application, analysis, synthesis and evaluation categories reflect Bereiter and Scardamalia’s knowledge-transforming model where writers coordinate and create knowledge. Thus, classifying students’ evidential sentences in terms of Bloom’s taxonomy forms a basis for analytics to guide students toward producing knowledge transforming texts with arguments strengthened by more thorough articulation of content with evidence.

<table>
<thead>
<tr>
<th>Category</th>
<th>Operationalization</th>
<th>Writing Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge</td>
<td>paraphrased/copied information form source</td>
<td>Knowledge-telling</td>
</tr>
<tr>
<td>Comprehension</td>
<td>elaborated source information</td>
<td>Knowledge-transforming</td>
</tr>
<tr>
<td>Application</td>
<td>source information applied to the real-world context</td>
<td>Knowledge-transforming</td>
</tr>
<tr>
<td>Analysis</td>
<td>inferential addition to information mentioned in sources</td>
<td>Knowledge-transforming</td>
</tr>
<tr>
<td>Synthesis</td>
<td>integration of information from different sources; a proposition</td>
<td>Knowledge-transforming</td>
</tr>
<tr>
<td>Evaluation</td>
<td>evaluation or discrediting of counterarguments</td>
<td>Knowledge-transforming</td>
</tr>
</tbody>
</table>

Next, I applied an ensemble of techniques from computational and cognitive linguistics to model features distinguishing knowledge-telling from knowledge-transforming evidential sentences. The computational tool will use those linguistic indices to generate and tailor writing analytics to post-secondary writers, helping them go beyond merely restating information from sources to engage in knowledge-transforming text production.

3.4. Hand coding – codebook

According to Bransford, Barclay and Franks (1972), sentences represent informational blocks that build wholistic semantic descriptions at a high level. In argumentative writing, an argument expressed and supported in a body paragraph may be considered as comprised of these building blocks that create particular rhetorical moves (Tanko, 2017). Accordingly, I use sentences as sampling units for the analysis of meaning in paragraph.
Since this study focuses on analyzing arguments and evidence, coders only examined sentences within the essay body; text in the introduction, conclusion and headings were ignored. Sentences presenting argumentation were coded as representing one of five functions:

- **Argument (A):** the sub claim supports the thesis statement (main claim)
- **Counterargument (C):** the sub claim opposes the thesis statement
- **Evidence (E):** support for the argument or the counterargument
- **Rebuttal (R):** discrediting the counterargument
- **Not applicable (NA):** a sentence that did not fit any argumentation category, e.g., definition or background information.

Elaborations were coded the same as the sentence they elaborated.

Last, evidential sentences were coded as knowledge-telling or knowledge-transforming following the 6-category framework for classifying evidential sentences in argumentative writing (Table 3.1).

A 3-point scale quantified the relation of each argument (or sub argument) to the thesis statement (or main argument), and the relation of evidence to arguments (sub arguments): 0 indicated not related, 1 described far-fetched, and 2 described related. Although not used in the subsequent analysis, this measure was extracted for each sentence in a body paragraph to get a sense of internal coherence of the essay and potentially exclude insufficiently coherent essays from the analysis.

<table>
<thead>
<tr>
<th>Sentence</th>
<th>Macro Structure</th>
<th>Argumentation</th>
<th>Writing mode</th>
<th>Relation to thesis statement/argument</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meeting the different needs of learners and allowing them to be included in classrooms can result in children achieving educational success.</td>
<td>Intro</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learner differences should be a primary concern when it comes to educating teachers and achieving inclusion, as the failure to incorporate learning needs can be disastrous for all students.</td>
<td>Intro</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>While most schools focus on bringing underachieving students up, individuals who are of high ability are neglected.</td>
<td>Body</td>
<td>A</td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>According to Northwestern University [2017], children are then left to rely on their parents to provide them with advanced instruction.</td>
<td>Body</td>
<td>E</td>
<td>Knowledge</td>
<td>2</td>
</tr>
<tr>
<td>Therefore, many students miss out on opportunities for achievement as many families cannot provide them with the resources such as tutoring services or enrichment activities.</td>
<td>Body</td>
<td>E</td>
<td>Comprehension</td>
<td>2</td>
</tr>
<tr>
<td>When teachers are given appropriate instruction, they are able to teach learners who need support.</td>
<td>Body</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 3.2. Hand-coding process**
The coding method is illustrated in the Figure 3.2. The sentence coded as argument (A) was rated for its relation to the thesis statement. The sentence coded as evidence (E) was rated regarding its relation to the preceding argument. In the table, the first evidential sentence was categorized as knowledge and rated as related to the preceding argument. The second evidential sentence was coded as comprehension and rated as related to the argument.

3.5. Hand coding – inter-rater reliability

To reach high interrater agreement among the three coders, coding involved three rounds of train together → code independently → calculate reliability. Round 1 included coding two randomly selected student essays together followed by coding four randomly selected essays independently. Altogether, the four papers consisted of 28 paragraphs (per text: \( M=7, \ SD=1.41 \)) and 245 sentences (per paragraph: \( M=8.75, \ SD=3.63 \)). After separate coding, the inter-rater agreement was calculated using the AC1 statistic (Gwet, 2002). This method corrects agreement among raters for the probability of chance agreement and is robust to skewed distribution of coding categories (Haley, Thomas, Petre, & De Roeck, 2008). The first round AC1 statistics are presented in Table 3.2.

<table>
<thead>
<tr>
<th>Code</th>
<th>AC1 Reliability</th>
<th>Standard Error</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macro-structure</td>
<td>0.97</td>
<td>0.01</td>
<td>[0.95, 0.99]</td>
</tr>
<tr>
<td>Argumentation</td>
<td>0.67</td>
<td>0.03</td>
<td>[0.61, 0.73]</td>
</tr>
<tr>
<td>Writing mode</td>
<td>0.77</td>
<td>0.02</td>
<td>[0.72, 0.82]</td>
</tr>
<tr>
<td>Relation to arguments/thesis</td>
<td>0.82</td>
<td>0.02</td>
<td>[0.78, 0.86]</td>
</tr>
</tbody>
</table>

Using Artstein and Poesio’s (2008) standard for high interrater agreement statistics in discourse studies of .80 or higher, the interrater reliability was low for Argumentation and Writing mode. The issue lay in identifying sentences that did not fit any argumentation category, i.e., reliability suffered due to coders’ failures to capture all NA sentences in the assigned essays. In addition, for Writing mode, coders struggled to discriminate synthesis from analysis, and analysis from comprehension.

In round 2, coders focused on sharpening coding of Argumentation and Writing mode. They coded two randomly selected student essays together, then coded four randomly selected essays independently. Altogether, the four papers comprised 26
paragraphs (per text: $M=5.2$, $SD=1.3$) and 247 sentences (per paragraph: $M=9.27$, $SD=2.47$). Round 2 AC1 interrater results are presented in Table 3.3.

**Table 3.3. Round 2 inter-rater agreement**

<table>
<thead>
<tr>
<th>Code</th>
<th>AC1 Reliability</th>
<th>Standard Error</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argumentation</td>
<td>0.76</td>
<td>0.02</td>
<td>[0.71, 0.81]</td>
</tr>
<tr>
<td>Writing mode</td>
<td>0.83</td>
<td>0.02</td>
<td>[0.78, 0.87]</td>
</tr>
</tbody>
</table>

The coders then worked to improve the reliability of coding the Argumentation. Round 3 included coding two randomly selected student essays together followed by coding six randomly selected essays independently. Altogether, the six papers included 53 paragraphs (per text: $M=8.83$, $SD=3.76$) and 458 sentences (per paragraph: $M=9.60$, $SD=3.20$). Round 3 AC1 interrater results are presented in Table 3.4. After training had established high enough reliability, each rater then coded independent subset (7, 7 and 6 essays, respectively, randomly assigned) of the 20 remaining essays.

**Table 3.4. Round 3 inter-rater agreement**

<table>
<thead>
<tr>
<th>Code</th>
<th>AC1 Reliability</th>
<th>Standard Error</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argumentation</td>
<td>0.81</td>
<td>0.02</td>
<td>[0.77, 0.84]</td>
</tr>
</tbody>
</table>
Sample of evidential sentences coded for the Writing mode is illustrated in Table 3.5.

<table>
<thead>
<tr>
<th>Category</th>
<th>Example Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge</td>
<td>When institutions and classrooms integrate self-directed learning into their curriculum, long term benefit have been observed through increased student retention and graduation rates (University of Texas at Austin, 2016).</td>
</tr>
<tr>
<td>Comprehension</td>
<td>With this type of learning, students can fully control their educational experience and focus on information they would like to explore.</td>
</tr>
<tr>
<td>Application</td>
<td>Having different interpretations based on cultural differences is a concern, particularly for schools in British Columbia and other Canadian metropolitan centers where we have and are projected to receive more international students particularly from Asia.</td>
</tr>
<tr>
<td>Analysis</td>
<td>Meaning engagement in some form of unstructured play could also result in an increase in academic performance.</td>
</tr>
<tr>
<td>Synthesis</td>
<td>However, this is not the case, because praise is not overly useful feedback, and if it is undeserved, it can cause students to feel like their teachers do not expect much from them.</td>
</tr>
<tr>
<td>Evaluation</td>
<td>One of the limitations is that the research is centered on a questionnaire survey which may result in certain biases including social desirability bias.</td>
</tr>
</tbody>
</table>

3.6. Linguistic features

Scholars in different fields could benefit from detailed methodology of cognitive linguistics (Croft & Cruse, 2004; Dancygier, 2017). For instance, cognitive linguistics offers means of analyzing linguistic choices writers made while constructing meaning in genre-specific texts (e.g., argumentation). In line with this, Sanders and Schihperoord (2006) posited the text structure may provide insights into cognition applied in writing, arguing appropriate analysis of written composition can reveal “significant traces of the writer’s cognitive representation” (p. 386). Moreover, Bereiter and Scardamalia (1987) emphasized the importance of the connection between linguistic research and cognitive models.

Accordingly, I modelled evidential sentences as sets of linguistic features (also called linguistic indices). The linguistic features selected for this study are proxies of cognitive processes a writer applied to relay features of source knowledge and create
evidential sentences. Each evidential sentence was modelled according to its rhetorical features and content, given the theoretical principles of knowledge-transforming model.

3.7. Linguistic features in rhetorical space

Rhetoric characteristics of evidential sentences in the essays were modelled as sets of structural features, anaphoric devices and rhetorical connectives.

*Structural features:* Stab and Gurevych (2017) found structural features were helpful in explaining differences between argumentative (thesis statement, sub-claim, evidence) and non-argumentative units in the text. Structural features selected for this study are computed at the paragraph level. The features are *relative position of evidential sentence in paragraph* and *absolute distance between evidential sentence and the most recent argument*.

*Relative position of evidential sentence in paragraph:* For each evidential sentence in a body paragraph, I extracted its relative position, scaled to the interval $[0, 1]$. This information identifies sentences that appear toward the beginning, middle or end of a paragraph, allowing for the analysis of the relationship between a sentence’s position and its writing mode. For example, researchers may want to investigate if evidential sentences near the beginning of paragraph are usually knowledge-telling ones, just introducing source information to readers. Or, for example, are sentences near the end of a paragraph knowledge-transforming, providing e.g., inferences, examples or comparisons which may be an indication of deeper elaboration of source knowledge writer engaged in.

*Absolute distance between evidential sentence and the most recent claim:* This linguistic feature counts the number of sentences separating an evidential sentence and the preceding claim (argument/counterargument/rebuttal). In case a continuous sequence of claim sentences is provided, I assume that evidential sentence that comes after this sequence is connected to the last claim in the sequence. The sentence(s) that separate an evidential sentence and the preceding claim could be other evidential sentences or sentences coded as NA. This feature combined with relative position of evidential sentences in a paragraph may approximate writer’s engagement in text structuring (e.g., arranging high-level propositions) and, indirectly, in constructive planning (e.g., organizing goals hierarchically). For example, a writer who created
multiple claims in the same paragraph, and mixed them with evidential and NA sentences creates an informationally overloaded paragraph and may have experienced challenges with structuring and constructive planning.

**Anaphoric Devices:** Anaphoric devices are linguistic markers denoting a preceding word or group of words (Erhlich, Remond, Tardieu, 1999). They are mostly noun phrases, pronouns and articles. Ariel (1990) distinguished between high- and low-accessibility anaphoric devices. High-accessibility devices are pronouns (personal and possessive) and definite article (the). They contain less linguistic material (Sanders & Spooren, 2007) and indicate a writer’s continuation of the previous topic. Low-accessibility anaphoric devices are noun phrases (e.g., bilingual children) and indefinite articles (a and an). Sanders and Spooren (2007) posit low-accessibility devices contain much linguistic material and, as such, signal a writer’s termination of a current topic and activation of another topic.

These two types of linguistic markers are proxies for change in topic which is one of the essential parameters distinguishing knowledge-telling from knowledge-transforming. In knowledge-telling texts, the writer tends to stay on topic. I computed the incidence of both high- and low-accessibility anaphoric devices for each evidential sentence. To account for effects that the sentence length may have on incidence of anaphoric devices in the sentence, these two values were normalized for the number of words in the sentence and scaled to the interval [0, 1].

**Rhetorical connectives:** To model rhetorical relations between an evidential sentence and information introduced earlier in paragraph, rhetorical connectives in each evidential sentence are extracted according to 13 groups (Celce-Murcia & Larsen-Freeman, 1983). The connectives selected for this study are:

1. Purpose – so that, in order that, in order to
2. Reason – since, as, because, now that
3. Simultaneous – while, as
4. Conditional – if, in case, provided that
5. Concessive – although, though, even though
6. Circumstantial – by + [gerund]
7. Substitutives – instead, rather, rather than
8. Additives-emphatic – in addition, moreover, furthermore, besides, also
9. Additives-appositional – *that is, in other words, for instance, for example*
10. Additives-comparative – *likewise, similarly, equally*
11. Causal-general – *therefore, consequently, for that reason, thus*
12. Causal-causal-conditional – *then, in that case, otherwise*
13. Sequential – *next, first, second, last, finally, up to now, to sum up*

### 3.8. Linguistic features in content space

Content characteristics of evidential sentences were modelled as sets of semantic overlap and content word overlap features. Number of sources the sentence drew upon was also a part of the content space features.

*Semantic overlap:* To model knowledge in content-space, I computed semantic overlap between: a) an evidential sentence and related source text, and b) evidential sentence and sentence coded as argument/counterargument/rebuttal that precedes the evidential sentence. Semantic similarity measures help to ensure that content the writer employed to support arguments is appropriate given the textual source cited. Even though the rhetoric of a particular evidential sentence may sufficiently indicate knowledge transforming (e.g., a sentence provides an example of a theoretical concept), low semantic similarity between the sentence and a source may suggest the writer used information outside source texts (e.g., an idea recalled from personal experience or just made up). This may alert the writer to perform additional monitoring relative to task requirements. Moreover, insufficient semantic similarity may indicate challenges in comprehending source material, potentially due to insufficient monitoring for comprehension.

To measure semantic similarity, I applied latent semantic analysis (LSA, Deerwester, Dumais, S., Furnas, G., Thomas, L., & Richard, 1990; Landauer, Foltz & Laham, 1998). LSA is a statistical technique that quantifies the meaning of a word with regard to context. The context, i.e., a semantic representation of domain knowledge (Foltz, Gilliam & Kendall, 2010), is created by training the LSA model on selected text corpora. Mathematically, this model is a high-dimensional matrix where the frequency of a word in a particular text is recorded in a cell of a matrix identified by the word (row) and source text (columns). To simplify the matrix while preserving important information, the matrix is decomposed using a matrix-algebra technique called singular value...
decomposition (SVD) then reduced to smaller matrix with predefined number of dimensions. During this transformation, a weighting function is applied over each cell to capture a word’s importance within a particular text and within a domain.

The LSA computational model implemented in this study has been trained on a 117 summary articles, 2 primary articles and the textbook in educational psychology. The corpus contained 32869 distinct words. I chose this set of texts to train the LSA model since this corpus well represents semantics of domain knowledge in educational psychology. Moreover, the topics students wrote about in their essays relate to concepts in educational psychology. Landauer and Dumais (2008) suggested reducing the term-document matrix to 50-1000 dimensions, depending on the corpus size. As LSA in this study was applied over relatively small document collection, the obtained high-dimensional matrix was reduced to 50 dimensions.

Content word overlap: Content words – nouns, verbs, adjectives, and adverbs (Crossley, Kyle & McNamara, 2015; Jagiah, 2017) – refer to real-word objects and their qualities. Content words are deemed helpful in modeling the variance of content in the text. For example, Field, Lewkow, Zimmerman, Boulanger and Seanosky (2016) used content words to measure the conciseness of text. Change in the ratio between number of content words in evidential sentence and number of content words in a related source text(s) as the relative position of evidential sentence in paragraph increases may indicate change in writer’s level of elaboration. For example, if the relative position of an evidential sentence in paragraph is proportional to the number of new content words introduced in evidential sentence, this may indicate writer’s tendency to extend source information (e.g., provide explanation or example) to support argument. The content word overlap features computed in this study are: a) content word overlap between evidential sentence and related source text, and b) content word overlap between evidential sentence and the preceding claim (argument/counterargument/rebuttal). Synonyms were taken into account in calculation of these features.

Number of sources a sentence refers to – Some sentences may cite two or more sources. I hypothesize this information is important since it may predict some knowledge-transforming categories given their operational definitions (Table 3.1). For example, synthesis is operationalized as “integration of information from different sources”.

27
If a sentence cites two or more sources, the semantic and content word overlap were obtained by adding up the values computed for each source separately. For example, if the LSA overlap between sentence A and source text 1 is 0.48, and the LSA overlap between sentence A and source text 2 is -0.22, the total semantic overlap between sentence A and its sources is 0.26.

3.9. Technical implementation

Preparation of the dataset for this study was done using Python. The state-of-the-art natural language processing system SpaCy (Honnibal & Johnson, 2015) has been used for sentence tokenization, part-of-speech tagging and noun phrase identification. The SpaCy system is based on neural network learning models and demonstrates very high accuracy of dependency parsing (Honnibal & Johnson, 2015).

The LSA model for computing semantic overlap indices was implemented by the gensim package (Rehurek & Sojka, 2010). This package demonstrated improved efficiency in preforming singular value decomposition over a large corpus.

Synonyms for content words are extracted using WordNet – a comprehensive lexical database for English, a part of the Natural Language Tool Kit (Loper & Bird, 2002). Other linguistic indices were computed using specifically created Python code.
Chapter 4. Results

4.1. Essay macrostructure

A total of 316 paragraphs were available from 40 essays (per essay: $M=7.90$, $SD=2.37$). Within this corpus, 48 paragraphs were classified as introductions (per essay: $M=1.20$, $SD=0.41$), 225 as body ($M=5.63$, $SD=2.05$) and 43 paragraphs as conclusions ($M=1.08$, $SD=0.47$). Using sentences as a metric, 2541 sentences comprised the full corpus (per essay: $M=63.52$, $SD=16.98$) of which 326 sentences were in introduction paragraphs (per paragraph: $M=8.15$, $SD=3.56$), 1933 in body paragraphs ($M=48.33$, $SD=14.63$) and 282 in conclusion paragraphs ($M=7.05$, $SD=4.08$). The details for individual essays in the corpus are provided in Table B.1.

A Kruskal-Wallis test revealed no statistically detectable difference in the essay length measured by the number of sentences between high- and low-achieving groups split at the median of essay grades assigned by teaching assistants ($H(1)= 0.002$, $p=0.968$; $M_{low}=61.55$, $SD_{low}=15.44$; $M_{high}=65.50$, $SD_{high}=18.59$). The same test revealed no statistically detectable difference in total number of paragraphs ($H(1)= 1.149$, $p=0.284$; $M_{low}=7.75$, $SD_{low}=2.79$; $M_{high}=8.05$, $SD_{high}=1.93$) created by the two groups. Neither the average sentence counts per body paragraph per essay ($H(1)= 0.534$, $p=0.465$; $M_{low}=9.47$, $SD_{low}=2.78$; $M_{high}=8.92$, $SD_{high}=3.36$) nor the number of body paragraphs created per essay ($H(1)=0.304$, $p=0.581$; $M_{low}=5.6$, $SD_{low}=2.37$; $M_{high}=5.65$, $SD_{high}=1.73$) was detectably different between the high- and low-achieving group.

4.2. Argumentation

I identified 573 argument sentences (per essay: $M=14.32$, $SD=8.27$), 108 counterargument sentences ($M=2.70$, $SD=2.88$), 111 rebuttals ($M=2.77$, $SD=3.68$), 706 evidential sentences ($M=17.65$, $SD=10.66$), and 435 other sentences ($M=10.87$, $SD=10.82$). In the sample, 2 essays did not include evidential sentences. Details of the distribution of these categories per essay are provided in Table B.2. Figure 4.1. shows frequency of argumentation categories in corpus.
A total of 792 sentences were claims – arguments, counterarguments and rebuttals. This represents 40.98 % of all the sentences in body paragraphs. Evidential sentences represented 36.52 % and other (NA) sentences accounted for 22.50 % of body paragraph data, respectively (Figure 4.2).
The Shapiro-Wilk normality test revealed normally distributed frequencies of evidential sentences in both achievement groups (high-scoring group: $W=0.960, p=0.548$; low-scoring group: $W=0.954, p=0.44$). An independent samples $t$-test was conducted to compare frequency of evidential sentences in the low- and high-scoring groups. There was no statistically detectable difference in the frequencies for the high-scoring group ($M=20.9, SD=10.38$) and low-scoring group ($M=14.4, SD=10.16$); $t(38) = -2.001, p=0.052$. The Shapiro-Wilk’s test showed the assumption of normality was violated in the distribution of the average number of evidential sentences per body paragraph in the low-scoring group ($W = 0.892, p = 0.030$). Thus, a Kruskal-Wallis test was conducted. It showed no statistically detectable difference in the average number of
evidential sentences per body paragraph for the high-scoring group ($M=3.90$, $SD=2.13$) and for the low-scoring group ($M=3.03$, $SD=2.60$), $H(1) = 2.68$, $p = 0.102$.

Last, a score essay received for quality of evidence (one of the items in scoring rubric, scored out of 5 points) strongly correlates with the essay score ($r=0.814$, $p<0.001$, $n=38$).

4.3. **RQ1: To what extent do undergraduate students engage in knowledge transforming while writing argumentative essays from multiple sources?**

479 sentences were categorized as knowledge-telling sentences (per essay: $M=12.61$, $SD=7.68$). This represents 67.85% of all evidential sentences in 38 essays. The remaining 227 evidential sentences were categorized into one of five categories representing the knowledge-transforming mode: 99 sentences were comprehension, $M=2.61$, $SD=2.49$; 20 were application, $M=0.53$, $SD=1.37$; 70 were analysis, $M=1.84$, $SD=2.28$; 17 were synthesis, $M=0.45$, $SD=0.89$; and 21 were evaluation, $M=0.55$, $SD=1.31$). Details for individual essays are provided in Table B.3. Figure 4.3. shows frequency of writing mode categories in corpus.
4.4. **RQ2: To what degree does engaging in knowledge telling and transforming correlate with essay scores?**

4.4.1. **Coefficient of knowledge transforming**

To quantify a learner’s engagement in knowledge telling or knowledge transforming in an essay, I modelled and computed the coefficient of knowledge transforming. The coefficient takes into account different degrees of cognitive engagement (Agarwal, 2018), as described in Bloom’s typology. To be able to elaborate source information (comprehension level), a learner intrinsically must operate at the knowledge level. Knowledge and comprehension are considered less complex forms of...
cognitive engagement. Further, to be able to apply, analyze, synthesize or evaluate source information, considered more complex forms of cognitive engagement, a learner logically must first comprehend information. Therefore, all categories subsume knowledge, while the categories of high-level cognitive engagement subsume comprehension, as well. Accordingly, each evidential sentence was assigned a weight ($\omega$) with respect to the sentence’s writing mode category:

- knowledge, $\omega = 1$
- comprehension, $\omega = 1.5$
- application, $\omega = 2$
- analysis, $\omega = 2$
- synthesis, $\omega = 2$
- evaluation, $\omega = 2$

The coefficient of knowledge transforming ($C_{\text{trans}}$) describing a student’s essay was obtained by averaging a sum of the weights across all the evidential sentences provided in the essay. For example, if the coefficient for an essay is $C_{\text{trans}} = 1$, no transformation of source knowledge occurred in the composition. This essay would be entirely knowledge-telling.

### 4.4.2. Correlation analysis

Obtained coefficients of knowledge transforming fell within the range [1, 1.57], with $C_{\text{trans}} = 1$ in 5 essays. To assess the relationship between the essay’s coefficient of knowledge transforming and the score assigned by teaching assistants, a Pearson correlation was computed. There was a weak and positive correlation between the coefficient of knowledge transforming ($M=1.23$, $SD=0.18$) and essay score ($M=22.21$, $SD=6.16$); $r=0.324$, $p=0.047$, $n=38$ (Figure 4.4.).
4.5. RQ3: How accurately does the supervised learning algorithm classify evidential sentences as knowledge telling vs. knowledge transforming?

4.5.1. Multicollinearity check

As noted in the Method chapter, 22 linguistic features were used as predictors in the model predicting a binary variable for each sentence where 0 denotes knowledge-telling and 1 denotes knowledge-transforming sentence. The test for multicollinearity revealed the correlation of more than 0.50 between several pairs of variables: Simultaneous (proportion of rhetorical connectives: *while, as*) and Reason (proportion of rhetorical connectives: *since, because, as, inasmuch as, now that*), \( r = 0.87 \); Sequential (presence of connectives: *then, next, first, second, last, finally, up to now, to sum up*) and Causal_Con (connectives: *then, in that case, otherwise*), \( r = 0.70 \); Sol_A (semantic overlap between evidential sentence and preceding claim) and CWol_A (content-word overlap between evidential sentence and preceding claim), \( r = 0.55 \) (Figure 4.5). The feature that theoretically captures more information than its pair has been retained in the dataset: Reason (includes more connectives), Sequential (includes more connectives) and Sol_A (computed over the knowledge space of the domain).
4.5.2. Random forest classification

The following four supervised machine learning algorithms were explored as candidate algorithms to build a predictive model for this study: logistic regression, random forest, support vector machine and neural network with backpropagation. Each algorithm belongs to a different group given its mathematical characteristics: regression-based, decision trees, kernel methods and artificial neural networks, respectively. Except logistic regression which yielded low prediction accuracy (nearly .57) other algorithms performed similarly on the study dataset (prediction accuracy between .71 and .73).

The supervised machine learning algorithm random forest (Breiman, 2001) was selected to build a classifier for this study. Random forest was easier to parametrize than...
other algorithms. Also, this algorithm provides means to reliably measure and report variable importance, which is needed to answer RQ4 in this study.

A decision tree is the heart of this algorithm. The tree uses a set of features (i.e., variables in the dataset) and applies particular criteria to split the dataset into smaller units (i.e., tree nodes) to learn the combinations of features and their values that are best predictors of the outcome class. For the purpose of illustrating this algorithm, a simplified version of the decision tree built on the data from this study is provided in Figure 4.6. In reality, the decision trees built in this study were much bigger.

![Decision Tree Diagram](image)

**Figure 4.6.** The decision tree model that uses 2 features from the dataset (Pos_P_norm and Sol_S) and two conditions on which the tree splits into branches; the final branch that does not split anymore is the class prediction

Decision trees struggle to capture variance in the dataset and are biased toward dominant classes in unbalanced datasets (Hastie, Tibshirani & Friedman, 2009). The decision tree algorithm alone is considered a “weak learner.” The random forest algorithm is an ensemble machine learning algorithm grounded in the idea of grouping weak learners together to average out noise in individual models and improve the prediction performance. The random forest algorithm is comprised of multiple decision trees. In a random forest, the group of weak learners grows over time and the members cast their weighted votes for the predicted class:

$$\hat{C}_f^B(x) = \text{majority vote}\{\hat{C}_n(x)\}_1^B$$
where $\hat{C}_b(x)$ denotes the class prediction of the $b$th random forest tree (Hastie, Tibshirani & Friedman, 2009). As such, random forests are among the top performing modern classification algorithms (Fernández-Delgado, Cernadas, Barro & Amorim, 2014).

While building the random forest classification model, each tree is created using a different bootstrap sample and validated on data points outside that select sample. A random subset of features is used every time when creating a new tree. The number of trees casting their votes ($ntree$) and number of randomly selected features ($mtry$) are tuning parameters crucial determiners of the final performance of a random forest classifier.

### 4.5.3. Model selection and testing

I applied a cross-validation to select the optimal combination of tuning parameters in a random forest model. Cross-validation was performed on the training data (80% sample of dataset), while 20% was the hold-out data for testing the model performance, following suggestions by Haykin (1994).

Out-of-bag error rate (OOB) has been used to assess model performance regarding varying numbers of trees ($ntree$) in the ensemble. The OOB error validates the ensemble's performance on data outside the bootstrap sample. The OOB error rate in my data stabilizes at ~0.28 when $ntree = 3500$ (Figure 4.7).
To select an optimal number of features in each tree, I used a 10 fold cross-validation, repeated 10 times. In each iteration of cross-validation, I examined 19 different values for mtry [1,19] where 19 instructs the tree to use all the features of the dataset. The best classification accuracy of 0.73 was achieved for mtry = 6 (Figure 4.8).
The random forest classifier using the obtained tuning parameters was applied over 30 different 80-20 random splits of the dataset. The mean classification accuracy measured on test sets was 0.726 (95% CI [0.714, 0.738]).

4.6. RQ4: What linguistic features predict whether an evidential sentence tells or transforms source knowledge?

4.6.1. Random forest feature importance

The random forest algorithm provides a means to measure the relative contribution of each feature to predicting the response class. At each node in the tree, a particular feature is tested against a criterion and the dataset is divided into two subsets accordingly. For example, at the node Pos_P_norm (Fig. 4.6) the dataset was divided into two subsets according to the boundary of 0.5 for the Pos_P_norm feature.
(normalized position of a sentence in a paragraph). According to the algorithm, all the sentences where the Pos_P_norm has a value less than 0.5 were assigned to a group classified as 0 (knowledge-telling sentences). Therefore, the more homogenous this new group is (i.e., having nearly zero instances of class 1 that “pollute” the group), the variable Pos_P_norm is deemed to be more important in predicting the response variable. Each new feature used down the tree is supposed to, to some extent, decrease impurity of created groups. At the leaves of the tree, each feature has accrued a value representing its importance. This value is averaged across all the trees in the ensemble. The Mean Decrease Gini impurity index is one of the measures used to quantify feature importance.

4.6.2. Feature importance results

The features ranked according to the Mean Decrease Gini index are presented in Table 4.1. and Figure 4.9.

Table 4.1. Feature importance measured by Mean Decrease Gini

<table>
<thead>
<tr>
<th>Rank</th>
<th>Feature</th>
<th>Description</th>
<th>Knowledge telling</th>
<th>Knowledge transforming</th>
<th>Mean Decrease Gini</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pos_P_norm</td>
<td>relative position of evidential sentence in a paragraph</td>
<td>45.00</td>
<td>28.44</td>
<td>36.81</td>
</tr>
<tr>
<td>2</td>
<td>CWol_S</td>
<td>content-word overlap between evidential sentence and source text</td>
<td>24.28</td>
<td>35.93</td>
<td>35.66</td>
</tr>
<tr>
<td>3</td>
<td>Sol_A</td>
<td>semantic overlap between evidential sentence and preceding/succeeding argument</td>
<td>14.29</td>
<td>11.69</td>
<td>27.83</td>
</tr>
<tr>
<td>4</td>
<td>LA</td>
<td>incidence of low accessibility anaphoric devices in a sentence</td>
<td>9.50</td>
<td>17.83</td>
<td>27.65</td>
</tr>
<tr>
<td>5</td>
<td>Sol_S</td>
<td>semantic overlap between evidential sentence and related source text</td>
<td>-4.73</td>
<td>0.71</td>
<td>27.03</td>
</tr>
<tr>
<td>6</td>
<td>Pos_Arg_Ev</td>
<td>absolute distance between evidential sentence and the most recent argument</td>
<td>42.34</td>
<td>20.73</td>
<td>23.99</td>
</tr>
<tr>
<td>Rank</td>
<td>Feature</td>
<td>Description</td>
<td>Knowledge telling</td>
<td>Knowledge transforming</td>
<td>Mean Decrease Gini</td>
</tr>
<tr>
<td>------</td>
<td>-----------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------------</td>
<td>------------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>7</td>
<td>HA</td>
<td>incidence of high accessibility anaphoric devices in a sentence</td>
<td>-1.62</td>
<td>5.12</td>
<td>22.54</td>
</tr>
<tr>
<td>8</td>
<td>Reason</td>
<td>connectives: <em>since, because, as, inasmuch as, now that</em></td>
<td>1.36</td>
<td>10.74</td>
<td>11.63</td>
</tr>
<tr>
<td>9</td>
<td>Causal_Gen</td>
<td><em>therefore, consequently, for that reason, thus</em></td>
<td>17.77</td>
<td>15.26</td>
<td>4.43</td>
</tr>
<tr>
<td>10</td>
<td>Conditional</td>
<td><em>if, even if, as long as, in case, provided that</em></td>
<td>11.68</td>
<td>4.08</td>
<td>4.17</td>
</tr>
<tr>
<td>11</td>
<td>Additives_Empatic</td>
<td><em>in addition, moreover, furthermore, besides, also</em></td>
<td>-9.36</td>
<td>-1.42</td>
<td>3.59</td>
</tr>
<tr>
<td>12</td>
<td>Sequential</td>
<td><em>then, next, first, second, last, finally, up to now, to sum up</em></td>
<td>-5.73</td>
<td>6.91</td>
<td>3.08</td>
</tr>
<tr>
<td>13</td>
<td>Circumstancial</td>
<td><em>by + [gerund]</em></td>
<td>-4.52</td>
<td>-6.08</td>
<td>2.72</td>
</tr>
<tr>
<td>14</td>
<td>Concessive</td>
<td><em>although, though, even though, while</em></td>
<td>6.25</td>
<td>-7.45</td>
<td>2.67</td>
</tr>
<tr>
<td>15</td>
<td>Substitutives</td>
<td><em>instead, rather, rather than</em></td>
<td>4.99</td>
<td>-6.26</td>
<td>1.96</td>
</tr>
<tr>
<td>16</td>
<td>Purpose</td>
<td><em>so that, in order that, in order to</em></td>
<td>-1.66</td>
<td>-0.41</td>
<td>1.18</td>
</tr>
<tr>
<td>17</td>
<td>Additives_Apos</td>
<td><em>that is, in other words, for instance</em></td>
<td>4.93</td>
<td>-0.86</td>
<td>1.13</td>
</tr>
<tr>
<td>18</td>
<td>Additives_Comp</td>
<td><em>likewise, similarly</em></td>
<td>-0.59</td>
<td>0.33</td>
<td>0.17</td>
</tr>
<tr>
<td>19</td>
<td>No_sources</td>
<td><em>Number of sources cited in a sentence</em></td>
<td>0.00</td>
<td>0.00</td>
<td>0.08</td>
</tr>
</tbody>
</table>
As can be seen, the features making the most contribution in the classifier are: Pos_P_norm, CWol_S, Sol_A, LA, Sol_S, Pos_Arg_Ev, HA and Reason (moderately important). The partial effects of these features, i.e., the effects marginalized over all other features, were further analyzed (Figure 4.10).

The partial dependence plot shows the marginal effect probability (Hastie, Tibshirani & Friedman, 2009) of a feature in predicting membership in class 1. In other words, it shows a probability (y-axis) a sentence is estimated to be a knowledge-transforming sentence given a particular value of a feature (x-axis). For example, starting from the top-left, the likelihood of a sentence positioned in the middle of a paragraph (relative position 0.30 – 0.60) being a knowledge transforming sentence is approximately 0.80. The plot next to it shows the effect the sentence-source content word overlap (CWol_S) on knowledge transforming probability. When the number of common content words between the sentence and source text exceeds 80%, the sentence is strongly predicted to be knowledge-transforming. Further, the sentences having evidence-argument semantic overlap (Sol_A) on the interval 10% - 70% are
moderately likely to transform source knowledge. However, this likelihood drops for sentences where Sol_A is outside this interval. It should be also noted that only 12 evidential sentences had a negative semantic overlap with the argument. By looking at the partial dependence on the LA plot, we notice that, as the presence of low-accessibility anaphoric devices (noun phrases and indefinite articles) in a sentence exceeds 25%, the sentence is more likely to be knowledge-transforming. Partial dependence on Sol_S (semantic overlap between evidential sentence and source text), on the other hand, shows quite uniform likelihood (0.5 – 0.6) regardless the value of this kind of semantic overlap. The evidential sentence positioned closer to the argument (1 – 3 sentences away) is more likely to be knowledge-transforming. Negative values in this variable capture the relative distance of evidential sentences that come before arguments they support. However, as I found only 10 of those sentences in the entire dataset, the probabilities when Pos_Arg_Ev < 0 could not be considered reliable. Further, the sentence is more likely to be knowledge-transforming should it contain fewer high-accessibility (HA) anaphoric devices (definite articles and personal pronouns). Last, the probability of a sentence to be knowledge-transforming drops as the number of reason-related connectives (since, because, as, inasmuch as, now that) increases.
Figure 4.10. Partial dependence on 8 most important features
Chapter 5. Discussion

5.1. Two thirds of all the evidential sentences were knowledge-telling

Undergraduate students’ essays examined in this study show, while writers cite evidence to support their arguments, they mostly tell rather than transform knowledge from sources they consult. In other words, undergraduates mostly paraphrase or copy information from sources rather than deeply engage with the source material through elaboration, application, inference, integration and evaluation of information they mine. This finding is in line with Petrić (2007) who reported an overall tendency of students to re-tell what is stated in sources by summarizing/paraphrasing or directly quoting it.

Furthermore, in this sample, nearly 82% of all the evidential sentences created were categorized as either knowledge or comprehension, both categories representing less complex cognitive engagement (Agarwal, 2018). Students were rarely processing source information at the levels beyond comprehension (i.e., application, analysis, synthesis and evaluation). This may indicate students’ tendencies to keep cognitive efforts within two least complex forms of cognitive engagement. This resonates with results of Hyytinen, Lofström, and Lindblom-Ylänne’s (2017) experiment sampling about three times more compositions than in this study. They demonstrated a vast majority of students from several levels of higher education faced challenges deciding on relevant source information, connecting main ideas and evaluating alternative positions presented in sources.

Building on previous research in writing cognition (e.g., Bereiter & Scardamaila, 1987; Stein, 1990) I offer two possible explanations for students’ not engaging in knowledge transforming. First, since genre-based multi-source writing is a cognitively demanding task, students may wish to avoid additional cognitive load. For instance, once they locate relevant source information to support their argument in a way it fits task requirements, students may prefer to paraphrase or copy information into their composition to maintain its organizational structure. In this way, students limit their elaboration to information selection while following schema-driven goals. Second, post-secondary writers may struggle to strategically apply cognitive processes required in
knowledge transforming: planning, monitoring, elaborating and structuring. For example, students may not recognize the opportunity to elaborate an idea introduced in a source, for example, by providing a real-world context for a theoretical concept, and translate this elaborated idea into knowledge-transforming sentence(s).

5.2. The correlation between the coefficient of knowledge transforming and essay score is positive and weak

The coefficient of knowledge transforming explains about 32 % of variance in the essay scores. The quality of evidence (item in the scoring rubric, scored out of 5 by the instructor) explains about 81 % of variance in the essay scores. Since the total essay score and evidence score correlate as much as reliability allows, the total essay score was selected for analysis as it would be a more conservative reference point.

While there could be other factors affecting the overall essay score (e.g., appropriate use of headings, citation and grammar mistakes,…), this finding may indicate that, from instructor’s perspective, relevant and convincing evidence can satisfactorily meet task requirements if presented as knowledge-telling sentences. This contrasts to Bereiter and Scardamalia’s (1987) position that knowledge-telling texts most of the time fail to fulfill writing task requirements.

While marking the argumentative essay, the instructor may focus on the relationship between a claim and relevant evidence in the rhetorical space (i.e., does the evidence support claim?). A scorer normally would not read sources a student cited (unless suspecting plagiarism) to locate relevant pieces of information and assess that information was transformed in evidential sentences. Marking this way or providing formative feedback on a student’s engagement in knowledge transforming would be highly time consuming. For this reason, feedback on source content usage in the argumentative essay has been rarely provided by the instructors and this characteristic of writing therefore has a meager effect on the essay score.
5.3. The machine learning algorithm accurately classifies nearly 3 out of 4 evidential sentences as either knowledge-telling or knowledge-transforming

The machine learning classifier developed and validated in this study accurately classified 72.6% of evidential sentences. This classifier and the Python routine that performs paragraph/sentence tokenization and computes linguistic features will be the text processing engines of a writing analytics tool planned to be developed in the future, building on findings from this study. The potential tool (Figure 5.1) identifies and highlights knowledge-telling sentences in a composition and, through a series of metacognitive prompts, guides writers toward making knowledge-transforming revisions. However, about one quarter of evidential sentences in the essay were misclassified, either as false positives (knowledge-telling sentences categorized as knowledge-transforming) or false negatives (knowledge-transforming sentences classified as knowledge-telling).

Figure 5.1. Writer’s response to the tool’s decision

When a writer clicks “Analyze my writing” (Figure 5.1) in the tool, the tool color-codes the sentence classified as knowledge-telling and prompts writer to evaluate this selection. For instance, if a writer agreed that the highlighted sentence was knowledge-telling, another prompt offering recommendations for revising the sentence to become knowledge-transforming is provided (Figure 5.2). Should the writer disagree with the
classifier’s decision (i.e., consider the classification a false negative), a new evidential sentence will be color-coded as knowledge-telling and a related prompt will ask writer to evaluate this new decision.

Figure 5.2. Guiding writer towards knowledge transforming

Some of the knowledge-telling sentences in the essay draft could go undetected (false positive). Should the writer notice a knowledge-telling sentence the classifier failed to identify, they may want to mod/right-click on the sentence and manually mark it as knowledge-telling (Figure 5.3). Then the prompt guiding the revision towards knowledge-transforming will show up (Figure 5.2). By allowing a user to evaluate classifier’s selection, the tool interface does not only promote metacognitive monitoring, but also collects data that will be used to validate and improve classification accuracy in the subsequent versions of the tool.
In addition, the tool will record the keyboard logs and the writer's interactions (e.g., text entry, deletion, request for analytics…) with the interface. The detailed design of the tool is left for future studies.

5.4. The eight linguistic features are important predictors of whether an evidential sentence tells or transforms source knowledge

5.4.1. Linguistic features in a rhetoric space

In the rhetorical problem space, five linguistic features are important predictors of knowledge transforming in three categories: (1) structural features: relative position of an evidential sentence in a paragraph and absolute distance between an evidential sentence and the most recent argument; (2) anaphoric devices: low- and high-accessibility devices; and (3) rhetorical connectives for reason.
From the structural point of view, claim(s) usually occupy the upper-third of a paragraph, knowledge-transforming sentences most often come in the middle (usually within a 3-sentence window from claim), and the occurrence of knowledge-transforming sentences drastically drops in the lower-third of paragraph. This finding reflects the idea that many writers are interested in responding to task requirements by putting less cognitive effort into it. For example, to reach a minimum word-count required for the essay, a writer may wish to extend some paragraphs with more textual material. To achieve this goal, a writer adds relevant knowledge-telling sentences to brief paragraphs. Future studies using keystroke logging may be able to further examine this hypothesis.

Knowledge-transforming sentences contain more noun phrases and indefinite articles (low-accessibility anaphora devices). For instance, a noun-phrase-rich knowledge-transforming sentence immediately following an argument could be a proxy for elaboration, one of the main cognitive processes in knowledge-transforming (Stein, 1989). For instance, through multiple noun phrases, a writer brings fresh information to the discourse by integrating prior knowledge with information acquired from a source. On the other hand, knowledge-telling sentences contain more definite articles and personal pronouns (high-accessibility anaphora devices). This indicates a writer’s tendency to generate text by referring to cues in text already produced, while staying on topic defined by the argument. This pattern aligns with Bereiter & Scardamalia’s (1987) definition of knowledge-telling model.

Knowledge-telling sentences contain more reason-related connectives (since, because, as, inasmuch as, now that). While one may expect that more of these connectives in a sentence should positively correlate with elaboration (e.g., approximating a writer’s reasoning on a topic) leading to knowledge transformation, the results show an opposite effect. This could be explained by a writer’s disposition to take the advantage of a chain of reasoning as already provided in a source article and just translate it into a composition, avoiding further transformation (e.g., by integrating that information with prior knowledge). The example of knowledge-telling sentence containing reason-related connectives is provided bellow:

There has been research that highlights that constructivist learning is effective because it presents learning in a way that would make students more willing and motivated to learn because they can create autonomous decisions around their learning (Association for Psychological Science, 2012).
5.4.2. Linguistic features in a content space

In the content problem space, three linguistic features are important predictors of knowledge transforming: content-word overlap between evidential sentence and source text, semantic overlap between evidential sentence and preceding argument, and semantic overlap between evidential sentence and source text.

A knowledge-transforming evidential sentence has more content words (nouns, verbs, adjectives, and adverbs) in common with the source text. Although this metric was expected to be high for knowledge-telling sentences, the result may indicate that writers producing knowledge-transforming sentences tended to be engaged in elaborating and structuring processes of knowledge transforming. For instance, a writer may wish to group pieces of a source text information into chunks, where each chunk could be a cluster of related content words (e.g., School Readiness: working memory, attention control, information processing; Self-regulation: executive functions, emotions; Good practices in early education: games, literacy, math, science). In the next stage, the writer connects the information chunks and manipulates related source text propositions to ensure that the content material was reshaped properly. The result is a knowledge-transforming evidential sentence like this example:

Before starting kindergarten, children in preschool could increase their readiness by playing a game to help them learn self-regulation skills. (content-word overlap with source: 84.6 %)

Semantic overlap between about 99% of all the evidential sentences in the dataset and their related sources is greater than 5%. However, the degree of the sentence-source semantic overlap cannot solely explain the sentence’s writing mode. There is almost the same probability for those sentences to be either telling or transforming, given its semantic overlap with the source. The evidence-argument semantic overlap feature could help further distinguish telling and transforming sentences in the content space with regard to the sentence’s semantics. A knowledge-telling sentence usually has high semantic overlap (more than 70%) with the argument sentence. This indicates a writer’s tendency to search for and employ source text cues semantically highly similar to the content of an argument. Moreover, such a piece of source information could have also been utilized in creating the argument itself (e.g., while (re)-outlining the essay in the planning stage).
5.5. Instructional and research implications

This study provides grounding for several implications for instruction and research.

1. Undergraduates struggle to engage in knowledge transforming. To help them advance those skills when writing from multiple sources, it is essential to teach them planning, elaborating, structuring and monitoring (Stein, 1990). Accordingly, applying writing and study tactics such as concept mapping, text marking, tagging and note taking may benefit learners throughout this process.

2. Technological solution is needed to provide formative feedback on knowledge transforming that instructors don’t have time to do. Such a solution should be imposing the vocabulary of knowledge transforming on writers and promoting metacognitive monitoring and control, towards improving arguing skills when writers are closely engaged with disciplinary content.

3. Having a large population of post-secondary students use the writing tool may benefit research in learning sciences by gathering ambient data in the “natural ecology of studying” (Winne, 2019, p. 159). The analysis of these ambient data may help in validating some known patterns or point out some new, yet to be discovered patterns in writing based on multiple sources.

4. This study proposed a novel methodology for classifying evidential sentences. The methodology synthesizes cognitive theories of writing and Bloom’s typology for the cognitive domain. It can be replicated and evaluated by researchers who investigate different forms of multi-source writing tasks beyond the argumentative form (e.g., expository texts or lab reports).

5. As a result of this research, a set of features can be proposed to profile a knowledge-transforming sentence in knowledge-transforming discourse. A knowledge-transforming sentence is typically positioned in the middle of a paragraph, within of no more than 3 sentences after the related claim with which it has a moderate semantic overlap. It contains relatively more noun phrases, indefinite articles and the content words from the source text it cites. These results may interest researchers in cognitive linguistics, particularly those interested in mapping characteristics of written discourse to cognitive processes.
5.6. Limitations

The following limitations are identified in this study.

1. Sometimes a continuous sequence of claim sentences appeared in a paragraph. Based on the linear nature of text, my assumption was that an evidential sentence coming after this sequence was connected to the last claim in the sequence. However, this may not always be the case. A more sophisticated NLP algorithm (e.g., for abstractive text summarization) is needed in subsequent research to reliably identify the central sentence/idea in the sequence of claims.

2. Some groups of rhetorical connectives in the study share the same elements. While this is linguistically acceptable, because one connective may play different roles in different contexts (e.g., as may label either simultaneousness of two events or a reason), it was a challenge to link a connective to its appropriate context during preparation of the data for analysis by the classifier. Due to this overlap, multicollinearity problems among some of the features were detected, so I removed three features (simultaneous connectives, causal connectives and content-word overlap between evidential sentence and preceding argument) prior to modelling the classifier.

3. Although well representing the domain knowledge, the corpus used to train the LSA model was relatively small. It would be worth extending this collection with new documents in future research, towards improving accuracy of the LSA model.
References


Appendix A. List of source text titles and modules

Module 1: What is Educational Psychology?
1. Top twenty principles from psychology for preK-12 teaching and learning
2. Intervention improves teacher practices, student engagement in early elementary classrooms
3. Measuring student engagement could help teachers, administrators adapt strategies
4. Are millennial generation students changing the roles of teachers?
5. Teachers more likely to use ineffective instruction when teaching students with mathematics difficulties
6. Principal plays surprising role in why new teachers quit
7. School curricula are a reflection of society's expectations
8. Empathetic teachers enhance children's motivation for learning
9. Positive teacher-student relationships boost good behavior in teenagers for up to 4 years
10. Poor quality teachers may prevent children from reaching reading potential, study finds
11. Targeted teacher turnover boosts teacher quality, student achievement

Module 2: Cognitive Development
1. Nature or nurture? It's all about the message
2. Cultural transmission: The most powerful learning 'tool'
3. Seeing the benefits of failure shapes kids' beliefs about intelligence
4. The marshmallow study revisited: Delaying gratification depends as much on nurture as on nature
5. Brain white matter changes seen in children who experience neglect
6. Nurturing during preschool years boosts child's brain growth: Mothers' support linked to robust growth of brain area involved in learning, memory, stress response
7. 'How much does it hurt?' For preschoolers, cognitive development can limit ability to rate pain
Brain waves show learning to read does not end in 4th grade, contrary to popular theory

All work and no play makes for troubling trend in early education

Reading: Brain waves study shows how different teaching methods affect reading development

Classroom focus on social, emotional skills can lead to academic gains, study shows

Preschool Kids Do Better When They Talk To Themselves, Research Shows

Preschoolers correct speaking mistakes even when talking to themselves

Engaging in fantasy play could benefit creative thinking in children

Positive interactions vital to pre-K learning

Preschoolers' language skills improve more when they're placed with more-skilled peers

Animals talk, sing and act like humans? Young children's reasoning about biological world is influenced by cultural beliefs

Module 3: Self and Social and Moral Development

1. Study challenges widely held view about children's moral judgement
2. The truth about lying? Children's perceptions get more nuanced with age
3. Children who understand others' perspectives found to be more popular among peers
5. Self-esteem in kids: Lavish praise is not the answer, warmth is
6. Seeing the benefits of failure shapes kids' beliefs about intelligence
7. How parents may help create their own little narcissists
8. Predicting long-term success in college
9. Math and me: Children who identify with math get higher scores
10. Facebook status updates reveal low self-esteem and narcissism
11. Are violent video games associated with more civic behaviors among youth?
12. Becoming bad through video games: Risk-glorying video games to increases in teens' high-risk behaviour
13. Poor behavior linked to time spent playing video games, not the games played
14. Helicopter parents take extreme approach to homework: Parents who take the overparenting approach, known as helicopter parenting, are possibly hindering their child's development by becoming too heavily involved in homework.

15. Ending the homework battle

16. Punishing a child is effective if done correctly: Some children need consequences to succeed, psychologists say.

17. Professor finds positive effects from bringing physical activity to the desk

18. Why cliques thrive in some schools more than in others

19. Combination of face-to-face and online bullying may pack a powerful punch: Victims of multiple forms of bullying have more than twice as likely to show aggressive behaviors such as verbal hostility, physical fighting and damaging property.

20. Students with influence over peers reduce school bullying by 30 percent.

Module 4: Learner Differences and Learning Needs

1. Learning styles: A once hot debate redshifts.

2. Gifted students benefit from ability grouping.

3. Gifted Children Shape Their Personalities According To Social Stigma.

4. Education reform urged: Age-based grade assignments hinder millions of students.

5. Black students more likely to be identified as gifted if teachers are black.

6. When it comes to classes, small is better.

7. Minority students are underrepresented in special education.

8. Children with ADHD sleep both poorly and less.

9. Movement in ADHD may help children think, perform better in school.

10. The rules of the game for children with ADHD.

11. Attention deficit hyperactivity disorder is both under and over diagnosed, study suggests.

12. Children with autism learn new words much like others do, study finds.


15. Bullying by students with disabilities reduced by social-emotional learning.

16. Inclusive classrooms don’t necessarily increase friendships for children with disabilities.
17. New study points to better classrooms for children with disabilities
18. Attention problems in early childhood can have lasting impact: Children with attention problems in early childhood were 40 percent less likely to graduate from high school, new Duke study finds
19. Low IQ students learn to read at 1st-grade level after persistent, intensive instruction
20. UK education: Special needs students and teachers are victims of 'muddled' approach to schooling

Module 5: Linguistic and Cultural Diversity
1. Language acquisition: From sounds to the meaning: Do young infants know that words in language 'stand for' something else?
2. Sound trumps meaning in first language learning
3. Language literacy in kindergarten important for success in learning English
4. Kindergarten boys less interested in language activities, study indicates
5. Speakers of two dialects may share cognitive advantage with speakers of two languages
6. Bilingual brains better equipped to process information
7. Bilinguals have an improved attentional control, study suggests
8. Practice makes perfect: Switching between languages pays off: Bilingual toddlers who obtain more practice in language switching are better at certain types of problem solving
9. Taking your ears back to square one to improve language learning
10. 'Now-or-never bottleneck' explains language acquisition
11. Are educators showing a 'positive bias' to minority students?
12. Refugee children's academic outcomes similar to non-refugee peers despite learning challenges
13. Social class makes a difference in how children tackle classroom problems
14. Do social factors affect children’s educational achievements more than cognitive ability?
15. Girls more anxious about mathematics, STEM subjects compared to boys: Gender equality, female role models not making a positive difference, study finds
16. Girls from progressive societies do better at math, study finds
17. Science curriculum tailored to English language learners boosts student achievement
18. Children and youth learning English require better support for academic success
19. Asian-American students have strong academic support But is it too much?
20. Do race-based stressors contribute to the achievement gap?

Module 6: Behavioral Views of Learning
1. Time flies when you're having goal-motivated fun
2. Teaching children with disabilities to monitor their behavior, improves their behaviour
3. When being called 'incredibly good' is bad for children
4. Simple reward-based learning suits adolescents best
5. Motivation through punishment may not work
6. Physical abuse and punishment impact children's academic performance
7. Punishing kids for lying just doesn't work
8. Task master: Categorizing rewards improves motivation
9. Narrow misses can propel us toward other rewards, goals
10. Parents of anxious children can avoid the 'protection trap'
11. Too much undeserved self-praise can lead to depression
12. Self-inflation harms kids' relationships at school
13. Individual rewards can boost team performance at work
14. Immediate rewards for good scores can boost student performance

Module 7: Cognitive Views of Learning
1. Don't multitask while you read this Distractions diminish people's ability to remember, but important facts still stick
2. The brain mechanism behind multitasking The brief reactivation of a learned memory can block interference from competing tasks
3. Picture overload hinders children's word learning from storybooks
4. Expectation may be essential to memory formation
5. Focusing on executive functions in kindergarten leads to lasting academic improvements
6. Neuropsychology: Power naps produce a significant improvement in memory performance
7. Greater working memory capacity benefits analytic, but not creative, problem-solving
8. New study reveals visual working memory may provide clues to autism’s social struggles
9. Stronger working memory, reduced sexual risk-taking in adolescents
10. How poverty may affect memory
11. No room to think: Depressive thoughts may have a negative effect on working memory
12. Higher-income students have an edge when it comes to working memory
13. Good working memory can make you a better liar
14. Gesturing with hands a powerful tool for children’s math learning
15. Emotionally positive situations boost memory for similar future events
16. New study decodes brain’s process for decision making
17. Pictorial mnemonics x sound contrasting = more effective English teaching

Module 8: Complex Cognitive Processes
1. Metacognition training boosts gen chem exam scores
2. Lecturing likely not effective for developing problem-solving skills in students
3. Student engagement more complex, changeable than thought
4. Critical thinking instruction in humanities reduces belief in pseudoscience
5. Student self-testing earns high marks as study tool
6. Scientific Literacy Happens -- When Students Think For Themselves
7. Why argue? Helping students see the point
8. Imagining dialogue can boost critical thinking
9. Grade-school students teach a robot to help themselves learn geometry
10. Day dreaming good for you? Reflection is critical for development and well-being
11. Feedback can have a negative impact on performance
12. Which study strategies make the grade?
13. Writing assignments boost critical thinking skills for landscape design students
14. Babies have logical reasoning before age one: Deductive problem solving was previously thought to be beyond the reach of infants
15. Meta-cognitive therapy more effective for adult ADHD patients
16. Benefits of online interaction for teens outweigh danger, professor says

67
Module 9: The learning Sciences and Constructivism

1. College Freshmen In US And China: Chinese Students Know More Science Facts But Neither Group Especially Skilled In Reasoning
2. Hands-on learning turns children’s minds on to science
3. Hands-on science courses shown to boost graduation rates, STEM retention
4. Students as teachers effective in STEM subjects Peer to peer learning model is gaining traction according to new study at Syracuse University
5. How the brain builds on prior knowledge
6. What makes self-directed learning effective?
7. Self-directed, iterative learning dramatically improves critical thinking in STEM classes
8. Learning By Blogging
9. Transforming teaching with Twitter: Social networking service helps teachers engage students in class and after
10. Digital games and classroom learning: Study finds helpful features, gaps
11. Learning chemistry within Minecraft video game
12. Cooperative classrooms lead to better friendships, higher achievement in young adolescents
13. Group learning makes children better decision-makers, study finds
14. Working together can help battle effects of fatigue: Teams show more flexible thinking when fatigued than individuals, study finds
15. Mobile apps make reading fun for children with dyslexia, occupational therapist says
16. Pros and cons of video games in schools

Module 10: Social Cognitive Theory

1. Thinking strategically about study resources boosts students' final grades
2. Students know about learning strategies -- but don't use them
3. Practice less and play like a pro, say researchers
4. Is risk-taking behavior contagious?
5. Copycats pave the way to problem-solving success
6. Why do chronically lonely teens stay lonely? Even the rare invitation to a social event is likely to be met with suspicion, study finds
7. People estimate their own abilities based on others' performance
8. Confident teachers help preschoolers more with language and literacy skills
9. Persistence makes the difference in minority participation in science, researchers say
10. Self-regulation game predicts kindergarten achievement
11. 'Simon says': Preschool-age kids in different countries improve academically using self-regulation game
12. At-risk children who can self-regulate behavior have higher test scores than their peers
13. Self-regulation Abilities, Beyond Intelligence, Play Major Role In Early Achievement

Module 11: Motivation
1. Talking to children about STEM fields boosts test scores and career interest
2. Will we succeed? The science of self-motivation
3. Brain tune-up may aid self-motivation
4. Conscientious people are more likely to have higher GPAs
5. Student confidence correlated with academic performance, horticultural science class study finds
6. Overconfidence linked to one’s view of intelligence: Those who think intelligence is fixed have confidence exceeding their ability
7. Students Who Believe Intelligence Can Be Developed Perform Better
8. Fear of failure from a young age affects attitude to learning
9. How emotions influence learning and memory processes in the brain
10. Just made a bad decision? Perhaps anxiety is to blame
11. Adolescents stress more with poor sleep
12. Stress inhibits spatial perception
13. Goals affect feelings of pride, shame after success, failure
14. Dutch students’ grades lower due to lack of sleep
15. How curiosity changes the brain to enhance learning
16. Group project? Taking turns, working with friends may improve grades
Module 12: Teaching Every Student
1. Understanding student weaknesses
2. 'Vital signs' of teaching captured by quick, reliable in-class evaluation
3. Negative classroom environment adversely affects children's mental health
4. Stress contagion possible amongst students, teachers
5. Interactive teaching methods help students master tricky calculus
6. More challenging content in kindergarten boosts later performance
7. Disruptive children benefit from tailored classroom intervention
8. Flipped classrooms turning STEM education upside down
9. Better student performance with peer learning
10. Improve grades, reduce failure: Undergrads should tell profs 'don't lecture me'
11. School environment affects teacher expectations of their students
12. Race biases teachers’ expectations for students: White teachers more likely to doubt educational prospects of black boys and girls
13. Improve learning by taming instructional complexity
14. Are you trying to be difficult?
15. How much math, science homework is too much?
16. Pre-lecture diagrams help students take better notes, learn more

Module 13: Assessment and Grading
1. Five recommendations for standardized test designers
2. Testing can be useful for students and teachers
3. Standardized testing creates 'toxic environment' in schools, professor says
4. Tools that assess bias in standardized tests are flawed, study finds
5. Study on the assessment of students: Overcoming bias in decision making
6. Epidemic Of Student Cheating Can Be Cured With Changes In Classroom Goals
7. Use of 'digital badges' in schools would motivate students, research shows
8. Exam anxiety may lead to better grades
9. Teachers' assessments not always conducive to fair education, researcher says
10. Even when test scores go up, some cognitive abilities don't
11. Verbal feedback gets pupils thinking
12. College readiness declines when school's focus is improving test scores, study finds
## Appendix B. Corpus statistics

### Table B.1. Macrostructure (per essay)

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Table B.2. Distribution of argumentative categories in body paragraphs (per essay)

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