Pegem Journal of Education and Instruction, Vol. 12, No. 1, 2022 (pp. 256-271)

RESEARCH ARTICLE WWW.PEGEGOG.NET

Corpus Analysis on Students' Counter and Support Arguments in Argumentative Writing

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Abstract

This study analyzes the linguistic features of counter-arguments and support arguments using two computational linguistic tools: Coh-Metrix and Gramulator. The research question investigates whether counter-argument paragraphs and support paragraphs are different in terms of their linguistic features. To conduct this study, a corpus of 78 argumentative papers was collected. The paragraphs in the papers were categorized in terms of their function. The categories included functions of Support, Counter-argument, Expostulation, Counter-argument and Expostulation, Background, and Other. The paragraphs were analyzed for their readability and writing quality through Coh-Metrix. With the exception of the measure of Deep Cohesion, the Coh-Metrix results suggest minimal differences in terms of readability and writing quality between counter-argument and support paragraphs. Following the Coh-Metrix analysis, both counter-argument and support corpora were analyzed through Gramulator for their lexical features. The Gramulator results suggest the presence of causal language and fixed expressions in counterarguments, as well as some tagged language in support arguments.

Keywords: Auto-Peer, Counter-arguments, tagged Language, Coh-Metrix, Gramulator,.

Introduction

At the heart of some of the most well-known models of argumentation in writing, including the Classical, Rogerian, or Toulmin, lies the concept of addressing alternate points of view. The presentation of such points of view is often expressed in the field of writing studies as counter-arguments. Research suggests that integrating counter-arguments in writing can 1) enhance persuasion by eliminating myside bias (O'Keefe, 1999; Rottenberg, 1988; Toulmin, Rieke & Janik, 1979) 2) cultivate critical thinking skills (Johnson, 2002; Kuhn, 2005) and 3) improve writing quality (Abdollazadeh, Farsani, & Beikmohammadi, 2017; Allagui, 2019; Benetos & Bétrancourt, 2020; Leitão, Leita, & Leitão, 2000; McCann, 1989; Qin & Karabacak, 2010). Thus, the consideration of alternative points of view in writing can yield many benefits to students in terms of personal development and skill acquisition.

Despite the apparent benefits of including counter-arguments, student written arguments are reportedly lacking in sensitivity towards alternative perspectives (National Center for Educational Statistics, 2012). Moreover, many studies have shown that students simply neglect integrating counter-arguments into their writing (Knudson, 1992; Leitão, 2003; Perkins, Farady & Bushey, 1991; Stapleton, 2001). This lack of counter-argument integration may be attributed to issues such as students experiencing high cognitive load (Coirier, Andriessen & Chanquoy, 1999; Darling-Hammond, 2020) or pre-existing cultural differences that affect cognitive processing (Rusfandi, 2015). This having been said, a lack of counter-arguments in student papers may simply be attributable to insufficient instructor requirements for their inclusion. Indeed, studies such as Lam, Hew and Chiu (2017), Nussbaum (2008) and Nussbaum and Schraw (2007) suggest that with effective instruction, students can learn to successfully integrate alternative points of view into their writing. As such, there seems to be empirical evidence that addressing counter-argumentation in writing instruction has a positive effect on the rates of counter-argument inclusion by students. However, it should be noted that there is some ambiguity as to whether successful counter-argument integration is dependent on instructors increasing an emphasis on their inclusion, students receiving more instruction as to their purpose, or materials designers including a wider array of features that exemplify their form.

With these issues in mind, the current study aims to assess argumentative student writing for the frequency of counter-argument integration as well as to compare the structural and lexical differences between counter-argument paragraphs and their supporting counterparts. Through such an analysis, the

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How to cite this article: McCarthy PM, Kaddoura NW, Al-Harthy A, Anuja M. Thomas, Duran ND, Ahmed K (2022). Corpus Analysis on Students' Counter and Support Arguments in Argumentative Writing. Pegem Journal of Education and Instruction, Vol. 12, No. 1, 2022, 256-271

Source of support: Nil

Conflict of interest: None.

DOI: 10.47750/pegegog.12.01.27

Received: 01.10.2021

Accepted: 18.12.2021 **Publication:** 01.01.2022

study may provide a greater understanding of 1) the degree to which instructors expect counter-arguments to be integrated into student text and 2) the features and language of counter-argument paragraphs that may contrast with their presumably more abundant supporting counterparts. The study also aims to provide instructors and material designers with some insight as to how students write and construct argument paragraphs. By gaining such knowledge, instructors can better identify student counter-argument writing issues and resolve them with appropriate instruction. With such instruction, students may be able to more efficiently and effectively integrate counter-arguments into their argumentative writing.

The Language of Counter-Arguments

A review of the literature, suggests that there are relatively few studies that directly investigate the linguistic features of written counter-arguments (c.f. Qin & Karabacak, 2010). Instead, the most widely available source of information about writing counter-arguments comes from writing center websites of various universities such as the University of Arizona, George Mason University, University of Nevada, and the University of North Carolina. Most notably, the Harvard University Writing Center recommends using certain transitions and fixed expressions to signal a counter-argument. Some examples of these fixed expressions include 'one might object here that…', 'it might seem that…', 'It's true that…', 'admittedly', or 'of course'. Similarly, some of the expressions suggested by Qin and Karabacak (2010) include words and phrases like "but," "even though," and "It is said that" (p. 449).

The use of fixed expressions to signal counter-arguments in writing has also been demonstrated in the findings of McCarthy, Kaddoura, Al-Harthy, Buck, Ahmed, Duran et al. (2021b). That study required expert judges to determine the non-contextualized function of a paragraph (as counter-argument or support argument). The experts' judgements were based on the linguistic cues found in the given paragraph. The findings suggest that expert judges were able to distinguish non-contextualized counter-arguments from support paragraphs. Their ability to distinguish the function of paragraphs was attributed to explicit cues found in the beginning of a paragraph. Some of the cues used to signal counter-arguments included expressions such as 'Some people may argue,' 'On the other hand,' 'Despite the fact that,' 'Those who oppose,' and 'Nevertheless, some argue.'

Effects of Counter-Argumentation Integration on Persuasion

In persuasive writing, writers present an argument so as to try to persuade the readers to agree with their claim (Rothery, 1996; Schleppegrell, 2004). However, when attempting to persuade the readers, writers are at risk of "myside bias." The issue of "myside bias" occurs when individuals present and evaluate evidence in a way that is biased towards their own beliefs and attitudes (Toplak & Stanovich, 2003). More specifically, student writers tend to support their preferred point of view while ignoring opposing claims (Perkins, 1985; Perkins et al., 1991). By choosing to focus on their preferred point of view, students risk compromising the persuasive element of their writing.

Numerous studies have demonstrated that including counter-arguments helps to mitigate myside bias as well as enhance the persuasiveness of an essay (Crammond, 1998; Hass & Linder, 1972; Stanovich & West, 2008; Wolfe & Britt, 2008; Yeh, 1998). To demonstrate, O'Keefe (1999) conducted a meta-analysis of 107 studies on persuasive messages. The study revealed that two-sided messages (i.e., those where opposing claims were presented and refuted) were more persuasive than one-sided messages (ones that did not include opposing claims). Therefore, by including counter-arguments in their writing, students also enhance the persuasiveness of their argument.

When addressing the issue of myside bias, it is also worth taking the 'familiarity backfire effect' into consideration. The backfire effect is a "process by which people implicitly counterargue against any information that challenges their worldview" (Lewandowsky, Ecker, Seifert, Schwarz & Cook, 2012, p. 119). As such, the 'familiarity backfire effect' entails that the repetition of an opposing viewpoint may further reinforce a person's originally held beliefs. As a result, when writers develop their counter-arguments, they need to take heed of how they are presented and addressed. For example, if a writer poorly integrates counter-arguments for the sake of strengthening their own position, it may further contribute to a confirmation bias. Therefore, it is important to report factual evidence when presenting the counter-argument.

To further counter-act possible bias, it may be helpful to consider different strategies when integrating counter-arguments in writing. Nussbaum and Schraw (2007) propose three strategies when addressing a counter-argument, which the authors refer to as a process of argument-counterargument integration. The first strategy is called a refutation strategy, in which the writers attempt to disprove the counter-argument. The second strategy is a synthesizing strategy, in which writers develop an in-between solution that offers a compromise between both arguments. The final strategy is weighing, in which writers assess both sides of an argument, discussing its advantages and disadvantages before reaching a conclusive position at the end of the essay.

In addition to *strategies*, there are also various *approaches* to addressing a counter-argument. A straw man argument approach is one example in which "one misrepresents an opponent's position in a way that imputes to it implausible commitments, and then refutes the misrepresentation instead of the opponent's actual view" (Talisse & Aiken, 2006, p. 345).

The aim of such an approach would be to downplay the validity of a counter-argument for the sake of strengthening one's own position. This approach largely contributes to the adversarial nature of persuasive writing (Pollock, 1987) in which writers aim to win against their opponent. Alternatively, a steel man argument approach is the opposite of a straw man. This type of argument was proposed by philosopher Daniel Dennet and recommends that one should construct a strong counter-argument, thereby respecting the opponent's position (Friedersdorf, 2017); only after constructing a plausible counter-argument, can the writer begin to refute it.

Cognitive Load and Counter-Argument Integration

Some research suggests that students may have difficulty developing counter-arguments because of experiencing high cognitive load (Coirier, et al. 1999; Darling-Hammond, 2020). Cognitive load theory posits that people have a limited working memory for processing information (Shehab & Nussbaum, 2015). When working memory is experiencing high load, there is an impairment to processing information, with subsequent feelings of confusion, frustration, and other negative emotions (Sweller, Ayres & Kalyugaet, 2011). This effect of an over-burdened working memory is what student-writers may experience when they attempt to integrate opposing viewpoints.

To counteract the effect of high cognitive load, students may resort to simplifying their task through developing just one side of their argument: the side they support. By doing so, the student remains coherent and consistent but loses the balance and persuasiveness in their writing (Simon & Holyoak, 2002). Keeping in mind that persuasion is an important factor in argumentative essays, appearing biased may severely impact the overall quality of a students' essay.

Lack of Counter-Argument Integration in Student Writing

Whatever the reasons or challenges for integrating counter-arguments, there is considerable research suggesting that students' written arguments tend to neglect including alternative points of view (Leitão, 2003; Stapelton 2001). For example, in a study with 202 participants, Knudson (1992) examined the written argumentative skills of students in the 4th, 6th, 10th, and 12th grade. The students' arguments were assessed according to Toulmin's (1958) model of argument. The results of the written arguments revealed that across any grade level, relatively few students included an opposition (counter-argument) or response to the opposition (refutation or rebuttal).

The lack of consideration for alternative points of view is also common among university-level students. For instance, also following the model of Toulmin (1958), Qin and Karabacak (2010) analyzed the structures of argumentative papers. The study involved 133 second-year university English majors at a Chinese university. The results revealed that while elements such as claim and data were abundant in many of the student-written papers, far fewer papers included elements of *counterargument claim*, *counterargument data*, *rebuttal claim*, and *rebuttal data*.

The lack of counter-argument integration seems to persist regardless of the first language of the writer (Abdollazadeh et al., 2017; Allagui, 2019; Hirose, 2003; Kamimura, 1996; Qin, 2009; Qin, 2016; Wolfersberger, 2003). This issue is demonstrated in Rusfandi's (2015) study on argument-counterargument structure in Indonesian EFL learners' essays. The participants of the study were required to write argumentative essays in both their native language (also referred to as L1) and non-native language (also referred to as L2). The results revealed that both L1 and L2 essays appeared to be one-sided and neglected considering other points of view. Such research suggests that the lack of counter-argument integration is a very common issue. Moreover, the issue seems to occur regardless of students' grade levels or their first/second language use. This issue is concerning since counter-arguments integration has been shown to enhance persuasion in a written paper (O'Keefe, 1999; Rottenberg, 1988) and promote critical thinking among students (Stapleton, 2001).

Instruction on Counter-Argument Integration

To remedy the issue of lack of counter-arguments in writing, research suggests that effective instruction may improve its integration. For instance, Ferretti, MacArthur & Dowdy (2000) investigated the effects of general goals vs elaborated goals on persuasive writing among 4th and 6th grade level students. Students who were given the general goal condition were asked to write a letter to persuade an audience with their position on a topic. Students in the elaborated goal condition were given the same goal, in addition to explicit sub-goals based on elements of argumentation. More specifically, the sub-goals required students to rebut alternative reasons offered by someone who disagrees with their position. The results showed that students with the elaborated goal condition produced essays that were more persuasive and included more argumentative elements than their peers who were given the general goal condition.

In a related study, Nussbaum and Kardash (2005) investigated the effects of goal instruction on undergraduate students' persuasive writing. Similar to Ferretti et al. (2000), students were given different conditions on the task of writing a persuasive essay. One condition, the control condition, simply asked students to write their opinion on a given prompt. A second condition, the reason condition, asked students to provide as many reasons as they could to support their position. A third condition, the counter-argument/rebut condition, gave the same instructions as the reason condition, but further requested students to produce counterclaims as

well as rebuttals. The results revealed that students in the counter-argument condition produced a greater number of counterarguments and rebuttals and better-quality essays in comparison to students in the reason condition and control condition. Overall, both studies corroborate the notion that specific goal instruction may help resolve the issue of lack of counter-argument integration in student writing.

Current Study

As discussed previously, students tend to write more paragraphs in their essays that support their positions (Leitão, 2003; Stapleton, 2001) than paragraphs that include alternative positions (i.e., counter-arguments). Despite this issue and the many studies that emphasize the importance of counter-argument integration, there has been little empirical research that analyzes the underlying linguistic structure of counter-arguments found in student-writing. Linguistic structure in this context refers to any language that may affect reading and or writing quality. By analyzing the linguistic structure of counter-arguments, this study seeks to uncover possible linguistic patterns that may be helpful for instructors to integrate into their teaching material. Hence, comparing the language used in counter-argument paragraphs with support paragraphs may provide information not yet fully considered.

The aim of the current study is to investigate the linguistic structure found in counter-argument paragraphs in contrast to support paragraphs. To investigate such an issue, the following research questions were considered: Does the language of counter-arguments differ from that of support arguments? If so, what language is used to construct counter-arguments? And how does this language differ from language used to construct support arguments?

To address this research question, we followed the recommendations of McNamara, Graesser, McCarthy, and Cai (2014) in forming contrasting hypotheses. One hypothesis proposes that counter-arguments are more difficult to construct than support arguments. The contrasting hypothesis proposes that counter-arguments are not more difficult to construct. Our justification for the contrasting hypothesis takes into consideration the possibility of instructional differences. This is because some research suggests that depending on the type of instruction, students can learn to include more counter-arguments in their writing (Ferretti et al., 2000; Nussbaum & Kardash, 2005).

Method

Tools

In order to investigate the research question and corresponding hypotheses, we used two computational linguistic tools, Coh-Metrix (McNamara et al., 2014) and Gramulator (McCarthy, Watanabe & Lamkin, 2012). These tools have been used in numerous textual analysis studies, often together (e.g., Al Habsi, 2014; Booker, 2012; McCarthy, Hall, Duran, Doiuchi, Duncan, Fujiwara, et al., 2009), and have established a solid reputation for informative diagnoses of contrastive text types such as those that are the subject of the current study. For example, previous Coh-Metrix studies have distinguished differences in L1 and L2 science texts, (e.g., McCarthy, Lehenbauer, Hall, Duran, Fujiwara & McNamara, 2007), differences in stylistic markers (McCarthy, Lewis, Dufty, & McNamara et al., 2006), and differences in genre (Louwerse, McCarthy, McNamara, & Graesser, 2004). Meanwhile, Gramulator has been used to distinguish linguistic features of American and Korean scientific writing styles (Min & McCarthy, 2013), texts by their genre features (Rufenacht, McCarthy, & Lamkin, 2011), deceptive and truthful discourse (McCarthy, Duran & Booker, 2012), news topics (Terwilleger & McCarthy 2011), newspaper articles (Haertl & McCarthy, 2011), and gendered language in news reportage (Wen, McCarthy, & Strain, 2013). The following section provides a description of a) the tools used to conduct this experiment, and b) the corpus as it was collected, categorized, and analyzed.

Coh-Metrix

Coh-Metrix is a computational tool that analyzes texts to produce various sophisticated measures of language and discourse (McNamara et al., 2014). The measures (often referred to as indices) correspond to various features of text, including cohesion relations, language, readability, and writing quality. In addition to its innovative indices, Coh-Metrix also provides traditional descriptive features such as average word length and average sentence length measures.

The value of Coh-Metrix has been demonstrated in more than 50 published research studies (e.g., Crossley, Greenfield & McNamara, 2008; Crossley, Salsbury & McNamara, 2009; Duran, McCarthy, Graesser & McNamara, 2006; Kim & Lim, 2019; 2010; Ryu & Jeon, 2020). For example, studies using Coh-Metrix have been able to distinguish between high-cohesion and low cohesion texts (McNamara, Ozuru, Graesser & Louwerse, 2006), analyze authentic and simplifies texts for L2 material development (Crossley, Louwerse, McCarthy & McNamara, 2007), and evaluate intelligent tutoring system dialogues (Wolfe, Widmer, Torrese & Dandignac, 2018).

Coh-Metrix has a total of 108 measures; however, many of them are redundant. For the purposes of this study, measures corresponding to functions of readability and writing quality verified in previously conducted Coh-Metrix studies were selected. More specifically, the measures for readability were based on the recommendations of McNamara et al., (2014) and the measures for writing quality were from recommendations of McNamara, Crossley, and McCarthy (2009). As such, a total of 18 measures were selected and their specifications are detailed in the following section (see Table 1).

Table 1: Description of all 18 measures used in Coh-Metrix

Function	*Measure*	*Measure Abbr.*
Descriptive	Number of sentences	DESSC
	Number of words	DESWC
	Average number of words in each sentence	DESSL
Readability	Narrativity	PCNARz
	Syntactic Simplicity	PCSYNz
	Word concreteness	PCCNCz
	Referential cohesion	PCREFz
	Referential cohesion	CRFAO1
	Deep cohesion	PCDCz
	Verb cohesion	PCVERBz
	Connectivity	PCCONNz
	Temporality	PCTEMPz
Writing Quality	Lexical diversity	LDMTLD
	Lexical diversity	LDVOCD
	Syntactic Diversity	SYNLE
	Syntactic Diversity	SYNMEDpos
	Syntactic Diversity	SYNMEDwrd
	Word Frequency	FREQ_log

The reason for selecting these measures is further detailed below:

Descriptive indices: Three descriptive measures were used to help with checking the output generated. These measures help in predicting patterns of data as well as making sure that the numbers are in line with expectations (McNamara et al., 2014). We used DESSC, which corresponds to the number of sentences in a text; DESWC, for the number of words in a text; and DESSL, for the mean number of words (length) of sentences.

Readability: A total of nine measures were selected to analyze for readability. According to McNamara et al. (2014) these readability measures "can provide robust predictors of sentence-level understanding and the amount of time it takes to read a passage" (p.78). The measures include PCNARz, which corresponds to narrativity; narrativity is closely related to word familiarity, word knowledge, and oral language. PCSYNz, for syntactic simplicity; this measure corresponds to "the degree to which the sentences in the text contain fewer words and use simpler, familiar syntactic structures that are less challenging to process" (McNamara et al., 2014, p. 85); PCCNCz, for word concreteness; this measures for content words that are concrete and meaningful and help the reader to more easily produce mental images. PCREFz and CRFAO1, for referential cohesion; a text said to have high referential cohesion implies overlapping words and ideas that connect the text for the reader. PCDCz, for deep cohesion; this measure reflects the degree to which a text contains causal and intentional connectives; PCVERBz, for verb cohesion; this measure reflects the degree to which there are overlapping verbs in a text; PCCONNz, for connectivity; this measure reflects "the degree to which the text contains explicit adversative, additive, and comparative connectives to express relations in the text" (p.85), and PCTEMPz for temporality, a measure that accounts for temporal cues (i.e. tense and aspect). The measures corresponding to readability aid in exploring the research question of this study. If the measures record significant differences in either direction for most measures, it implies that both argument types are distinguishable in terms of readability; and thus, contain distinct linguistic features.

Writing quality: A total of six measures were selected to analyze for writing quality. The measures attributed to evaluating writing quality are based on the findings of McNamara et al., (2009) and include syntactic diversity, lexical diversity, and word frequency. As such, for lexical diversity, I included LDMTLD and LDVOCD; SYNLE, SYNMEDpos, and SYNMEDwrd for syntactic diversity (the number of words before the main verb); and FREQ_log for word frequency (logarithm for all words). To elaborate, a text of high writing quality contains high values of lexical diversity and syntactic diversity. The justification for using such measures corresponds to the contrasting hypotheses proposed in this study. If counter-arguments contain higher measures of lexical diversity, syntactic diversity and word frequency, this supports the hypothesis that counter-arguments are more difficult to construct than support arguments. On the other hand, if such measures recorded no significant difference between the two argument types, it provides support for the contrasting hypothesis, in which counter-arguments are not more difficult to construct and may be similar to support arguments.

Gramulator

Gramulator is a computational linguistic tool used to provide an in-depth analysis of the explicit lexical features of text. Gramulator allows for both qualitative and quantitative types of analysis and helps researchers identify indicative lexical features of texts (McCarthy et al., 2012). More specifically, Gramulator was created to identify differential linguistic features of correlative text types. The notion of 'correlative text types' implies the use of sister corpora, which is within the scope of the current study. Accordingly, by contrasting one corpus to another, we can reveal the features indicative of each corpus, relative to each other.

The concept of correlative text types is perhaps best demonstrated through a simple analogy. For example, we could consider a comparison between raspberries and blackberries. Upon comparing such closely related fruits, we uncover features of each fruit that are relative to the contrasting one. The merits

of such a comparison lie in the assumption that both items are relatively similar. This results in meaningful distinctions in the identified features. In contrast, if we were to compare a raspberry to a potato, the differences would be so vast (and obvious) to the point where all identified differential features would be rendered meaningless. As such, since this study focuses on the linguistic structures of two seemingly similar types of paragraphs (counter-arguments and support paragraphs), these two sub-corpora were assessed through Gramulator.

The Gramulator processes text using N-grams. Simply put, N-grams are "a sequence of N units, or tokens, of text, where those units are typically single characters or strings that are delimited by spaces" (Banerjee & Pedersen, 2003, p. 370). N-grams typically consist of one word (uni-grams), two words (bi-grams) and/or three words (tri-grams). In Gramulator analyses, the most frequently identified n-grams are called typicals. However, most typicals are generally common to both corpora under analysis, meaning that the typicals do not have the power to differentiate. As such, Gramulator analysis usually considers the n-grams known as differentials. McCarthy et al. (2012) defines these differentials as follows: "Differential N-grams are those N-grams that are among the most commonly occurring in one corpus (i.e., among the 50% most frequent n-grams) but are uncommon to the contrasting corpus (i.e., not among the 50% most frequent n-grams)" (p. 6). Thus, differentials have the power to differentiate corpora because they are high frequency for one corpus while being low-frequency to the other.

Gramulator consists of several modules that permit different types of analyses. These modules include the *Main Module*, the Cleanser, *the Sorter*, *the Viewer*, *the Concordancer*, and *the Evaluator*. Of all the modules, *the Viewer*, *the Concordancer*, and *the Evaluator* modules were used to analyze the target corpora in this study.

The Viewer allows for comparing typicals and differential outputs in two contrasting corpora. *The Concodancer*, allows for searching specific words or n-grams in a selected corpus. *The Evaluator* allows evaluating specific indices against any corpus; after performing an analysis, the module has the option to perform either a t-test or Fisher's exact text of the generated outputs. A t-test can be performed by comparing the respective *Values* of each corpus. To clarify, the *value* of a text "is the degree to which the text is composed of the index selected" (McCarthy et al., 2012, p. 15). For example, a text can be analyzed for the degree to which it is composed of function words. In such a case, the value would be *function words* and the numerical proportion of function words (relative to the entire text) would be the evaluation used in the t-test analysis.

Corpus

Our corpus for this study stems from a collection of 111 college-level papers (for full details, see Thomas, 2021). The papers in the corpus were all written by students studying a course in advanced writing at a prestigious Gulf State university. The students themselves come from a wide variety of backgrounds (both in terms of ethnicity and academic majors). To ensure diversity in the quality of the argumentative papers, the papers were collected from seven different classes of the same course, taught by six university professors over the span of two semesters. Three of the professors come from a background in linguistics while the other three have a background in literature studies. Although grades for the papers were not available, we can assume the over-all quality of the papers was relatively high as the course was for "advanced" writing, was taken over a period of 16 weeks, the papers received numerous rounds of instructor evaluation and feedback, and ultimately the papers were "passed" in the evaluation stage. In accordance with the goal descriptions of the specified course, the papers were assumed to be argumentative in nature. As such, the corpus was deemed appropriate as the papers were likely to employ a large number of argumentative strategies including support, counter-argumentation, refutations, and rebuttals.

As the current study focuses on paragraphs rather than complete papers, we set a goal of at least 1000 paragraphs for analysis as a reasonable point of departure. For the purposes of this study, only the body paragraphs were collected. The reason for this being that introduction and conclusion paragraphs serve a different function within the essay. Accordingly, after 78 random papers had been prepared for paragraph assessment, a total of 1,071 paragraphs were available. Note that, on average, each essay contained about 13 paragraphs ($M = 13.358$). While conducting the final analysis of the results, six papers were excluded as outliers based on their excessive average paragraph length (i.e., > 3 SD). This resulted in a total number of 1,025 paragraph.

One of the authors of this study categorized the paragraphs according to their function following the recommendations and definitions proposed in McCarthy and Ahmed (2021) and McCarthy et al. (2021b). As further independent verification of such categorization is welcome, the corpus will be available to researchers upon request. The paragraphs included in the corpus were labeled and categorized as follows.

- *Support:* A support paragraph is one that aims to support either the author's main claim or a subclaim by providing evidence, examples, and research. Typically (but not exclusively), a support paragraph would be structured in a way such that it 1) begins with a topic sentence that clearly states a claim supporting the author's main argument, 2) provides evidence and/or examples to support the claim made in the topic sentence, and 3) is completed with a sentence that summarizes, evaluates, or reinforces the claim of the paragraph (see Appendix for sample).

- *Counter-argument:* A counter-argument paragraph is one that aims to challenge the author's main claim either directly or indirectly. A counter-argument consists of a counterclaim that is further backed up by evidence. Similar to support, an effective counter-argument paragraph (typically, but not exclusively) would be constructed in a way such that 1) It begins with a counterclaim that challenges the author's main argument, 2) provides evidence and examples to support the counterclaim, and 3) is completed with a sentence that summarizes, evaluates, or reinforces the counterclaim of the paragraph.
- *Expostulation:* A paragraph that is distinct from but related to a counter-argument. For example, an expostulation could be a refutation or rebuttal of the counter argument. As such, an expostulation paragraph cannot exist on its own; it has to be preceded by a *Counter-argument* paragraph.

Counter-argument with expostulations: As suggested by its name, this type of paragraph is a counter-argument that contains some form of expostulation. The expostulation functions as a response to the counter-argument brought up in the same paragraph. The expostulation may perform various functions such as acknowledging the validity of the counter-argument or offering a common solution. However, while expostulations may take many forms, they are most typically an attempt to discredit the counter-argument.

Choose one of the above depending on the nature of the study. Quantitative studies should contain detailed and clear information regarding the population of the study, the sample and the sampling method. Relevant characteristics of the sample should be stated. Background: A paragraph that provides the reader with background information about the topic discussed. This type of paragraph may include definitions of key terms or historical information related to the topic proposed. This type of paragraph aims to set the context for what the author will be arguing. Typically, *background* paragraphs occur at the beginning of an essay, but they may also appear in later sections of the paper.

- *Other:* Paragraphs that were classified as *other* were those that did not perform clear functions of any of the previously discussed types. Paragraphs in this category served various functions. For example, some paragraphs served as introductory paragraphs for upcoming sections. Other paragraphs contained background information for sub-topics introduced in the discussion of the essay. Additionally, some of the paragraphs categorized in this type also contained combinations of support arguments and counter-arguments as well as support, counter-argument and refutations. Since McCarthy and Ahmed (2021) recommend separating paragraphs in terms of their function (i.e., supporting, counter-arguing…) no further categorization of these paragraphs was conducted.

Results

The following section presents the results generated by Coh-Metrix and Gramulator.

Coh-Metrix Results

Paragraph Function Count: The results for the paragraph-function-count (see Table 2) suggest that Support is both the most common type and also significantly more frequent than Counter-Arguments (Support: $N = 452$; Counter-Argument: $N = 112$; $X2$ (2, $N = 1025$) = 282.757, $p < .001$). Even when the counts for Counter-Arguments/Expostulations and Expostulations are added to Counter-Arguments, the Support type remains significantly more frequent (X^2 (2, $N = 1025$) = 144.078, $p < .001$). Indeed, the three combined types of Counter-Arguments, Counter-Arguments/Expostulations and Expostulations are significantly less frequent than the uncategorized type of Other (X^2 (2, $N = 1025$) = 21.319, $p < .001$). The results suggest that student argument papers are overwhelmingly composed of paragraphs that support the thesis whereas paragraphs addressing the positions of the presumed audience (i.e., counter-arguments) receive very little attention.

Overall analysis: To assess which paragraph type(s) demonstrated the greatest number of differences, we used an Analysis of Variance (ANOVA) together with a Bonferroni comparison of main effect. It is important to note that the analysis in this section was not meant to form a model. This type of analysis was exploratory in nature and was conducted to determine where potential differences may occur across all six paragraph types. All six paragraph types (considered independent variables) and all 18 selected Coh-Metrix measures (considered dependent variables) were included in the analysis; however, only 11 of the measures recorded differences (see Table 3). It is worth noting that the recorded differences here were between any of the included paragraph types and not specifically to counter-argument and support paragraphs. Based on an equal probability of occurrence, two of the paragraph types recorded a significant number of differences (Other: 21 out of 76, $p = .005$; and Expostulation: 20 out of 76, $p = .011$). The measures that recorded the most

Table 2: Number of examples for each paragraph function

Support	*Counter-Argument*	*CA/Expostulation*	*Expostulations*	*Background*	*Other*
452	112	32	55	25	349

differences were Easability-Referential (Count: $N = 14$; $p < .001$; ANOVA: $F = 12.937$, $p < .001$) and Argument Overlap (Count: $N = 14$; $p < .001$; ANOVA: $F = 10.749$, $p < .001$). The results provide initial evidence that the uncategorized paragraph type of Other, along with the Expostulation paragraph type, are constructed significantly differently in terms of readability and writing quality. The results also provide evidence to suggest that the differing function of paragraphs have a corresponding effect on readability and writing quality, and that these differences can be detected by a wide variety of computational measures produced by a system such as Coh-Metrix. In short, the Coh-Metrix results suggests that there are differences among the various types of paragraphs; however, those differences do not extend to Support and Counter-argument paragraphs.

Support and Counter-Arguments: In this portion of the analysis, the target paragraphs of the study (support and counter-argument paragraphs) were assessed. ANOVA results comparing Support and Counter-Arguments suggest minimal differences between the two paragraph types. Of the 18 measures assessed, each run independently, only Easability-Deep Cohesion (PCDCz) was significant: Support: M = 0.512; SD = 1.210; Counter-Arguments: M = 0.961 = SD = 1.189: F = 12.468, p <.001, ηp2 = .022). Deep cohesion implies that the text contains causal and intentional connectives. The language choices that may have contributed to this result for Deep Cohesion is discussed below in the Gramulator section of results. However, given that just one of the Coh-Metrix variables identified a significant result, the findings suggest that student writers appear to be constructing Support and Counter-Arguments paragraphs similarly with regard to readability and writing quality.

Support, Counter-Arguments, and Counter-Arguments/ Expostulations: Since the category of 'counter-arguments' may share similarities with 'counter-arguments with expostulations,' both categories were independently included in the comparison with support arguments. The ANOVA results comparing Support, Counter-Arguments, and Counter Arguments/Expostulations produced six measures with significant differences between the three paragraph types (See Table 4). All six of these measures demonstrated significant differences between Support and Counter-Argument/ Expostulation paragraph types. Coupled with the previous results for Expostulation paragraphs, these findings suggest that the language of refuting and/or rebutting significantly impact Counter-Arguments in terms of measures of readability and writing quality.

Coh-Metrix: Summary: The Coh-Metrix results suggest that in terms of measures of readability of writing quality, various types of paragraphs tend to differ as a function of their purpose. As shown in the over-all analysis discussion, Coh-Metrix was able to detect some differences across the six paragraph types. This suggests that there are differences in terms of readability and writing quality across some of the paragraph types. However, the target paragraphs of the current study (Support and Counter-Arguments) demonstrated minimal differences, suggesting that student writers construct both paragraph types with relative consistency. As such, given that Support and Counter-Arguments can be distinguished during manual reading, the most likely difference between

Table 3: The significant recorded measures across all six paragraph types

Measure	*BG*	*CA*	*CA/ Exp*	*Other*	*Exp.*	*Sup.*	*Total*	*Sig.*	*F*	*Sig.*
EREFz	1	1	1	3	4	2	12*	<.001	12.937	<.001
Arg-Ov	3	2	1	3	3	2	14*	<.001	10.749	<.001
ECNCz	0	1	1	4	1	1	8*	.026	9.432	<.001
EVERBz	1	1	0	3	2	1	8*	.026	7.954	<.001
ENARz	1	0	1	2	3	1	8*	.026	6.224	<.001
EDCz	0	1	0	2	3	2	8*	.026	6.157	<.001
ECONNz	0	0	0	1	0	1	2	N.S.	4.466	<.001
MTLD	0	0	0	1	0	1	2	N.S.	3.742	0.002
SYNLE	1	1	0	1	4	1	8*	.026	3.53	0.004
VOCD	2	0	1	0	0	1	4	N.S.	3.295	0.006
WC	0	0	0	1	0	1	2	N.S.	2.707	0.019
Total	9	7	5	21*	20*	14	76	/	/	/

Note: * indicates numbers are significant at $p < .05$; *Background (BG)*, *Counter-argument (CA)*, *Counter-argument with Expostulation (CA/Exp)*, *Expostulation* (*Exp*), *Support (Sup)*, *Easability referentials (EREFz)*, *Argument overlap (Arg-Ov)*, *Easability word concreteness (ECNCz)*, *Easability Verbs (EVERBz)*, *Easability narrativity (ENARz)*, *Easability deep cohesion (EDC)*, *Easability connectivity (ECONNz)*, *Syntactic complexity left embeddedness (SNYLE)*, *Lexical diversity (MTLD, VOCD)*, *Word count (WC)*

Table 4: Significant results across different combinations of three types of paragraphs

	Support v CA	*Support v Caref*	*CA v Caref*
PCNARz	/	0.004	/
PCCNCz	/	0.015	/
PCDCz	0.002	0.024	/
PCCONNz	/	0.027	/
CRFAO1	/	0.03	0.015
LDMTLD	/	0.032	0.031

Table 5: Concordances of the Word research in Counter-arguments

The main aspects that marketers mainly research by categorizing each people into cognitive
Mal-ware detection systems. According to lozic (2018), research discovered that ai-agents have the
Be treated just as regular waste would. Research is underway to prevent batteries being discarded
Colleagues who showed some results of a research that observe the link between narcissistic
Shortage of studies is caused by the lack of research on both factors, substance use disorder as well
However, due to the lack of research, this project proposes many challenges to
True scope of impact investments is under researched and the possibility of making it

Table 6: Concordances of the Word research in Support Arguments

To men, Cartwright and Gale's (1995) UK research insists that women have significantly
According to a recent customer service research, an astounding forty two percent of
(Trujillo-jenks & Jenks, 2016). Some research studies have confirmed that online buying
energy-efficient (Sammer & Wustenhagen, 2006). These research findings prove that
and sleeping problems. Rechert's (2015) research shows significant placebo and nocebo
further research has also been conducted on alcohol addiction
Additionally, new research has included 1,800 persons and monitored

Table 7: Fixed expressions for signaling counter-arguments

Critics argue
Critics may argue
Many people argue
One problem with
Opponents argue that
Other people argue
People argue that
People may argue that
Some argue against
Some critics argue
Some people may argue
Despite… some argue
Opponents of… argue

the types may be the integration of specific signal language: a hypothesis that we assess in the sections below.

Gramulator Results

In order to gain more insight on the lexical features of counter-arguments and support arguments, these two sub-corpora of paragraph types (i.e., support and counter-arguments) were processed through Gramulator.

Features of Counter-Arguments

The following section provides the features of counter-arguments uncovered through the Gramulator analysis.

Tagged language in counter-arguments: Of the 18 measures tested in Coh-Metrix, only Deep cohesion (*PCDCz*) was significant when comparing Supports and Counter-arguments. This implies the possibility of some type of causal language occurring in counter-arguments. Following this finding, a bi-gram differential analysis was conducted on both corpora using Gramulator. The results revealed that the most frequently occurring differential bi-gram in counter-arguments was '*can cause*'; presumably, therefore, the *cause* element was primarily driving the Coh-Metrix Deep cohesion analysis.

In order to more clearly establish whether causal language (as a whole) or whether a single word is a defining feature of counter-arguments, a list of words indicative of causal language was assessed through *The Evaluator module*. Based on the recommendations of Thapa, Visentin, Hunt, Watson, and Cleary (2020), we compiled a list of causal words. The list of words included variations of the word *cause* (i.e., *causes*, *caused*, *causing*), *result*, *as a result* and some causal conjunctions such as *since* and *due to*.

An independent t-test was conducted to assess the effect of the causal words list in counter-arguments and support arguments based on the index of *Value*. The index of value here corresponds to the density of the selected words across all the words in a text (i.e. number of causal words divided by the total number of words in a text). The result was in the predicted direction but was only approaching a level of significance ($t(1,565) = 1.805$, $p = 0.072$, $d = 0.19$). The effect size (d) of 0.19 can be described as small. The result provided some evidence for the greater presence of causal words in the counter-arguments corpus in comparison to support arguments corpus. This being said, although causal language may not be a definitive feature of counter-arguments, the results suggest that such wording may be more noticeable in counter-arguments than they are in support arguments. As such, we could assume that causal language is potentially (but marginally) a tagged feature of counter-arguments.

Fixed expressions in counter-arguments: Upon examining the tri-grams (i.e., three-word clusters) of both corpora, patterns of how claims are introduced in counter-arguments can be observed. More specifically, the tri-grams present some of the most commonly found fixed expressions in counter-arguments. Some of these tri-grams included expressions such as *argue that the*, *might argue that*, *may argue that*, *makes them feel*, *people believe that*, and *some might argue*. These expressions are in line with some of the findings presented by McCarthy et al. (2021b), which suggests such expressions are common in counter-arguments.

Upon further inspection, those expressions could be generalized as structures which consist of '*auxiliary verb + argue+ that-clause*', '*quantifier+ auxiliary verb+ argue*' and '*people+ believe+ that-clause*'. The verbs 'believe' and 'argue' could be further categorized as argumentative verbs and used interchangeably in any of the listed structures. In order to determine whether such expressions are a distinct feature of counter-arguments, we ran a list of the tri-grams as well as many possible variations in each sub-corpus. The list included expressions such as 'might argue that,' 'may argue that,' 'some may argue,' 'some might argue,' 'people believe that,' 'people argue that,' 'makes them feel'.

After evaluating the list through both sub-corpora, an independent t-test was conducted comparing the fixed expressions as the value index. The result was in the predicted direction and reached a level of significance ($t(1,565) = 6.095$, $p < 0.001$, $d = 0.643$). The effect size of 0.643 can be described as medium. The result provides evidence for the greater presence of fixed expressions in counter-arguments. Therefore, it seems that the such expressions could be considered a feature of the language of counter-arguments.

Features of Support Arguments

The following section provides the features of support arguments uncovered through the Gramulator analysis.

Tagged language in support arguments: Though the scope of this study is more targeted towards the language of counter-arguments, it is worth noting some of the possible features of support arguments. Out of the most occurring bi-grams and tri-grams, a pattern of comparatives and superlatives was observed. Some of these examples include clusters such as 'are more', 'are more likely', 'most of', 'of the most'. In addition to comparatives and superlatives, words that express emphasis and exaggeration were also detected. Some of these words include examples such as 'a significant', 'a huge', 'a major', 'a high', 'an important'. In order to determine whether such patterns could be classified as distinctive features of support paragraph, we ran a list of the mentioned words through *The Evaluator module* and conducted an independent t-test.

Upon conducting the independent t-test, the result was in the predicted direction and reached a level of significance ($t(1,565) = 3.433$, $p < 0.001$, $d = 0.362$). The effect size of 0.362 can be described as small. The result provides some evidence for the greater presence of superlatives and words of emphasis in the corpus of support arguments in comparison to counter-arguments. As such, words that show comparison and emphasis may be indicative of support argument language.

Biased-language in argument types: Upon examining the uni-grams in both corpora, one word that was of interest was 'research,' which occurred more in the counter-argument corpus than the support corpus. Considering the fact that both support arguments and counter-arguments require students to back up their claims using evidence, examples, and research, it would be reasonable to examine how the word is used in each respective corpus. It is worth noting that the following analysis is qualitative and largely exploratory. As such, the following tables show how the word 'research' occurs in each corpus.

When comparing tables 5 and 6, perhaps the most notable aspect to point out is the biased language surrounding the word 'research' in support arguments, which is absent in counter-arguments. In support arguments, the word *research* is coupled with words that express certainty such as 'insists', 'confirmed', and 'prove'. On the other hand, such language is absent in counter-arguments. In fact, the term 'research' in counter-arguments is coupled with expressions such as 'the lack of' and 'shortage of studies.'

Based on the evidence in this context, it seems that students are more eager to present research that supports their main claim (thesis) in a way that shows validity. In contrast, students tend to downplay the validity of research that supports counter-arguments that challenge their main claim. This being said, it is worth mentioning that absolute objectivity is always challenging to achieve in argumentative research; however, this usage may still be of value in teaching students.

Discussion

This section offers a brief discussion of the results generated by both of the computational tools used in this study. The results of both Coh-Metrix and Gramulator are discussed and analyzed in relation to the proposed research question and corresponding hypotheses. The implications for teaching, limitations, and avenues for future research are further discussed.

Discussion of the Findings

The results generated by Coh-Metrix suggests that the most common type of paragraphs was that of support (significantly more frequent than counter-argument paragraphs). This implies that students write more paragraphs that support their main claim as opposed to ones that challenge it. This finding supports previous literature that claims students often neglect integrating counter-arguments in writing (e.g., Knudson, 1992; Leitão, 2003; Perkins et al., 1991; Stapleton, 2001).

The main research question for this study investigated whether counter-arguments and support differed in terms of linguistic features. The ANOVA results of the Coh-Metrix data suggest that counter-arguments and support paragraphs are constructed with minimal difference in terms of readability and writing quality. However, the paragraph types differed in terms of Deep Cohesion, which implies a possible feature of causality. Upon investigating this feature through Gramulator, the results suggest that causal language may be a feature of counter-arguments and thus can be considered a tagged feature of counter-arguments.

Furthermore, the results generated through Gramulator highlighted a pattern of fixed expressions commonly found in counter-arguments. The fixed expressions reflected how students signal the counter-arguments they introduce. Students use expressions such as 'some may argue' and 'people believe that', thereby giving a signal to the reader of the shift in position. This finding supports the suggestions proposed by McCarthy et al. (2021b) as well as the recommendations made by university writing center websites.

Although the target features of this study focused on counter-arguments, features of support arguments were also identified through the analyses. Support arguments feature tagged language that is apparent through the use of superlatives as well as words of emphasis. The results generated by Gramulator suggest that such features are more present in the support argument corpus than they were in the counter-argument corpus. The combination of both features suggests that students use such strategies to present their arguments in a favorable way in an attempt to persuade their audience.

As for the proposed hypotheses, it seems the results of this study support the second of the contrasting hypothesis, which suggests that counter-arguments are not more difficult to construct than supporting paragraphs. As the results show, students do write counter-arguments and they are not linguistically very different from support paragraphs. However, students seem to construct counter-arguments in an attempt to downplay the validity of the opposing side. This issue could be addressed by teaching students to avoid using a straw man approach, in which the opposing argument is disproven without being properly addressed; and instead, students would be encouraged to utilize a steel man approach, in which the opposing argument is strengthened and developed with great care before attempting to refute it.

Implications for Teaching

The features uncovered within this study may be of use to instructors specifically teaching argumentative writing in their classrooms. First, teachers need to consider the notion that students tend to either 1) neglect writing counter-arguments or 2) write more support paragraphs than they do counter-arguments. Neglecting counter-arguments could compromise persuasion and while writing more support paragraphs may not compromise the quality of the entire essay, it could lead to combative argumentation. Hence, following the advice of Nussbaum and Schraw (2007) in promoting balanced argumentation, it may be worth introducing counter-argument integration strategies to students.

Second, using fixed expressions when signaling counter-arguments is important as it alerts the reader to the shift in viewpoints. Using such expressions is also recommended by various writing centers from top level universities. Table 7 is a compiled list of some of the fixed expressions that may be helpful in signaling counter-arguments. It is worth noting that the main verb (argue) could be substituted for different types of verbs (*believe*, *suggest*, *propose*, etc.).

Finally, as the features of support arguments revealed, some of the language that students use when writing support arguments contains words that express emphasis and to some extent, express exaggeration. On the other hand, students seemed to construct counter-arguments in a negative way as an attempt to downplay their opponent's position and further strengthen their main argument. As a recommendation, students should be taught to employ a steel man approach to properly persuade their audience. Using this approach, writers would construct a strong, well-supported argument in an attempt to acknowledge the position of their critics. Only after doing so, will the writers be able to properly address the counter-arguments of their opponents using appropriate strategies such as those suggested by Nussbaum and Schraw (2007).

Conclusion

The results of this study provide insight on the common student practices in argumentative writing. It is apparent that students tend to either neglect writing counter-arguments or write significantly fewer counter-arguments in comparison to support arguments. The analyses performed using the two computational linguistic tools highlighted that support and counter-arguments may be more similar than they are different. The differences that were identified appear to be largely in the form of tagged language. We conclude that instructors may benefit from informing students as to specific expressions used in counter-arguments and support paragraphs, and that instructors emphasize the importance of including counter-arguments in argumentative writing.

Suggestion

Although relatively few Coh-Metrix variables showed differences, future research should consider constructing a statistical model. Such a model could be constructed through procedures such as discriminant analysis and/or logistic regression. In addition, all Coh-Metrix variables should

be included in such an assessment. Furthermore, although Coh-Metrix assessed the paragraph types in terms of word frequency, these frequencies were based on a generalized list covering numerous genres. Future research should therefore consider frequency in terms of the language deployed in the current corpus. As such, a study of the distribution of the language deployed across counter-arguments and support arguments may reveal differing levels of diversity relative to the actual language used to construct these paragraph types.

Future research could also further investigate the effectiveness of the fixed expressions presented in Table 7 (above). For example, participants would have to rate on a Likert scale which expressions they consider to be most effective in signaling a counter-arguments. Doing so would provide further validation to the findings of this study.

One final avenue of interest concerns automated writing evaluation (AWE) systems. One such tool, Auto-Peer (McCarthy et al., 2021a) currently attempts to inform student writers as to possible writing issues in argumentative papers. These issues include cohesion, paragraph structure, as well as a variety of word choices. The research presented here could facilitate future Auto-Peer development by better assessing the degree to which counter-arguments have been represented in the paper. Keywords would be one such approach for this identification; however, the findings reported here that counter-arguments and support paragraphs differ from other types of paragraph is itself useful. That is, an algorithm that can at least detect paragraphs that are neither countering nor supporting may assist student-writers in better identifying and/or constructing their papers.

Limitation

This study has a number of limitations that could affect the interpretation of the results. First and foremost, the categorization of the paragraphs in terms of their function were conducted by one of the researchers of this study. Although the criteria for categorizing the paragraphs were carried out following McCarthy and Ahmed (2021), there may still be a margin of error. Additionally, the papers collected from for the corpus of this study comprised mostly students who speak English as a second or other language. Results may vary if the study was replicated with a corpus comprising speakers of English as a first language.

In addition, some people may deem refutations and rebuttals an essential part of counter-argumentation, but such expostulations were separated from counter-arguments for the purposes of this study. This was carried out following the recommendations provided in McCarthy and Ahmed (2021). Future research could look into possible patterns when expostulations are taken into consideration.

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Appendix

Paragraph Type Example: Support Paragraph

Firstly, up to date technologies can be used to detect bombs used for blast fishing. Blast fishing, which is commonly used in Asia, is destructive to the environment since dynamites are used. These dynamites explode underwater and cause extensive damage to the surrounding area. To alleviate fish bombing, new and up to date technology can be used. This shows that with the use of technology, bombs that are used to catch fish can be easily monitored and tracked. This alleviates the issue of blast fishing, thus maintaining a safer environment.

Paragraph Type Example: Counter-Argument Paragraph

Some might argue that social media can be good for mental health in different ways, such as decreasing depression and improving self-esteem. Similarly, as Edwards (2018) argues, social media has been known to decrease depression and improve self-esteem. This happens when people chat with each other, which makes them feel like they are a part of a group. Many people now believe that social media shows different aspects of life and you can learn a lot of new things and know many more people on social media which provides comfort and joy. Social media can also offer emotional support during hard times by chatting with others, or maybe by seeing some other people that are like them so they will feel that not everyone is having a perfect life. Research has also suggested that the use of social media has increased collaboration and tolerance, access to social support networks, and health communication (Guinta & John, 2018).

Paragraph Type Example: Expostulation Paragraph

Despite the mentioned challenges, the concept of advancing the manufacturing firms into smart factories are worth the effort of overcoming those challenges. The aim of having sustainable and productive production lines help the rise of more sustainable communities that the world needs because of its current environmental crises. Furthermore, to have more efficient production lines, technologies such as IoT and CPSs that Industry 4.0 uses, have some issues that in the long run should be addressed. Further experience with the technology when applied solves these minor issues.

Paragraph Type Example: Counter-Argument With Expostulation Paragraph

Even though incineration is an adequate waste management practice, there are many problems with the use of this practice. A problem with the waste incineration practice is the release of many different types of harmful gases. Some of these gases are greenhouse gases such as carbon dioxide, which trap heat in the Earth's atmosphere and therefore enhance the effect of global warming. While incinerators do emit a considerable amount of greenhouse gases, they are still less than the greenhouse gases emitted from landfills. According to estimates by the Environmental Protection Agency, the damage costs related to greenhouse gas emissions of landfills is more than $25 per ton, while it is only about $12 of damage costs per ton of waste related to incineration (Papa, 2016, p. 213).

Paragraph Type Example: Background Paragraph

At the start of the 20th century, American innovators returned to electric vehicles. William Morrison came up with the first electric car that was considered the first practical electric vehicle though it still did not have a range. Hybrids were as well invented during this period to solve several issues with electric cars (Dijk & Yarime, 2010). Presently, electric cars are more widespread than ever, as well as their solid ability to travel further distances on their batteries. The Tesla Roadster, for instance, which was released in 2008, was able to cover over 200 miles on one charge of a battery. It was followed by Mitsubishi i-MiEV. The development of these two electric cars marked the start of the modern electric cars period.

Paragraph Type Example: Other (Background to a Sub-Topic)

Turkey – a growing economy applied for joining the European Union gathering but was faced with a series of regulations that were to be installed for consideration of their application. A significant component of the list of activities to be fulfilled by Turkey composed greening practices, especially at the state level that led to the publishing of the Climate Change Action Plan 2011 – 2023. In particular, this included aims of heat insulation renewable energy increase and reduction of energy usage were highlighted. Although there are no institutes for certifying the authenticity of green buildings in Turkey such as LEEDS or BREEAM, around 43 commercial buildings obtained certificates for sustainability from these organizations in 2003.

More than 150 buildings had received the certification by 2014, while three private houses also lined up in the queue. For entering the fraction of EU and developed nations, it requires at least 7 million such homes by 2023 (Yilmaz & Bakis 2015).

Paragraph Type Example: Other (Support and Counter-Claim Paragraph)

At the same time, digitalization permits electricity system operators and customers to regulate how, when, and where electricity is being utilized, with new models of business development. New and additional energy uses are going to be captivated with transportation taking a center spot. However, it is important to note that there are countries that mainly depend on the petroleum industry and the entire globe has a well-developed platform for petroleum products hence making it more difficult for the electric car to penetrate the market effectively.

Paragraph Type Example: Other (Unidentifiable Function)

Furthermore, a portion of students did not adopt to technology-driven classrooms, as they were not used to organizing their studies and inhibiting active leaning. Also, students needed a lot of supervision and extra meetings, as they had negligible experience on how to handle flexible assignments (Klomseri, Muianga, Tedre and Mutimucuio, 2018). On the other hand, a study proved that correctly implementing flipped pedagogy in classrooms made a big difference in the results, as according to Marks (2015), "With carefully selected online pedagogies, students were challenged, engaged, and informed. The design of the online materials was also critical in the success of the flipped model" (pg.244.) Therefore, having a well-designed outline for the students is an important aspect of technology-based classrooms which many instructors fail to apply, as they do not pay small attention to detail when designing the curriculum which suits technological classrooms. On the other hand, all these down sights could easily be avoided by directing surveys and opinion polls for schoolchildren, implementing technology-based classrooms based upon the feedback provided. According to Snelling, Winning and Karanicolas (2016) "Those teachers who did not complete surveys reported that they felt less prepared than those who had conducted surveys(pg.787.) Therefore, conducting surveys and gaining feedback would satisfy not only the students, however, it would also make the instructors' job easier as they have a clear idea of what students prefer.