The Motivational Effects of Feedback: Development of a Machine Learning Model to Predict Student Motivation from Professor Feedback

Zachary Hall Mastrich

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E. S. Geller. Chair
Jorge I. Hernandez
Neil M. Hauenstein
Jyoti S. Savla

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ABSTRACT

The application of feedback to enhance motivation is beneficial across various life contexts. While both feedback and motivation have been studied widely in psychological science, most of this research has used close-ended approaches to study feedback empirically, which limits the scope of investigation. The present study was one of the first applications of text-analysis to assess the impact of feedback on the recipient's motivation. A transformer machine-learning model was used to create a tool that can predict the average motivating influence of a particular feedback statement, as perceived by a recipient within an academic context. Feedback was defined and evaluated from the perspective of Feedback Intervention Theory (FIT). Both research hypotheses were supported, given that the model's motivation predictions were positively associated with the actual motivation scores of feedback statements, and the model was closer to estimating the true motivation scores than expected by chance. These findings, paired with additional exploratory analyses, demonstrated the utility and effectiveness of the model in predicting perceived student motivation from feedback statements. Thus, this research provided a reliable tool researchers and practitioners in academia could use to evaluate the motivating influence of feedback for students, and it might inspire future studies in this domain.

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GENERAL AUDIENCE ABSTRACT

The use of feedback to enhance motivation is beneficial across various life domains. While both feedback and motivation have been studied widely in psychological science, most of this research has used close-ended (not text-analytic) approaches to study feedback empirically, which limits the scope of investigation. The present study was one of the first applications of text-analysis to assess the impact of feedback on the recipient's motivation. A machine-learning model was used to create a tool that can predict the average motivating influence of a particular feedback statement, as perceived by a recipient within an academic context. Both research hypotheses were supported. The motivation predictions were positively associated with the actual motivation scores of feedback statements, and the model was closer to estimating the true motivation scores than would be expected by chance. These findings, paired with additional exploratory analyses, demonstrated the utility and effectiveness of the model in predicting perceived student motivation from feedback statements. Additionally, based on this study it is recommended that professors include specific behaviors to be modified when delivering feedback. Thus, this research provided a tool that researchers and practitioners in academia could use to evaluate the motivating influence of feedback for students, and it might certainly inspire future studies in this domain.

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Chapter 1

Introduction

One of the primary tasks of a teacher or supervisor is to motivate those they manage to perform to the best of their ability. When employees, students, or athletes have the requisite knowledge and skills, motivation becomes a critical determinant of performance (Van Knippenberg, 2000). Interpersonal feedback is a performance-improvement tool that is commonly used in a variety of contexts--academic, occupational, and athletic. Feedback is most often designed to make the recipient aware of a discrepancy between actual and desired performance, and thereby motivate the recipient to close the gap and improve. However, that is not always the outcome. Research indicates that feedback does not always have a beneficial effect on the recipient and may at times debilitate performance (Kluger & De Nisi, 1996).

One way feedback can improve performance is to enhance the motivation of the feedback receiver (Ryan, Koestner, & Deci, 1991). Motivation is a rather complex construct loosely defined as the force that drives and directs behavior (Clancy, Herring, & Campbell, 2017). Given that motivation tends to have positive effects on performance, the impact of feedback on motivation should be a topic of significant interest to both researchers and practitioners. Kluger and DeNisi (1996) have proposed Feedback Intervention Theory (FIT) to help predict the effects of feedback and highlight the importance of task-related and ego-boosting feedback.

The relationship between feedback and motivation has been examined within many domains of psychological science (Geister, Konradt, & Hertel, 2006; Vallerand, 1983). However, the vast majority of these studies have used traditional close-ended empirical approaches to investigate feedback (Alvero, Bucklin, & Austin 2001; Kim, Atwater, Patel, & Smither, 2016; Kluger & DeNisi, 1996, Li, Harris, Boswell, & Xie, 2011), thereby limiting the scope of investigation and leaving open the possibility of bias (DeVellis, 1991; Motowidlo, Hooper, & Jackson, 2006). While close-ended approaches are beneficial, text-based approaches, such as the use of machine-learning models, can be an extremely unbiased, accurate, and efficient method to examine feedback and predict outcomes based on particular feedback statements.

The present study applied a text-based machine-learning model, termed a transformer model, to create a tool for predicting the motivating influence of written feedback statements in an academic context. This transformer model can help identify those words and phrases that have the largest impact on perceived motivation. The current study examined feedback from the perspective of FIT (Kluger & DeNisi, 1996).

1.1 Motivation

Motivation is often referred to as a force that drives and directs behavior (Clancy, Herring, & Campbell, 2017). Work motivation has been defined as the set of internal and external forces that inspires task-related behavior, and determines the form, intensity, direction, and duration of those behaviors (Ambrose & Kulik, 1999). Motivation is also viewed as a process by which behavior is energized, directed, and maintained (Diefendorff & Chandler, 2011). Given that motivation cannot be directly observed, it must be inferred from behavior. Researchers have operationalized motivation in a variety of ways. For example, some have measured motivation as goal-directing behavior (Kluger & DeNisi 1996; Locke & Latham, 1990), time spent on a particular task (Deci & Ryan, 2000), and/or resource allocation (Vancouver, More, & Yoder, 2008). Self-reports of motivation are also used, whereby individuals are presumed to recognize a state of being energized, interested, enjoying, and willing to expend energy on a task (Ryan & Deci, 2000).

The vast majority of research suggests that higher motivation leads to positive performance outcomes (Grant & Sonnetag, 2010; Van Knippenberg, 2000). For example, Cerasoli, Nicklin, and Ford (2014) conducted a meta-analysis of motivation, incentives, and performance, and found motivation to be a medium-to-strong predictor of performance across studies. They also found that intrinsic motivation--experiencing natural positive consequences from ongoing behavior--predicted more unique variance in the quality of performance than did incentives (i.e., extrinsic motivation).

High motivation is actually beneficial beyond task performance, with empirical evidence demonstrating links between motivation and such positive outcomes as job satisfaction, engagement, and subjective well-being (SWB) (Alsawaier, 2018, Bishay, 1996; Milyayskaya & Koestner, 2011). Given these findings, understanding and improving motivation should be a research and application priority for industrial/organizational (I/O) psychology.

1.2 Feedback

Feedback has been identified as a mechanism with the potential to improve motivation in a variety of contexts, including the home, the workplace (van der Rijt, van de Wiel, Wan den Bossche, Segers, & Gijselaers, 2012), sports (Carpentier & Mageau, 2013), and education (Mouratidis, Vansteenkiste, Lens, & Sideridis (2008). Essentially, feedback is information regarding the behavior or the performance of the feedback receiver (Baker, Perreault, Reid, & Blanchard, 2013; Geller, 2016). Performance and behavior are unique constructs that are used in tandem throughout this paper, not because they are interchangeable, but because both are affected by feedback and motivation. Behavior is an observable activity in which a person engages, whereas performance is an outcome that includes behavior, as well as dispositional and situational factors.

1.2.1 Feedback Intervention Theory. Kluger and DeNisi (1996) proposed Feedback Intervention Theory (FIT) as a way to integrate and understand varying empirical and theoretical perspectives of the influence of feedback on performance. According to FIT, once feedback is received, goals and standards become the benchmark from which behavior is assessed. The difference between an individual's current performance and the desired performance criteria (the goal) is referred to as the feedback-standard gap (FSG).

When feedback is used to convey the existence of a FSG, feedback recipients should be motivated to reduce the gap. However, from their review of the literature, Kluger and DeNisi (1996) found that while feedback often improved performance, in over one third of the studies reviewed, feedback actually had a negative impact on performance. These results are explained by FIT, such that feedback can direct the recipient's attention in ways that may or may not facilitate performance.

1.2.2 Locus of Attention. A key assumption of FIT is that feedback changes the locus of the recipient's attention between three levels of control: 1) the task-level, 2) the motivational-level, and 3) the self-level. Task-focused feedback directs the recipient's attention to specific behaviors relevant to the task itself. Task feedback tends to create action goals, which are physical and behavior-focused (Kluger & DeNisi, 1996). Motivational feedback is focused on increasing relevant effort by the recipient. Like task feedback, motivational feedback involves the focal task but targets the effort and time spent on the task, and encourages the setting of deadlines in order to reduce the FSG.

Self-focused feedback provides information about the recipient's past performance, while targeting aspects or characteristics of the self. An example of self-focused feedback might be "I expect better from you." Self-focused feedback can create situations that challenge an individual's self-esteem, autonomy, and self-motivation (Ryan, 1982).

1.2.3 Ego-Threatening and Ego-Boosting. Another important distinction in FIT is whether the feedback is delivered after sub-optimal or good performance. Feedback delivered after poor performance is referred to as ego-threatening (Kluger & DeNisi, 1996). Feedback delivered in a sub-optimal manner following poor performance can have a negative effect on the recipients, despite the fact that it is intended to make recipients aware of a discrepancy between their desired and actual performance and to motivate them to achieve their goal(s) (Kluger & DeNisi, 1996).

While ego-threatening feedback does not always have the intended effect, some research has found a positive correlation between the amount of ego-threatening feedback received and performance quality and/or quantity (Carpentier & Mageau, 2013). However, other findings suggest that ego-threatening feedback reduces motivation (Deci & Ryan, 2000). Fisher (1997) found that when supervisors gave ego-threatening feedback to low performers, they often distorted the feedback in order to make the interaction less negative and uncomfortable. It is possible that ego-threatening feedback is ineffective when it is delivered in a suboptimal manner by diverting the recipient's attention from the task to negative aspects of the self or ego.

Feedback delivered after good performance is referred to as ego-boosting feedback because it can boost the recipient's self-esteem and self-motivation (Kluger & DeNisi, 1996). The purpose of ego-boosting feedback is to confirm and support desired behavior in order to maintain or increase its frequency of occurrence (Carpentier & Mageau, 2013). The recipient of ego-boosting feedback perceives that the task presents an opportunity for self-enhancement which should then lead to an elevation of the individual's standard for performance (Kluger & DeNisi, 1996). Overall, research tends to support a link between ego-boosting feedback and positive outcomes, including higher motivation and improved performance (Amorose & Anderson-Butcher, 2000; Deci & Ryan, 2000; Vallerand, 1983).

1.3 Feedback and Motivation

In general, task-focused feedback has been found to improve motivation, especially when compared to meta-task-focused feedback (i.e., self and motivation feedback). This positive association was observed in academic contexts from elementary to post-secondary students (Butler, 1987; King, 2016; Koka & Hein, 2005). Relatedly, self-focused feedback from coaches was linked to lower motivation among the athletes (Amorose & Anderson-Butcher, 2015). These results support one of the main premises of FIT, namely that feedback that directs attention toward the task at hand will be most effective in improving behavior and performance, likely by its positive effect on motivation (King, 2016). At least one study involving online groups found that feedback focused on motivation, team process, and communication was most effective in motivating team members who had low motivation at the beginning of the group process (Geister et al, 2006).

According to FIT, locus of attention also interacts with personality traits and the nature of the task to determine how feedback will affect the recipient. There is some empirical support for this contention as well. King (2016) noted that sensitivity to feedback--the tendency of the feedback recipient to form or refrain from forming negative attributions--affects how feedback is perceived. This attributional sensitivity combined with the perceived utility of the feedback were instrumental in predicting behavior change among students completing a speech-delivery task.

The predictions of FIT about the timing and the benefits of task-focused feedback over meta-task feedback have some empirical validation. However, many tenets of FIT remain untested, and there are times when feedback is needed following poor performance (ego-threatening) and when feedback about effort and character (or self) may be helpful. It is therefore important to continue to investigate how best to deliver feedback in ways that motivate improved performance.

1.3.1 Close-Ended Approaches. Close-ended approaches to measure feedback are used most commonly to conceptualize and assess feedback in psychological research (Alvero, et al., 2001; Kim et al., 2016; Kluger & DeNisi, 1996, Li, Harris, Boswell, Xie, 2011). These methods are limited by a range defined by the researcher and are based on the operational definition of feedback. For example, intervention-based feedback studies can involve researchers delivering scripted feedback to participants (Johnson, 2013; Oc, Bashshur, & Moore, 2015), whereas in observational studies researchers' code naturally-occurring feedback according to predetermined categories.

Closed-ended approaches have certain advantages as an assessment tool. They can be applied across domains by simply altering the scale (King, 2016), and they are very easy to control–a benefit analogous to that of controlled experimental research (Breaugh, 2008). Questionnaire or rating scales include items selected by the researcher, and are designed to evaluate specific dimensions of feedback. The researchers have complete control over the questions they are asking and the possible responses participants can record. Additionally, closed-ended approaches can be used with any type of feedback, beyond verbal and written statements, including video or graphical performance feedback (Alvero, 2001).

While these approaches are dominant in the psychological research on feedback, there are some drawbacks. Closed-ended approaches are limited in scope and do not capture the full range of feedback that participants could experience. Closed-ended approaches are also susceptible to the bias existing in any questionnaire-based research–the use of double-barreled questions, ambiguous pronoun references, and the use of complex or jargon-based wording (DeVellis, 1991). It is also very likely that lexical miscomprehension occurs in close-ended techniques, in which participants may not interpret each question in the same way (Hardy & Ford, 2014). Moreover, other biases such as social-desirability bias and halo effects can affect close-ended methods (Motowidlo, Hooper, & Jackson, 2006).

1.3.2 Text Analysis in Psychology. Text-based analysis has been around since the mid-1900's (Fucks, 1954), and continues to grow and improve to this day (MuthuSelvi, Mahalakshmi, & Sendhilkumar, 2016; Tweedie & Baayen, 2003). However, to date this method has not been used very much in psychological science, and remains driven by computer scientists and linguists (Iliev et al., 2015). Some social psychologists have adopted text analysis to examine word use, the underlying meaning behind words, and individual differences in word use (Tausczik & Pennebaker, 2010). In I/O psychology, text analysis is primarily applied for authorship identification, organizational reviews such as Yelp, interviews, narratives, articles, and reports (Juola, 2015; Short, Mckenny, & Reed, 2018; Yelp, 2018).

1.3.3 Text-Based Approaches to Conceptualize Feedback. Text analysis is an innovative method to measure feedback. This approach involves training a model on text similar to the feedback that will be examined, and then using the model to predict an outcome. This can be accomplished by pairing each feedback sample with an outcome score or a category of feedback (Sebastiani, 2002). A machine-learning model computes a classifier that trains, tests, and cross-validates itself. Then, the model is used to input text and predict an outcome. Text-based approaches can be accomplished without categorization, but by training a machine-learning model to predict an outcome based on certain text. This machine-learning approach was used in the present study.

The features identified within the text are generally determined by the researchers prior to training a model. These features can take two main forms: content-based features and style-based features (Argamon et al., 2009). Style-based features reflect how the feedback was presented through written text. Markers of style-based features include lexical, syntactic, and vocabulary-complexity-based features. Content-based features target actual words used and the content of the text. Some of the most common text features include part-of-speech variables, lexical diversity, punctuation variables, function-word variables, speech-complexity variables, and effectiveness variables. A description of these text features is provided later in the literature review.

These modern, text-based, machine-learning approaches to study feedback have many benefits. Less labor is needed than with close-ended approaches. Most of the work occurs on the front end when training a model. After a model is trained, little work is needed when applying a model to analyze samples of feedback text and predict an outcome (Iliev et al., 2015). Additionally, these approaches can be used with brief samples of text. For example, Green and Sheppard (2013) conducted an authorship-identification study using a machine-learning text-analysis approach in a Twitter context. The researchers were able to train a model to identify key features of text with writing samples that were extremely short--140 characters or less.

Also, text-based approaches are somewhat domain portable. While the same coding scheme or machine-learning model cannot be applied from one context to another, text-based approaches can be altered for new domains. Machine-learning text analysis can readily be shifted from one domain to another by adjusting the features of the model and collecting data in the new context (Sebastiani, 2002).

The main advantage of text-based approaches is their high accuracy and low bias. Because of the use of cross validation, machine-learning approaches tend to have very little bias in estimation when making predictions (Bengio & Grandvalet, 2004). While these models evidence some errors, the error rate is consistent and is clearly stated in the model output. Machine-learning approaches to text analysis are also very accurate for text classification and prediction (Iliev et al., 2015).

The drawbacks to text-based approaches include the substantial work required on the front end to train a model and obtain large samples (Putka, Beatty, & Reeder, 2017). However, after the model is trained for a particular context and a large number of writing samples are acquired, the process of analyzing text requires minimal work.

Text-analytic machine-learning approaches are not frequently used in psychological studies of feedback. This is not a weakness of the approach, but rather reflects lack of familiarity and interpretation among psychologists (Yarkoni & Westfall, 2017). Additionally, machine-learning approaches are not very useful for theoretical explanation, because they essentially put predictors into a ‘black box’ that provides a prediction (Breiman, 2001). This technique does not tell the researchers which features of the text are the most useful in classifying feedback style, or what mechanisms underlie the prediction with text analysis. This limits the theoretical application for text classification, but is advantageous for practical utility.

1.4 Transformer Models

The present research used a text-based machine-learning approach to examine feedback, specifically a transformer model (Vaswani et al., 2017). Transformer models are able to take text as input and provide a predicted score as the output. This type of machine-learning model receives text samples paired with a perceived motivation score. The model then converts text into numbers and vectors that represent the words and the meaning behind the words. This model is able to receive feedback text and predict average perceived motivation. It can also indicate which words and phrases are the most influential at affecting the perceived motivation score.

This cutting-edge machine-learning model has several benefits. Transformers are unbiased. There is an element of error, but this can be identified in the model output. In addition, with transformer models the input sequence is passed in parallel, which means that all sentences can go through the model simultaneously (Vaswani et al., 2017), enabling the model to capture many levels of relevant information.

Transformer models are also able to include context (Vaswani et al., 2017). Once the word vectors are generated and the text is inputted in the model, words with similar meaning are assigned numbers that are close together, and very different words are given different numbers. The same word could have several different meanings in different contexts within the English language. Transformers are able to include the context of words, as well as their underlying meaning. Some more simple natural language processing will not be able to include the meaning behind the words and sentences in the model.

Another advantage of transformer models relates to attention. Attention refers to which words have more or less influence on the meaning of a sentence. Transformers know what parts of speech, words, phrases, and more to give varying amounts of attention when generating a predicted score. This helps to improve the accuracy of prediction with transformer models.

1.5 Current Study

The present study is one of the first applications of text-analysis to assess feedback with regard to its influence on motivation. A transformer machine-learning model was used to create a tool that can predict on average how motivating a feedback statement will be perceived by a recipient. In accordance with FIT, the current study incorporated two different feedback taxonomies: ego-threatening or ego-boosting, and task, motivational, or self-focus (Kluger & DeNisi, 1996). This 2 (ego-threatening vs. boosting) x 3 taxonomy (task, motivational, or self-focus) created six different feedback categories considered in the present research.

Chapter 2

Review of Literature

2.1 Motivation

Motivation is often defined as a *force* that drives and directs behavior, as well as perceived *reasons* for engaging in a particular behavior or activity (Clancy, Herring, & Campbell, 2017). Similarly, motivation is described as a *process* by which behavior is energized, directed, and maintained (Diefendorff & Chandler, 2011). With regard to occupational settings, Ambrose and Kulik (1999) argued that motivation describes the set of *internal and external forces* that inspire task-related behavior, and determine the form, intensity, direction, and duration of those behaviors. Hence, motivation may be considered an antecedent, a correlate, or an outcome of behavior (Diefendorff & Chandler, 2011).

Some consider motivation to be one of the most difficult and complex constructs to study in psychology, especially since it does not operate in isolation. Many factors affect motivation simultaneously (Diefendorff & Chandler, 2011). Distal external influences, such as local and national culture affect motivation, while proximal external factors like social influences and job characteristics also play a role. Personal dispositions, including personality, gender, needs, and values all impact motivation substantially. Adding to the complexity of studying motivation is the fact that it is not an observable entity and must be inferred from behavior (Ambrose & Kulik, 1999; Clancy, Herring, & Campbell, 2017).

Researchers have operationalized motivation in a variety of ways. For example, some define motivation as: a) goal achievement (Kluger & DeNisi 1996; Locke & Latham, 1990), b) time spent on a particular task (Deci & Ryan, 2000), and/or c) resource allocation (Vancouver, More, & Yoder, 2008). These operational definitions of motivation were derived from a variety of theoretical perspectives.

For instance, Deci and Ryan (2000) examined motivation within self-determination theory. This need-based humanistic theory claims that motivation is influenced by the extent to which these psychological needs are met–competence, autonomy, and relatedness. In contrast, goal-setting theory posits that the setting and pursuit of goals drives human motivation (Locke & Latham, 1990). Vroom's (1964) expectancy theory suggests that motivation reflects people's expectations of the consequences of their behavior.

Although motivation has been examined from a variety of theoretical perspectives and measured in many ways, researchers and laypersons alike generally agree on the basic definition of motivation–a force that drives and directs behavior–and that motivation is a construct positively associated with many beneficial outcomes. Incentives (e.g., money, reward points, paid time off) are often referred to as extrinsic motivators (Cerasoli, Nicklin & Ford, 2014).

2.2 Motivation and Performance

The positive relationship between motivation and performance is strong, robust, and important. Cerasoli et al. (2014) conducted a meta-analysis on over four decades of research on motivation, incentives, and performance, and found motivation to be a medium-to-strong predictor of performance across studies. They noted that intrinsic motivation predicted more unique variance in the quality of performance than did incentives, which predicted more unique variance in terms of quantity. Thus, the relationship between intrinsic motivation and performance was the strongest in those settings that favor quality of work over quantity.

Quantity of performance was defined as output that could be measured by counting discrete units (e.g., number of problems solved), whereas quality of performance was identified when output was compared to an evaluative standard other than quantity, such as creativity or the characteristics of the finished product. Reflecting on the value of intrinsic motivation, these authors concluded that poor performance would be rare for people who derive personal satisfaction from the execution of their tasks.

Researchers have found motivation to be mediated by various factors, including ability, exhaustion, and group identity. Van Knippenberg (2000) reviewed the empirical literature on work motivation from social-identity and self-categorization theory, and found that the positive relationship between work motivation and performance was strongest when social identity was salient, and when the group or organization perceived high performance to be in their best interest. Furthermore, Grant and Sonnetag (2010) found that the emotional exhaustion (often called burnout) predicted by low intrinsic motivation was mitigated by the perception of the positive prosocial impact of the work. It could be argued that the perception that one's work is important to others is in fact another, and important, aspect of motivation. Grant and Sonnetag defined intrinsic motivation as enjoyment of the act of doing one's work.

High motivation is beneficial beyond its effect on improving task performance. Research using experienced-sampling methodology on teachers found that employee motivation and job satisfaction were highly correlated (Bishay, 1996). Additionally, high motivation has also been linked with higher task engagement. Alsawaier (2018) conducted research on increasing motivation and engagement in an educational context by making the curriculum game-based, and found a strong positive link between motivation and task engagement. Further, motivation has been found to relate to SWB. In one study, Milyayskaya and Koestner (2011) found a strong association between motivation and SWB across many contexts, including work, school, and social domains.

Motivation and ability function in tandem to determine performance (Ambrose & Kulik, 1999). In fact, one of the primary tasks of a manager is to motivate subordinates to perform to the best of their ability. When employees, students, or athletes have the requisite knowledge and skills to perform, motivation becomes a critical factor in determining the results of their endeavors (Van Knippenberg, 2000). Given the key role that motivation plays in performance, SWB and job satisfaction, it is crucial for all organizations to try to maximize the work-related motivation of their employees. Therefore, motivation is the primary outcome of interest in the present study.

2.3 Feedback

Feedback influences performance outcomes by motivating the recipient to achieve higher performance goals. Feedback is generally defined as conveyed information regarding the behavior or the performance of the feedback receiver (Baker et al., 2013; Geller, 2016). There are many different aspects of feedback, including; a) the content of the message, b) the tone of delivery, c) the timing of delivery, d) the mechanism of delivery, and e) the reaction of the receiver (Carpentier & Mageau, 2013; Levy & Williams, 2004). Feedback occurs in a variety of contexts, ranging from performance appraisals (Levy & Williams, 2004) to interpersonal feedback in the workplace (van der Rijt et al., 2012) and in sports (Carpentier & Mageau, 2013).

While feedback benefits both behavior and performance, a review of the literature indicates that feedback does not always have a beneficial effect. In fact, Alvero, Bucklin, and Austin (2001), Kluger and DeNisi (1996), and Van den Broeck, Carpini, and Diefendorff (2019) found feedback to be detrimental to subsequent performance in over one third of observed cases.

Therefore, it is important to understand the mechanisms by which feedback can be improved in order to motivate improved performance more consistently.

2.4 Feedback Intervention Theory

Kluger and DeNisi (1996) proposed Feedback Intervention Theory (FIT) to integrate the disparate empirical and theoretical perspectives of motivation, and to provide direction for further investigation of ways to understand and improve the feedback-performance relationship. According to FIT, once feedback is received, goals and standards become the benchmark from which behavior is assessed. The feedback-standard gap (FSG) reflects the difference between an individual's current performance and the desired performance criteria (i.e., the goals). When feedback suggests the presence of a FSG and inadequate performance, individuals typically increase their effort to attain the standard set by their goal (Kluger & DeNisi, 1996). While increasing effort is the most common strategy, the reaction to such feedback is not always constructive and motivating. Some feedback recipients choose to abandon the standard. This is more likely to happen when the individuals do not believe their increased effort can eliminate the FSG.

A third mechanism for reducing a discrepancy between feedback and a goal is to adjust the standard, rather than change or abandon the standard completely. Finally, a fourth method to eliminate a perceived FSG is to simply reject the feedback message. The person who delivered the feedback might be discredited and/or the content of the message could be discounted. If no large FSG exists because an individual's performance is close to the goal, then the supervisor, coach, or mentor should create a FSG by setting or by encouraging the individual to set a new stretch goal–a goal that is challenging but achievable.

2.4.1 Task, Motivation, Self-focus. A primary assumption of FIT is that feedback changes the locus of the recipient's attention between three levels of control: 1) the task-level, 2) the motivational-level, and 3) the self-level. Locus of attention is considered a hierarchy with task-focused on the bottom, followed by motivational-focused, and finally, self-focused on top. With task-focused feedback, the message of the feedback statement places the recipient's attention on the specific behaviors of the task itself. In behavioral science, this type of feedback is also referred to as behavior-based feedback (DePasquale & Geller, 1999). Task feedback tends to create action goals, which are physical and behavior-focused (Kluger & DeNisi, 1996).

Feedback interventions that focus above the task level are considered meta-task processes and include motivational and self-feedback. The term meta-task process reflects the fact that the feedback has the potential to control the focal-task process by linking the task with higher-order goals (Kluger & DeNisi, 1996). Motivational feedback sits on the hierarchy between task and self-feedback. Like task feedback, motivational feedback involves the focal task but directs attention toward increasing relevant effort and time spent on the task, as well as encouraging the setting of deadlines to accomplish the task and thus reduce the FSG. The term "motivational" here does not denote that the feedback *is* motivating, but rather that the feedback is directed toward one of the inferred elements of motivation--namely, the effort expended on a task.

Self-focused feedback sits atop this feedback hierarchy. Self-feedback is delivered to provide information about the recipient's past performance or behaviors, while targeting the self or ego of the feedback receiver. Self-focused feedback can drive individuals to attempt self-enhancement, which can be beneficial to performance. However self-focused feedback can potentially be detrimental to the feedback recipient, since self-feedback may divert attention away from the details of the task and create an ego-oriented situation in which the individual's self-esteem is threatened or challenged. Receiving self-feedback can also be accompanied by a feeling of lost autonomy, since receivers of self-feedback may feel unable to choose their own course of action and believe the supervisor or coach is controlling them. This reduction in perceived autonomy lowers self-motivation and may lead to lower self-esteem (Ryan, 1982).

Meta-task-focused feedback, such as motivational or self-feedback are considered non-behavioral feedback by behavioral scientists because the target of the feedback is not the behavior of individuals but some higher-level person-state such as the recipient's internal motivation or self-esteem (Geller, 2018). Behavior-based and nonbehavioral feedback may be more useful terminology when referring to different types of feedback with laypersons. However, for the purpose of this research and for consistency with FIT, the terms task, motivational, and self are used when referencing the focus of feedback.

2.4.2 FIT, Performance, and Motivation. In general, task-focused feedback is preferred over meta-task-focused feedback (i.e., self and motivation feedback). Geller (2018) indicated that feedback is not as effective at influencing task-relevant behaviors of the recipient when it is not focused on the specific behaviors involved in a target task. Butler (1987) studied four categories of feedback given to 5th and 6th grade students after completing several cognitive tasks. The results revealed that performance on a task was superior when the feedback was task-involved compared to when feedback was ego-involved (self-focused). Another study conducted with athletes found that ego-involved feedback from the coach influenced lower motivation among the athletes (Amorose & Anderson-Butcher, 2015).

King (2016) found that evaluative feedback in the form of grades attenuated students' performance in a speech-delivery task. Similarly, Koka and Hein (2005) found that feedback from teachers was the strongest predictor of student motivation. Moreover, performance feedback that was task-focused had the strongest influence on student motivation, followed by general teacher feedback. Therefore, according to FIT, feedback that directs attention toward the task at hand and away from meta-task processes is most effective at improving performance (King, 2016).

According to FIT, locus of attention interacts with personality traits and the nature of the task to provide an understanding for how feedback will affect the recipient. King (2016) noted that sensitivity to feedback, or more specifically the tendency of the feedback recipient to form or refrain from forming negative attributions, may affect the impact of feedback. This attributional sensitivity, along with the perceived utility of the feedback were instrumental in predicting behavior change in a speech-delivery task for students.

Another study found that students with an intrinsic task orientation spent less time on the task when they received controlling feedback compared to competence-related feedback. In contrast, when students with an extrinsic orientation received controlling feedback, they spent more time on the task than when they received competence-related feedback (Ryan et al., 1991). Additionally, Martocchio and Webster (1992) found that the effectiveness of feedback at influencing performance depended on the motivational orientation of the recipient.

Geister et al. (2006) provided further evidence to support the relationship between feedback and motivation by incorporating a feedback intervention to online teams. The researchers found that increasing the frequency of feedback team members received regarding motivation, task-related and relationship-related aspects of the group process led to higher motivation and better performance, especially among the less motivated team members. Thus, understanding the relationship between feedback and task orientation and the various other factors involved is key to maximizing the benefits of feedback on performance and other related outcomes.

2.4.3 Ego-Threatening vs. Ego-Boosting Feedback. FIT also distinguishes between feedback that has negative or positive effects on the recipient's self-worth. According to FIT, feedback delivered after poor or sub-optimal performance is referred to as ego-threatening, because it can have a negative impact on the recipient's sense of self (Kluger & DeNisi, 1996). On the other hand, feedback delivered after good performance is referred to as ego-boosting feedback because it can enhance the recipient's self-esteem and self-motivation (Kluger & DeNisi, 1996).

Ego-threatening feedback has also been referred to as change-oriented, corrective, or negative feedback. The term "ego-threatening" was used for this research, although "corrective feedback" is suggested when disseminating the research findings. Ego-threatening feedback occurs after an undesirable behavior, and indicates that the target behavior has room for improvement (Carpentier & Mageau, 2013). Ego-threatening feedback informs recipients of a discrepancy between their desired and actual performance. This will ideally lead to improved performance in order to reduce this discrepancy and improve performance (Kluger & DeNisi, 1996). Carpentier and Mageau (2014) found a direct relation between the frequency of corrective feedback from coaches and motivation among athletes, as assessed by athletes' perceptions of coaching feedback and the coaches' perceptions of the athletes' motivation.

While some researchers have found ego-threatening feedback to reduce intrinsic motivation (Deci & Ryan, 2000), such results are not replicated if the ego-threatening feedback is delivered well--based on behavior and focused on the task. Carpentier and Mageau (2013) and Mouratidis et al. (2010) found that ego-threatening feedback can still increase relevant motivation if it is delivered in a way that supports the autonomy of the feedback receiver by providing a choice of future behaviors. To expand on these findings, Carpentier and Mageau (2013) conducted a study with athletes, and concluded that ego-threatening feedback can increase an athlete's motivation and performance if: a) it is delivered empathically; b) choices are offered for solutions; c) the feedback is based on clear, known, and obtainable objectives; d) the feedback avoids person-related statements; e) it is paired with performance-improvement tips; and f) it is delivered in a considerate manner.

On the other hand, ego-boosting feedback is delivered after a desirable behavior. This type of feedback has also been referred to as supportive, promotion-oriented, and positive (Geller, 2018). Similar to ego-threatening feedback, the term ego-boosting was maintained for this research in order to be consistent with the terminology of FIT. However, the term supportive feedback is encouraged when sharing feedback information with the public.

Ego-boosting feedback aims to confirm and support desired behavior in order to maintain or increase the frequency of that behavior (Carpentier & Mageau, 2013). Ego-boosting feedback may indicate to the recipient that the task presents an opportunity for self-enhancement and could then lead to an elevation of the individual's standard for performance (Kluger & DeNisi, 1996). Ego-boosting feedback could influence the recipient to set higher goals for continuous improvement. This creates new discrepancies between performance and goals, and thus inspires a need to improve performance in order to reduce this discrepancy and reach a new, higher-level goal.

Research has found ego-boosting feedback to increase perceived competence and motivation (Deci & Ryan, 2000). Two studies by Mouratidis, Vansteenkiste, Lens, and Sideridis (2008) provide further support for the beneficial impact of ego-boosting feedback on motivation.

Their first study involved students in a middle-school gym class completing a shuttle-run task. The second study involved competitive student athletes and their coaches' subjective performance assessments. The findings from both of these studies indicated that supportive, ego-boosting feedback correlated positively with perceived competence, vitality, greater intention to participate, and the SWB among young athletes.

This direct relation between ego-boosting feedback and intrinsic motivation has been observed for Division I college athletes (Amorose & Anderson-Butcher, 2000) and adolescent male hockey players (Vallerand, 1983). In the latter study, participants completed a decision-making task and received varying amounts of ego-boosting, supportive feedback, or no feedback during the task. The results revealed that ego-boosting feedback resulted in higher self-motivation as compared to no feedback. In addition, the more often the athletes received ego-boosting, supportive feedback, the higher was their reported intrinsic motivation. Similarly, Weinberg and Gould (2011) reported that ego-boosting feedback can help reduce the loss of intrinsic motivation after a defeat in sports competition.

From the feedback-giver's point of view, it is more pleasant to deliver ego-boosting feedback than ego-threatening feedback. Research by Fisher (1997) found that supervisors who gave more ego-threatening feedback to their subordinates thought their subordinates liked them less than did supervisors who gave more ego-boosting feedback. Also, supervisors expected their subordinates' reactions to the feedback to be more negative following ego-threatening feedback, compared to ego-boosting feedback. A key finding of that study was that when supervisors gave ego-threatening feedback to low performers, they often distorted the feedback in order to make the interaction less negative and uncomfortable.

Research by Nelson and Craighead (1977) revealed that people with clinical depression recall less ego-boosting and more ego-threatening feedback than do control participants. While their research was not able to suggest causality, these findings highlight the critical impact of feedback on recipients' behavior and SWB.

Both ego-threatening and ego-boosting feedback are intended to improve the behavior of the feedback recipient. Ego-boosting feedback influences behavior by pinpointing desired behaviors and encouraging individuals to maintain or increase the frequency of the target behavior (Geller, 2018). On the other hand, ego-threatening feedback provides information for improving future occurrences of a target behavior, suggesting that the actual behavior of the individual does not meet a desirable standard. Ideally, ego-threatening feedback provides individuals with information to enable improved behavior and performance by recommending a specific course of action. This is accomplished by focusing on specific changes needed to improve behavior and future performance (Weinberg & Gould, 2011).

The present study incorporated six different feedback categories in accordance with FIT (Kluger & DeNisi, 1996). The first category is ego-threatening task feedback, which occurs when performance is below standard, and the focus of the feedback message is on the task. Secondly, ego-threatening motivational feedback occurs after sub-par performance and calls for more effort from the recipient. Third is ego-threatening self-feedback, which is delivered after sub-optimal performance, and is focused on the self or the ego of the recipient. Next, ego-boosting task feedback is delivered after a good performance and is focused on specific desirable behavioral features of the task. Fifth is ego-boosting motivational feedback, which is also delivered after a good performance, but directs focus to the relevant timely effort of the individual. Finally, ego-boosting self-feedback occurs after above-standard performance, and is focused on the individual who receives the feedback.

2.5 Methods to Study Feedback and Motivation

A variety of methods have been used to examine feedback in psychological science research. However, the use of text-based approaches that incorporate machine-learning models have not been applied in studies of feedback. Text-based approaches allow for an examination of the language used to determine those features that may contribute to improved motivation. This section focuses on the measurement of feedback with an emphasis on written and verbal feedback, since written feedback is the most commonly used (Alvero et al., 2001) and since verbal feedback can be transcribed to written feedback. In psychological science, two main approaches are currently used to measure feedback: close-ended approaches and text-based approaches.

2.5.1 Close-Ended Approaches. The close-ended approach to measuring feedback is the more frequent and traditional way to study feedback empirically (Alvero et al., 2001; Kim et al., 2016; Kluger & DeNisi, 1996, Li et al., 2011). This approach is referred to as close-ended because it is limited by a range and scope decided by the researcher. The researcher determines which dimensions of feedback are important in the context of a particular study and then restricts the possible responses of the individual(s) based on how feedback is conceptualized.

Close-ended approaches to studying feedback vary as a function of how feedback is manipulated and assessed. When feedback is manipulated, it can take place in the field or in a laboratory setting. Some of these feedback intervention-based studies involve researchers delivering scripted feedback to participants (Oc, Bashshur, & Moore, 2015). For example, Johnson (2013) tested which kind of feedback–objective, evaluative, a combination of these, or no feedback–influenced the highest task performance. The study design involved the researchers delivering one of the four different scripted feedback conditions to participants in a laboratory setting in order to determine whether a combination of evaluative and objective feedback led to the best task performance. Feedback-intervention studies can also occur in field settings where a feedback manipulation is implemented. Zohar and Polachek (2014) implemented an individualized feedback condition to managers in a manufacturing company and compared their subordinate's safety-related behavior to that in a control condition.

Examining naturally-occurring feedback is the other close-ended approach to measuring feedback. This is usually accomplished with surveys designed to assess perceived feedback, but often includes behavioral observations, as well. While these two methods are quite different, they are grouped together in this section because for both approaches, researchers create scales and either record the participant's responses or have an observer code the participants' behavior before and after receiving feedback. Examining naturally-occurring feedback delivery and reception is more common in feedback research than experimental manipulations.

The use of Likert scales to assess self-report perceptions of feedback is the most common close-ended technique to assess feedback (Alvero et al., 2001; Li et al., 2011). This can be accomplished by rating one's own feedback style or rating the perceived feedback that an individual receives from others. Rating feedback received from others can come in the form of rating the feedback a subordinate receives from a supervisor or, in the case of 360 or multisource feedback ratings, feedback can be delivered by peers and clients, as well as relevant supervisors (Bracken, Rose, & Church, 2016). For example, Amorose and Horn (2000) had college athletes complete a Likert scale survey--the Coaching Feedback Questionnaire–in order to evaluate athletes' perceptions of their coach's feedback style.

2.5.2 Strengths and Weaknesses of Close-Ended Approaches. *Context flexibility.* An advantage of the close-ended approach to measuring feedback is that it can be applied across domains. Consider the procedure used by King (2016) whereby participants completed a short task (i.e., gave a speech), received interpersonal corrective feedback, and then evaluated the feedback with a Likert-scale questionnaire. The close-ended approach involves the administration of a scale to assess the feedback style the participants receive. This same scale could be administered across domains to athletes who receive feedback after completing a sport-related task, or to a workforce where employees complete a questionnaire after receiving feedback from a supervisor. Close-ended approaches across domains have an obvious implementation advantage.

An additional advantage of the close-ended approach to evaluating feedback is the fact that researchers can control and restrict the questions asked. When evaluating feedback or feedback perceptions with a close-ended approach, participants usually fill out a survey or researchers code observed behaviors of participants on a checklist. These surveys include items selected by the researcher, designed to evaluate specific dimensions of feedback, depending on how feedback types are conceptualized in the study. The researchers have complete control over the questions they are asking and the possible responses the participants can record. This dimension of control is an important aspect of experimental research (Breaugh, 2008).

Close-ended approaches can examine feedback in a wide variety of forms. Alvero (2001) found that feedback research can come in the form of written, verbal, graphical, or video feedback. Close-ended approaches can use any of these mediums for feedback delivery. Asking participants to rate their perceptions of feedback can address any of the above-mentioned forms of feedback.

Behavioral observation can also apply to any type of feedback mentioned above. On the other hand, text-based approaches to feedback focus on written (or verbal) feedback (Sabastiani, 2001). However, with modern technology, it is possible to transform verbal feedback into text, thereby enabling researchers to apply text-based approaches to verbal feedback.

A disadvantage of the close-ended method is that it is limited by the researcher's scope, as implied by the name "close-ended." These approaches do not encompass the full range of possible feedback that participants might deliver or receive. For example, when Vallerand (1983) examined the feedback and motivation of athletes, the information provided by the athletes about perceptions of their coaches' feedback was limited by the items included in the questionnaire. Text-based approaches enable the researcher to obtain open-ended responses, and thereby gain more information regarding feedback perceptions, and obtain a more comprehensive understanding of reactions to feedback without being limited by the researcher's survey questions (Poncheri, Lindberg, Thompson, & Surface, 2008).

A major limitation of close-ended approaches to studying feedback styles is the fact that they are susceptible to bias. When researchers construct surveys or coding schemes, a countless number of small errors can bias and influence error. DeVellis (1991) discussed some of the errors that can occur in scale development, including the use of double-barreled questions, ambiguous pronoun references, and the use of complex or jargon-based wording. Additionally, Hardy and Ford (2014) report that lexical miscomprehension is common in survey research, and it is difficult to know if all respondents are interpreting a question in the same way. Survey methodologies can be riddled with some amount of measurement error, which can lead to a biased evaluation of feedback due to item wording. Behavioral observation and coding of feedback behaviors are limited by bias in the wording of the feedback-related behaviors observed and coded.

Moreover, social-desirability bias and halo effects can affect these methods (Motowidlo, Hooper, & Jackson, 2006). Respondents to feedback questionnaires may want to give a positive impression for how they or their supervisor delivers feedback. Bias does not exist to the same extent with text-based approaches. These approaches are not completely free of bias, but with text analysis, the naturally-occurring text is analyzed. Therefore, one can obtain all available information regarding the feedback.

2.5.3 Text-Based Approaches to Conceptualizing Feedback. Another more recent approach to examine feedback is with the use of text analysis. The most relevant techniques in this domain include an automated categorization of text into predetermined categories and using text to predict an outcome (Sebastiani, 2002). This process involves the application of machine learning to text categorization (Argamon, Koppel, Pennebaker, & Schler, 2009). This approach first involves training a model on documents that are similar to the written feedback text that will be examined. In a feedback context, one approach is for each of these training feedback documents to be paired with a feedback style corresponding to characteristics of the text. First, the researcher defines the characteristics of the text that correspond to each category--a process called feature extraction (Iliev et al., 2015). In this case, each category represents a style of feedback.

The model then produces a vector with elements that represent features of the text that determine the relevant feedback categories. A machine-learning model computes a classifier that categorizes the training samples correctly based on the associated feedback style. Then, the classifier is used on the feedback data in question in order to classify the feedback style or styles present in the feedback text. Text-based approaches can be accomplished without categorization by training a machine-learning model to predict an outcome based on text. This is the method that was used in the present study.

Researchers can use text-based approaches without involving an algorithm, which consists of taking text samples and having human coders identify key features of the text. Humans have been found to be quite competent and reliable at extracting meaning from text (Iliev et al., 2015). However, the human-based methods are less suitable for prediction because of their small effect sizes. Additionally, the labor and time involved in using human-based approaches make them much less efficient than machine-based approaches to text analysis (Sebastiani, 2002).

Prior to training a model, the researcher determines features identified within the text. These features can take two main forms: content-based features and style-based features (Argamon et al., 2009). Style-based features reflect how the feedback was presented through text. Markers of style-based features include lexical syntactic, and vocabulary-complexity-related features. Content-based features address the actual words used and the content of the text. Some of the most common text features are listed and explained below.

Each word within the text can be categorized and converted into a part of speech. This enables researchers to examine the frequency of nouns, adjectives, adverbs, and prepositions. Part-of-speech tagging has historically been conducted manually through human supervision, but advances in computational linguistics have led to systems that can accurately identify the parts of speech in written expression with approximately 97% accuracy (Andor Koppel, Pennebaker, & Schler, 2016). While sentence length and word length were historically the most common parts of speech variables used (Forsyth & Holmes, 1996; Fucks, 1954), researchers can account for text length using the ratio of each feature to text or sentence length, and thereby examine how often people tend to invoke a certain part of speech when presented with the opportunity.

Lexical diversity refers to the variance of people's vocabulary. This can be examined using several common, pre-existing measures (Tweedie & Baayen, 1998). For example, the Measure of Linguistic Textual Diversity (MLTD) is considered to be less confounded with document length compared to other measures (McCarthy, 2005). The MLTD reflects the average number of consecutive words for which a certain type token ratio (i.e., ratio of unique words) is sustained.

Common punctuations are features that researchers can examine in text analysis, as well. This includes the frequency and rate of common punctuations such as commas, quotation marks, apostrophes, and exclamation marks.

Function words typically express grammatical relationships, including conjunctions, prepositions, articles, negations, and other connections (Miller, 1995). The presence of function words is a feature that can help analyze text. To provide a conservative and consistent estimate of accuracy and to use features that are context independent, researchers should refrain from using words specific to one topic. Examples of ways to assess function words include measuring frequency of adjectives, adverbs, pronouns, contractions, negations, coordinating conjunctions, prepositions, and articles. Higher-order constructs created from conceptually-related function words can include: a) comparisons ("better," "worse," "higher,"); b) tentative ("almost," "sometimes," "depends"); c) weak language ("I think," "I believe," "various"); d) transition words ("additionally," "furthermore," "however"); e) temporal words ("henceforth," "previously," "newly"); and f) easy words with high familiarity (Dale & Chall, 1948).

Speech-complexity variables refer to the intricacy of an individual's sentence structure. This can be calculated with: a) the automated readability score (Senter & Smith, 1967), b) the mean word difficulty, c) the average word length and sentence length, and d) the variability of the word and sentence lengths.

2.5.4 Strengths and Weaknesses of Text-Based Approaches One of the most obvious benefits of text-based approaches in examining feedback style is the effectiveness and efficiency of these methods. Sebastiani (2002) reported that the use of human coders is an extremely effective method to interpret the meaning from text. The author also found that text-based machine-learning approaches are extremely accurate and consistent in terms of their categorization. While machine-learning approaches do not provide evidence for explanation, they are very accurate in their capability to predict (Yarkoni & Westfall, 2017). In a feedback context, the objective of text-based approaches can be to use features of the feedback to create a classification or predict an outcome. The accuracy of the prediction ability of machine-learning methods is extremely high in comparison to close-ended approaches (Iliev et al., 2015), and thus this is a major strength of the text-based approach.

The text-based approaches do require human coders if researchers want to use a manual approach, but these methods can still be efficient if the text samples are short and the coding scheme is clear. However, it is more accurate and more efficient in terms of human labor and time to use a machine-learning approach (Sebastiani, 2002). When applying the machine-learning approach to text-analysis, most of the work occurs on the front end when training a model. After a model is trained, little work is needed to apply a model to analyze samples of text and categorize the feedback style(s) present in a sample of text (Iliev et al., 2015).

Related to the efficiency advantage mentioned previously, another advantage of text-based approaches is that researchers do not need long samples of text to train or test a model. Human coders should be able to accurately interpret the meaning behind text with brief samples of writing (Sebastiani, 2002). Additionally, while much research using machine learning for text analysis has used either long or a large number of writing samples (Raminal, Panchoo, & Pudaruth, 2016; Qian, Lui, Chen, & Peng, 2014), this is not necessary to analyze text accurately. Green and Sheppard (2013) conducted an authorship-identification study using a machine-learning text-analysis approach in a Twitter context. The researchers were able to train a model to identify key features of text with writing samples that were extremely short–140 characters or less. Additionally, Mastrich and Hernandez (2020) were able to use text-analysis and machine learning with a single, brief writing sample of approximately 250 words or less.

The fact that text-based approaches are somewhat domain portable is another benefit to their use. While the same coding scheme or machine-learning model cannot be transferred from one context to another, it is quite simple to alter text-based approaches to be appropriate for a new domain. With human coders, the coding schedule simply needs to be adjusted to fit the context of the new domain in order to apply a similar coding scheme for a different setting. Machine-learning text-analysis can be readily shifted from one domain to another by adjusting certain features of the model (Sebastiani, 2002). Data will need to be collected in a different setting to train a model in a different context, but shifting a model from one domain to another is relatively simple and easily accomplished.

Finally, text-based approaches to evaluate feedback type are relatively unbiased. From a machine-learning perspective, bias is never a major concern. Because of the use of cross validation, machine-learning approaches tend to have very little bias in estimation (Bengio &

Grandvalet, 2004). A researcher does have some freedom when including the features for model training. The model is then trained on data and cross-validated such that there is no bias involved when making predictions. There will be some error in these models, but the error rate will be consistent and is clearly stated in the model output.

Along with the benefits of text-based approaches, there are drawbacks. An issue with the use of text-based approaches is that many require substantial work on the front-end of the project. If behavioral observation of feedback is applied, a coding scheme for training coders is required, as well as obtaining consent to observe individuals. Machine-learning approaches require time to train and feature-engineer an accurate model. They also require a larger sample size in order to train the model. Putka, Beatty, and Reeder (2017) found that samples sizes of at least three hundred are needed to improve cross-validated R-squared. Their study incorporated many techniques, such as random forests, that are commonly used in machine-learning models. After training the model for a given context and obtaining a large number of writing samples, this process of attributing a feedback style to text requires minimal work.

The use of text-analytic approaches, primarily machine-learning approaches, has not been used in psychological science research to address interpersonal feedback, and these techniques are not well known by many psychologists. The only research that examined feedback with a text-analysis machine-learning approach was accomplished with reviews of organizations (Wu et al., 2014). The fact that many researchers in psychological science are not very familiar with the details and implementation of machine-learning methods can be a barrier to the use of these techniques to study interpersonal feedback (Yarkoni & Westfall, 2017). While this is not a criticism of the text-based method, it is acknowledgement of a factor that may inhibit the use of this text-based method to study feedback.

Another weakness in the use of machine-learning text-based approaches to study feedback is the inability to infer explanation. Machine-learning approaches essentially put predictors in a ‘black box’ that provides predictions (Breiman, 2001). Iliev et al. (2015) reported that while machine-learning methods are extremely valuable for giving accurate text classification, they do not inform theory very well. This technique does not tell the researchers which features of the text are the most useful in classifying feedback style, or what mechanisms underlie prediction using text analysis. This limits the theoretical application for text classification.

2.6 Text Analysis in Psychology

The use of some version of text-analysis has existed since the mid-1900’s (Fucks, 1954), and continues to grow and improve to this day (Muthuselvi et al., 2016; Tweedie & Baayen, 2003). However, text analysis has not been used much in psychological science, and remains driven by computer scientists and linguists (Iliev et al., 2015). Some clinical-psychology research in the mid-1900s used a simple form of text analysis (Gottschalk & Gleser, 1969; Gottschalk, Gleser, & Daniels, 1958). This research involved patients speaking into a recording device, which was then transcribed to text. Then the researchers evaluated each phrase manually to determine relevance to psychological issues like anxiety, hostility, and others. Psychologists first used computerized text analysis in 1966, when researchers used patients’ recordings with a computer to identify mental disorders and assess personality dimensions (Stone, Dunphy, Smith, & Ogilvie, 1966). However, this practice was limited because the weighting and manipulations were not clearly visible to the researchers.

Since then, some social psychologists have incorporated text analysis (Tausczik & Pennebaker, 2010), primarily to examine word use, the underlying meaning behind words, and individual differences in word use. While text analysis is infrequently used in psychological science, its utility has been shown and has been recommended for use in the future by practicing psychologists (Iliev et al., 2015). A limited number of studies have used text analysis to examine human cognition and behavior, leadership behaviors, and team cognition and performance (Short et al., 2018). In I/O psychology, text analysis is still being integrated into the field. Short et al. (2018) conducted a review of research that utilized text analysis in organizational psychology and found the majority of such studies involved interviews, narratives, articles, or reports.

Limited research has used text-based analysis to examine traditional interpersonal feedback–from one individual to another. A review of text analysis in organization psychology revealed that no studies used text analysis to study interpersonal feedback (Short et al., 2018). The majority of text analyses of feedback is related to reviews. An example of a review is a customer leaving feedback about a company on a website like Yelp (2018). Online reviews present a plethora of data for researchers to use in ways that were not possible before the conception of the modern internet and social media (Iliev et al., 2015). This type of feedback is different than traditional interpersonal feedback because it is often anonymous and involves an individual providing feedback to an organization, as opposed to one individual providing feedback to another. Although in a unique form, feedback via online reviews is still relevant when discussing interpersonal feedback.

2.7 Transformer Models

The present research adopted a text-based approach to study feedback. Specifically, the researchers used a machine-learning model, known as a transformer model, which was introduced by Vaswani et al. (2017). Transformer models are able to incorporate text as input and provide a predicted score as the output. This model was used to input feedback text, paired with motivation scores to train the model. Model training determines how the transformer knows what parts of speech, words, phrases, and more to give varying amounts of attention when generating a predicted score. Then when feedback text is inputted, the trained transformer model will output a predicted motivation score.

When text is first inputted into a transformer model, the words and sentences are converted into numbers (Vaswani et al., 2017). Because computers do not understand words, an important first step is to convert text to numbers, vectors, and matrices. Transformer models map words onto an embedding space. In this space, words more similar in meaning are closer together. The embedding space then maps words to vectors, which creates a numeric representation of each word.

However, it is common for the same words in different sentences to have different meanings. Transformer models deal with this issue very well with the use of positional encoders (Vaswani et al., 2017). Positional encoders are vectors with information about distances between the words in a sentence. In other words, positional-encoder vectors give context based on the position of the word in a sentence. The fact that transformer models account for context is a major strength in accurately evaluating the meaning behind text.

Next, these vectors with positional encoding are passed through an encoder block (Vaswani et al., 2017). This encoder block consists of two layers: a multi-head attention layer and a feedforward layer. Attention refers to which words have more or less influence on the meaning of the sentence than others. In other words, it determines which parts of the sentence should be focused on more or less, thereby capturing contextual relationships between words. In the multi-head attention layer (or attention block), the word vectors are converted into attention vectors, which include information about the relevance of each word relative to other words in the sentence. The feedforward neural layer involves the application of a feedforward neural network to transform the attention vectors into a form that can be understood by the next block in the transformer model.

The word vectors are then passed into a decoder block with three main components: an attention block, an encoder-decoder attention block, and a feedforward block (Vaswani et al., 2017). The attention block creates attention vectors again to examine how words relate to one another. These attention vectors are then passed through the encoder-decoder attention block, along with the attention vectors from the encoder. This block determines the relationship between word vectors, relative to one another. These vectors are then passed through the feedforward block in the decoder, which makes the output interpretable to the next step of the transformer model.

Finally, the output vectors from the decoder are passed through a linear feedforward layer and then through a softmax layer, which transforms the vectors into a probability distribution (Vaswani et al., 2017). This probability distribution is now interpretable by humans. The final output shows how motivating a feedback statement would be perceived on average. A full diagram of the processes used for transformers is provided in Appendix A.

With transformer models, the input sequence is passed in parallel, which means that all sentences can go through the model simultaneously (Vaswani et al., 2017). Recurrent neural networks must pass each sentence through one at a time and generate word embeddings one step at a time. Since transformer models do not include any time steps, they are able to generate all word embeddings simultaneously, which is a revolutionary advantage of transformer models. All of the strengths of these cutting-edge models make them ideal for processing natural language, and thus excellent tools to analyze the impact of feedback statements on recipients' perceived motivation.

2.8 Current Study

The present study developed a machine-learning model to predict how motivating, on average, a feedback statement will be to the feedback recipient. This is the first study to examine feedback and motivation with a text-based, machine-learning approach. Specifically, this research used a machine-learning model--a transformer model--in the context of academia and incorporated six different feedback taxonomies in accordance with FIT (Kluger & DeNisi, 1996). The six feedback categories are ego-threatening task, ego-threatening motivational, ego-threatening self, ego-boosting task, ego-boosting motivational, and ego-boosting self-feedback. These categories are not exhaustive, but rather a parsimonious way to categorize most feedback statements.

The researchers included feedback from each of the six feedback categories, as well as open-ended feedback that may not fit within any one category. The output of the model provides predicted motivation scores for feedback statements, and can thereby inform what characteristics of text are more or less influential for students' perceived motivation. This research is exploratory in nature, and training a machine-learning model in this context is innovative. The following hypotheses were proposed:

Hypothesis 1: The motivation predictions of the model will show a positive linear association with the actual motivation that participants report.

Hypothesis 2: In addition to a linear association, the model will be closer to estimating the true perceived motivation score than the expected motivation score based on chance.

Chapter 3

Method

3.1 Participants

The participants for the present study were 315 students from a large land-grant university in the Southeastern United States. The initial sample consisted of 421 individuals. Of these, 35 were removed because of insufficient responding, 33 were removed because English was not their first language, and 35 were removed because they did not pass the psychological antonym attention checks, yielding a final sample of 315 participants. Of the final sample, 74.6% were female and the mean age was 19.6 years old. Regarding race, 73.3% of the participants were white, 13.0% Asian, 7.0% Black, 5.1% two or more races, 0.3% Alaska Native, and 1.3% of participants selected ‘other’. Table 1 provides descriptive statistics of the research participants, who were recruited through two university classes and the online system the university uses to manage research.

3.2 Procedure

Approximately 50 students participated in Part 1. The goal of this part of the procedure was to create a list of feedback statements for Part 2. Once students agreed to participate in Part 1, they were instructed to provide some examples of feedback they receive in academic settings. This feedback can come from teachers, professors, lab coordinators, teaching assistants, or anyone who is in a supervisory role to them in an academic context.

The students were prompted to provide 16 statements. Specific prompts targeted the six different feedback styles reviewed earlier: ego-threatening task feedback, ego-threatening motivational feedback, ego-threatening self-feedback, ego-boosting task feedback, ego boosting motivational feedback, and ego-boosting self-feedback. Two prompts were included for each of these statements. Additionally, four prompts allowed students to include any additional feedback statements they have received from academic supervisors beyond what is captured by the six feedback categories. Students were instructed to provide hypothetical feedback statements if they could not think of a real-world example. The six different prompts are provided in Appendix B.

A total of 624 statements were obtained from students. Once the feedback statements were collected, the author reviewed them to correct spelling errors and make sure the statements were appropriate. When a student responded in the third-person (e.g., “S/he would say”), the statement was not included. If a student omitted punctuation to conclude a statement, a period was added. Any repeated statements were removed. If a student included vague language (e.g., “please do x, y, and z”), the statement was not included. After removing items that were not appropriate in content or format, 451 statements were available for inclusion in the study.

The researchers prepared additional statements for the total statement pool. The goal was to include a comprehensive array of possible feedback statements. To do so, 35 statements were written to align with each of the feedback categories, yielding 210 total feedback statements that increased the total pool of statements to 661.

In Part 2, undergraduates were presented with 75 randomly-selected feedback statements and asked to rate how motivated they would be if they received each feedback statement from a supervisor or teacher. The feedback statements generated by the researchers are provided in Appendix C. Participants were also asked to provide an affect rating of how each statement makes them feel.

Once the data were collected, perceived motivation and affect scores were aggregated for each feedback statement. This resulted in each feedback statement being paired with a mean perceived motivational score and a perceived affective response score. The Pearson correlation between motivation and affect scores was $r = .78$.

To ensure that perceived motivation and not the affective response was assessed, affect was controlled. To accomplish this, a regression analysis was conducted with motivation as the outcome and affect as the predictor. The residual of motivation was then used in place of motivation for the remainder of the analysis. This new variable was uncorrelated with affect and accounted for all of the variance in motivation that was not explained by its linear association with affect.

3.3 Measures

3.3.1 Motivation. The students' perception of the motivating influence of each feedback statement was recorded as the primary outcome. A single item was used to measure perceived feedback: "If I received the following feedback from an academic advisor, I would be…" This was measured on a seven-point Likert-scale from "Extremely less motivated" to "Extremely more motivated."

3.3.2 Affect. Each participant's emotional reaction to each feedback statement was assessed with one item: "If you received this statement from an academic supervisor, how would it make you feel?" Respondents were instructed to answer with a seven-point Likert-scale from "Extremely unpleasant" to "Extremely pleasant." Recording the affective response of each item enabled control for affect in the motivation ratings.

3.4 Analyses

A transformer machine-learning model was developed with the vision of predicting perceived student motivation from a feedback statement. The transformer model in this study was trained with a batch size of 16, using the AdamW optimizer, with a learning rate of 1e-6, and from the distillBert-Base-Uncased model (Abadeer, 2020). This model was trained using 661 feedback statements that were collected in Part 1 and paired with the residual motivation scores. The final model was able to predict how motivating students would perceive a feedback statement on average.

The model demonstrated an acceptable level of reliability among raters, G(q,k) = .91. Putka's G(q,k) was used to calculate reliability because the present study involved an ill-structured measurement design (ISMD), since statements and raters were neither fully crossed nor nested (Putka, 2008). When dealing with ISMDs, traditional reliability measures, such as Pearson's *r* or interclass correlation (ICC), tend to underestimate reliability calculations. Putka's G(q,k) is the least biased estimate of reliability by overcoming three problems that occur when dealing with ISMDs: 1) different estimates can arise from the same underlying dataset, 2) failing to model rater main effects leads to biased reliability estimates, and 3) failing to model rater main effects presents proper scaling of rater variance. The model reliability of G(q,k) = .91 reflects the proportion of expected observed score variance that can be attributable to true score variance.

The model was evaluated by examining correlations between predicted scores and actual motivation scores. Additionally, mean absolute error of the model was compared to mean absolute error that would result from chance. This model can also serve as a tool to indicate what part of a statement has a larger, smaller, positive, or negative effect on perceived motivation.

This information can be used to teach individuals how to provide feedback with a particular motivating style.

Chapter 4

Results

First, the correlation between perceived affect and perceived motivation was examined. The Pearson correlation between motivation and affect scores was $r = .78$. This large correlation suggests that both constructs are closely related to one another, which raises the question as to if motivation can accurately be modeled while controlling for affect. When feedback is delivered, the affective and motivational responses of the feedback receiver will be strongly related and nearly indistinguishable. However, this research was concerned with predicting perceived motivation. There is no reason to change the a-priori decision of controlling for affect, if the model is able to predict even when controlling for affect. Additionally, because affect and motivation scores were collected cross-sectionally, this correlation may be inflated.

4.1 Testing if Model Predictions Relate to Actual Motivation

The first hypothesis states that the models' motivation predictions will show a positive (non-zero) linear association with the actual mean residual motivation scores aggregated from participants' ratings. A non-zero association reveals whether the model offers predictions that linearly correspond to the typical perceptions of how motivating a statement was (independent of the valence of the statement). A statistically significant non-zero correlation indicates that the linear association is better than expected by random guessing. A correlation coefficient that is statistically different from the average correlation of a single rater, indicates that the model offers utility beyond a single person's guess, and is able to make realistic predictions regarding how motivating (on average) a student would perceive a particular feedback statement from a supervisor.

4.1.1 Testing Hypothesis 1 with a Correlation. To test Hypothesis 1, the Pearson correlation between predicted and actual aggregated residual motivation scores was examined after the model has been trained. A correlation above 0 would provide support for this hypothesis by indicating a positive, linear association between the residual motivation scores participants reported and the motivation scores the model predicted. A correlation statistically above the correlation between the typical correlation obtained from a randomly-selected individual and the mean of the rest of the ratings would imply that the model outperforms how well a single rater can predict.

4.1.2 Model Correlation Findings. The residual motivation scores reported by participants was correlated with the residual motivation scores predicted by the model above zero. The correlation was r = .71 with a 95% confidence interval of (.67, .75), which lends support to Hypothesis 1. Given the unreliability of the outcome, if corrected for attenuation, the observed correlation would be r = .74.

Additional evidence in support of Hypothesis 1 and demonstrating the value added by the model can be seen by further examining the correlation of the predicted and actual residual motivation scores. First, a calculation was obtained for each individual in the sample to determine how correlated their motivation rating for a statement was to the average motivation rating of everyone else for those same statements, while controlling for affect. The average correlation coefficient was r = .23 (*SD* = .16). This indicates how accurately a randomly-selected individual would be on average at estimating the motivating influence of a statement. The lower bound of the confidence interval for the model's correlation was r = .67, which indicates that the model's prediction performance was statistically significantly superior to that of a typical rater. The highest individual correlation coefficient was $r = .57$, which shows that the model demonstrated greater consistency with the average residual motivation rating than even the most skilled individual rater from the present sample.

4.2 Does the Model Predict Closer to True Values than Chance Levels?

Hypothesis 2 states that in addition to a linear association, the model will be closer to estimating the true perceived motivation score than the expected motivation score based on chance. This analysis provides additional information than the prior analyses because it estimates the amount of deviation from actual motivation ratings in raw units, rather than simply illustrating a linear association.

4.2.1 Using Mean Absolute Error to Test Hypothesis 2. In order to test Hypothesis 2, the author calculated the mean absolute error (MAE) between the predicted residual motivation scores and the actual participant reported residual motivation scores. This statistic measures the error of two ratings of the same statement, and is calculated with the absolute value of the average difference between the predicted and actual residual motivation scores. Ideally, MAE should be as close to zero as possible, indicating that the model's predictions never differed from the value they are trying to predict.

To test this hypothesis, two MAEs must be calculated--one representing the MAE of the model and the other representing the MAE based on chance. To estimate MAE obtained by chance, the author subtracted the mean residual motivation score from each residual motivation score and calculated the absolute value for each pair. The mean of these values represents the MAE based on chance.

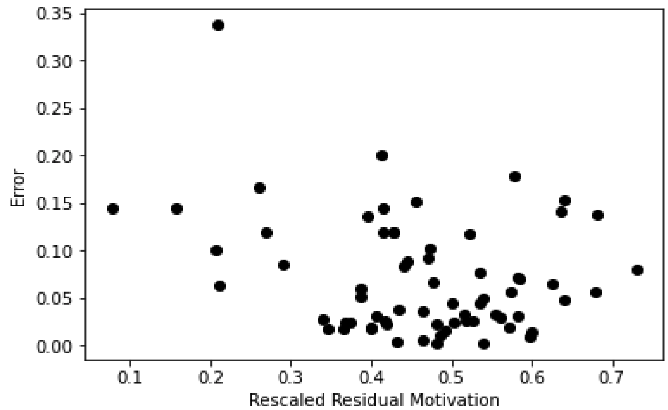
4.2.2 Findings from Mean Absolute Error Analysis. The MAE calculated by guessing the mean for all residual motivation ratings was .09. The obtained MAE of the model's predicted residual motivation and reported residual motivation was .07, 95% CI = (.05, .08). The MAE of the model was closer to zero than the MAE which would be obtained by chance. This finding indicates that the model was able to predict perceived student motivation above chance levels, which supports Hypothesis 2.

4.3 Exploratory Analyses

In addition to testing the research hypotheses, several exploratory analyses were conducted to evaluate the model further, including the predictions, and the feedback-motivation relationship.

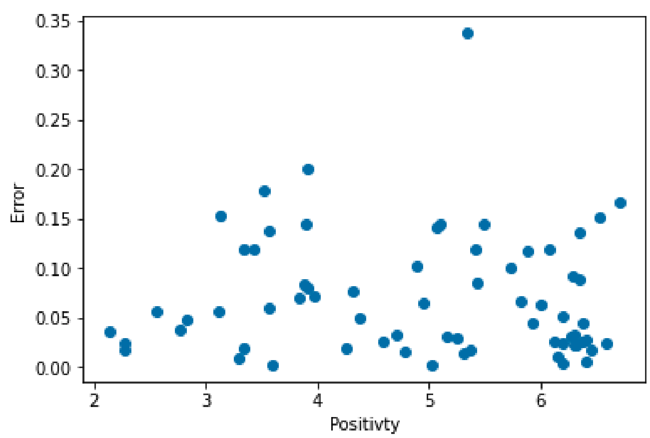
4.3.1 Exploratory Analysis 1. The first exploratory analysis examined where along the range of the outcomes the model is more or less accurate. To explore this question, residual motivation was plotted with the model prediction error. As depicted in Figure 1, no linear or curvilinear trend was detected. This lack of trend suggests that the model's predictions were equally accurate at both low and high levels of residual motivation. The Spearman correlation between residual motivation scores and error was $r = -.27$, $p = .02$. A Spearman correlation was used because one of the data points appears to be an outlier, which could bias the relationship between error and rescaled residual motivation. The Spearman correlation is a monotonic, rank correlation, which makes it less sensitive to outliers that a Pearson correlation.

Figure 1. Plot of Error and Motivation



Additionally, prediction error was plotted with affect to examine if the model was more or less accurate for positive, negative, or neutral statements. Figure 2 reveals no pattern, suggesting that the model accuracy was consistent, regardless of the affect associated with feedback statements. The Spearman correlation of $r = -.30$, $p = .01$, indicates that no trend exists between the prediction error and affect of the statements.

Figure 2. Plot of Error and Affect



4.3.2 Exploratory Analysis 2. The second exploratory analysis examined differences in perceived motivation among the six structured feedback categories. Thirty-five structured feedback statements were generated by the researchers to represent each of the six feedback categories, yielding 210 structured feedback statements. The six categories were ego-threatening task feedback, ego-threatening motivational feedback, ego-threatening self-feedback, ego-boosting task feedback, ego-boosting motivational feedback, and ego-boosting self-feedback. A one-way ANOVA was conducted to examine differences in perceived motivation between these categories.

The ANOVA revealed a significant main effect, suggesting that at least one of the means for the motivation scores of the feedback categories differed from the rest, $F(5,204) = 147.31$, $p < .05$. Post hoc comparisons using the Tukey test indicated that ego-threatening task feedback was not significantly different from ego-threatening motivational feedback, but was significantly different from all of the other four feedback categories. Ego-threatening motivational feedback was not different from ego-threatening task or self-feedback, but was significantly different from all three ego-boosting feedback categories. Ego-threatening self-feedback was not significantly different from ego-threatening motivational feedback, but was significantly different from all other feedback categories. Additionally, none of the ego-boosting feedback conditions were significantly different from one another, but each ego-boosting feedback category was significantly different from each of the ego-threatening feedback categories. Table 2 provides the means and standard deviations of each feedback category. The means and standard deviations of the affect rating of each feedback category are provided in Table 3.

Overall, ego-boosting feedback was perceived as more motivational than ego-threatening feedback. Within ego-threatening feedback, task-focused feedback was found to be the most motivational, followed by motivational-focused, and then self-focused feedback. Within ego-boosting feedback, the opposite trend occurred, such that self-focused feedback was the most motivational, followed by motivational-focused and then task-focused feedback.

4.3.3 Exploratory Analysis 3. Exploratory Analysis 3 targeted understanding the inner workings of the model. This analysis potentially offers insight into people's processes when evaluating statements by understanding the positive/negative effects of individual words on the predicted residual motivation scores. To examine which words most strongly affected the predicted scores in the model, the author iterated through and within each statement. Each word was removed from its statement and the predicted motivation score of the statement with the word omitted was compared to the baseline prediction of the statement with all words included. For each word, the author kept track of the difference (positive numbers signify the increase in predicted score when the word is included). The author then averaged across differences to calculate the mean improvement score for each word. To minimize the influence of outliers and small samples, the author only retained words that occurred at least 5 times in the sample of statements.

The 20 words with the highest average influence on motivation are provided in Table 4. It appears that the majority of the most motivating words are action words. Revise and revision are number one and two on the list. There are additional words that call students to action, such as resubmit, send, improve, deadline, change, date, and continue. Each of these words relates to direct action students can take. The word please also appears on the list, indicating that feedback being delivered in a polite and respectful way was perceived as more motivating.

4.3.4 Exploratory Analysis 4. Next, the consistency of the model was examined by exploring the similarity between the predicted motivation scores of two similar statements. First, all statements were paired with the statement most similar in meaning. This was accomplished by converting all sentences to vectors of length 512, that represented the latent sematic meaning. This latent representation was calculated by submitting the statement to the Universal Sentence

Encoder (Cer et al., 2018), and using the 512 number embedding it produced. These embeddings allow statements to be compared using a cosine distance metric, to examine the semantic similarity between the statements. Next, each statement was paired with the statement that was most similar, as determined by the embeddings and cosine distance metric. The model was used to calculate a predicted residual motivation score for each statement, and a list was created with two columns--the predicted residual motivation score of half of the statements, and the predicted residual motivation score of the corresponding most similar statements. Finally, the correlation between statement pairs was examined. The results revealed a correlation of $r = .68$ between statement pairs. This strong correlation indicates that the model is generally consistent in its predictions when encountering statement that have similar underlying context.

4.3.5 Exploratory Analysis 5. Exploratory Analysis 5 examined if statements that are very negative in valence can still be motivating to students. In order to examine this question, the author first generated a list of the feedback statements with the most negative valence. To do so, only statements with a perceived positivity rating below two were included in this analysis. This filtering produced a list of 56 qualifying negative statements. Next, the author examined the rescaled residual motivation scores of these statements to determine whether these negative statements can be perceived as motivating. Thirteen statements with negative affect scores had rescaled residual motivation scores above the mean of all statements in the study ($M = .47$). The model included 56 statements that had an affect rating below 2. Therefore, 23% of such statements were above average in motivating students. These findings indicate that even feedback with extremely negative valence can increase student motivation.

4.3.6 Exploratory Analysis 6. The final exploratory analysis examined whether sentence length impacts perceived motivation. In order to examine the sentence length – motivation relationship, the author calculated the correlation between sentence length and rescaled residual motivation. This correlation was $r = .44$, 95% CI = (.37, .50), indicating a moderate relationship. This is not surprising given that sentence length should not be the driving force determining students' perceived motivation from feedback. However, this finding does suggest that longer feedback statements tend to be perceived as more motivating by students.

4.3.7 Stress Testing the Model. Additionally, the researchers include a link (https://psych.x10host.com/motivation/motivationapp.html) to a web-based program where individuals can access the model and plug in any number of feedback statements to obtain predictions for how motivating students will perceive the statements to be on average. Testing was done to examine if certain types of text input would be problematic for the model. Because the model was trained with complete sentences of feedback, there are three main types of stressors that must be examined to understand possible shortcomings of the model: a) predictions with nonsensical statements, b) predictions for single words, and c) predictions for no text. These are the unique types of feedback text that may exist in the context of academic text feedback, which may stress the model.

The first type of stressor is nonsensical sentences. The model was trained using only full sentences of coherent feedback text. Therefore, nonsensical sentences could be problematic and lead to fallacious motivation predictions. To test if these stressors will negatively impact model predictions, 45 nonsensical sentences/fragments were put into the model using the web-based program. The number of statements was determined by a power analysis for a one sample *t*-test with alpha = .05. The 45 nonsensical sentences were formed by randomly selecting words from the feedback statements obtained from participants, and compiling these words in such a way that there is no coherent meaning behind the sentence. If the model is robust to nonsensical sentences, the model predictions for such sentences should be low because gibberish should not be perceived as motivating. If all feedback statements have a predicted motivation score below .25 (first quartile) then the model can handle nonsensical feedback. If the model cannot handle nonsensical feedback then the predicted feedback for these statements will range above .25. A one-sample *t*-test was conducted to examine if the predicted residual motivation scores for nonsensical sentences was significantly below .25. The results reveal a non-significant effect, $t(44) = 8.09$, $p = 1.0$, indicating that predicted residual motivation scores of nonsensical statements tend to be above .25. The predicted residual motivation scores of these nonsensical statements ranged from .18 to .58 and the mean was $M = .39$ ($SD = .12$). The list of sentences and predictions can be found in Appendix D. These findings suggest that the model cannot appropriately generate predictions from feedback that has no coherent meaning and instead puts weight on the single words that comprise the nonsensical statement.

The next potential stressor for the model is single word feedback. The model was trained on full sentences and no single word feedback. Therefore, presenting the model with single word feedback may lead the model to provide inaccurate predicted motivation scores for these single words. To test this, 104 random words from the feedback statements included in the study were input into the web-based model program and predicted motivation scores were obtained. Of these words, 52 were words that could be coherently understood as single word feedback and 52 words would be meaningless without context as single word feedback. Words that are meaningless single word feedback, such as “very”, should receive lower motivation scores than words that are coherent single word feedback, such as “great”. The list of words and predicted scores is presented in Appendix E. An independent sample *t*-test was conducted to examine if there is a different in predicted residual motivation scores between coherent and meaningless single words.

The predicted motivation scores ranged from .11 to .58. The results revealed a significant effect, $t(102) = 22.96$, $p < .05$, indicating that there is a significant different in mean predicted residual motivation scores between meaningful and meaningless single word feedback. However, coherent single word feedback had lower residual motivation scores ($M = .32$, $SD = .11$) than incoherent single words ($M = .36$, $SD = .11$). Random words should not have higher motivation scores than single words that are interpretable as feedback. Therefore, it appears that the model cannot handle single words and predictions from single word feedback should not be trusted.

The final stressor is if the model makes predictions for empty cells (no text). This could be problematic because no feedback should not receive a predicted motivation score. Model predictions were obtained for five empty cells with no text. The predicted motivation of each cell was .29. The output is presented in Appendix F. These results reveal that the model predicts that no text will be more motivating that 29% of feedback statements.

Chapter 5

Discussion

The model that was trained and examined in the present study provides a significant contribution to researchers and practitioners who examine feedback in academic contexts. In support of Hypothesis 1, the model showed a positive linear association with actual motivation reported by students. The large correlation between actual and predicted motivation scores was $r = .71$, which supported this hypothesis and demonstrated the strength of the model. Additional support for the quality of the model is evidenced by the model predicting motivation from a statement more accurately than did any individual rater from the sample. The second hypothesis was also supported by calculating the Mean Absolute Error (MAE), and determining that the predictions of the model were closer to the true motivation score than would be expected by chance. Support of these hypotheses indicates the accuracy of the model. The fact that both hypotheses were supported, endorses the decision to control for affect in order to predict motivation without the influence of affect in the present study. While affect and motivation both play a role when an individual receives feedback, this research is examining the construct of motivation, without the influence of affect.

This model can be used to test how motivating a particular feedback statement would be perceived, on average. Professors could enter their feedback statements into the model before they deliver the feedback to students and examine how motivating the average student will perceive it to be. Additionally, when reviewing the teaching performance of professors, a list of feedback statements the professors gave to their students over a semester could be compiled and run through the model to estimate how motivating their feedback tends to be on average and how motivating certain feedback statements were perceived to be. This process could be used to train and teach professors how to give students motivating feedback.

Exploratory analyses were conducted to further examine the model and feedback in general. The first such analysis revealed that the model was equally accurate in making predictions with statements that are high and low in motivation, and with statements that are highly positive and highly negative. These findings suggest that the model can be trusted equally for all feedback statements. If the error had been higher for a particular situation, then the model should be used with caution when examining such feedback. This was not the case, and therefore the model can be used to make predictions for any feedback presented for evaluation within an academic context.

The second exploratory analysis examined differences in the motivating influence of the six feedback categories based on FIT (Kluger & DeNisi, 1996). The results revealed that mean perceived motivation of ego-threatening task feedback was not different from ego-threatening motivational feedback, but was significantly more motivating that ego-threatening self-feedback. This is not surprising because self-focused feedback after a poor performance should be most detrimental to the recipients' motivation, because such feedback is likely to be internalized (Ryan, 1982). In contrast, task-focused feedback after a poor performance should be more motivating because it draws the locus of attention to the task and provides guidance for behavioral improvement instead of targeting the self-esteem of the recipient (Kluger & DeNisi, 1996).

Ego-threatening task feedback was significantly less motivating than all ego-boosting feedback categories. It is not surprising that feedback delivered after a positive performance is more motivating than feedback delivered after a poor performance (Carpentier & Mageau, 2013). Similarly, Ego-threatening motivational feedback did not differ from task or self-focused ego-threatening feedback, but was significantly less motivating than each of the ego-boosting feedback categories.

None of the ego-boosting feedback categories were significantly different from one another. However, ego-boosting self-feedback had the highest mean motivation score. This is likely because people internalize positive feedback when it targets the self (Ryan, 1982). Ego-boosting task feedback had a non-significant but lower mean motivation score than did ego-boosting motivational feedback. This may be because after a positive performance, the recipient does not need the feedback to focus on the specific aspects of task to improve motivation since the performance was acceptable and no action is needed.

The third exploratory analysis targeted the impact of individual words on student motivation. As mentioned previously, the majority of the most impactful words on increasing student motivation were action words. The complete list of action words are provided in Table 4. These are words that call the student into action by, a) asking a student to revise his or her work and resubmit it, b) presenting a specific date or deadline for a student to meet, or c) pushing a student to do better with words like ‘improve,’ ‘change,’ or ‘performance’.

The majority of the most motivating words implied direct action for students. This is consistent with FIT because the feedback that recommends behavior focuses the student’s locus of attention on the task itself (Kluger & DeNisi, 1996). Carpentier and Mageau (2016) point out that the most effective feedback is accompanied with choices of solutions to improve performance. When using action words and providing behavioral solutions for their students, professors increase the motivational impact of their feedback.

This is valuable information because it informs those who provide feedback to students that students will be more motivated if the feedback outlines future behaviors the student can perform to achieve a goal. If the feedback provides no direction, students will likely not be as motivated. It is interesting that the word “please” was one of the 20 most motivating words that students perceived. This is consistent with a conclusion from prior research that feedback is most effective when delivered empathically (Carpentier & Mageau, 2016).

Additionally, this finding is consistent with feedback research from the perspective of Self-Determination Theory (SDT), which states that to improve motivation and satisfy a recipient’s need for competence, the feedback must come from a trusted source (Cerasoli et al., 2016). A professor who is an expert in his/her field and demonstrates respect to a student with polite words, is likely to be trusted by the student, and thus his/her feedback is likely to be motivational.

The fourth exploratory analysis examined model consistency by calculating the correlation between the predicted motivation scores of the most similar statement pairs. A strong correlation of $r = .68$, indicated that the model was generally consistent in its predictions. This is crucial for any application of the model predictions. This correlation may not be as high as one might expect, given that it represents predicted scores between the most similar statement pairs. However, the similarity of statements was determined by their embedding, which reflects underlying meaning. Embeddings take all elements of the statement into account, including affect.

However, the predictions were made with the residual motivation score, which removes variance accounted for by affect. Therefore, it would be unlikely for the correlation between statements to be much higher. The strong correlation reported here indicates that the model was quite consistent in the predictions it made about the motivating influence of feedback statements.

Exploratory Analysis 5 provided another interesting and informative examination of the model whereby it was determined that thirteen statements with very negative affect scores were above average in their perceived motivation. This is a thought-provoking finding because one might expect very negative statements to be de-motivating, but in fact 23% of these statements were above average in motivating students. Upon examination of the statements, it appears that many of the highly motivating, yet extremely negative statements, included a specific element for which students have demonstrated sub-standard performance. For example, “Your lack of involvement in group discussions is very disappointing” was found to be more motivating than, “This assignment was terrible” because the first statement indicates what aspect of the task on which the student is not performing well. This information provides guidance for future behaviors that should be modified in order to improve. These findings suggest that professors do not need to “sugar-coat” the feedback they provide their students to motivate them to improve. Instead, they should make sure to provide specific behaviors students can perform in order to improve. This is aligned with FIT and the stipulation that task-level feedback tends to be the most motivating, especially with ego-threatening (i.e., negative) feedback (Kluger & DeNisi, 1996).

The sixth exploratory analysis revealed that sentence length had only a moderate correlation with residual motivation. While the content of the sentence accounts for much of the variance in the perceived motivation of a statement, sentence length contributes as well. Sentence length itself is likely not a motivating factor but is confounded with the true motivational factor. It is possible that longer sentences indicate to students that the professor is willing to take more time to guide the student. This could be perceived as the professor caring for the student, liking the student, and respecting the student, and thereby enhances the trust the student has for the professor. These reasons could explain the motivating influence of sentence length, given that prior research has found feedback to be most effective in improving motivation when it is delivered with empathy from a trusted source (Carpentier & Mageau, 2016; Cerasoli et al., 2016).

Additionally, some research suggests that sentence length alone influences motivation. Specifically, Langer, Blank, and Chanowitz (1978) found that when asking to cut in line to use a copy machine, people waiting in line were significantly more likely to allow the individual to cut in line if they received a reason for the request, even if that reason conveyed no new information. A reason with no information is essentially making the same request with a longer sentence, to which people were more receptive. It is possible that students are simply more receptive to feedback when presented in longer sentences.

A stress test of the web-based version of the model was done to examine how the model deals with a) nonsensical sentences, b) single words, and c) no text. Nonsensical feedback statements received predicted residual motivation scores well above the .25 cutoff. This suggests that the model will provide fallacious predicted residual motivation scores for sentences that do not make sense. Therefore, only feedback with a clear semantic meaning and sentence structure should be used in the model. Additionally, meaningless single words received significantly higher mean predicted residual motivation scores than did single words that can be perceived as coherent feedback. Words that should be motivating, such as “fantastic” and “great” received significant lower predicted residual motivation scores than did words like, “job”, “very”, and “time”. Therefore, this model should only be used for full sentences and single word feedback should not be examined using the model. Finally, the model made predictions for five empty cells. The predicted motivation for each was .29, suggesting that no feedback at all is more motivating that 29% of other feedback statements. This may be due to a coefficient that is used to make the final predicted scores. Use caution when interpreting this finding because the model was not trained on empty cells. It may be that "silence is golden" and no feedback can be motivation but it is also likely that the model is providing an estimated predicted motivation score because it did not encounter "no-text-feedback" during training. The model should only be used with full sentences of coherent feedback.

5.1 Limitations and Future Directions

A main limitation of this research was the fact that it was restricted by the data included in the present study. The majority of participants were white and female. This should be kept in mind when using this model because sex and race differences may occur. Ideally the population that the model is used on is similar to the sample from the present study. If not, retraining the model on a representative sample may be beneficial.

The model was also trained using only full sentences of feedback. Therefore, the model should not be used with nonsensical sentences, sentence fragments, or individual words. Additionally, the predicted outcome in the present study was perceived motivation. The actual behavioral change of the participants was not recorded. Future research should examine changes in motivation with actual behavioral modification by participants. Examining behavior to evaluate motivation would likely reduce the large correlation between perceived affect and perceived motivation that was obtained in this research and provide a more accurate metric of the motivation and affect relationship pertaining to feedback. Clearly, the influence of feedback involves both motivation and affect. Additional future research could compare models that predict motivation while both controlling and not controlling for affect.

The present study was also conducted in an academic context. It is unclear if the findings from this research would generalize across contexts. It is likely that there would be some similarities across contexts, but this study can only draw speculation on the matter. Future research should train and test similar models in different contexts. It would be interesting and informative to conduct a similar study in a workplace or sport context, or in a different educational level, from elementary school to professional training.

This research was also limited because the statements were generated by students and researchers, instead of from naturally-occurring sources. It is possible that many of the statements submitted by students were actual feedback they received from professors, but this cannot be known this for sure. Future research should assess the feedback-motivation relationship using text-analysis from actual feedback statements, and obtain motivation-related affect from the recipients of that feedback.

Future research could examine other factors that influence feedback, aside from the content of the message. For instance, the timing of when the feedback is given in reference to a task could influence the motivational impact of the feedback. It has been recommended that feedback should be delivered in a timely matter (Carpentier & Mageau, 2013; Levy & Williams, 2004), meaning that feedback is most effective when it follows immediately after the target behavior.

5.2 Conclusion

Overall, the present study provided a significant contribution for researchers and practitioners who use feedback. The model was able to accurately predict how motivating students perceive feedback from professors. Various applications of this model could aid professors, coaches, students, and administrators. Additionally, this was the first study to examine the feedback-motivation relationship using text-analysis, and could inspire other researchers to apply text-analytic methods to examine feedback and other psychological phenomenon.

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Table 1
Descriptive Statistics of the Sample

	Overall
Age in Years *M* (*SD*)	19.57 (2.44)
Gender *N* (%)	
Male	79 (25.1%)
Female	235 (74.6%)
Race *N* (%)	
White	231 (73.3%)
Black or African American	22 (7.0%)
American Indian or Alaska Native	1 (0.3%)
Asian	41 (13.0%)
Two or more races	16 (5.1%)
Other	4 (1.3%)
Total *N*	315

Table 2
Average Motivation of Each Feedback Category

Feedback Category	M (SD)
Ego-Threatening Task Feedback	3.95 (.68)
Ego-Threatening Motivational Feedback	3.65 (.63)
Ego-Threatening Self Feedback	3.32 (.75)
Ego-Boosting Task Feedback	5.60 (.46)
Ego-Boosting Motivational Feedback	5.75 (.38)
Ego-Boosting Self Feedback	5.92 (.39)

Table 3
Average Affect Score of Each Feedback Category

Feedback Category	M (SD)
Ego-Threatening Task Feedback	3.03 (.76)
Ego-Threatening Motivational Feedback	2.55 (.56)
Ego-Threatening Self Feedback	2.30 (.54)
Ego-Boosting Task Feedback	5.81 (.58)
Ego-Boosting Motivational Feedback	5.78 (.55)
Ego-Boosting Self Feedback	6.13 (.45)

Table 4
Words with the Largest Motivational Influence

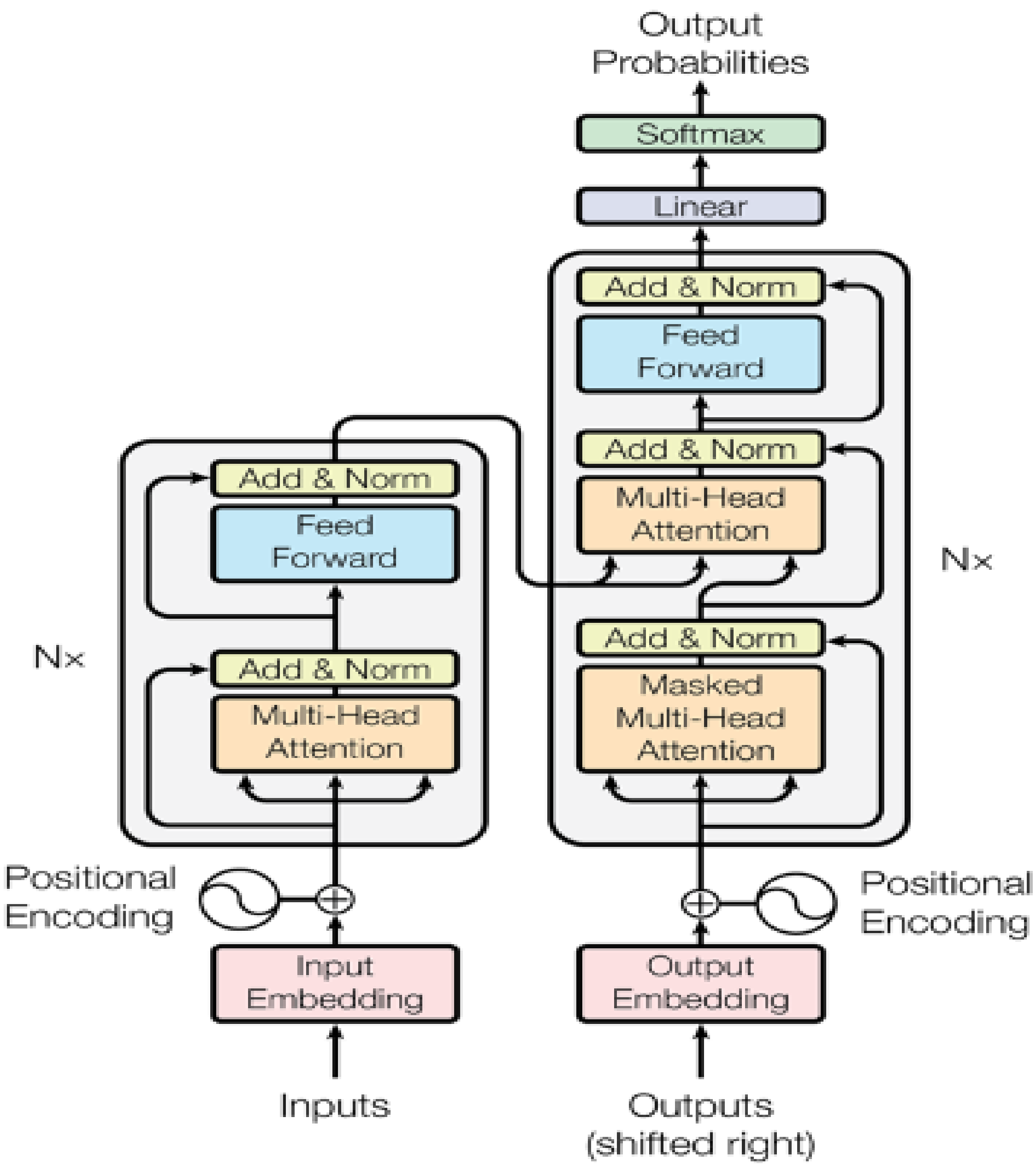
Word	Impact on Motivation
Revise	7.8%
Revision	6.7%
Performance	6.6%
Date	6.5%
Yourself	6.5%
Send	6.4%
Deadline	6.4%
Improve	6.4%
Expect	6.2%
Resubmit	6.2%
Need	6.1%
End	6.0%
Conclusion	5.9%
Change	5.8%
Your	5.7%
Final	5.6%
Project	5.6%
Continue	5.6%
Improvement	5.6%
Please	5.5%

Note: The impact on motivation is based on the rescaled residual motivation score from 0–1. The percentage reflects how much the predicted motivation score of a sentence would change if a word was not included in the sentence.

Appendix A

Reference: Mwiti, D. (2019, October). Research guide for transformers. Retrieved March 14, 2021, from https://www.kdnuggets.com/2019/10/research-guide-transformers.html

Transformer model architecture.



Appendix B

Prompts to obtain feedback statements. Note: Prompts were randomized and not accompanied with the feedback category label.

Instructions:
You are going to be presented with 16 prompts in the contexts of school/academics. Please type your response to each in complete sentences with proper spelling and grammar to the best of your ability.

Each response should be about 1-3 sentences.

Note: The term Academic Supervisor is used: this reflects anyone who you worked under in a school setting (e.g., professor, TA, Graduate Student, Lab coordinator, etc.)

Prompts to get feedback samples of each Feedback Style:

Ego-Threatening Task Feedback:

- What is an example of some feedback that you received where your supervisor told you what needs to be adjusted in order to improve on your project/task/work? If you cannot think of one please come up with a realistic hypothetical statement.
- When your assignment is not up to standards, what would a professor say to give you specific instructions on how to improve the assignment? If you cannot think of one please come up with a realistic hypothetical statement.

Ego-Threatening Motivational Feedback:

- When you perform poorly on a project, what would a professor say to get you to improve on it within a certain timeline? If you cannot think of one please come up with a realistic hypothetical statement.
- In a sentence or two, provide some feedback that you would receive from a professor after a below-average assignment when they tried to get you to work harder? If you cannot think of one please come up with a realistic hypothetical statement.

Ego-Threatening Self Feedback:

- What would a professor tell you when you turn in a below-standard report, that hurt your feelings? If you cannot think of one please come up with a realistic hypothetical statement.
- What is an example of feedback that you received from a professor that lowered your self-esteem? If you cannot think of one please come up with a realistic hypothetical statement.

Ego-Boosting Task Feedback:

- After an academic supervisor reviewed a good assignment from you, what is some advice that was given to you in order get you to build upon the specific content of the good assignment? If you cannot think of one please come up with a realistic hypothetical statement.
- When you perform well on an assignment, what do academic supervisors say to add more quality content to the next one? If you cannot think of one please come up with a realistic hypothetical statement.

Ego-Boosting Motivational Feedback:

- What would a professor say when you did well on an assignment and they want to motivate you to do even better in the future? If you cannot think of one please come up with a realistic hypothetical statement.
- After a good assignment, what feedback would an academic supervisor provide to get you to add to it in a short timeline? If you cannot think of one please come up with a realistic hypothetical statement.

Ego-Boosting Self Feedback:

- What feedback would you receive from an academic supervisor when they liked your work and want to build your confidence for future academic work? If you cannot think of one please come up with a realistic hypothetical statement.
- When you do well on work for a class, what would a professor say to make you feel self-assured in your work so that you strive higher on future assignments? If you cannot think of one please come up with a realistic hypothetical statement.

General/Additional: (4x)

- What is another example of feedback that you regularly receive from professors/academic supervisors? If no examples come to mind, what is a hypothetical feedback statement that a student could receive in an academic context?

Appendix C

The feedback statements generated by the researchers that all participants rated. Note: All labels were removed and the items were randomized when presented to participants. Each statement was paired with two items assessing perceived motivation and affect, respectively.

<u>Prompt:</u>
You will be presented with a series of feedback statements and questions. Imagine that an academic supervisor (professor, TA, lab coordinator, etc.) gave you the feedback.

The term motivation is used in some questions. By **<u>motivation</u>** we mean **<u>the energy or drive to achieve a goal</u>**.

Please respond to the following questions as if you had just received the feedback from an academic supervisor.

<u>Rating Scale:</u>

If I received the following feedback from an academic supervisor, I would be...

Extremely less motivated	Less motivated	Slightly less motivated	Neither more nor less motivated	Slightly more motivated	More motivated	Extremely more motivated
○	○	○	○	○	○	○

If you received this statement from an academic supervisor, how would it make you feel?

Extremely unpleasant	Unpleasant	Somewhat unpleasant	Neither pleasant nor unpleasant	Somewhat pleasant	Pleasant	Extremely pleasant
○	○	○	○	○	○	○

<u>Feedback Statements that all participants will rate:</u>
Ego-Threatening Task Feedback:

- This report needs a revision, let me explain what information is still needed in the report.
- This paper was not up to standards, I can point out a few key concepts that were missing.
- Your presentation was subpar, you did not use the elements that we discussed in class.
- Your assignment needs a revision, let's set up a meeting to discuss the material that needs to be adjusted.

Ego-Threatening Motivational Feedback:

- This project is below standards. You need to spend more time on the next one.
- Your last assignment needs a revision; please make these changes by the end of the week.
- This paper is not up to standards in the rubric. Please put more time into the next draft.
- This report needs to be revised, please send me your revisions in three days.

Ego-Threatening Self Feedback:

- This report needs a revision, you failed to perform up to your standard.
- Your project needs improvement; you did do as well as I expected.

- Your assignment was not adequate, please make sure you pay attention so that your next assignment is as good as you are capable of.
- This paper needs to be revised. I expect better from you in your next draft.

Ego-Boosting Task Feedback:

- Nice work on your paper; I challenge you to think of ideas to improve on this paper further.
- This report is great, let's sit down together and talk about ideas to expand on your report.
- This presentation looks good, let's try to add even more detail.
- This report is very good; I challenge you to add two more quality arguments.

Ego-Boosting Motivational Feedback:

- This paper has some excellent ideas. I'd like to see your next draft by the end of the week.
- Nice work on this assignment. I'd like to hear ideas to expand upon this by next class.
- This report is great; I want to hear ideas for your next project in three days.
- Your project is very good; Let's talk about ideas for your next project. Send me some general ideas by next class.

Ego-Boosting Self Feedback:

- Nice job on the exam, I'm looking forward to you doing even better on the next one.
- This report great, I expect even better things from you in the future.
- Your assignment was great. I know you can do even better next time.
- This project was very good. Let's make sure that your future work continues to improve from where you are now.

Appendix D

Predicted Motivation of 20 Nonsensical Sentences.

Text	Motivation
Great want you reader original student look questions additional short.	0.1814
Lens where filler but, give looking journal answers more could I like specific.	0.1929
Good but bad.	0.197
Due your presented defended contact presentation eye.	0.2124
Reviewing process remember better help.	0.2307
Encourage know better extra fully answer few. Still questions based far tried full.	0.2317
Disappointed add standard this next draft.	0.2477
This a was paper text in with the academic.	0.2613
Made needed there if tone audience. Drop fix time errors better even practice.	0.2681
Admire could done effort. Assignment do future pushing paper.	0.2739
Fascinating mind next assignment keep it this.	0.2892
Enjoy examining no up class work.	0.294
Attention success cite lead please sources.	0.2948
Adequate the for higher school grade level goal.	0.3186
Quality keep great up education very class ability.	0.3298
Don't lacking part project time had need questions. Back despite credit see referencing hello; helps look lecture.	0.3309
Frankly look full ask once it more grade poor still office discuss intelligence report.	0.3442
Section reference please apply students quality outside submission.	0.3627
Revise enjoy paper turn in near.	0.385
Performance good needs effort, focus and the method section. Conclusions think don't added comments.	0.3923
If pay study perspective.	0.4013
Paper amazing this job enoy this reading.	0.4026
Paper confusion time bad now score grade work.	0.4036
Time should to project send need studying next effort time. Three enough days good of.	0.4073
Give exact thing when number high is.	0.4124
Try to bad assignment work. Exceeding keep grading due well.	0.4186
Results the left need have paper assignment but in right on time.	0.4272
Need make read sure to rubric assignments. Part short redo include time these.	0.4344
You need to this paper has to be if the grade it what happens if you do.	0.4515
Hit enjoyed points job paper variable small section point.	0.4527
Study if the paper wasn't up to you but work. Need more have academics.	0.4543
Provide alright project rubric look.	0.458
Job submission example correct to no mind show errors.	0.4848

Assignment job wonderful help. Assignment! Just interesting keep harder improving.	0.4877
Title good consider to the advice rework deadline.	0.5076
Closer do well to attention insufficient love test. Grasp continue well.	0.5119
Excited done keep work it.	0.5163
No model needs determine to this now.	0.5237
Idea paper right exam short but execution	0.5417
Need usually not better next project time of the tomorrow.	0.546
Understand how suggested best improve.	0.5702
Yourself more continue improve needed better.	0.5754
Spent detail falling assignment effort do not observe concept future. Work especially covered don't catch effort.	0.5754
Job you assignment make organization well work page.	0.5774
You goal maybe some other acceptable work poor embarrassing.	0.5829
Great want you reader original student look questions additional short.	0.1814
Lens where filler but, give looking journal answers more could I like specific.	0.1929
Good but bad.	0.197
Due your presented defended contact presentation eye.	0.2124
Reviewing process remember better help.	0.2307
Encourage know better extra fully answer few. Still questions based far tried full.	0.2317

Note: The motivation scores are predicted residual motivation scores.

Appendix E

Testing single words in the model

Coherent Feedback	Predicted Motivation	Incoherent Feedback	Predicted Motivation
Better	0.1222	Exam	0.1077
Wonderful	0.1541	Was	0.1548
Awesome	0.166	Spend	0.1963
Outstanding	0.1686	Needs	0.2194
Excellent	0.1696	Enough	0.2244
Fantastic	0.1781	Put	0.2277
Interesting	0.1845	Please	0.2509
Amazing	0.1901	Make	0.2574
Best	0.1944	Version	0.2717
Great	0.2016	Problems	0.272
Reevaluate	0.2143	Presentation	0.2806
Redo	0.2176	Response	0.2936
Rename	0.2229	Given	0.2956
Clear	0.2285	Shows	0.2973
Nice	0.2443	Support	0.3053
Superior	0.2491	Material	0.3078
Good	0.2572	Written	0.3079
Lovely	0.2648	Challenge	0.3172
Choppy	0.2662	Studying	0.3196
Right	0.267	Assignment	0.324
Adequate	0.2751	Overall	0.3329
Thoughtful	0.2906	Effort	0.3346
Revise	0.2937	Apparent	0.3363
Terrific	0.3011	Lack	0.3396
Try	0.3282	Different	0.3414
Expand	0.3302	Include	0.3416
Impressed	0.3305	Very	0.3495
Lackluster	0.3317	Questions	0.3557
Lazy	0.3326	Specific	0.3682
Exactly	0.3366	Specific	0.3682
Lacking	0.3406	Performance	0.3747
Surprising	0.3459	Disinterest	0.3814
Disappointed	0.3467	About	0.3836
Wrong	0.3488	Time	0.388
Subpar	0.3522	Report	0.3881
Unsatisfactory	0.3523	Research	0.3973
Wow	0.3557	Confusion	0.3981
Impressive	0.3563	Keep	0.4056

Exceptional	0.3838	Job	0.4243
Failed	0.4101	Stage	0.4348
Disappointing	0.4126	Point	0.4351
Fix	0.419	Slides	0.4451
Proud	0.4371	Terms	0.4563
Pleasure	0.4374	Expect	0.4658
Elaborate	0.4679	Structure	0.4928
Engaging	0.468	Done	0.4989
Improve	0.4793	Deeply	0.5458
Rework	0.4842	Week	0.5494
Poor	0.4901	Work	0.561
Edit	0.5461	Article	0.562
Success	0.5506	Goals	0.5631
Failure	0.5752	Today	0.5842

Note: The motivation scores are predicted residual motivation scores.

Appendix F

Testing model predictions with no text.

	Text	Predicted Motivation
1		0.2993
2		0.2993
3		0.2993
4		0.2993
5		0.2993