



VCU

Virginia Commonwealth University
VCU Scholars Compass

Theses and Dissertations

Graduate School

2019

Investigating Daily Writing Emotions, Attention Regulation, and Productivity: An Intensive Longitudinal Study

Eric Ekholm
Virginia Commonwealth University

Follow this and additional works at: <https://scholarscompass.vcu.edu/etd>



Part of the [Educational Psychology Commons](#)

© The Author

Downloaded from

<https://scholarscompass.vcu.edu/etd/5977>

This Dissertation is brought to you for free and open access by the Graduate School at VCU Scholars Compass. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of VCU Scholars Compass. For more information, please contact libcompass@vcu.edu.

Investigating Daily Writing Emotions, Attention Regulation, and Productivity: An Intensive
Longitudinal Study

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of
Philosophy at Virginia Commonwealth University

by

Eric Ekholm

Master of Teaching, Virginia Commonwealth University, 2012
Bachelor of Arts, Virginia Polytechnic Institute and State University, 2010

Director: Sharon Zumbrunn, PhD
Associate Professor, Foundations of Education
School of Education

Virginia Commonwealth University
Richmond, Virginia
2019

Acknowledgement

There's no way I could have gotten to this point on my own, and I want to take the opportunity to acknowledge people who have helped me along my path toward earning this degree. First, I want to thank Kendall for supporting me emotionally, intellectually, and otherwise throughout grad school and beyond. Thank you for letting me work early mornings and late nights. Thank you for listening to my struggles and triumphs, even when they were related to figuring how to write lines of code. And thank you for loving me even when I was being difficult (which was probably a lot during the dissertation phase).

Second, I want to thank my committee. Jason – I'm so thankful that I got to work with you. Thank you for your mentorship as well as helping me think about what it means to be a scholar. Christine – thank you for your advice and for allowing me to wander into your office to talk through academic and life problems. Matt – thank you for your support and guidance throughout this last stage of the PhD adventure. Mike – thank you for your mentorship and friendship, for your statistical troubleshooting over coffees at Buzzy's (RIP), and for your willingness to venture out into weird new statistical territories with me over the past few years. And Sharon – I owe you more than I could possibly fit into this acknowledgment. Thank you for your constant friendship and encouragement over the past 8 (!!) years. Without your support, there's no way I'd be where I am today.

Lastly, I want to thank all of my friends and mentors at VCU. Morgan and Ashlee – I'm so happy that we got to go on this journey together. CCC Breezeway friends – thank you for making me step out of my ed psych comfort zone. David, Sarah, JK, Savanna, and Drew – thanks for leading the way. I've been incredibly fortunate to have all of you in my life.

Dedication

This dissertation is dedicated to my parents. Thank you for your constant love and support.

Table of Contents

Acknowledgement	ii
Dedication	iii
List of Tables.....	viii
List of Figures	ix
Abstract	x
Chapter 1 – Introduction.....	1
Statement of the Problem.....	9
Purpose of the Current Study	12
Brief Overview of Methodology.....	13
Definition of Terms	14
Chapter 2 – Review of Literature.....	16
Models of Writing Production.....	16
Self-Regulation and Writing	21
A Lack of Emphasis on Emotions in Writing Models.....	24
Models of Emotions and Emotion Regulation	26
Emotion Regulation.....	30
Relations between Emotions and Writing Processes.....	32
Emotions, Cognitive Mechanisms, and Writing Performance	33

Emotions and Self-Regulatory Writing Behaviors	35
Emotions and Beliefs about Writing Competence.....	37
Emotions and Writing Content.....	39
Stability of Writers' Emotions.....	42
Methods of Studying Emotions	43
Conceptual Framework	47
Chapter 3 – Methodology	51
Research Design.....	51
Participants	53
Recruitment	53
Incentives.....	54
Final Sample.....	56
Measures	57
Initial Demographics Survey	57
Contextual Measures and Covariates	58
Writing Emotions.....	58
Writing Attention Regulation.....	59
Writing Productivity	61
Distinguishing between Missingness and Non-Writing	61
Procedure.....	62
Data Analysis	63

Missing Data	63
Estimating Variance Components	65
Intensity of Average Emotions.....	66
Writers' Emotional Stability	66
Relations between Emotions and Daily Outcomes	71
Chapter 4 – Results.....	74
Preliminary Analyses	75
MLCFA and Reliability Analyses	75
Estimating Variance Components	76
Proportion of Days Writing	77
Primary Analyses	78
Descriptive Statistics	78
Stability of Writers' Emotions.....	81
Relations between Writers' Emotions and Attention Regulation	106
Relations between Writers' Emotions and Productivity	112
Chapter 5 – Discussion	123
Overview of Current Study.....	123
Discussion of Major Findings.....	123
Intensity of Writers' Average Emotional Experiences	123
Stability, Inertia, and Change of Writers' Emotions.....	127
Relations between Writers' Emotions and Attention Regulation	133

Relations between Writers' Emotions and Productivity	138
Summary	143
Practical Implications.....	146
Limitations and Recommendations for Future Research	148
Conclusion	154
References	156
APPENDIX A – Email Invitation to Participate in the Study	174
APPENDIX B – Participant Information Form.....	175
APPENDIX C – Demographic Questions	178
APPENDIX D – “Gatekeeper” Email Template	179
APPENDIX E – Screenshots of Shiny App	180
APPENDIX F – Daily Survey Questions	182
APPENDIX G – Writing Self-Regulation Scale Items Piloted.....	184
APPENDIX H - Email Message Template for Daily Surveys	185

List of Tables

Table 1. Demographics of Final Sample	57
Table 2. Intraclass Correlation Coefficient (ICC) Estimates	77
Table 3. Descriptive Statistics for Daily Measures	79
Table 4. Mean Comparisons for Emotions	80
Table 5. Reliable Changes by Emotion	82
Table 6. Reliable Change Indices by Person by Emotion.	85
Table 7. Results from Emotional Inertia Models 1-3.	94
Table 8. Results from Emotional Inertia Models 4-6.	97
Table 9. Results of Attention Regulation Models.	107
Table 10. Results of Minutes Spent Writing Models.....	113
Table 11. Results of Number of Words Written Models.....	115

List of Figures

Figure 1. Intrapersonal mechanisms in Graham's WwC (2018) model	20
Figure 2. Community features in Graham's WwC (2018) model.	21
Figure 3. Gross's (1998) process model of emotion regulation.	32
Figure 4. Missingness by Variable.....	65
Figure 5. Emotion Means across Participants with 95% CIs.	80
Figure 6. Proportion of Reliable Changes by Emotion.	82
Figure 7. Distribution of Proportion of Reliable Changes across People.	84
Figure 8. Distribution of Proportion of RCIs across People, by Emotion.	85
Figure 9. Proportion of RCIs over Time for Positive Emotions, All Changes.	87
Figure 10. Proportion of RCIs over Time for Negative Emotions, All Changes.	88
Figure 11. Proportion of RCIs over Time for Positive Emotions, Negative Changes.	89
Figure 12. Proportion of RCIs over Time for Positive Emotions, Positive Changes.....	90
Figure 13. Proportion of RCIs over Time for Negative Emotions, Negative Changes.....	91
Figure 14. Proportion of RCIs over Time for Negative Emotions, Positive Changes.	92
Figure 15. Preliminary View of Shiny App.	180
Figure 16. Final View of Shiny App, Screen 1.....	180
Figure 17. Final View of Shiny App, Screen 2.....	181
Figure 18. Final View of Shiny App, Screen 3.....	181

Abstract

Investigating Daily Writing Emotions, Attention Regulation, and Productivity: An Intensive Longitudinal Study

by Eric Ekholm

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

Virginia Commonwealth University, 2019

Director: Sharon Zumbrunn, Ph.D.
Associate Professor, Foundations of Education
School of Education

Emotions pervade academic situations and influence the ways that learners think, behave, and achieve (Pekrun, 2006; Schutz & Lanehart, 2002). Writing may be a particularly emotion-laden activity, and especially so for students concentrating in fields that value writing production. However, very few studies have quantitatively investigated writers' emotional experiences. The goal of the current study was to examine the writing-related emotions of graduate students enrolled in writing-intensive disciplines as well as how these emotions related to writers' daily productivity and attention-regulation behaviors. To do so, the study employed a daily diary design (Gunthert & Wenzel, 2012) in which participants completed brief daily surveys over 28 days. Data from a final sample of 183 participants were analyzed in several frameworks, including descriptive statistics, reliable change indices, and longitudinal modeling via generalized estimating equations. Results from these analyses indicate that writers tend to experience positive valence emotions (e.g. enjoyment, pride) more strongly than negative valence emotions (e.g. anxiety, shame) and that, for most of the emotions studied, writers' emotional states tended to vary considerably from day to day. Furthermore, results indicate that

writers' emotional states are differentially related to daily writing outcomes such as attention regulation, time spent writing, and number of words written, and that state emotions are more predictive of these outcomes than are trait emotions. Theoretical implications and suggestions for future research are also presented.

Chapter 1 – Introduction

“There is nothing to writing. All you do is sit down at a typewriter and bleed.”

-Ernest Hemingway

“I can shake off everything as I write; my sorrows disappear, my courage is reborn.”

-Anne Frank

Emotions influence how people think, behave, act, react, and achieve (Aspinwall, 1998; Clore & Huntsinger, 2009; Gross, 2015a; 2015b; Pardos, Baker, San Pedro, Gowda, & Gowda, 2014; Pekrun, 2006; Slovic, Finucane, Peters, & MacGregor, 2007). However, until relatively recently, educational psychologists have largely ignored the affective domain (Boekaerts & Pekrun, 2016; Brand, 1990; Meyer & Turner, 2002; Schutz & Lanehart, 2002). With some notable exceptions (e.g. Pekrun, 2006; Weiner, 1985; Zeidner, 1998), educational psychologists have mostly focused their efforts on investigating cognitive, conative, and behavioral phenomena. These research traditions have resulted in rich bodies of knowledge and refined theories in areas such as working memory (e.g. Cowan, 2014; Paas & Sweller, 2014), self-regulated learning (Winne & Hadwin, 1998; Muis, 2007; Zimmerman, 2013; Zimmerman & Schunk, 2011), and motivation (Bandura, 1997; Usher & Pajares, 2008; Wigfield & Eccles, 2000). More recently, perhaps due to calls from prominent researchers (e.g. Schutz & Lanehart, 2002), research on emotions and affect in academic contexts has become more prominent. Researchers have proposed and tested broad theories and models of emotions/affect in achievement contexts (D’Mello & Graesser, 2012; Muis, Chevrier, & Singh, 2018; Pekrun, 2006; Pekrun, Frenzel, Goetz, & Perry, 2007), and they have applied more general theories of

emotions to academic settings (Forgas, 1995; Gross, 2015b; Gross & Jazaieri, 2014). This has led to exciting advancements in our understanding of the role emotions play in learning contexts.

To a large extent, research around writing has followed a similar trajectory. Models of writing proposed by Hayes and Flower in the 1980's (e.g. Flower & Hayes, 1981; Hayes & Flower, 1986) primarily emphasized the cognitive processes implicated in writing production. Although later work by Hayes (e.g. Hayes, 1996; 2012) expanded upon these models to further account for motivational, affective, and environmental influences, this work still seemed predominantly concerned with cognition. In the wake of these models, many other researchers proposed different, yet still cognitively-oriented, frameworks describing how writing is produced and how writers develop (e.g. Bereiter & Scardamalia, 1987; Kellogg, 2008; McCutchen, 1996). Somewhat more recently, scholars have expanded the scope of writing research beyond the cognitive domain and into the areas of motivation and self-regulation. Motivation research on writing has been carried out by several researchers investigating a diverse set of constructs such as self-efficacy, task value, attitudes, goal orientations, and interest, among others (e.g. Bruning & Horn, 2000; Ekholm, Zumbunn, & DeBusk-Lane, 2018; Hidi, Berndorff, & Ainley, 2002; Pajares, 2003; Pajares, Johnson, & Usher, 2007; Troia, Shankland, & Wolbers, 2012), and research on writing self-regulation has investigated how goal-oriented writing behaviors can lead to writing success (e.g. Graham & Harris, 2000; Harris, Graham, & Mason, 2006; Zimmerman & Risemberg, 1997). These bodies of research tell us a lot about writing and writing processes, particularly about how relatively stable characteristics of writers are implicated in writing. For instance, we know that several key writing processes, including planning, translating (i.e. drafting), and revising, are constrained by writers' working memory capacity (McCutchen, 1996). We also know that writers' beliefs about writing and about themselves as writers

influence their success and persistence on writing tasks (Ekholm et al., 2018; Graham, 2018; Pajares, 2003; Troia et al., 2012). And we know that teaching students to habitually engage in self-regulatory writing behaviors can improve writing performance (Graham & Perin, 2007; Harris et al., 2006; Lane, Harris, Graham, Weisenbach, Brindle, & Morphy, 2008). However, we know much less about how (potentially) instable, in-the-moment experiences – such as emotional experiences – relate to writing processes, including self-regulatory processes and writing productivity. Given that writing can elicit strong, varying emotions in all writers (e.g. Brand, 1990) regardless of their level of proficiency, and given that learners' emotions have been shown to relate to key academic outcomes and behaviors – including achievement, engagement, and goal pursuit – in other domains (Beymer, Rosenberg, Schmidt, & Naftzger, 2018; Bjornebekk, 2008; Goetz, Sticca, Pekrun, Murayama, & Elliot, 2016; Lichtenfeld, Pekrun, Stupinsky, Reiss, & Murayama, 2012; Pekrun, Lichtenfeld, Marsh, Murayama, & Goetz, 2017; see also Pekrun, 2006), it seems reasonable to assume that writers' emotional experiences will relate to their writing behaviors. These relations need to be more thoroughly investigated.

Although research on emotions in academic contexts is scarce in most domains, it is especially so in the domain of writing. The relatively limited amount of research on emotions during writing indicates that they may affect writing processes in several ways. Negative emotional experiences may consume cognitive resources and direct attention away from writing tasks (Cleary, 1991; Fartoukh, Chanquoy, & Piolat, 2012; Schmeichel, 2007), inhibit writers' use of top-down self-regulatory behaviors (Boice, 1997; Stewart, Seifert, & Rolheiser, 2015; see also Boekaerts & Niemivirta, 2000), and foster poor self-efficacy beliefs (Pajares et al., 2007). Negative emotional states during writing may also, at least in some cases, promote deeper, more critical thinking and may therefore contribute to improved idea generation (Bohn-Gettler &

Rapp, 2014; Prebel, 2016), particularly in creative writers (Olthouse, 2013). On the other hand, positive emotional experiences during writing may relate to more intentional strategy use (Miedijensky & Lichtinger, 2016), more positive self-beliefs and interest in writing (Collie, Martin, & Curwood, 2016; Hidi, Berndorff, & Ainley, 2002; Pajares et al., 2007), and improved creative ideation (Kopcsó & Lang, 2017; Larson, 1990; Ye, Ngan, & Hui, 2013). However, some research suggests that, like negatively-valenced emotional experiences, positively-valenced emotions may also consume cognitive resources and distract writers from the writing task at hand (Fartoukh et al., 2012). Though these studies provide useful starting points for those interested investigating how emotions relate to writing processes, they are just that – starting points. For instance, several of the studies that have been conducted are qualitative (e.g. Olthouse, 2014; Prebel, 2016), so those findings may not generalize. Likewise, a relatively limited range of discrete emotions have been studied, or else studies refer to positive affect and negative affect more broadly without distinguishing between discrete emotions. Finally, the predominant use of cross-sectional (or pre-post) designs and limited analyses (e.g. bivariate correlations) may not fully capture the complex and dynamic relationships between writers' emotions and behaviors. Many questions in this area still remain, including how writing-related emotions persist from day to day and how they relate to writing behaviors both in a given day and over time.

Theoretically, emotions are short-lived affective states that (may) vary considerably from moment to moment, context to context, and day to day (Frijda, 1986; Rosenberg, 1998).

Researchers from psychological disciplines beyond educational psychology (e.g. social psychology) have described several patterns of both affective stability and instability. For instance, studies employing linear autoregression models have found significant emotional

inertia between measurements, indicating some degree of emotional carryover between occasions (e.g. Kuppens, Allen, & Sheeber, 2010). Other researchers have examined alternative patterns of affective change, including curvilinear patterns and sinusoidal patterns (e.g. Larsen and Kasimatis, 1990) as well as patterns representing affective “spin” and “pulse,” signifying changes in intensity and arousal, respectively (Kuppens, Van Mechelen, Nezlek, Dossche, and Timmermans, 2007). In educational contexts, researchers have demonstrated both temporal stability and instability of learners’ beliefs, including achievement goal orientations (Fryer & Elliot, 2007; Muis & Edwards, 2009) and self-efficacy beliefs (Bernacki, Nokes-Malach, & Alevan, 2015). Likewise, several other studies have found that learners’ emotions can change or persist over time (Baker, D’Mello, Rodrigo, & Graesser, 2010; D’Mello & Graesser, 2011; 2012) and that this relative stability or instability may depend on the specifics of the affective states. However, only very little research on emotional inertia, stability, and change has been conducted specific to the domain of writing (Brand, 1990).

Insight gained from studying the persistence, or inertia, of writers’ daily emotional experiences can impact future investigations into writers’ emotions as well as future interventions or strategies that take writers’ emotional states into account. If writers’ emotions show little inertia from day to day – that is, if writers’ previous emotional states are not strongly related to subsequent emotional states – then future researchers and those who design intervention activities ought to take this instability into account. However, if writers’ emotions demonstrate considerable inertia (i.e. persistence of emotional states from day to day) or stability (i.e. relatively little change over time), this also has implications for future research and interventions. For instance, in the case of relative stability, researchers would be justified in making inferences about writers using single time-point measures of emotions typical of cross-

sectional study designs. Extending upon this, the relative stability or instability of daily emotional experiences may be contingent upon writers' characteristics, including their gender or academic discipline. Therefore, investigating the extent to which these experiences are stable, and what personal characteristics of writers moderate this stability, is necessary to inform future work.

Further exploring the relations between writers' emotions and their self-regulation also seems especially valuable. Since writing is often a long, self-directed, and cognitively-demanding undertaking, effective self-regulation is crucial for writers (Graham & Harris, 2000; Zimmerman & Risemberg, 1997). Indeed, Graham and Harris (2000) argue that expert writers will almost invariably be more self-regulative than less-proficient writers. There are plenty of anecdotal accounts of highly-skilled and productive writers enacting self-regulatory strategies that support this idea. Although these self-regulatory strategies tend to differ somewhat from writer to writer, the notion of being able to focus one's attention on the writing at hand frequently comes up. One example of this is the National Book Award-winning novelist Jonathan Franzen's rental of office space to avoid the distractions of his apartment. Likewise, research documenting the habits of highly-productive educational psychologists tells a similar story (Flanigan, Kiewra, & Luo, 2018; Mayrath, 2008; Patterson-Hazley & Kiewra, 2013). Many of the scholars interviewed in these pieces attribute their writing success – to some degree – to their ability to avoid distractions and concentrate on a piece of writing for whatever amount of time they have available. In other words, they note that their ability to regulate their attention helps them to be productive with the time they have available to write. Finally, a robust body of research indicates that, at all schooling levels, teaching students to employ self-regulatory writing strategies, including metacognitive strategies such as attention regulation, leads to

improved writing performance, especially in struggling writers (Graham & Perin, 2007; Gillespie & Graham, 2014). Together, this evidence leaves little doubt that effective attention regulation is essential for consistently producing good writing.

Nevertheless, attention regulation is still difficult for many writers. The academics interviewed by Flanigan and colleagues (2018) and Patterson-Hazley and Kiewra (2013) are exemplary in their fields, and their ability to avoid distractions and concentrate on writing tasks may not be so common amongst most academics. There are likely several reasons for this. According to Boekaerts (1997; Boekaerts & Pekrun, 2016), a person's motivations, goals, background knowledge, and situational factors interact to influence their attempts at self-regulation, including attention regulation. In this model, emotional states are situational factors that play a role in attempts at attention regulation. Although this proposition aligns with tenets of self-regulation theory (Boekaerts, 1997), achievement emotions theory (Pekrun, 2006), and working memory theory (Cowan, 2014; Derakshan & Eysenck, 2010), it has yet to be studied in the domain of writing using a design that can appropriately capture writers' short-lived emotional experiences.

Furthermore, although most writers, regardless of their age or writing proficiency, will likely experience a wide range of emotions while writing (see e.g. Brand, 1990), it may be particularly worthwhile to investigate the emotional experiences and behaviors of graduate students. In academia, publishing is the coin of the realm, and academics are often judged by both the quality and quantity of the writing they produce (e.g. Mayrath, 2008; Patterson-Hazley & Kiewra, 2013; Rawat & Meena, 2014). This pressure for academics to constantly publish manuscripts, most popularly summarized by the darkly humorous phrase "publish or perish," manifests itself in the plethora of books dedicated to teaching academics how to write more and

better (e.g. Becker, 2007; Goodson, 2016; Silvia, 2007) as well as in university interventions intended to increase faculty publication rates (McGrail, Rickard, & Jones, 2006). And, although they are not (yet) tenured or tenure-track academics, the pressure for graduate students to write and publish is equally intense. Karen Kelsky (2015) begins her book, *The Professor Is In* – a widely-read book providing job searching advice to graduate students eager to become academics – by chronicling the disappearance of tenure-track jobs over the past several years and arguing that, due to job scarcity, applicants for these tenure-track jobs must be exemplary. Meaning, among other things, they must write well and write a lot.

This pressure to write well and often may amplify the emotions associated with writing. Because the stakes are so high, graduate students may often feel anxious or frustrated before and while writing (Castello, Inesta, & Corcelles, 2013; Holmes, Waterbury, Baltrinic, & Davis, 2018; Sikes, 2006). Likewise, graduate students may not feel as confident about their ability to succeed on academic writing tasks, and these value appraisals may consequently elicit writing-related emotions (Pekrun, 2006). Furthermore, because writing is such a valued activity in academia, writers may feel particularly strong positive emotions, such as enjoyment or pride, when they successfully write because they are aligning their actions with disciplinary norms and expectations. These emotional experiences may be implicated in several facets of these writers' production and behaviors.

Beyond the substantive reasons for studying writing-related emotions in this population, graduate students provide a uniquely suitable group in which to investigate relations between daily writing-related emotions and behaviors. Because graduate students are expected to produce a great deal of writing, they likely write more often than people in other professions or than K-12 students, who may write for considerably less than 25 minutes per day on days that they do write

(Gilbert & Graham, 2010). Therefore, it may be easier to longitudinally study daily emotional experiences in behaviors in these academics.

Statement of the Problem

Writing can clearly be an emotional ordeal, replete with highs, lows, and everything in between. Further, most writers, regardless of their proficiency, will experience a variety of emotions while writing (Brand, 1990). Currently, we know a lot about how several person-level and environmental factors contribute to writing outcomes. For instance, we know that writers' self-efficacy beliefs are related to their writing performance (Bruning, Dempsey, Kauffman, McKim, & Zumbrunn, 2013; De Smedt, Merchie, Barendse, Rosseel, De Naeghel, & Van Keer, 2018; Troia et al., 2012). We also know teaching students self-regulatory writing strategies, building peer support into writing activities, and creating encouraging writing environments can promote writing success and motivation (Bruning & Horn, 2000; Graham & Perin, 2007; Graham, McKeown, Kiuahara, & Harris, 2012; Harris et al., 2006). We know much less about how writers' emotional experiences influence their behaviors, productivity, and performance. Early research in this area, along with studies investigating emotions in other academic domains, suggests that emotions are likely implicated in several writing processes. More so, it may be particularly important to better understand these relations in populations who are expected to write a lot, such as burgeoning academics.

Theories of emotions in academic contexts posit that students' emotions are closely tied to their behaviors, motivation, attention, strategy use, and achievement (Boekaerts & Corno, 2005; Boekaerts & Pekrun, 2016; Muis, Chevrier, & Singh, 2018; Pekrun, 2006; Pekrun et al., 2007). Among the propositions of these theories are that task-relevant activating positive emotions, such as enjoyment, are typically beneficial, whereas negative activating (e.g. anxiety)

and deactivating (e.g. shame) emotions tend to be mostly detrimental (Pekrun, 2006). Generally, findings from empirical studies support these propositions (see Boekaerts & Pekrun, 2016, or Goetz & Hall, 2013, for reviews). For example, a learner who feels joy during a learning task may experience deeper task engagement (Beymer et al., 2018; Csikszentmihalyi, 1990) and may have more cognitive resources available for (meta)cognitive strategy use (Boekaerts & Corno, 2005; Cowan, 2014; Paas & Sweller, 2014), whereas a learner who feels frustrated during a task may struggle to enter a flow state (D’Mello & Graesser, 2012) and may have diminished cognitive resources available to put toward the task. Over time, these affective experiences seem also to relate to students’ academic achievement. In a longitudinal study of approximately 3,400 students between grades 5-9, Pekrun and colleagues (2017) found long-term reciprocal effects between students’ affective experiences and math achievement, with discrete positive emotions consistently (albeit modestly) predicting higher achievement and discrete negative emotions consistently (and modestly) predicting lower achievement. Once again, however, these theoretical propositions are domain-general, and most of the empirical evidence in these areas has been conducted in domains other than writing. Even Bohn-Gettler and Rapp’s (2014) recent book chapter on emotions in reading and writing processes draws heavily from domain-general and reading-specific research to make inferences about emotions in writing. But we know that writing differs from other domains, including reading, in many respects (Fitzgerald & Shanahan, 2000), and we know that students’ emotions, beliefs, and behaviors differ by academic domain (e.g. Goetz et al., 2016; Wigfield, 1997). Therefore, it may be inappropriate to simply assume that theoretical propositions and empirical evidence from other domains are equally applicable to writing.

The ephemeral nature of emotional states introduces a relevant methodological consideration as well. By definition, emotions are short-lived and often intensely-experienced phenomena (Rosenberg, 1998), which can make them difficult to measure accurately. As a solution to this issue of temporal instability, educational psychologists have developed instruments that measure participants' typical emotional experiences in a given learning context or with respect to a given object (Lichtenfeld, Pekrun, Stupinsky, Reiss, & Murayama, 2012; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011; Pekrun et al., 2017). That is, they ask students to mentally average their emotional experiences in, say, math class, to arrive at a measurement representing how they usually feel. Though useful in many respects, particularly for understanding longer-term developmental trends (e.g. Pekrun, 2017), the length of these questionnaires makes them unsuitable for capturing meaningful short-term emotional states or fluctuations between these states. Additionally, scores on these measures may be biased by participants' current emotional states (Kahneman, 1999). Employing designs and measures more suitable for measuring writers' short-term emotional experiences can provide a more nuanced understanding of how these emotional states relate to one another over time as well as how they relate to meaningful proximal outcomes, such as words written on a given day. Better understanding potential short-term variability in writers' emotions over time could also lead to the development of tools, interventions, and strategies that accommodate the more stable characteristics of writers, such as their self-beliefs and long-term goals, as well as potentially instable factors, such as emotional states. These tools, interventions, and strategies could, in turn, promote more positive writing outcomes as well as more beneficial emotional experiences in writers.

Purpose of the Current Study

The purpose of the current study is to further explore graduate student writers' daily emotional experiences, both in terms of their stability over time and their relations to daily writing behaviors and productivity. To do so, I will employ a daily diary design (Gunthert & Wenzel, 2012) to measure graduate students' feelings of enjoyment, pride, boredom, anxiety, frustration, shame, contentment, excitement, and confusion during writing as well as their daily attention regulation while writing and their writing productivity each day over the course of four weeks. In doing so, I will address the following research questions:

1. How strongly do writers feel each emotion over the course of the month, and are there differences between emotions in average intensity?
2. How stable are writers' day-to-day emotional experiences, and does this stability change over time?
 - a. Is this stability moderated by writer characteristics such as gender or academic affiliation?
3. To what extent do writers' writing-related emotions predict their daily attention regulation while writing?
4. To what extent are writers' emotional experiences related to their writing productivity?

Answering these questions will provide researchers and educators with a better understanding of 1) the intensity with which writers feel a variety of emotions, 2) how stable these emotional experiences are over time, including how much day-to-day emotional inertia writers experience, and 3) the extent to which daily emotional experiences relate to key proximal writing outcomes. Though this is admittedly an early foray into this area, these findings can

potentially lead to the development of empirically-based writing strategies, tools, and instructional practices that take writers' emotions into account.

Brief Overview of Methodology

The current study used a daily diary design to investigate writers' emotions, attention regulation, and productivity over time. Daily diary studies ask participants to complete a brief survey regarding the constructs or behaviors of interest each day over the course of several days or weeks (Gunthert & Wenzel, 2012). This type of design is particularly useful for researchers interested in phenomena, such as emotional states, that may vary considerably from day to day.

More generally, daily diary designs are a type of intensive longitudinal design (ILD). ILDs can vary in terms of several methodological features, including how data is collected, how often data is collected, and study duration, among others, but they are alike in that ILDs seek to understand participants' momentary experiences in natural environments (Mehl & Conner, 2012). Although ILDs are longitudinal designs that capture both intra- and interpersonal differences, they differ from more traditional longitudinal panel designs in terms of the scope of phenomena they are adept at studying. Whereas studies employing traditional panel designs are typically interested in constructs that develop over extended periods, such as intelligence, studies employing ILDs tend to be interested in constructs, such as emotional states, characterized by meaningful day-to-day or moment-to-moment fluctuations. Researchers in a variety of fields, including psychology, public health, medicine, economics, and education, have used ILDs to explore numerous aspects of people's daily lives (Hektner et al., 2007; Zirkel, Garcia, & Murphy, 2015). Within the domain of education, these designs have been used to investigate students' momentary affective states, interest, engagement, and goal-setting behaviors as well as teachers' instructional practices, among other phenomena (e.g. Beymer et al., 2018; Goetz et al.,

2016; Patall et al., 2016; Zirkel et al., 2015). This type of design offers a promising way to study relations among writers' daily emotions, behaviors, and productivity, including capturing potential time-varying covariates that relate to changes in these phenomena.

Definition of Terms

Achievement Emotions. Emotions tied directly to achievement activities or outcomes (Pekrun, 2006).

Activation/Arousal. The degree to which an emotion promotes or inhibits action (Russell, 1980).

Attention Regulation. The process of directing attentional resources toward a task and away from potential distractions (Randall, Oswald, & Beier, 2014).

Control Appraisals. Subjective appraisals learners make regarding their perceived causal influence over learning actions and outcomes (Pekrun, 2006).

Emotions. Multi-component, coordinated processes of psychological subsystems including affective, cognitive, motivational, expressive, and peripheral physiological processes that are typically short-lived and elicited by a specific stimulus (Pekrun, 2006; Rosenberg, 1998).

Emotion Regulation. The activation of a goal or process to influence the emotion trajectory (Gross, Sheppes, & Urry, 2011).

Emotional Inertia. The carryover of an emotional state from one measurement to the next (Hamaker, 2012).

Self-Regulation. A complex process in which learners sustain cognitive, affective, and behavioral processes that enable them to pursue learning goals or demonstrate learning (Zimmerman & Schunk, 2011).

Valence. The degree to which an emotion is pleasurable or unpleasurable (Russell, 1980).

Value Appraisals. Subjective appraisals learners make regarding the perceived importance of learning actions and outcomes (Pekrun, 2006).

Chapter 2 – Review of Literature

The purpose of this study is to examine writers' emotions over time, including which emotions writers experience most strongly, how stable writers' emotions are from day to day, how much day-to-day emotional inertia writers experience, and how daily emotional experiences relate to writing attention regulation and writing productivity. In pursuit of these aims, the current chapter will review the relevant literature. To begin, I will review models of writing production, emphasizing the role of self-regulation – and specifically attention regulation – in these models, and theories of achievement emotions, emphasizing emotion regulation processes. Following this, I will discuss findings from existing studies that have examined the role of emotions in the writing process, including how writers' emotional states relate to their cognitive processes, self-regulatory behaviors, motivation, and ideation. Then, I will describe methodological considerations relevant to the current study. Finally, I will conclude the chapter by discussing how the previously-reviewed theories and empirical findings inform the conceptual framework and hypotheses of the present study.

Models of Writing Production

In addition to applying domain-general theories of cognition (e.g. Cowan, 2014; Paas & Sweller, 2014), motivation (e.g. Wigfield & Eccles, 2000; Bandura, 1997; Wigfield, Tonks, & Klauda, 2009), and self-regulation (e.g. Winne & Hadwin, 1998; Zimmerman, 2013) to studies

of writing, writing researchers have also advanced multiple domain-specific theories related to writing. Although several models have been advanced to describe writing-specific phenomena, including how writing skills develop over time (e.g. Berninger, Fuller, & Whitaker, 1996; Hacker, 2018; Kellogg, 2008) and how to best teach students to write (e.g. Calkins, 1986; Graham, Harris, & Mason, 2005; Graves, 1983), for the purposes of this study I focus primarily on models that describe how writers produce texts (e.g. Flower & Hayes, 1981; Graham, 2018; Hayes, 2012; Hayes & Flower, 1986). The purpose of the current section is to provide a broad overview of these models. In a later section, I focus more explicitly on the lack of emphasis these models place on writers' emotional experiences, and in doing so I offer some critiques of these models.

Hayes and Flower's cognitive process theory of writing (Flower & Hayes, 1981; Hayes, 1996; Hayes & Flower, 1986) posits that the act of writing is a recursive, goal-directed pursuit that requires writers to enact, coordinate, and switch between three sub-processes: planning, translating, and revising. A writer's goals for a given task will differ in scope, aim, and purpose, with some superordinate goals guiding the entire task and other subordinate goals pertaining only to certain aspects of the writing task. For example, a superordinate goal might be persuading a reader to accept a certain premise (e.g. that dogs are superior to cats), whereas a subordinate goal might be writing a description that evokes a specific emotion in service of this argument (e.g. describing the joy of a dog greeting you when you come home after being at work all day). As writers progress through a task, subordinate and even superordinate goals may be resolved or may change. To meet these goals, writers employ (and switch between) three recursive processes. The planning process entails generating ideas and organizing these ideas into a structure appropriate for the writing task. We may think of planning in terms of outlines and

graphic organizers, but planning can (and often does) occur absent any physical manifestation, and it occurs throughout a writing task rather than solely at the beginning of a task. The translating process entails drafting an idea structure into written text. This may be as straightforward as translating a sentence that a writer has already completely formulated in her mind into text, or it may require translating an abstract semblance of an idea into a coherent piece of text. The revising (or reviewing) process entails evaluating the extent to which a text meets a writer's goals and, if necessary, altering the text to better address these goals. Writers enact these three processes to accomplish both superordinate and subordinate goals. That is, the planning, translating, and revising processes are equally applicable to understanding writing production at the whole-text level as they are to understanding writing production at the word, phrase, or sentence level. Finally, the cognitive process model argues that these three composing processes are highly recursive. Writers switch between these processes frequently throughout a writing session, with a cognitive regulatory mechanism Flower and Hayes (1981) refer to as the "metacognitive monitor" cueing transitions between processes.

As its name suggests, the Hayes and Flower cognitive process model focuses primarily on intraindividual cognitive processes that facilitate writing production. Although this model does acknowledge other factors that influence writers, such as task features and social environments, and Hayes has elaborated on these other factors in later writings (e.g. 1996; 2012), the model is most widely known for its formulation of writing as a cognitive process. In contrast, Graham's (2018) Writer-within-Community (WwC) model emphasizes both the intrapersonal and the social influences on writing production. In doing so, the WwC model draws from sociocultural (e.g. Greeno, 1998), cognitive (e.g. McCutchen, 1996; Paas & Sweller, 2014), and conative (e.g. Eccles, 2005; Schunk, 2012) perspectives. In this model, Graham specifies several

intrapersonal factors involved in producing a text. These include production processes, control mechanisms, long-term memory resources, and modulators. The production processes in the WwC model are similar to those set forth in the models by Hayes and colleagues (Chenoweth & Hayes, 2001; Flower & Hayes, 1981; Hayes, 1996; Hayes & Flower, 1986) and include constituent processes such as conceptualization (creating a “mental road map” [Graham, 2018, p. 300] of what the writer needs to do), ideation (generating potential ideas to include in the text), translation (turning ideas into coherent structures), transcription (creating a physical representation of the text via writing or typing), and reconceptualization (revising). Control mechanisms in the model direct cognitive resources toward aspects of the task and facilitate individualized self-regulation. In the WwC model, these include attention, working memory (a limited cognitive workspace, e.g. Baddeley, 2000), and executive control (establishing agency over a writing task). The long-term memory resources specified in the model refer to knowledge and beliefs. In this model, knowledge can represent a writer’s knowledge about a topic to be written about, knowledge about the audience for whom the writing is intended, and knowledge about language and linguistic features. Beliefs represent writers’ conceptualizations of themselves as writers and of the task of writing more generally. These include writers’ beliefs about their writerly competence (Pajares, Johnson, & Usher, 2007), about the utility and intrinsic value of writing (Wigfield & Eccles, 2000), about the causes of their writing successes and failures (Weiner, 1985), about their goals for writing (Elliott, 1999), and about their identities as writers (Bazerman, 2016). Finally, the WwC model also specifies several modulating mechanisms that interact with these aforementioned factors. These modulators include emotional states, personality traits, and temporary physiological states (e.g. hunger, tiredness). Figure 1 illustrates the within-person features of the WwC model.

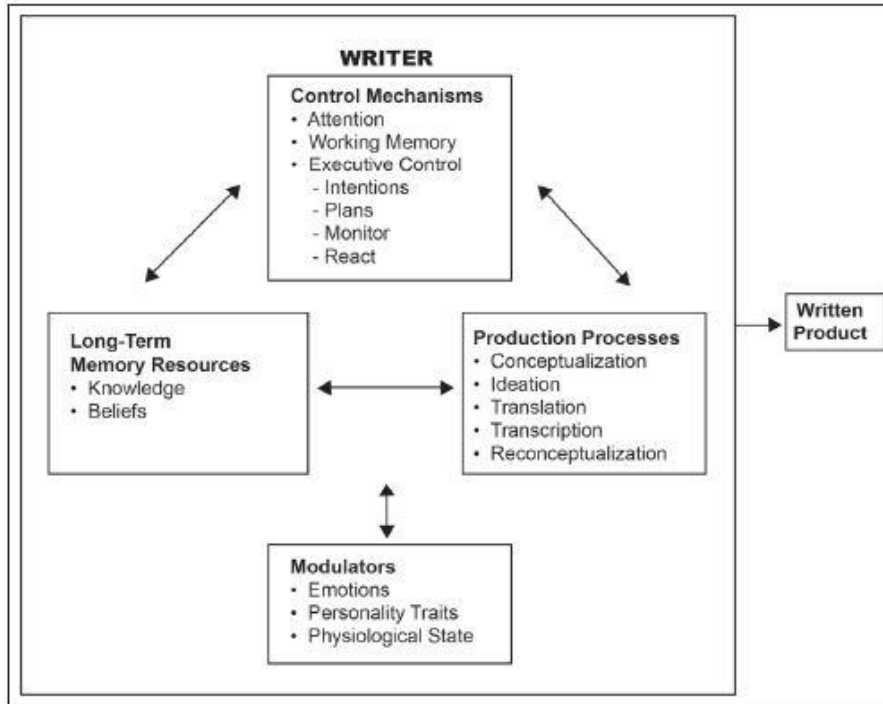


Figure 1. Intrapersonal mechanisms in Graham's WwC (2018) model

In addition to these intraindividual factors influencing writing production, Graham (2018) theorizes that several sociocultural factors – features of the community, in the parlance of the model – can facilitate or constrain writing production. In this model, communities refer to a specific writing context in which multiple people (largely) share a common set of goals, assumptions, and norms regarding writing. Further, communities can be small, proximal entities, such as a local writers group, or expansive, distal entities, such as the American Psychological Association, with smaller communities often embedded within – or influenced by – larger communities. According to Graham (2018), writing communities comprise several basic components. These include the community's purpose for writing, the members of the community (which includes writers, collaborators, and their potential audience), the tools frequently used by the writing community, the actions communities employ to reach their goals, the texts produced by the community, and the community's physical and social environments. Figure 2 illustrates the community features in the WwC model.

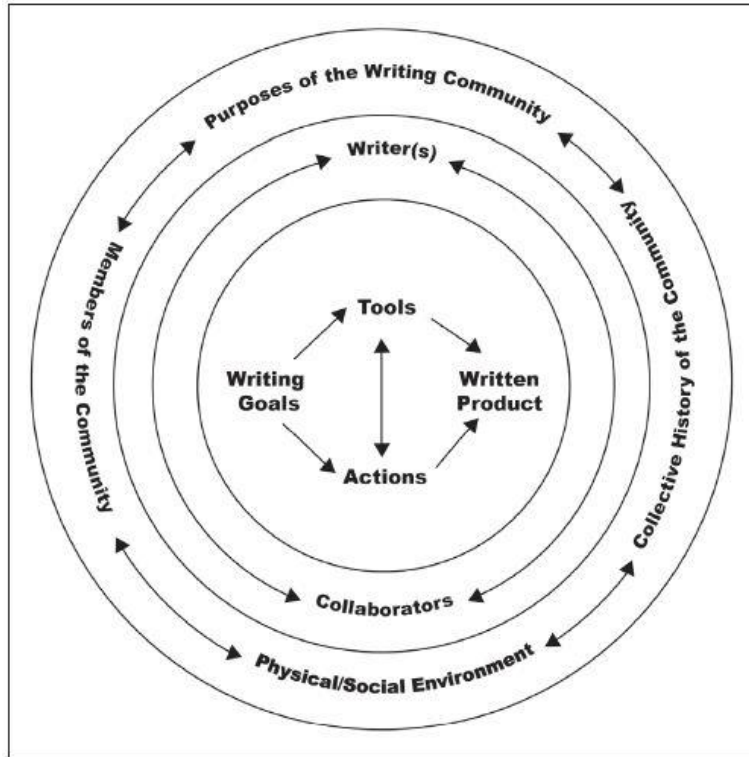


Figure 2. Community features in Graham's WwC (2018) model.

Self-Regulation and Writing

In academic contexts, self-regulation refers to a complex process in which learners sustain several constituent subprocesses that enable them to pursue learning goals or to demonstrate learning (Bernacki et al., 2013; Zimmerman, 2013). These subprocesses can include cognitive, metacognitive, social, motivational, and affective components (Muis, Chevrier, & Singh, 2018), with various models of self-regulation emphasizing these components differently (Muis, 2007). Because writing is often a prolonged, goal-directed, and recursive endeavor, effective self-regulation is critical for writers (Graham & Harris, 2000; Zimmerman & Risemberg, 1997). Both the Hayes and Flower cognitive process model and Graham's WwC model explicitly specify self-regulatory mechanisms as the means through which writers set goals, enact explicit strategies, and self-monitor while writing (see also Winne & Hadwin, 1998, for a more general model of self-regulation). In the original cognitive process model by Flower

and Hayes (1981), this self-regulatory mechanism was termed the “metacognitive monitor,” which served to monitor the overall writing process and initiate transitions between planning, translating, and revising processes. More recent models proposed by Hayes (e.g. 1996; 2012) are organized somewhat differently, with the role of the monitor represented in the “text interpretation” and “reflection” processes in the 1996 model (see p. 4) and represented by the “evaluator” and the “goal setting” processes in the 2012 model (see p. 371). Nevertheless, functions commonly associated with self-regulation – such as setting goals, enacting strategies to pursue these goals, focusing attention on the writing task, and reflecting on one’s progress – are still prominent in these more recent models. Graham’s (2018) WwC model specifies self-regulation as part of the control mechanisms and executive control processes, which include focusing attention, setting goals, acting to achieve these goals, monitoring progress toward goals, and modifying goals, actions, and self-monitoring strategies as necessary.

As the definitions and models described in the previous paragraph illustrate, self-regulation is a complex meta-process that can refer to a wide range of processes learners employ in academic situations. Graham and Harris (2000) describe numerous cognitive and metacognitive self-regulatory strategies that writers may enact, including (but not limited to) attention monitoring, goal setting, information seeking, self-monitoring, self-evaluating, time planning, self-consequating, seeking social assistance, and environment structuring. Likewise, Zimmerman and Risemberg (1997) propose a set of writerly self-regulatory strategies that largely overlap with those described by Graham and Harris (2000), although these authors categorize self-regulatory processes somewhat differently. Further still, self-regulatory processes can be combined with cognitive writing strategies, such as the POW + TREE strategy described by Graham and colleagues (2005), in line with the Self Regulated Strategy Development (SRSD)

framework (Harris et al., 2006; Lane et al., 2008). Therefore, there are countless ways in which writers can self-regulate, depending on which strategies they employ, which they neglect, and how they combine strategies. As a result, writing self-regulation is an idiosyncratic process contingent upon multiple factors, including the writer's preferences and the nature of the writing task (see also Bazerman, 2018, for more discussion of personal differences in writing processes).

That said, there are some components of self-regulation that may be more common across writers. In the current study, I focus on attention regulation, which refers to the process of directing attentional resources toward a specific task (Randall et al., 2014). Successful attention regulation entails both attending to task-relevant information and ignoring task-irrelevant information, such as distractions (Engle & Kane, 2004; Kane, Poole, Tuholski, & Engle, 2006). In a broad sense, attention regulation requires managing both internal (e.g. emotions, conflicting interests) and external (e.g. other obligations, distractions) stimuli that might interfere with a writing task as well as actively focusing attention on that writing task. Given that writing is a cognitively-demanding task that (often) requires a long time to complete, the writers' abilities to direct their attention toward writing tasks (and simultaneously avoid distractions) seems particularly important. Indeed, many of the highly-productive scholars interviewed by Flanigan and colleagues (2018), Mayrath (2008), and Patterson-Hazley and Kiewra (2013) mentioned some aspect of attentional control or distraction avoidance as reasons for their writing success. In addition to these, famous writers including Jonathan Franzen (2002), Stephen King (2002), and Marcel Proust (see Zimmerman & Risemberg, 1997) describe idiosyncratic strategies for focusing on writing and avoiding distractions. For instance, Franzen described writing in a sparsely-furnished rented office with a laptop that didn't connect to the internet to help him maintain focus on writing. Proust wrote in a room that he soundproofed with cork. And

Zimmerman, perhaps unsurprisingly, employs a suite of self-regulation strategies to execute his research and writing (Patterson-Hazley & Kiewra, 2013). Additionally, we know that reaching expert levels of writing performance requires sustained, directed effort over long periods of time (Ericsson, 2006; Kellogg, 2008), and so the ability of writers to focus attention on their writing may lead to both short-term productivity and longer-term proficiency.

In line with Boekaerts' dual-process model (1997; Boekaerts & Corno, 2005), attention regulation is a top-down process driven by writers' goals, motivations, and values (see also Winne, 1995). However, when writers lack sufficient volitional strategies, situational influences, including affective states, can undermine attention regulation (Boekaerts, 2007; Boekaerts & Corno, 2005). Generally, these ideas, though framed somewhat differently, are present in Graham's WwC model (2018) as well. According to Graham, writers' beliefs – including their self-efficacy, identities, values, goal orientations, and attributions – will influence their control processes, including their abilities to regulate their attention; however, emotional experiences may modulate the relations between these top-down beliefs and attention regulation, with positively-valenced emotions leading to greater effort and negatively-valenced emotions leading to reduced effort. The magnitude of these hypothesized relations has not been studied in the domain of writing, however, nor have relations between discrete emotional states (e.g. states of enjoyment, anxiety, or boredom) and attention regulation.

A Lack of Emphasis on Emotions in Writing Models

The models proposed by Hayes (e.g. 1996; 2012) and Graham (2018) acknowledge that emotions can and do influence text production. That said, the role of emotions in writing production processes is not central to either of these models, nor is the role of emotions in self-regulatory processes, and specifically attention-regulation. For instance, much of Hayes' (1996)

discussion of affect is combined with a discussion of motivation, and the sections specific to affect predominantly describe affective responses to written text rather than the role of affect in producing text. Graham's WwC model (2018) presents emotions in the category of modulators, which influence writing processes by interacting with the production processes, control mechanisms, and long-term memory resources specified in the model. These interactions are not elaborated on in great detail, though, so much remains to be explored about how and why emotions are implicated in writing processes. For instance, Graham acknowledges broadly that positive and negative emotions can "enhance or reduce effort allocation and management" (p. 302). More specifically, he posits that emotions such as pride and joy could lead writers to persist during writing, whereas feelings of shame and anxiety might impede writers' attention. In the model, Graham does not posit specifically which emotions might have stronger (or weaker) influences, nor does he explicitly mention potentially relevant emotions such as confusion or boredom. In fairness to Graham and the WwC model, it does delineate relationships between a wide range of diverse factors, including broad sociocultural factors, physiological factors (e.g. handwriting), cognitive factors, and motivational factors, and so providing a minutely detailed account of any subset of these factors is somewhat beyond the scope of the model.

Furthermore, little research in the domain of writing has explicitly investigated how emotions might be implicated in writers' self-regulatory behaviors (Sala-Bubare & Castello, 2018), although extant research indicates that negatively-valenced emotions may undermine self-regulation (Boekaerts, 2007; Boice, 1997; Stewart et al., 2015).

Before delving into how, and to what extent, emotions might influence writing, we need to first understand what emotions are, how they arise, how they relate to achievement generally, and how learners may attempt to regulate their emotions. Therefore, in the subsequent section, I

will describe domain-general models of emotions and emotion regulation, specifically focusing on models relevant to academic or achievement contexts. In doing so, I will discuss different categorizations of emotions, antecedents and consequences of emotions, and strategies for regulating emotions in learning situations.

Models of Emotions and Emotion Regulation

Across the literature, emotions are generally considered to be affective states characterized by shifts in subjective experiences, cognition, behavior, and physiology (Boekaerts & Pekrun, 2016; Frijda, 1986; Gross, 2015a; Pekrun, 2006; Weiner, 1985). For example, feeling joy while writing might lead to more favorable perceptions of one's surroundings, use of global problem-solving strategies and improved creative thinking, increased engagement with the writing task, and slightly elevated heart rate or a happy facial expression (Baas, de Dreu, & Nijstad, 2008; Boekaerts & Pekrun, 2016; Bohn-Gettler & Rapp, 2014). Emotions unfold and persist over time, but emotional states are typically rather brief, especially in comparison to other affective states such as moods (Rosenberg, 1998). Additionally, emotions are commonly considered in terms of their valence (the degree of associated goodness or badness), their activation or arousal level (the degree to which they promote or inhibit action), and their object focus (the object or situation eliciting the emotion; Clore & Huntsinger, 2009; Pekrun, 2006). Finally, the benefits or detriments of emotions are context-dependent (Gross, 2015a; Gross & Jazaieri, 2014). We often consider some emotions to be *a priori* "better" than others, particularly in academic contexts (e.g. enjoyment in school is typically considered better than anxiety), but the merits of a given emotion should be considered relative to the context in which these emotions are elicited and the outcomes they produce. For instance, some research has found that anticipatory shame at the prospect of failing an assignment may compel students to invest more

time and effort to avoid failure (Turner & Schallert, 2001). In such a context, shame may actually benefit learners, at least in the short term.

Within educational contexts, researchers distinguish between several types of emotions based on their object focus (Boekaerts & Pekrun, 2016; Muis et al., 2018; Pekrun, 2006). These types of emotions include achievement emotions, epistemic emotions, topic emotions, and social emotions. Achievement emotions are related to either achievement-related activities, such as writing an essay for class, or outcomes of achievement-related activities, such as receiving a grade on an essay. Further, achievement emotions can be elicited prospectively, concurrently, or retrospectively in relation to the activity or outcome. That is, a student might feel joy when anticipating a writing assignment, while working on the writing assignment, or when reflecting on a previously completed writing assignment. Epistemic emotions result from “appraisals...about the alignment or misalignment between new information and existing beliefs, existing knowledge structures, or recently processed information.” (Muis et al., 2018, p. 6). In other words, their object focus is not necessarily the content itself, but rather the congruence or incongruence between sources of information. An example of an epistemic emotion might be joy while reading a blog about nutrition that aligns with one’s current beliefs about nutrition. Topic emotions refer to emotions that students feel about a specific set of content. For example, a child who likes dinosaurs might experience joy when working on a research project on the Jurassic period. Finally, social emotions refer to emotions associated with interactions during learning tasks. Enjoying collaborating with peers during a group assignment would be an example of a social emotion. As these examples illustrate, the same emotion (e.g. joy/enjoyment) could belong to any of these categories, so these categories are most useful for discerning between objects of emotions rather than emotions themselves. Also, learning environments can be incredibly

complex, and though these types of emotions provide us with a useful taxonomy, student emotions may not be so easily attributed to a single category in practice. Imagine a student who likes dinosaurs (a topic) and likes writing (an achievement activity). If this student is enjoying writing a poem about velociraptors, this enjoyment is likely a function of both the topic and the activity.

According to Pekrun's control-value theory of achievement emotions (2006; Pekrun et al., 2007), the achievement emotions a person experiences during a task depend on that person's control and value appraisals of the task. Control appraisals refer to the extent to which people believe they have control over success on the task, where high control appraisals indicate people strongly believe success on the task is under their control and low control appraisals indicate they believe they have little or no control over succeeding on the task at hand. Value appraisals refer to the relative importance that people attribute to a given task. The confluence of these two types of appraisals then elicits an emotion. For example, if a student believes a given writing task is interesting and important (value appraisals) and believes herself capable of doing well on the task (control appraisal), she will likely experience joy while working on the task. In contrast, if she believes a given writing task is unimportant (value appraisal) and believes herself incapable of succeeding on it (control appraisal), she may feel frustration while working on it. As mentioned previously, Graham's WwC model (2018) specifies these relations to some extent, and some quantitative (e.g. Collie, Martin, & Curwood, 2016) and qualitative studies (Holland, 2013; Olhouse, 2013; 2014) support these propositions in the domain of writing.

Emotions can affect learning and performance on academic tasks in several ways. These propositions will be more fully described later in this chapter, but it is necessary to briefly preview some of these mechanisms to allow for a more meaningful discussion of emotion

regulation strategies. First, emotions can either direct cognitive resources toward or divert them away from a learning task. According to Boekaerts's (1997; Boekaerts & Corno, 2005; see also Boekaerts & Pekrun, 2016) dual-processing model of self-regulation, students seek to balance mastery strivings and well-being strivings when learning. When students experience negatively-valenced emotions, some attentional resources are siphoned from the mastery pathway to the well-being pathway and enacting emotion-regulation strategies (Gross, 2015a; Gross, 2015b). In line with capacity-limit approaches toward working memory (e.g. Cowan, 2014), this dedication of resources toward promoting well-being leaves fewer resources available to pursue learning goals and enact (meta)cognitive strategies. Even positively-valenced emotions may similarly consume or divert attention if these emotions are irrelevant to the current learning task. Second, emotions may impact academic achievement via reciprocal links between emotional experiences, achievement, task appraisals, and motivation (Pekrun et al., 2017). Recall that emotional responses arise from control and value appraisals of a task. If a student feels anxious during a learning task, this anxiety could lead to impaired task performance, which could in turn lead to diminished self-efficacy beliefs (control appraisals) and task interest (intrinsic value appraisals). Furthermore, differently valenced emotions may elicit different cognitive processing approaches, with positively-valenced emotions generally producing creative or global thinking and negatively-valenced emotions producing more analytic, detail-oriented thinking (Bohn-Gettler & Rapp, 2014; Forgas, 1995). However, the influence of emotions of processing approaches seems to be ancillary to the influences of task-specific features (e.g. Forgas, 1992); that is, if an academic task, such as critiquing a poem, requires an analytic, substantive processing approach, experiencing positive emotions during the task would not preclude such an approach.

Finally, beyond valence, discrete emotions even with the same valence may elicit different cognitive or motivational processes. For instance, excitement and enjoyment are both positively-valenced emotions, yet excitement is a more arousing emotion than is enjoyment. Therefore, these emotions may differentially relate to writers' psychological processes and behaviors. Indeed, Ashby and Isen (1999) describe how heightened arousal can cue physiological processes that may be detrimental for sustained attention. Similarly, although boredom, anxiety, and shame are all negatively-valenced emotions, past research suggests that they relate differently to learning processes and outcomes (Baker, D'Mello, Rodrigo, & Graesser, 2010; Pardos, Baker, San Pedro, Gowda, & Gowda, 2014). In some select cases, negatively-valenced emotions such as shame (Turner & Schallert, 2001), frustration (Pardos et al., 2014), and anxiety (Wang et al., 2015) may even be beneficial in academic contexts.

Emotion Regulation

In situations where emotions might interfere with learning or academic performance, learners may attempt to regulate their emotions. Gross's process model (1998) and extended process model of emotion regulation (2015a; 2015b; Gross & Jazaieri, 2014; Gross, Sheppes, & Urry, 2011) describe how people are presented with opportunities to enact emotion-regulation (ER) strategies at various stages in an emotion-generating situation. The extended process model further elaborates how these emotion-regulation choices, along with personal valuation systems, influence patterns of emotion elicitation and regulation in future situations. ER strategies can be grouped into families of strategies that become more or less viable as emotion-generating situations unfold. These families of strategies include situation selection (behaving to minimize or maximize the likelihood that one is in a situation that will elicit a certain emotion), situation modification (behaving to change a situation and thereby change its emotional impact),

attentional deployment (redirecting attention to change an emotional response), cognitive change (altering an appraisal of an emotion-inducing situation to change the associated emotional response), and response modulation (behaving in a way to directly change an emotion that one is currently experiencing).

An example may help illustrate these strategies. Let's assume Orin, a hypothetical writer, is working on a writing assignment. If Orin anticipates that writing will lead to anxiety, he might employ a situation selection strategy and simply choose not to write. If he believes that the writing assignment would be more enjoyable if he could complete it as a blog rather than as a traditional essay, he could employ a situation modification strategy by changing the writing format to a blog post. If, after having completed the assignment, Orin feels shame at earning a failing grade on the assignment, he could employ an attentional deployment strategy by flipping the page of the essay so he can no longer see the "F" on the front. Alternatively, Orin could employ a cognitive change strategy to reappraise his failing grade by thinking "rather than view this as a failure, I can view it as an opportunity to learn from my mistakes" and thereby diminish his feelings of shame. Finally, Orin could enact a response modulation strategy in this situation by going for a long run to directly alter the physiological and biological components that contribute to the shame he's experiencing. Figure 3 presents a depiction of the process model of emotion regulation.

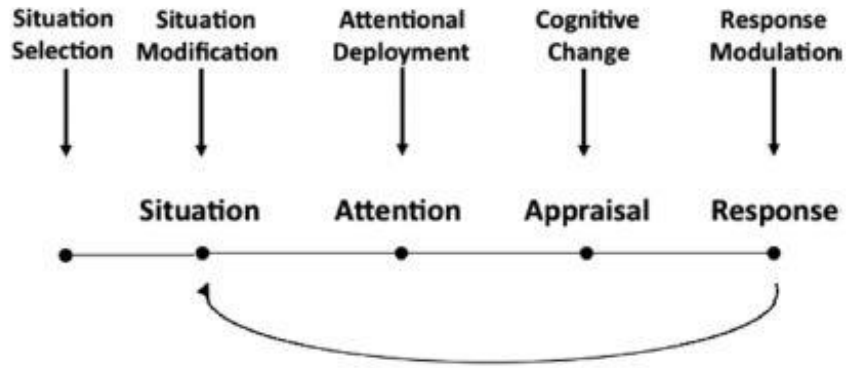


Figure 3. Gross's (1998) process model of emotion regulation.

Gross's extended-process model of emotion regulation (2015a; 2015b) builds on this by including a second-level valuation system through which people consider how the emotions they experience and the strategies they use to regulate these emotions align with their personal values. This second-level valuation system affects subsequent emotional experiences and ER strategy choices. Returning to Orin, assume he chooses not to write one day to avoid feeling anxious. Through the second-level system, Orin might then consider whether this ER strategy (avoiding writing) aligns with his personal values. If Orin considers writing important, then his strategy choice would not align with his values. This valuation process would then influence subsequent choices regarding ER strategies, which, in turn, would affect his emotional experiences relating to writing. This second-level valuation system may have implications for how writers' emotional states carry over – or don't carry over – from day to day in that it influences the emotion regulation strategies writers may choose to employ or not employ.

Relations between Emotions and Writing Processes

In the previous sections, I described models of writing production, theories of academic emotions, and theories of emotion regulation to lay the theoretical foundation for the current project. In the current section, I will build upon this foundation by describing results of primary studies that have examined relations between emotions and writing processes. As appropriate, I

will draw from the models described previously as well as other models relevant to the topics at hand to further contextualize the findings described. In some cases, I also consider domain-general research on emotions and production or attention processes, particularly when research in the domain of writing is scarce.

Emotions, Cognitive Mechanisms, and Writing Performance

There is some ambiguity as to how emotions might affect writing performance via modulating cognitive mechanisms. Some capacity-limit models of working memory suggest that strongly-experienced emotions – regardless of their valence – will consume a person’s cognitive resources and thereby hinder performance on cognitively demanding tasks, such as writing (Cowan, 2014; Derakshan & Eysenck, 2010; Ellis & Moore, 1999; Schmeichel, 2007). However, the control-value theory suggests that positive task-relevant activating emotions (e.g. enjoyment) can focus a person’s attention on the task at hand, which would facilitate flow experiences and a greater allocation of cognitive resources to the task (Pekrun et al., 2007). This explanation is consistent with work by Isen (e.g. Isen, Daubman, & Nowicki, 1987; Ashby & Isen, 1999) indicating that positive emotions facilitate problem solving and cognitive flexibility due, at least in part, to the association between positive emotions and dopamine levels in the brain. Graham’s WwC model (2018) seems to further support the latter notion of positive emotions as attention-enhancing rather than as attention-mitigating. Research on negatively-valenced affect and cognitive performance is more consistent and suggests a negative relationship between these constructs (e.g. Derakshan & Eysenck, 2009; 2010; Ellis & Ashbrook, 1988). Of these negative affective states, anxiety has received the most attention. Theoretically, anxiety may impair writers’ ability to inhibit attention from task-irrelevant stimuli as well as their ability to switch

attention between composing processes (e.g. planning, translating, and revising) within a writing task (Derakshan & Eysenck, 2009).

The extant research mostly supports the idea that negatively valenced emotions hurt writing performance, although this area has not been researched extensively. In a longitudinal study of first grade students, Monette and colleagues (2011) found that teacher ratings of student anger fully mediated the predictive relationship between student working memory capacity as well as student inhibition and student writing achievement as measured by the WIAT-II. Similarly, students in a qualitative study conducted by Cleary (1991) reported that feeling frustrated during writing severely hindered their ability to concentrate. Two recent studies employing emotion-induction in young children report similar findings. Cuisinier and colleagues (2010) found that children asked to transcribe a dictated text with negative emotional content made more spelling errors than children asked to transcribe an emotionally neutral text, and Fartoukh and colleagues (2012) found that children wrote shorter autobiographical narratives when instructed to write about the saddest day of their life (negative emotional induction) than when asked to write about what they had done in class the previous morning (emotion-neutral).

These latter two studies also found that inducing positive emotions had similarly negative impacts on students' spelling (Cuisinier et al, 2010) and text length (Fartoukh et al., 2012), although Fartoukh et al. found no between-condition differences in number of spelling errors. Given these findings, it seems possible that positive emotions can, at least in some circumstances, impede performance on writing tasks. However, these studies considered emotions only in terms of valence, and it is possible that the arousal associated with emotional states confounds the findings presented here. As Ashby and Isen (1999) report, heightened arousal is associated with increased production of norepinephrine, a neurotransmitter associated

with increased heart rate, muscular contractions, and alertness. Therefore, when positively-valenced emotions are also associated with arousal (e.g. in the state of excitement), the cognitive benefits of the pleasantness of the experience may be mitigated by the deleterious effects associated with a state of heightened arousal.

Emotions and Self-Regulatory Writing Behaviors

Successfully regulating emotions that might interfere with writing is a hallmark of self-regulation (Boekaerts & Corno, 2005), and, as the immediately preceding paragraphs indicate, failure to do so may impair writing performance. However, little research has explicitly investigated the role that emotions play in writers' self-regulation (Sala-Bubare & Castello, 2018). That said, negative valence emotions may impair writing performance, at least in part, by undercutting writers' abilities to implement other self-regulatory processes, including regulating their attention. For instance, Stewart and colleagues (2015) found that writing anxiety negatively predicted undergraduates' self-reported use of metacognitive writing strategies such as considering the purpose of the writing assignment, dividing the writing task into more manageable chunks, and searching for gaps in argumentation. Theoretically, this may be due to anxiety siphoning away attention necessary for self-regulation (Kaplan & Berman, 2010). In a study of academic writers, Boice (1997) found that anxiety, euphoria, writing self-regulation, and writing productivity ebbed and flowed together, particularly in writers who did not adhere to a daily writing routine. Procrastination – a failure to focus one's attention on writing and avoid distractions – led to anxiety, which led to more procrastination, and so forth. Eventually, writers freed themselves from this downward spiral via a creative binge in which they produced a lot of writing in a short period of time. However, like most binges, these manic writing episodes led to writing "hangovers" characterized by further anxiety and procrastination. These findings align

with the dual-processing model of self-regulation and the extended-process model of emotion regulation. In this study, when writers experienced anxiety, they employed an emotion regulation strategy to reduce this writing anxiety. Unfortunately, this strategy was task avoidance (i.e. a situation selection strategy; Gross, 2015a). Further, the second-level valuation system described in the extended-process model then detected discordance between this ER strategy and the writer's personal values, which led the writer to eventually employ another emotion regulation strategy to address his or her anxiety that allowed him or her to engage in top-down, goal-oriented writing, which is what occurred during the writing binges described by Boice (1997).

Inversely, successfully enacting writing self-regulatory strategies, including attention regulation strategies, can reduce writers' negative affective experiences. In a study examining the impact of a seminar teaching self-regulatory strategies to graduate students who were writing their thesis papers, Miedijensky and Lichtinger (2016) found that students felt less anxious about their writing after they learned several adaptive self-regulation strategies, including strategies to help them concentrate on their writing. This complements the findings of Boice (1997) in that, by employing explicit attentional strategies and implementing writing routines, writers may be able to avoid unhealthy writing habits that elicit deleterious emotional responses.

Although the relationships between frustration and writing self-regulation haven't been extensively studied, it is possible that the two could, at least in some cases, be positively linked. Feeling frustrated in and of itself likely isn't beneficial for writers, since it ought to divert attentional resources. However, previous work has shown that frustration can be positively related to learning outcomes (Pardos et al., 2014), perhaps due to frustration co-occurring with higher levels of task valuation. That is, students may be more likely to feel frustrated when working on tasks that they perceive as important, and they may also tend to invest more effort in

such tasks. Additionally, feeling frustration may cue writers to take a short break from a task as an emotion regulation strategy (Sabourin, Rowe, Mott, & Lester, 2011) rather than giving up on the task altogether. This break is an off-task behavior in the very short term, but in the longer term it may be an effective attention regulation strategy that ultimately promotes extended engagement with the writing task. Anxiety may function similarly in that, to some extent, it might be beneficial in that it co-occurs with task importance. Likewise, some research has found that increased anxiety up to a certain point can promote learning and engagement (e.g. Wang et al., 2015), although this has yet to be replicated in the domain of writing.

Emotions and Beliefs about Writing Competence

Regardless of one's proficiency, writing requires a great deal of motivation. Even Jonathan Franzen, one of the most accomplished contemporary novelists in the United States, described how hard it was to find motivation to write his third novel in his aptly-titled essay, "Why Bother?" (Franzen, 2002). Consistent with Graham's WwC framework and the control-value theory, emotions seem to be closely tied to writing motivation. As Graham (2018) puts it, "emotions make writers want to do things or not do them" (p. 302). Acknowledging this power of emotions, Bruning and Horn (2000) recommend that educators can help increase students' writing motivation by creating positive emotional environments in the classroom. The results of several empirical studies lend further credence to these theoretical connections between writing emotions and motivation.

Most of the research examining relations between emotions and writing motivation have focused on writers' self-efficacy beliefs – their beliefs about their ability to succeed in a given writing task (Pajares, Johnson, & Usher, 2007). According to Bandura (1997), self-efficacy beliefs are informed by, among other sources, writers' physiological and emotional states. More

specifically, several studies have shown that writers' feelings of anxiety negatively relate to self-efficacy beliefs and writers' feelings of joy relate positively to self-efficacy beliefs (Collie, Martin, & Curwood, 2016; Hidi, Berndorff, & Ainley, 2002; Martinez, Kock, & Cass, 2011; Pajares et al., 2007). In these studies, correlations between writing enjoyment and writing self-efficacy typically fall in the moderate to high range. Indeed, perhaps due to these consistently strong relations, some researchers have collapsed writing enjoyment and self-efficacy to form a single construct (e.g. De Smedt, Van Keer, & Merchie, 2016, see also Ekholm, Zumbrunn, & DeBusk-Lane, 2018). Writing anxiety, on the other hand, has been consistently negatively associated with writing self-efficacy, with correlations across studies falling in the small to medium range (Collie et al., 2016; Pajares et al., 2007; Stewart et al., 2015), and qualitative research attests that students may feel anxiety due to beliefs that they cannot meet the standards of a given writing task (Ross, Burgin, Aitchison, & Catterall, 2011). Some researchers have noted relations between writing self-efficacy and other emotions as well. For instance, after analyzing interviews with high school students, Tomas and Ritchie (2012) noted that many students described feeling proud of their work and, consequently, more confident in their abilities to meet the demands of a specific cross-curricular writing task as they progressed through the assignment. Such relations are consistent with propositions of the control-value theory, which suggests that negatively-valenced emotions (e.g. anxiety) can lead to subsequent negative control appraisals, whereas positively-valenced emotions (e.g. enjoyment) can lead to subsequent positive control appraisals. These control appraisals then, in turn, contribute to subsequent emotional experiences before, during, and after writing.

Emotions and Writing Content

Writers write about things – topics, experiences, people, and abstract phenomena. Even in rather prescriptive writing tasks, such as responding to a standardized prompt, writers have a tremendous amount of freedom to decide what to include in their writing. Writers responding to the same prompt will differ considerably in the words they use, the supporting details they choose to include, their syntactical styles, and much more. In this sense, writing has many characteristics that align with creative tasks, such as painting (Sharpley, 1996).

At least in some circumstances, emotions are related to creative endeavors and creative achievement. In a meta-analysis of over 100 studies examining the relations between affect and creativity, Baas, de Dreu, and Nijstad (2008) found that positive, activating emotions (e.g. enjoyment) tend to be modestly associated with higher levels of creativity ($r = .17$), whereas negative avoidance-activating emotions (e.g. fear, anxiety) tend to be modestly associated with lower levels of creativity ($r = -.12$). Similarly, in a daily-diary study assessing the relations between daily affect and daily creative thinking, Amabile and colleagues (2005) found a small but significant relationship between positive emotions and creative thinking after controlling for the previous day's level of creative thinking. Given these findings, and given that generating ideas during writing is itself a creative undertaking, it would seem that emotions are implicated in how writers generate ideas (see also Bohn-Gettler & Rapp, 2014; Vass, 2007).

With some qualifications (e.g. Zenasni & Lubart, 2011), the literature supports this notion. Broadly, enjoyment of writing seems to be positively related to the originality of a writer's text (Larson, 1990), and writers who are happy during writing may infuse their writing with positive emotions (Lynton & Salovey, 1997). Additionally, people in states of nostalgia – a positive emotional experience – have been shown to produce more creative written texts than

people not in states of nostalgia (Ye, Ngan, & Hui, 2013). High-achieving creative writers may be especially proficient at using their emotions to inform writing. Creative writers are adept at identifying, distinguishing, and describing emotions in themselves and others (Lennartsson, Horwitz, Theorell, & Ullen, 2017) and can harness their emotions to generate original yet situation-appropriate texts (Kopcsó & Lang, 2017; Trnka, Zahradnik, Kuska, 2016). For example, in a study of talented writers enrolled in MFA programs, Olthouse (2013) noted that many writers seemed to channel their emotions into their writing by asking themselves “how would this same emotion I am feeling be felt by a different person in a different context?” (p. 297). In sum, these studies affirm that emotions, and particularly positive emotions, can facilitate creative writing performance.

Emotions may also spur ideation during writing by encouraging deeper thinking. Recall that topic emotions refer to students’ emotions regarding a specific set of content. If students feel particularly strongly about the topics they are writing about, these emotions may spark idea generation, with both positive and negative emotions galvanizing ideation. For instance, Prebel (2016) describes how stereotypically unpleasant emotions such as unease and anger can lead students to rich ideas that they might not have arrived at in the absence of such emotions. Similarly, certain epistemic emotions such as surprise, curiosity, and confusion may trigger deeper processing (Muis et al., 2018). This is similar to explanations put forth by D’Mello and colleagues (2014), who suggest that there is an optimal level of confusion in which learners are most likely to resolve confusion – and therefore learn – whereas minimal confusion may not spur the cognitive dissonance often associated with learning and too much confusion may lead to frustration, boredom, and disengagement. It is important to note that the potential benefits of negative emotions may hold only for certain types of emotions, including topic emotions and

epistemic emotions, and that negative emotions associated with the act of writing itself may not benefit writers. Although this is important to mention, it is beyond the scope of the current study to collect data that can classify the types of emotions writers experienced or what, exactly, during a writing session prompted a specific emotion.

Somewhat counterintuitively, boredom may also relate to ideation during writing, although this area is not well researched. Boredom can indicate that something is amiss in the current situation and that the person experiencing boredom should do something differently (Gaylin, 1979; Harris, 2000). In this sense, feelings of boredom may trigger self-regulatory processes, including cognitive strategies associated with ideation. That is, a writer may realize that he is bored and may try to make his writing more creative to alleviate this boredom, thereby enacting a situation modification ER strategy. Similarly, boredom may also promote creativity via inducing daydreaming (Bell, 2011; Singer, 1981). That is, when people are bored, they daydream and, while daydreaming, they grapple with problems in ways that they otherwise wouldn't. However, daydreaming requires some appropriation of cognitive resources. Because writing is a cognitively demanding task, writers may not have sufficient cognitive resources to simultaneously write and daydream. Therefore, writing may actually inhibit daydreaming and negate the potential benefits of boredom (Mann & Cadman, 2014). Once again, more research is needed in this area to better understand the benefits and detriments of boredom during writing, and particularly how boredom relates to writers' assessments of their productivity.

In sum, these findings indicate that emotions likely influence the content writers produce, with evidence suggesting that positively-valenced emotions promote creative ideation. Further, in some circumstances, emotions such as confusion or even perhaps boredom may lead to greater creativity or deeper critical ideation. Therefore, emotions seem to be implicated in writing

productivity, particularly in a qualitative sense. That is, if writers consider both the quality of ideas and quantity of writing produced as indicators of productivity, then productivity seems at least partially contingent upon emotional states.

Stability of Writers' Emotions

By definition, emotions are relatively brief states that can – and often do – change over time. Researchers in other fields have shown that the persistence of emotional states, their patterns of stability or instability, and the patterns by which they unfold may differ between people and contexts. For instance, research indicates that emotional inertia may be common across many emotions (Kuppens et al., 2010), some people may be more prone to affective instability than others (Miller, Vachon, & Lynam, 2009), specific emotions may persist for longer than others (Baker et al., 2010; D'Mello & Graesser, 2011), and that a given person will often display remarkably consistent patterns of “if...then” emotional responses across similar situations (Shoda, Mischel, & Wright, 1994).

Within the domain of writing, there has been little research on the relative stability or instability of writers' emotional experiences, particularly so across days. Many of the current studies examining change in writers' emotions have mapped changes in writers' emotions over a single composing session. For instance, in a study of gifted adolescent writers (Olthouse, 2014), one student described how she tended to feel bored when beginning a writing session but then “gets really into it and stuff” (p. 179) as time goes on. In a review of research, Bohn-Gettler and Rapp (2014) discuss that less skilled writers tended to experience higher levels of negative emotions at the beginning of writing tasks than do more skilled writers; however, the emotional experiences of both groups were similar at the end of a writing task. That is, the negative emotions of less skilled writers diminished more over the course of writing. In a series of studies

(Brand, 1987; 1990; Brand & House, 1987; Brand & Leckie, 1988; Brand & Powell, 1986), Brand presents findings describing the emotional trajectories of several different types of writers, including English majors, professional writers, and undergraduate students, among others. Across these studies, positive emotions tended to intensify throughout a writing session, feelings of boredom and confusion dissipated, and feelings of anxiety stayed relatively stable. Additionally, and in contrast to the findings presented by Bohn-Gettler and Rapp (2014), Brand's studies indicate that the more adept writers (e.g. professional writers and self-proclaimed student poets) tended to feel more negative activating emotion (e.g. anxiety) than did other writers. Furthermore, Brand found that writers' emotional trajectories were influenced by contextual features of the writing task, including whether the task was self-sponsored (i.e. one they chose to write on their own).

Once again, the researchers conducting these studies have explored the stability, inertia, and instability of writers' emotions within a single writing session. They mostly have not investigated how writers' emotions might change or persist across days, although some research suggests that apprehension/anxiety might demonstrate considerable inertia across days (Boice, 1997). Given that the control-value theory posits that past emotional experiences will, at least indirectly, influence later emotional experiences, these day-to-day patterns of change and inertia ought to be investigated more closely.

Methods of Studying Emotions

Across educational and psychological literature, researchers have employed several different approaches to study affect, including emotions. For the purposes of the current study, I will focus on survey-based methods, although other approaches using open-ended interviews, physiological indicators, inference from video capture, and/or neurological imaging have been

employed as well (e.g. Citron, 2012). By “survey-based methods,” I mean designs in which participants are tasked with self-reporting their emotional or affective experiences via closed-ended questions with several response options. When considering survey-based methods of studying emotion, it is important to reflect on the extent to which the measures used in the study capture critical features of emotions and/or affect. In this section, I will describe two issues of measurement that are pertinent to the current project.

First, researchers sometimes distinguish between studying affect and studying emotion, and there are some idiosyncrasies within different research traditions regarding the terminology used to describe the constructs under investigation. Affect refers broadly to a state that can be described by valence and activation, with valence ranging from negative to positive and activation ranging from low to high. Further, affect may refer to brief states with clear object referents (i.e. emotions) or longer, more diffuse states with less-clear object referents (i.e. moods). The affective dimensions of activation and valence can be thought of in terms of a Cartesian plane, with activation mapped onto the y -axis and valence mapped onto the x -axis. In fact, several popular measures of affect ask participants to indicate their affect using such a coordinate system (e.g. Russell, Weiss, & Mendelsohn, 1989; Morris et al., 2010; Pollak, Adams & Gay, 2011), whereas others, such as the Positive Affect and Negative Affect Scale (PANAS; Watson, Clark, & Tellegen, 1988), infer these dimensions from Likert-type responses. Emotions, on the other hand, refer to theoretically discrete locations on this affective grid with clear object referents. For example, enjoyment represents a state characterized by high activation and positive valence, whereas contentment represents a state characterized by low activation and positive valence. Since specific degrees of valence and affect are *a priori* associated with certain emotions, measures of emotions often ask participants to rate the intensity with or degree to

which they experienced a given emotion (e.g. Goetz et al., 2016). Prior research has employed confirmatory factor analyses and structural equation modeling to map discrete emotions onto factors representing positive and negative affect (Pekrun et al., 2011; Pekrun et al., 2017), which supports the notion that emotions can be considered within the broader category of affect. Furthermore, some researchers and research traditions refer to emotions as “affective states” or “cognitive-affective states” (e.g. Baker et al., 2010; D’Mello & Graesser, 2012; D’Mello et al., 2014). When considering how these researchers conceptualize and operationalize these states, it is clear that these constructs align more with emotions than they do with affect more broadly, at least according to the definitions provided here. In the current study, I focus specifically on emotions rather than on affect more broadly.

Second, because emotional experiences are transient, time plays a critical role in studies of emotion. Acknowledging this, researchers often distinguish between trait measures of emotions and state measures of emotions, although there is some overlap between these classifications depending upon the time intervals most relevant to a given study or research question. Generally, trait measures of emotions seek to understand how respondents typically feel. In other words, these measures attempt to get at a person’s average emotional experiences in relation to a certain object. Given that respondents are asked to indicate their average emotional experience rather than their current emotional experience, time may not be as important a consideration in studies employing trait measures – although participants’ scores on trait measures may potentially be biased by current emotional states (Kahneman, 1999). In contrast, state measures of emotions seek to understand how participants feel in a given moment or in a relatively brief time frame (e.g. the current day). Unlike trait measures, which “average out” potentially meaningful moment-to-moment or day-to-day emotional variability, state

measures can capture this variability and therefore provide a more nuanced understanding of how emotions relate to proximal outcomes, such as daily behavior (Augustine & Larsen, 2012; Hektner, Schmidt, & Csikszentmihalyi, 2007). Researchers interested in studying such short-term variability often turn to intensive longitudinal research designs (ILDs; Mehl & Conner, 2012). In these designs, participants are asked to respond to several surveys over the course of a few days or weeks, with some studies asking for upwards of 10 survey responses per day (e.g. Delespaul, Reis, & DeVries, 2004). These frequent, in situ measures provide rich data on participants' daily emotional experiences and are well-suited to capture day-to-day fluctuations in these experiences. However, because such designs place a considerable burden on participants, measures of emotions used in ILD studies are typically quite short and may even employ single-item scales (Goetz et al., 2016; Gogol et al., 2014), which can complicate or preclude some canonical psychometric analyses (Gogol et al., 2014; Nezlek, 2012). Because I am concerned with daily emotional experiences related to writing in the current study, I will employ a state-like measure of emotions using a daily diary design (Gunthert & Wenze, 2012), and, in line with previous studies, this measure will employ single-item scales for each emotion.

Although the distinction between state and trait measures is certainly not arbitrary, what constitutes a state versus a trait will depend, to some degree, on the purposes of the research and the phenomena under investigation. In the context of the current study, I refer to daily measures of emotions as state measures rather than as trait measures in order to further distinguish my approach in this study from the cross-sectional or panel-model approaches more common in educational psychology (Augustine & Larsen, 2012). However, even over the course of a single day, or a single writing session within a single day, writers' emotional experiences may fluctuate (Brand, 1990), and so there is some amount of aggregation (and loss of nuance) in daily diary

studies when compared to alternative designs, such as experience sampling designs. In other words, there is something of a trait-like quality to daily measures of emotions, and such measures may not, in the strictest terms, be “pure” state measures (Gunthert & Wenzel, 2012). The degree to which this aggregation matters seems to depend on the research problems being investigated. In the current study, I am investigating relations between daily writing outcomes (e.g. number of words written) and daily emotional experiences, so employing a once-per-day measure of emotions makes sense both theoretically and analytically (Augustine & Larsen, 2012). Further methodological considerations are discussed in Chapter 3.

Conceptual Framework

The theoretical models, primary studies, and methodological literature described throughout this chapter contribute to the conceptual framework of the current study, which seeks to examine the stability, change, and inertia of writers’ daily emotional experiences as well as the relations between these daily experiences and daily writing behaviors and productivity. One overarching assumption, supported by models of writing and models of academic emotions, is that the act of writing elicits emotions, and these emotions likely play a role in writing processes and behaviors (Brand, 1990; Boekaerts & Pekrun, 2016; Graham, 2018). Beyond this, several other propositions inform the conceptual framework of the current study. First, achievement emotions are short-lived states that can (but may not necessarily) vary from day to day (Augustine & Larsen, 2012; Pekrun, 2006). The stability of these experiences will be contingent upon daily control and value appraisals of writing tasks, which likely interact reciprocally with previous emotional experiences (Pekrun, 2006; Pekrun et al., 2007; Pekrun et al., 2017). However, the specific demands of a given day’s writing task are also unlikely to be identical to the previous day’s demands. Therefore, both emotional inertia and emotional variability seem

plausible. Second, writing-related emotions should influence daily attention regulation (Boice, 1997; Boekaerts & Corno, 2005). Negatively valenced emotions may undercut writers' attempts to control the attention they put toward writing tasks, whereas positively valenced emotions may facilitate such efforts. More specifically, negative writing-related emotions may direct cognitive resources, such as attention, away from writing and toward promoting well-being. Inversely, positive writing-related emotions may direct cognitive resources toward writing because devoting one's attention toward writing also promotes well-being by continuing to elicit positive emotions (Boekaerts & Corno, 2005; Boekaerts & Pekrun, 2016; Cleary, 1991; Derakshan & Eysenck, 2009). Additionally, though I expect these general tenets to apply, differential relations may emerge for specific emotions such as anxiety, which may not be universally good or bad (Wang et al., 2015; Yerkes & Dodson, 1908). Third, daily writing-related emotional experiences will relate to daily writing productivity. This relationship may be partially explained by the influence of emotions on self-regulatory behaviors; however, emotions may also relate to writing productivity through their influence on content production. Specifically, emotions may influence the quality and nature of ideas a writer produces while writing, which are themselves indicators of productivity (Baas et al., 2008; D'Mello et al., 2014; Larson, 1990). It is likely that positively-valenced emotions would support more creative ideation and would, therefore, be associated with greater writing productivity (Baas et al., 2008; Bohn-Gettler & Rapp, 2014); however, in certain circumstances, specific negatively-valenced emotions may also facilitate deeper thinking and, likewise, greater productivity (D'Mello et al., 2014; Prebel, 2016). Similarly, positive emotional experiences with writing may lead to more time spent writing and more text production by facilitating engagement and flow during writing, whereas negatively-valenced emotional experiences may disrupt engagement and thereby lead to less time spent writing and

fewer words written (D’Mello & Graesser, 2012). In line with this framework, the current study will investigate the following research questions:

1. How strongly do writers feel each emotion over the course of the month, and are there differences in average emotional intensity?
2. How stable are writers’ day-to-day emotional experiences, and does this stability change over time?
 - a. Is this stability moderated by writer characteristics such as gender or academic affiliation?
3. To what extent do writers’ writing-related emotions predict their attention regulation during writing?
4. To what extent are writers’ emotional experiences related to their writing productivity?

In response to each of these research questions, I hypothesize the following:

1. In line with previous research (e.g. Brand, 1990), I hypothesize that writers will, on average, feel enjoyment and anxiety more strongly than other emotions. I also hypothesize that boredom will be the least-intense emotion that writers experience, on average, over the course of the study.
2. I hypothesize that writers’ emotional experiences demonstrate considerable inertia from day to day, and that all autoregressive parameters will be significantly different from zero. I further hypothesize that daily frustration and boredom will be the least stable (i.e. will have the smallest autoregressive relations) from day to day, whereas enjoyment and anxiety will be the most stable from day to day. Additionally, I hypothesize that writers will experience a moderate amount of day-to-day instability in writing emotions, corresponding with low-to-mid range rates of reliable changes.

- a. Because the question regarding person-level characteristics is exploratory in nature, I have no hypotheses about what interactions might exist.
3. I generally hypothesize that negatively-valenced emotions such as frustration, shame, and anxiety will relate negatively to daily writing attention-regulation, whereas positively-valenced emotions will relate positively to daily writing attention-regulation. I further hypothesize that enjoyment will have the strongest positive relation to daily attention-regulation and boredom will have the strongest negative relation to daily attention-regulation. I also hypothesize that writers' average levels of a given emotion will be less predictive of daily attention-regulation than will daily levels of that emotion.
4. As with RQ3, I hypothesize that negatively-valenced emotions will related negatively to daily writing productivity, whereas positively-valenced emotions will relate positively to daily writing productivity. I hypothesize that boredom will have the strongest negative effect on daily productivity and enjoyment will have the strongest positive effect on daily productivity. Finally, I hypothesize that writers' average levels of a given emotion will be less predictive of daily productivity than will daily levels of that emotion.

Chapter 3 – Methodology

This chapter describes the methodology that I employed to address the research goals and questions of the study. The study is guided by two broad aims: 1) to better understand the day to day stability of writers' various writing-related emotions over the course of one month, and 2) to understand how writers' daily emotions relate to their attention regulation and productivity.

In this chapter, I describe the study design, sampling procedures, measures, and data analysis approaches, including the handling of missing data, that I employed to answer the research questions that guided the current study.

Research Design

As the research aims and questions indicate, this study is concerned with investigating the stability, inertia, and change of writers' writing-related emotions over time and how these emotional experiences relate to writing behaviors and productivity, both in a given day and over time. Given these concerns, I used a design suitable for capturing daily measures of writers' emotions, behaviors, and productivity. Intensive longitudinal designs (ILDS; Mehl & Conner, 2012) are a broad category of quantitative study designs that obtain frequent measurements from participants on variables of interest. Although various types of ILDs differ in many respects, they are alike in that they are concerned with shorter-term variations in experiences, behaviors, and even physiological states that traditional longitudinal panel designs are not well-suited to study.

Depending upon the research questions being addressed, ILDs can obtain measures from participants as frequently as several times per day, as is the case in studies employing an experience sampling method (Csikszentmihalyi & Larson, 1987), or as infrequently as once every few days or weeks, as is the case in event-contingent designs focusing on relatively infrequently-occurring events (e.g. Moskowitz & Sadikaj, 2012).

In the current study, I employed a daily diary design (Gunthert & Wenzel, 2012; Reis, Sheldon, Gable, Roscoe, & Ryan, 2000). In daily diary studies, participants typically respond to brief surveys once per day – often in the evening – and these surveys are designed to measure aspects of their daily experiences. These daily experiences can include behaviors, emotions, thoughts, and physiological symptoms, among other phenomena. Because participants are asked to complete surveys each day throughout the study, researchers employing daily diary designs often try to reduce the response burden on participants by using measures that focus on only a handful of variables and take less than 5 or 10 minutes to complete (Gunthert & Wenzel, 2012), although some studies have employed instruments that capture a wider array of phenomena and require upwards of 60 minutes to complete (e.g. Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004). Daily diary studies also differ with respect to the overall study length, with shorter studies collecting measurements for one or two weeks and longer studies potentially collecting measurements for well over one month. In the current study, participants responded to brief surveys measuring their daily writing emotions, behaviors, and productivity each day over the course of four weeks. Surveys were designed to take less than 5 minutes to complete. Additional information on the administration and content of these surveys is presented in subsequent sections.

Participants

Recruitment

Because the purpose of the current study was to examine graduate student writers' daily emotions, behaviors, and productivity, it was important to identify and recruit participants who write on a daily, or near-daily, basis. Therefore, I intentionally recruited graduate students enrolled in writing intensive disciplines to ensure that participants in the study wrote consistently enough. People were eligible to participate in the study if they 1) were enrolled in a graduate degree program during the four-week data collection window (March 7 – April 3, 2019), 2) were at least 18 years old at the time of the study, and 3) were enrolled in a writing-intensive discipline. For the purposes of this study, I considered writing-intensive disciplines to include domains typically categorized as social science or arts and humanities disciplines, such as education, psychology, English literature, creative writing, sociology, public health, and history, among others.

I used a snowball sampling strategy to recruit participants into the study. First, I emailed potential participants whom I know personally to invite them to participate in the study (see Appendix A for a copy of the message sent in these emails). These initial emails were sent only to people whom I knew met all eligibility/inclusion criteria. An information sheet with a more complete description of the study was also included in these emails (see Appendix B). People who were interested in participating in the study were instructed to complete a short demographics questionnaire (see Appendix C).

Next, I emailed several “gatekeepers” likely to have connections to graduate students in writing-intensive disciplines and asked them to forward the recruitment message (Appendix A), information sheet (Appendix B), and demographics questionnaire (Appendix C) to any people

they knew who met the aforementioned inclusion criteria and might be interested in participating in the study (see Appendix D for a copy of the message sent in these emails). These gatekeepers included professors in several fields, directors of various graduate programs, and people who maintain relevant mailing lists, such as the mailing list for graduate student members of Division C of the American Educational Research Association, the mailing list for the Cognitive Development Society, and the mailing list for student members of the American Sociological Association. When contacting gatekeepers at VCU or at institutions near Richmond, Virginia (e.g. gatekeepers at the University of Virginia), I indicated that I would be willing to meet with any interested participants in person to discuss the study; however, no prospective participants requested an in-person meeting.

Recruitment for the study began on February 20, 2019. Anyone who met the inclusion criteria and who completed the initial demographics survey before the first daily writing experiences survey was sent out on March 7, 2019, was invited to participate in the study. Participants were informed that they could be asked to be removed from the study at any point by contacting me via email.

Incentives

Participating in daily diary or other ILD studies places a considerable burden on participants beyond that associated with many other cross-sectional, pre-test/post-test, or even laboratory experimental designs. Therefore, many ILD studies provide participants with incentives to encourage both initial and continued participation throughout the study (e.g. Forand, Gunthert, German, & Wenze, 2010; Patall, Vasquez, Steingut, Trimble, & Pituch, 2016). To motivate initial and continued participation, I provided both monetary and non-monetary incentives to participants in this study. With funding obtained from the VCU School of

Education's (SoE) Graduate Student Seed Funding Grant, I created a modified raffle to incentivize continued participation in the study. As part of this raffle, participants earned one point per each daily survey they completed, with a maximum of 28 points possible. After data collection ended, all participants who had earned at least 14 points (i.e. those who had responded to at least 50% of the surveys) were entered into the raffle with their total number of entries corresponding to the number of points earned. For example, a participant who completed 21 surveys would be entered 21 times, whereas a participant who completed 14 surveys would be entered 14 times. Eight winners were selected from this raffle, and each winner received a \$100 Target gift card. Regardless of how many points they accumulated, no single person was eligible to earn more than one gift card.

Beyond the monetary compensation, all participants received access to a Shiny app (Chang, Cheng, Allaire, Xie, & McPherson, 2018) throughout the study that allowed them to view preliminary reports of their own data and the study aggregate data. Since all participants are invested in writing, these preliminary reports on their emotions, behaviors, and productivity was hypothesized to serve as a non-monetary incentive for participants. During the study, the app displayed preliminary data trends over time using a scatter plot and line graph. Participants could input their unique ID# and variable they wanted to view (e.g. enjoyment, words written), and the app would produce a color-coded scatterplot displaying that participant's values over time for the chosen variable as well as the group average over time for the chosen variable. A display of the preliminary version of the app is presented in Appendix E. Participants were first given access to the app on Sunday, March 10, 2019 (the fourth day of data collection). At minimum, preliminary data in the app was updated each Wednesday during the data collection phase; however, the data

was sometimes updated more frequently. The app is hosted on Rstudio's Shiny apps server and is available at the following URL:

https://ekholme-vcu.shinyapps.io/Daily_Writing_Experiences/. Funding for web hosting was provided by the VCU School of Education Graduate Student Seed Funding Grant.

After data collection was completed, the app was updated to include additional features and finalized data. The final app included the same scatter plot and line graph that was present in the preliminary graph, and it also included a bar graph displaying person-mean centered values for all variables over time as well as a data table displaying data on selected variables for participants. Features of the final app are displayed in Appendix E.

Final Sample

I received 285 responses to the initial demographics survey. Over the course of the study, five of these participants withdrew. Additionally, participants who did not complete at least 50% of the daily surveys were dropped from the study. This resulted in a final sample of 183 participants¹. The majority of the participants in the final sample identified as female (88.5%, $n = 162$), with a smaller proportion identifying as male (11.5%, $n = 21$). No participants identified as another gender or opted not to respond to the question. The sample included participants who self-identified as White (76.5%, $n = 140$), Asian (9.3%, $n = 17$), two or more ethnicities (5.5%, $n = 10$), Black (3.8%, $n = 7$), and Latinx (3.8%, $n = 7$). Two participants (1%) opted not to indicate their ethnicity. In response to the question asking which academic discipline participants were primarily affiliated with, the majority of participants indicated being affiliated with education (55.2%, $n = 101$); however, participants also indicated being affiliated with psychology (33.9%,

¹ Of these included participants, four completed at least 14 surveys but indicated not writing on every completed survey. These participants were ostensibly included in the final sample for demographics purposes; however, they did not contribute any data to the primary analyses.

$n = 62$), English (1%, $n = 2$), history (1%, $n = 2$), other social sciences disciplines (6%, $n = 11$), other hard sciences disciplines (2.2%, $n = 4$), and other humanities disciplines (.5%, $n = 1$).

Finally, the average age of participants in the study was 32.4 years old with a standard deviation of 8.5 years. The youngest participant indicated being 23 years old, and the oldest participant indicated being 67 years old. Four participants did not indicate their age. This demographic data is also presented in Table 1.

Table 1. Demographics of Final Sample

Characteristic	<i>N</i>	%
<i>Gender</i>		
Female	162	88.5
Male	21	11.5
<i>Ethnicity</i>		
White	140	76.5
Asian	17	9.3
Two or More	10	5.5
Black	7	3.8
Latinx	7	3.8
<i>Academic Affiliation</i>		
Education	101	55.2
Psychology	62	33.9
English	2	1
History	2	1
Other Social Sciences	11	6
Other Hard Sciences	4	2.2
Other Humanities	1	0.5
	<i>M</i>	<i>SD</i>
<i>Age</i>	32.4	8.5

Measures

Initial Demographics Survey

Before participating in the daily-diary portion of the study, participants completed a short demographics survey. In this survey, participants were required to include their name and email address for identification purposes and to facilitate distribution of the daily surveys.

Additionally, participants were asked to indicate their gender, ethnicity, age, and which academic discipline (e.g. education, psychology, English) they are primarily affiliated with. A complete version of this survey is presented in Appendix C. Some of these covariates were included as controls and/or moderators in several of the analyses described subsequently.

Contextual Measures and Covariates

Initial Items. As part of each daily survey, participants were asked to provide their email address (for purposes of matching records), and they were also asked to indicate whether or not they wrote that day. If participants indicated that they did not write, no additional questions populated the survey. If participants indicated that they did write, they were able to complete the subsequent portions of the survey. These two initial items were the only required items on each daily survey. All items included in the daily surveys are presented in Appendix F.

Types of Writing Activities. Participants were asked to indicate the types of writing activities they engaged in that day. These options included planning, drafting, and revising, and these categories were chosen based on their alignment with the writing processes specified by Hayes and Flower (1986). Participants were not limited in terms of the number of options they could select.

Project Type. Participants were asked to indicate whether the writing they worked on that day was predominantly an individual project or a collaborative project. This question was included to explore whether writers' experiences and behaviors differed according to whether the writing activity for the given day was individual or collaborative.

Writing Emotions

Writers' daily experiences of enjoyment, pride, anxiety, shame, frustration, boredom, excitement, confusion, and contentment were measured using single-item scales with an eight-

point Likert-type response option, ranging from 1 (not at all) to 8 (very strongly). The intensity with which writers felt each emotion will be assessed with the item “Today when writing, I felt [EMOTION].” Single-item scales are appropriate for use in daily diary studies because, as mentioned previously, they reduce the overall response burden on participants. Further, single-item scales have been proven to be reliable and valid indicators of several constructs in a variety of academic disciplines, including marketing (Bergkvist & Rossiter, 2007), medicine (West, Dyrbye, Sloan, & Shanafelt, 2009), psychology (Wanous, Reichers, & Hudy, 1997), and education (Gogol et al., 2014). Finally, a recent study by Goetz and colleagues (2016) successfully employed a similar single-item measure of students’ achievement emotions to assess in-the-moment emotional experiences. Although the study by Goetz and colleagues (2016) used a five-point response scale, I opted to expand the response options of all emotion items to be on an eight-point scale. I chose to do so to capture more variance in emotion scores. Using response scales with larger ranges is in line with previous studies that have used single items to assess psychological constructs (e.g. Bernacki et al., 2015; Paas, 1992; Yeo & Neal, 2008). All items included in the daily surveys are presented in Appendix F. Reliability of single-item scales cannot be estimated using typical measures such as Cronbach’s alpha. Although there are procedures that can estimate reliability of averaged state scores (e.g. Goetz et al., 2016; Ludtke et al., 2007), these are similar to the analyses I use to model stability in emotional states and are therefore described later.

Writing Attention Regulation

I measured writers’ daily attention regulation using a four-item Likert-type scale I developed for this project. To develop this scale, I first pilot tested 9 writing self-regulation items drawn from previous studies investigating writers’ self-regulation, including studies conducted

by Pintrich and colleagues (1991), Kaplan and colleagues (2009), and Zumbunn and colleagues (2017). Twenty five graduate students and university professors responded to the pilot test items and provided feedback on the wording of each item. To arrive at the final four-item scale, I considered bivariate correlations among items, qualitative feedback on items from respondents, and construct relevance. All pilot tested items are included in Appendix G. Because this scale has not been validated in previous research, I conducted a multilevel confirmatory factor analysis (MLCFA) to investigate the extent to which items load onto a single factor at the within-person level while accounting for between-person differences. This MLCFA was conducted using the `lavaan` package (Rosseel, 2012) in R. Model fit was assessed according to guidelines described by Hu and Bentler (1999). Reliability of the scores for this scale were estimated in a multilevel framework using the `multilevel.reliability` function in the `psych` package (Revelle, 2018) in R and following suggestions by Shrout and Lane (2012) and Cranford and colleagues (2006). More specifically, I estimated the R_{KR} coefficient, which represents the generalizability of the average across k time points while allowing for random time effects. This coefficient is appropriate for the current study because all participants had opportunities to respond an equal number of times (where $k = 28$ in this case); however, this 28-day period was random for all participants. In other words, the 28-day period was not necessarily attached to a meaningful event for participants (e.g. the first 28 days of a new job), but rather represented an arbitrary span of four weeks. As is the case with other reliability coefficients, possible values the R_{KR} coefficient range from 0 to 1, with larger values indicating greater reliability. Results of these analyses are described subsequently in the “Preliminary Results” section. All items included in the final attention regulation scale are presented in Appendix F.

Writing Productivity

Writers' daily productivity was assessed using several metrics. First, participants responded to a four-item scale asking them to self-assess their daily writing productivity (items presented in Appendix F). I employed similar procedures for investigating the dimensionality and measurement properties of the Writing Productivity scale as I did for the Writing Attention Regulation scale. Likewise, results of these analyses are described in the "Preliminary Results" section.

Second, participants were asked to estimate the number of minutes they spent actively writing that day. This was an open-ended question that required a numeric value as a response. In the directions for this question, participants were told not to count time spent doing background reading as time spent writing. Third, participants were asked to estimate the number of words they produced when writing that day. Exact wordings of these items are presented in Appendix D. Number of words written and time spent writing are common and meaningful indicators of writers' productivity and behavior (e.g. National Commission on Writing, 2003), and both indicators have been linked to overall writing quality (Graham, Harris, & Santangelo, 2015; Scott, 2009; Troia, Harbaugh, Shankland, Wolbers, & Lawrence, 2013).

Distinguishing between Missingness and Non-Writing

Each daily survey began with the question "did you write today?" and a binary yes/no response option. If participants selected "no" in response to this question, the survey completed for the given day. If participants selected "yes," they were directed to the remainder of the daily survey. This feature allowed me to distinguish between nonresponse (i.e. participants not completing a survey) and non-writing (i.e. participants foregoing to rate their daily emotions, attention regulation, and productivity because they did not write that day).

Procedure

Data from this daily diary study were collected each day (including weekends) over the course of four weeks, ranging from March 7, 2019 to April 3, 2019. All prospective participants who completed demographic surveys prior to March 7 were included in the study. Beginning on March 7, participants completed daily surveys measuring their daily writing-related emotions, attention regulation, and writing productivity. Participants in the study received an initial email and a reminder email each day. The initial email with a link to the daily survey was sent to all participants at 8 a.m. EST each morning. A reminder email was sent at 5 p.m. EST each day to participants who had not yet completed the daily survey. Because previous literature on daily diary studies has found that providing encouragement to participants and reinforcing that they are contributing to scientific discovery can help prevent attrition (e.g. Bolger, Davis, & Rafaeli, 2003; Christensen, Barrett, Bliss-Moreau, Lebo, & Kaschub, 2003), the exact content of each of these daily emails differed slightly so that the encouragement was not part of the email template and therefore felt more authentic when provided. A template for these emails is presented in Appendix H.

These emails instructed participants to complete the daily survey after they had written on the current day. One drawback of this approach is that it requires participants to reflect on the emotions they experienced while writing after they had finished writing, and potentially several hours after they had written. However, I decided on this approach because it was the only way that I could capture the daily measures of productivity I was interested in while only asking participants to complete a single survey each day. In other words, if I had asked participants to complete surveys on their emotional states just before they wrote, I would have to ask them to complete a separate survey measuring the daily outcomes after they had finished writing.

Data Analysis

Unless otherwise specified, all analyses were conducted using R (R Core Team, 2019) and RStudio (RStudio Team, 2016). Specific packages used for each analysis are mentioned where appropriate.

Missing Data

As described previously, any participants who did not complete at least 50% of their daily survey responses were excluded from the study. I decided on this approach because it is a common tactic in other studies employing daily diary or experience sampling designs (e.g. Lischetzke, Angelova, & Eid, 2011). However, even after the exclusion of this subset of participants, some data were still missing in the dataset. On any given survey, data could have followed one of four possible patterns of missingness². Before describing these patterns, recall that at the beginning of each daily survey, writers were asked the binary question “did you write today?” Only when they responded “yes” to this question did they receive access to the remainder of the survey.

In Pattern A, writers indicated having written on day i , and they fully completed the survey for day i . This pattern yielded no missing data. In Pattern B, writers indicated having written on day i , and they partially completed the survey for day i . This pattern yielded some missing data for day i . In Pattern C, writers indicated not writing on the day i . This pattern yielded missing data for day i for every survey question other than “did you write today.” Finally, in Pattern D, participants did not respond to any items on the survey on day i , including the initial “did you write today” question. This pattern yielded no data for day i .

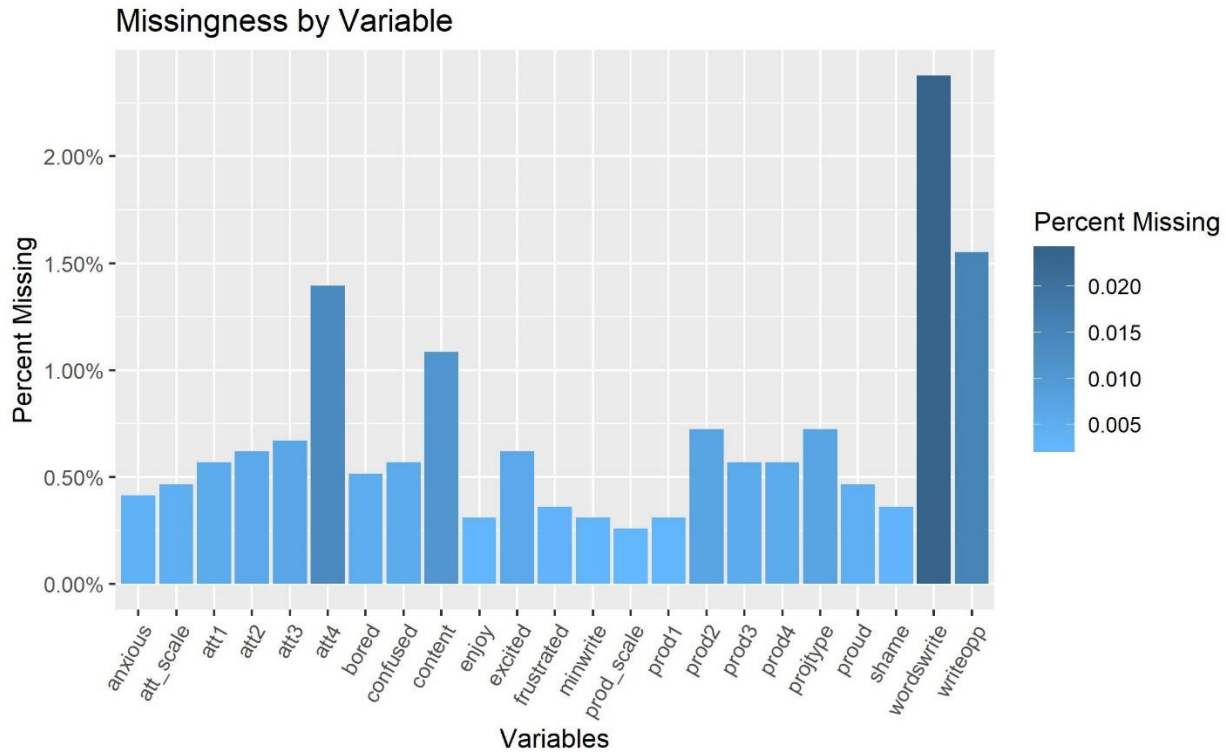
² It is important to note that these patterns of missingness say nothing about the mechanisms of missingness.

I considered data following Pattern A as complete and therefore included these data in all analyses. Inversely, I excluded data from surveys following Pattern C and Pattern D from all subsequent analyses³. On days that participants indicated not writing (Pattern C), they would not have had opportunities to experience writing-related emotions or regulate their attention while writing, nor would they have spent any time writing or written any words. Therefore, it did not seem reasonable to impute this data. Likewise, on days that participants did not respond to the surveys at all (Pattern D), it seemed more reasonable to assume that participants didn't write and didn't complete a survey than that they did write and forgot to complete a survey.

Missing data following Pattern B more closely aligns with a circumstance in which it would be appropriate to impute data. In these cases, participants indicated that they did write on day *i*, and therefore any missing data is due to nonresponse rather than a lack of a generative situation. Given this, I further investigated missingness in of cases following patterns A and B to determine how to handle missingness. This investigation indicated that very few data were missing, with missingness ranging from .2% to 2.3% by variable. Figure 4 presents a display of the proportion of missingness by variable for each variable in the dataset. Given these small amounts of missingness, I opted not to impute data and instead to use pairwise deletion, which is best suited for the generalized estimating equations (GEE) modeling approach described later.

³ The one exception to this is using data from surveys following these patterns to describe the number of days participants indicated writing, not writing, or didn't respond to surveys. This analysis is presented in the "Preliminary Analyses" subsection in the "Results" section.

Figure 4. Missingness by Variable.



Estimating Variance Components

As a preliminary analysis, I examined the extent to which variance in each outcome could be explained by factors at the daily level (Level 1) and factors at the person level (Level 2). To do so, I estimated intraclass correlation coefficients (ICCs; Raudenbush & Bryk, 2002), which, in this case, represent the proportion of variance in the outcome attributable to between-person factors. If ICCs are greater than .05 – which corresponds to the circumstance in which more than 5% of the variance in a daily outcome is attributable to between-person differences – modeling approaches should account for these between-person dependencies (Raudenbush & Bryk, 2002). I estimated ICCs using the `lme4` package (Bates, Maechler, Bolker, & Walker, 2015) and the `sjstats` package (Ludecke, 2019) in R.

Intensity of Average Emotions

To investigate the average intensity of writers' emotions over the course of the month, I examined descriptive statistics for each of the measured emotions (enjoyment, pride, anxiety, shame, frustration, and boredom) over the month. This entailed computing a grand mean, a standard deviation, and a standard error of the mean for each emotion across all writers and all measurement occasions. Next, to investigate whether emotions differed in their average intensity across all writers and time points, I calculated a 95% confidence interval for the mean of each emotion. I then compared the confidence intervals of each emotion. I considered emotions with confidence intervals that did not overlap to be significantly different from one another.

Writers' Emotional Stability

I used two approaches to investigate the day-to-day change, stability, and inertia of writers' writing-related emotions. First, I used a reliable change index (RCI; e.g. Bernacki et al., 2015; Christensen & Mendoza, 1986; Muis & Edwards, 2009), which allows researchers to distinguish between changes in a construct's score due to measurement error and reliable changes, or changes in the true score of the construct between observations. RCIs are particularly suitable for capturing intraindividual change between measurement occasions, which, in the current study, correspond to day-to-day changes in emotional intensity. To calculate the RCIs, I first calculated the difference between a person's score on an emotion at time t and their score at the last occasion for which they had a non-missing score on that same emotion. In the simplest case, this would be at time $t-1$; however, if a person did not complete a survey at time $t-1$, the difference would be calculated using time $t-2$, etc⁴. Next, I calculated the standard error of the

⁴ This approach sufficiently captures change from one measurement occasion to the next, but it also creates circumstances in which the intervals between measurements are not equal, which is worth keeping in mind when interpreting the results of the RCI analyses.

difference score at each measurement occasion for each emotion. Since there could not be a difference score at time 1 (i.e. on the first survey), this process resulted in the calculation of 243 standard errors (9 emotions multiplied by 27 measurement occasions, i.e. surveys 2-28). Next, I divided each difference score by its standard error. For example, I divided Participant 1's difference score for enjoyment at time 5 by the standard error of all enjoyment difference scores at time 5. If this value was less than -1.96 or greater than 1.96, which are common thresholds in this type of analysis (e.g. Bernacki et al., 2015) and in hypothesis testing more generally, I concluded that this indicated a reliable change in that emotion since the previous measurement. This led to a binary yes/no variable indicating reliable change (or lack thereof) for each person for each emotion at each measurement occasion, exception occasions with missing data. Beyond this binary variable indicating the presence of a reliable change, I also calculated two dummy variables that corresponded to the direction of the change. A change in the negative direction indicated that a writer felt enjoyment (for example) less intensely on the current day than on the previous day, whereas a change in the positive direction indicated that a writer felt enjoyment (for example) more intensely on the current day than on the previous day. Reliable change is inversely related to stability in that more instances of intrapersonal reliable change for a given emotion correspond to less intrapersonal stability of that emotion.

Second, I estimated several models that extended upon traditional first-order autoregressive time-series models (AR(1) models; Hamaker, 2012; see also Enders, 2008). Initially, I intended to estimate these models in a multilevel framework. Multilevel models (MLMs) are commonly used to model data in nested structures (Raudenbush & Bryk, 2002), as is the case in this study, where measurement occasions are nested within writers. That is, MLMs provide a commonly-used framework for modeling data in which observations violate the

assumptions of independence made by single level ordinary least squares (OLS) regression models. However, after exploring the data, I instead opted to fit these models using generalized estimating equations (GEE; Liang & Zeger, 1986; Zeger, Liang, & Albert, 1988). Similar to MLMs, GEE can account for dependencies in nested data structures. They do so by iteratively estimating within-cluster – in this case, within-person – correlation matrices and using these to adjust regression coefficient estimates until the models arrive at an optimal estimate (McNeish, Stapleton, & Silverman, 2017). One strength of GEE is that they can more readily accommodate data where some clusters are sparse or imbalanced, which is the case with the current study (McNeish, 2014). Some participants in this study had only one useable response, whereas others had as many as 27, which resulted in both sparse and imbalanced clusters. In such cases, MLMs may fail to detect group-level effects, provide inflated standard error estimates, or run into convergence issues (McNeish, 2014; Theall et al., 2011). One drawback of GEE is that they estimate population-averaged effects and therefore do not allow for the estimation of any random parameters. Another drawback of GEE is that, because they use quasi-likelihood methods to estimate parameters, no fit statistics are available to facilitate model selection. Therefore, when presenting the results of these models, I do not make any inferences about which models might be “better” or “worse” than others.

In contrast to the RCI analyses described previously, which examine intrapersonal stability or variability in writers’ emotional experiences, these GEE extensions of autoregressive time-series models examine population-level stability or variability in writers’ emotional experiences by capturing both intra- and inter-personal features. In their simplest forms, these models summarize two phenomena: inertia and innovation. In the context of the current study, inertia refers to the extent to which a writer’s current emotional experience is dependent upon his

or her emotional experience with writing yesterday and is captured via an autoregressive parameter (Hamaker, 2012). This is the focal parameter of these analyses. Innovation, on the other hand, refers to the unpredictable portion of the current emotional state and is analogous to the residual in a typical OLS regression model. As is the case with MLMs, the GEE models here can be extended to include additional within-person and between-person predictors, and such models in the MLM framework have been used previously to examine emotional stability over time (e.g. Kuppens, Allen, & Sheeber, 2010), albeit not related to writing.

All of these GEE models were fit using the `geepack` package (Halekoh, Hojsgaard, & Yan, 2006) in R. Before fitting models, all emotion and lagged emotion ratings were group-mean centered. Centering in this manner facilitates the interpretation of within-person effects by removing all between-person effects from the ratings (Enders & Tofighi, 2007; Nezlek, 2001; Raudenbush & Bryk, 2002) and aids in the interpretation of variables measured on a Likert scale. Afterward, I followed a modeling approach described by Hox, Moerbeek, and Van de Schoot (2017), which entails beginning with the simplest models and then gradually increasing complexity by adding predictors and/or interaction effects. All models were fit using an identity link function and an AR(1) correlation structure as options in the `geeglm` function. Finally, because the `geepack` package cannot handle missing data, cases with missing values for any of the variables included in each model were dropped.

In this paragraph, I use enjoyment as an example to describe the model-building process; however, I employed the same approach for all emotion variables. First, I fit Model 1, in which lagged enjoyment⁵ predicted current enjoyment. Model 1 also included time as a covariate⁶.

⁵ Unless otherwise specified, all lagged terms are lagged in the same manner as described above for the RCI analysis.

⁶ As an exploratory step, I also fit models with quadratic lagged effects; however, because none of these effects were significant and because I had no research questions or hypotheses around these models, I do not report them here.

Next, I fit Model 2, which retained the terms from Model 1 and added additional time-varying covariates, including an indicator representing whether the day's primary writing project was an independent project or a collaborative project as well as indicators representing the type of writing activities undertaken, including planning, drafting, and revising. Next, I fit Model 3, which retained all terms from Model 2 and added a time-by-lagged enjoyment interaction. This term captured the extent to which the day-to-day inertia of writing-related enjoyment might be moderated by time. Next, I fit Model 4, which retained all terms from Model 2 and included gender and academic department as predictors. This model allowed me to control for person-level factors when examining emotional inertia. In this model, gender was dummy-coded where males were assigned a value of 1 and females were assigned a value of 0⁷. Likewise, academic department was dummy coded where participants affiliated with departments or schools of education were assigned a value of 1 and participants affiliated with other departments or schools were assigned a value of 0. I chose this coding scheme for academic department due to limited variability in responses, and I likely would not have had power to detect any effects using another coding scheme, even if these effects were present in the population. Next, I fit Model 5, which retained all terms from Model 4 and included a gender-by-lagged enjoyment interaction. This model allowed me to test the extent to which males and females differed in their emotional inertia related to writing. Finally, I fit Model 6, which retained all terms from Model 4 and included an academic department-by-lagged enjoyment interaction. This model allowed me to test the extent to which writers enrolled in education graduate programs differed in their emotional inertia when compared to students enrolled in other types of programs. The

⁷ No participants in the study indicated identifying as a gender other than male or female.

interactions described in Models 5 and 6 were exploratory in nature, and I had no specific hypotheses regarding what sorts of effects I would find.

Relations between Emotions and Daily Outcomes

Models predicting daily attention regulation. To test the predictive relations between writers' daily writing-related emotions and their daily attention regulation while writing, I estimated several GEE models using a model building process somewhat similar to the one described previously to investigate emotional inertia. All models were fit using the `geepack` package (Halekoh, Hojsgaard, & Yan, 2006) in R, and all daily emotion scores and lagged attention regulation scores were group-mean centered. Additionally, all models were fit using an identity link function and an AR(1) correlation structure. Once again, cases with any missing data on the variables included in each model were dropped.

First, I fit Model 1, in which all of the current day's emotion ratings predicted current attention regulation. Model 1 also included lagged attention regulation and time as covariates. Next, I fit Model 2, which retained the terms from Model 1 and added additional time-varying covariates, including an indicator representing whether the day's primary writing project was an independent project or a collaborative project as well as indicators representing the type of writing activities undertaken, including planning, drafting, and revising. Next, I fit Model 3, which retained all predictors from Model 2 and added gender and academic affiliation as person-level covariates. As before, gender was dummy coded where males were coded as 1 and females were coded as zero, and academic affiliation was dummy coded where writers affiliated with a school of education were coded as 1 and those affiliated with any other school or department were coded as 0. Finally, I fit Model 4, which retained all predictors from Model 4 and added in person-level averages for each of the nine measured emotions. These emotion averages, or

contextual effects (Enders & Tofighi, 2007; Kreft, de Leeuw, & Aiken, 1995), allowed me to examine both the influence of writers' daily emotional states and their average emotional states on their attention regulation.

Models predicting daily minutes spent writing and words written. To test the relations between writers' daily writing-related emotions and their daily minutes spent writing as well as the daily number of words written, I fit models in a process very similar to that described previously when modeling attention regulation. As previously, all outcome scores, lagged outcome scores, and daily emotion ratings were group-mean centered. All models were fit in a GEE framework using an identity link function and an AR(1) correlation structure. Cases with missing data on the variables included in each model were dropped before fitting each model.

First, I fit Model 1, in which all of the current day's emotion ratings predicted the current outcome – either minutes writing or words written. Model 1 also included the lagged outcome and time as covariates. Next, I fit Model 2, which retained all predictors from Model 1 and added gender and academic affiliation as person-level covariates. Both of these covariates were coded as described previously. Finally, I fit Model 3, which retained all predictors from Model 2 and added in person-level averages for each of the nine measured emotions.

Unlike in Models 2-4 predicting writers' daily attention regulation, I do not report the results of models that included daily covariates, including whether the writer worked on an individual project as well as what phase of the writing process – planning, drafting, or revising – the writer engaged in. When I estimated models with these terms, the estimated intercept terms were large and negative, which could lead to incoherent interpretations of the results. For example, in several cases, models with these terms included indicated that people who did not engage in drafting (i.e. they primarily revised, planned, or both) wrote negative words on a given

day and spent negative minutes writing. Therefore, I opted to leave these controls out of the models predicting daily minute writing and daily words written.

Chapter 4 – Results

In this chapter, I begin by presenting the results of preliminary analyses, including multilevel confirmatory factor analyses (MLCFA) and reliability analyses of the Writing Attention Regulation Scale and the Writing Productivity Scale, estimates of intraclass correlation coefficients (ICCs; Raudenbush & Bryk, 2002) for any variables serving as outcomes in models, and descriptive statistics representing the daily response patterns of participants retained in the final sample. Next, I present descriptive statistics for participants' emotional experiences during writing, their attention regulation during writing, the time they spent writing each day, and the amount of words they wrote each day. In doing so, I address Research Question 1, which seeks to explore potential differences in mean levels of average emotional experiences across writers and across time over the course of the study.

Next, I address Research Question 2, which seeks to explore the change and inertia of writers' emotions over time, using several analyses. First, I present reliable change indices, which represent changes in a given emotion between days corresponding to true change (rather than measurement error) in the given emotion. Second, I present results from a series of adapted first-order autoregression (AR(1)) models in which a writer's emotional experience on a given day is predicted by his or her emotional experience on the previous day along with several control variables.

Next, I address Research Question 3, which seeks to examine the extent to which writers' emotional experiences relate to their daily attention regulation while writing. To do so, I present the results of several GEE models that explore the relationships between daily emotional experiences and daily attention regulation as well as between person-level average emotional experiences and daily attention regulation.

Finally, I address Research Question 4, which seeks to examine the extent to which writers' emotional experiences relate to two measures of writing productivity – daily minutes spent writing and daily words written. To do so, I present the results of several GEE models for each outcome that explore the relationships between daily emotional experiences and daily productivity as well as between person-level average emotional experiences and daily productivity.

Preliminary Analyses

MLCFA and Reliability Analyses

Writing Attention Regulation Scale. To assess the dimensionality and measurement properties of the Writing Attention Regulation Scale, I estimated two MLCFA models. In the first model, I loaded responses onto a single factor at the within-person level of the model and a single factor at the between-person level of the model. However, the fit of this model was not acceptable (CFI = .983; RMSEA = .140, 90% CI [.121, .159]; SRMR_{within} = .006, SRMR_{between} = .054). Given this, I then fit a model in which responses were loaded onto a single factor at the within-person level, whereas the between-person model was saturated (i.e. all variances of and covariances among scale items were freely estimated). The fit of this model was acceptable (CFI = .998; RMSEA = .068, 90% CI [.043, .097]; SRMR_{within} = .006, SRMR_{between} = .001), which suggests that the scale adequately captures a unidimensional factor representing attention regulation during writing at the daily level while accounting for between-person dependencies. Given the acceptability of these fit indices, I then proceeded to estimate reliability of scores on this scale. The R_{KR} coefficient representing generalizability of the average time points across items was .93, which is excellent.

Writing Productivity Scale. I followed the same procedures described in the subsequent paragraph to assess the measurement properties of the Writing Productivity Scale. The fit of the first MLCFA model, where item responses were loaded onto a single factor at the within-person level of the model and a single factor at the between-person level of the model, was poor (CFI = .86; RMSEA = .299, 90% CI [.28, .32]; SRMR_{within} = .068, SRMR_{between} = .085). Likewise, the fit of the second MLCFA model, where variances and covariances at the between-person level were freely estimated, was also unacceptable (CFI = .879; RMSEA = .397, 90% CI [.37, .42]; SRMR_{within} = .066, SRMR_{between} = .020). Given that these fit indices were not acceptable, I opted not to conduct any further analyses using this scale.

Estimating Variance Components

For any variable that serves as a dependent variable in any analysis, I estimated intraclass correlation coefficients (ICCs; Raudenbush & Bryk, 2002) to investigate the extent to which variance in responses at the daily level could be attributed to factors at the person level. These ICCs ranged from .25 (for number of words written) to .47 (for feelings of shame while writing). All ICCs were above the threshold of .05 at which accounting for nesting is recommended when building models, and these results support the modeling approaches used in subsequent analyses. All ICCs are presented in Table 2.

Table 2. Intraclass Correlation Coefficient (ICC) Estimates

Variable	ICC Estimate
Anxiety	0.406
Attention Regulation (Full Scale)	0.303
Boredom	0.420
Confusion	0.356
Contentment	0.409
Enjoyment	0.369
Excitement	0.358
Frustration	0.325
Minutes Writing	0.259
Pride	0.338
Shame	0.472
Words Written	0.250

One important caveat is that these ICCs are likely overestimates of the variance attributable to person-level factors. As Theall and colleagues (2011) found, ICCs tend to be inflated when data are sparsely clustered, which is the case in the current data. Nevertheless, even given this inflation, the magnitude of these ICCs still seem to warrant accounting for dependencies when building models.

Proportion of Days Writing

I conducted an exploratory analyses to investigate the number of days participants in the final sample indicated writing, not writing, or didn't respond to the daily survey. Across the 28 days of the study, 51% ($n = 2611$) of the daily surveys indicated that participants didn't write on that day, 38% ($n = 1934$) of the daily surveys indicated that participants did write on that day, and 11% ($n = 554$) were missing.

On average, participants indicated writing on 10.8 ($SD = 5.16$) days over the duration of the study. The minimum number of days writing for participants included in the final sample was 0 (out of a possible 28), and the maximum number of days writing for participants included in

the final sample was 27. Although the four participants who wrote for 0 days did not contribute any data to the models, I consider them to be part of the final sample because they did respond to at least 14 daily surveys.

Primary Analyses

To help readers situate and interpret the results below, I will occasionally describe results in terms of two hypothetical writers, Orin and Joelle. These fictitious writers are meant to illustrate the results of the analyses and situate them within “average” writers. These writers were not actual participants in the study.

Descriptive Statistics

To investigate the intensity of writers’ average emotional experiences related to writing over the course of the study, I examined descriptive statistics and confidence intervals for each of the nine measured emotions. Generally, averages of emotional intensity across all writers and time points were around 3 on a scale of 1-8, where lower options on the scale corresponded to weaker agreement/intensity. These means ranged from 1.84 (shame) to 4.38 (enjoyment). Consider Orin, one of our hypothetical writers. Across the four weeks of the study, he would have experienced moderate degrees of positive emotional experiences, including enjoyment ($M = 4.37$), contentment ($M = 3.88$), pride ($M = 3.75$), and excitement ($M = 3.51$) and somewhat weaker degrees of negative emotional experiences, including anxiety ($M = 3.22$), frustration ($M = 3.01$), boredom ($M = 2.52$), confusion ($M = 2.41$), and shame ($M = 1.84$).

These results were somewhat in line with my hypotheses. This average level of enjoyment was in line with my hypothesis that writers would feel enjoyment more strongly than other emotions. The findings regarding the average level of anxiety ($M = 3.22$), however, were

not in line with my hypothesis that writers would feel anxiety more strongly than other emotions. Although, on average, writers reported feeling higher levels of anxiety than some other emotions, such as frustration or confusion, they indicated feeling lower levels of anxiety than some other emotions, particularly positive-valenced emotions, including contentment, excitement, and pride. The findings regarding the average level of boredom ($M = 2.52$) were somewhat aligned with my hypothesis that writers would feel boredom less intensely than other emotions. Shame ($M = 1.84$) was the only emotion that writers reported feeling significantly lower levels of than boredom; the mean of reported confusion during writing ($M = 2.41$) was slightly lower than the mean of boredom during writing ($M = 2.51$), but these means were not significantly different when their 95% confidence intervals were compared. Descriptive statistics for all emotions as well as for the attention regulation scale, the daily minutes spent writing outcome, and the daily words written outcome are presented in Table 3. Additionally, mean 95% confidence intervals for all emotion variables are presented in Figure 5, and formal mean comparisons among average emotion scores are presented in Table 4.

Table 3. Descriptive Statistics for Daily Measures

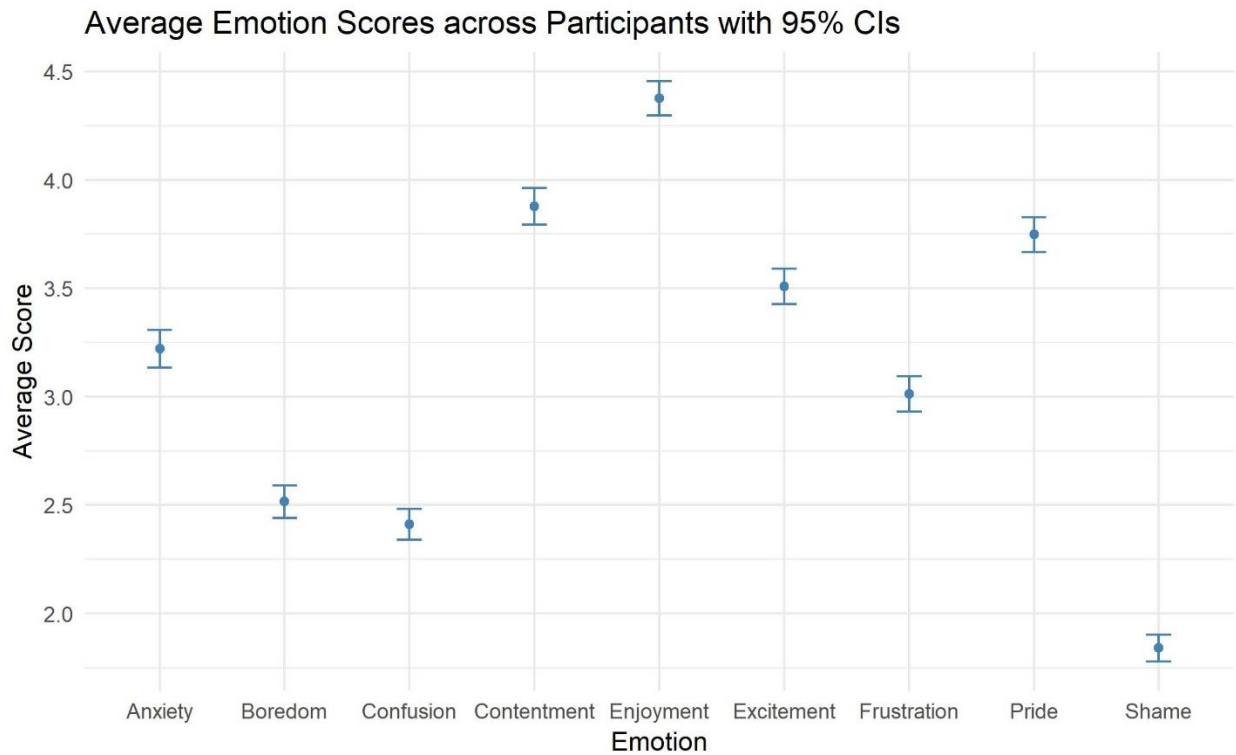
Variable	Mean	SD	SE	95% CI
Anxiety	3.22	1.96	0.04	[3.13, 3.31]
Attention Regulation (Full Scale)	5.03	1.80	0.04	[4.95, 5.11]
Boredom	2.52	1.66	0.04	[2.44, 2.59]
Confusion	2.41	1.60	0.04	[2.34, 2.48]
Contentment	3.88	1.86	0.04	[3.79, 3.96]
Enjoyment	4.38	1.78	0.04	[4.3, 4.46]
Excitement	3.51	1.84	0.04	[3.43, 3.59]
Frustration	3.01	1.83	0.04	[2.93, 3.1]
Minutes Writing	135.06	104.33	2.38	[130.4, 139.71]
Pride	3.75	1.79	0.04	[3.67, 3.83]
Shame	1.84	1.40	0.03	[1.78, 1.9]
Words Written	682.15	713.40	16.42	[649.97, 714.33]

Table 4. Mean Comparisons for Emotions

	Anxiety	Boredom	Confusion	Contentment	Enjoyment	Excitement	Frustration	Pride
Anxiety								
Boredom	-							
Confusion	-	ND						
Contentment	+	+	+					
Enjoyment	+	+	+	+				
Excitement	+	+	+	-	-			
Frustration	-	+	+	-	-	-		
Pride	+	+	+	ND	-	+	+	
Shame	-	-	-	-	-	-	-	-

Note: Comparisons are made horizontally such that a "+" in a cell indicates that the variable listed in the row is significantly greater than the variable listed in the column, and a "-" in a cell indicates that the variable in the row is significantly less than the variable in the column. Cells will contain "ND" when there is no significant difference between the row and column.

Figure 5. Emotion Means across Participants with 95% CIs.



Stability of Writers' Emotions

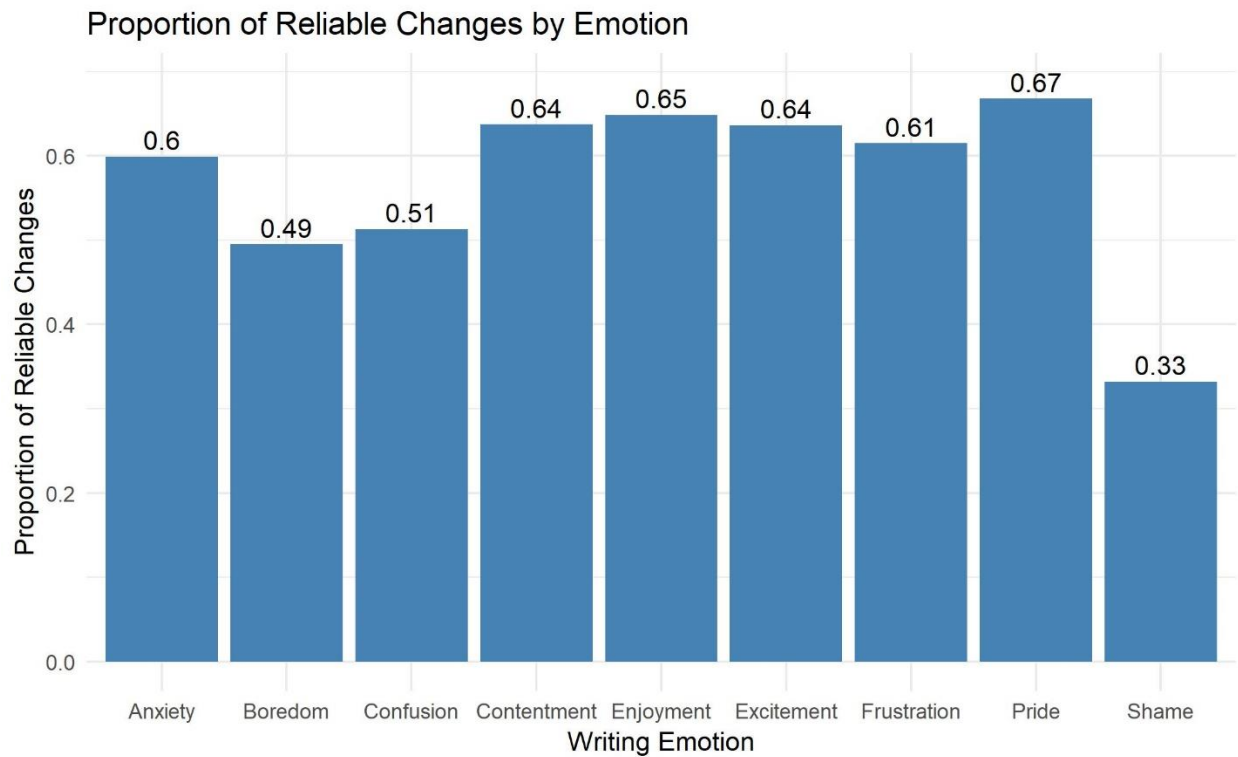
Reliable change indices. First, to investigate variability (i.e. lack of stability) in writers' day-to-day emotional experiences, I estimated reliable change indices (RCIs). Since it would be impractical to summarize these RCIs for each emotion at each time point, I instead present several statistics and figures to summarize these analyses more broadly. Due to the large number of potential RCIs and the fact that, due to missing data, there may be different numbers of both reliable changes and total measurement occasions for various participants and emotions, I focus on the proportion of reliable changes in these results, which represent the total number of reliable changes divided by the total number of non-missing measurements.

On average, pride was the least stable emotion, with 66.7% of the total measurements indicating reliable change from the previous measurement. Shame, on the other hand, was the most stable emotion, with only 33% of the total measurements indicating reliable change from the previous measurement. Furthermore, all of the positively-valenced emotions included in the survey (i.e. pride, enjoyment, contentment, and excitement) were less stable than all of the negatively- (i.e. frustration, anxiety, confusion, shame) or neutrally-valenced (i.e. boredom) emotions. All averages of proportion of reliable changes by emotion are presented in Table 5. Additionally, these averages are displayed in Figure 6.

Table 5. Reliable Changes by Emotion

Emotion	% Reliable Changes	% Positive Changes	% Negative Changes
Pride	0.668	0.336	0.331
Enjoyment	0.648	0.331	0.317
Contentment	0.637	0.325	0.312
Excitement	0.636	0.315	0.321
Frustration	0.615	0.288	0.327
Anxiety	0.599	0.275	0.324
Confusion	0.513	0.245	0.268
Boredom	0.495	0.239	0.256
Shame	0.332	0.161	0.171

Figure 6. Proportion of Reliable Changes by Emotion.



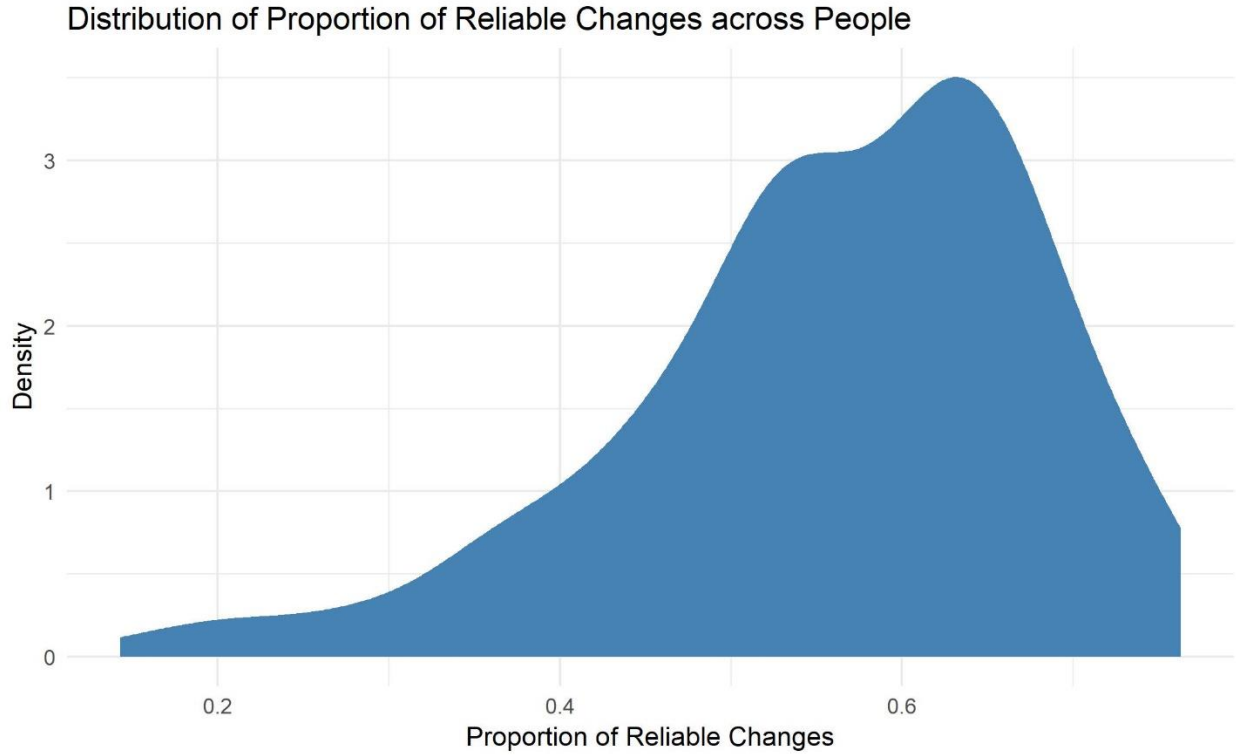
In addition to examining whether writers experienced any reliable changes, I further broke apart reliable changes into reliable increases (i.e. positive changes) and reliable decreases (i.e. negative changes). For each emotion, the ratio of reliable increases to reliable decreases was roughly equal. These estimates are presented in Table 5. I describe these reliable increases and

decreases in more detail later when I consider how they relate to writers' emotional states over time.

Next, I investigated the distribution of proportion of all reliable changes across people. In doing so, I first present results with all emotions grouped together, and then I present results broken apart by emotion. Across all emotions, the average proportion of reliable changes per participant was 55.3%. In other words, slightly over half of all writing-related emotion scores were significantly different than the previous score on that emotion for a given person. The standard deviation of the distribution of changes was approximately 13.5%. The least stable participant in the analysis recorded reliable changes in 76.3% of his/her emotion scores, and the most stable participant in the analysis recorded reliable changes in 14.2% of his/her emotion scores. The distribution of these person-level averages is presented in Figure 7⁸.

⁸ Because the shapes these distributions were similar when considering proportion of all reliable changes (i.e. both increases and decreases), only reliable increases, and only reliable decreases – albeit with different x axis values – I present only the aggregate distributions here.

Figure 7. Distribution of Proportion of Reliable Changes across People.



The statistics describing proportion of reliable changes broken apart by emotion at the person level are similar to those previously presented at the aggregate level. As before, pride was the least stable emotion for writers, with the average proportion of reliable changes per person at 70.2%, indicating that, for the average person, nearly three-quarters of his/her feelings of pride related to writing were significantly different between measurement occasions. Likewise, shame was the most stable emotion for writers, with the average proportion of reliable changes at 35.4%, indicating that, for the average person, roughly one third of his/her feelings of shame related to writing were significantly different between measurement occasions. For all emotions, the range of person-level reliable changes went from 0%, indicating perfect stability over time, to 100%, indicating no stability over time. These results are presented in Table 6. Additionally, the distributions of the person-level proportions of reliable changes by emotions are presented in

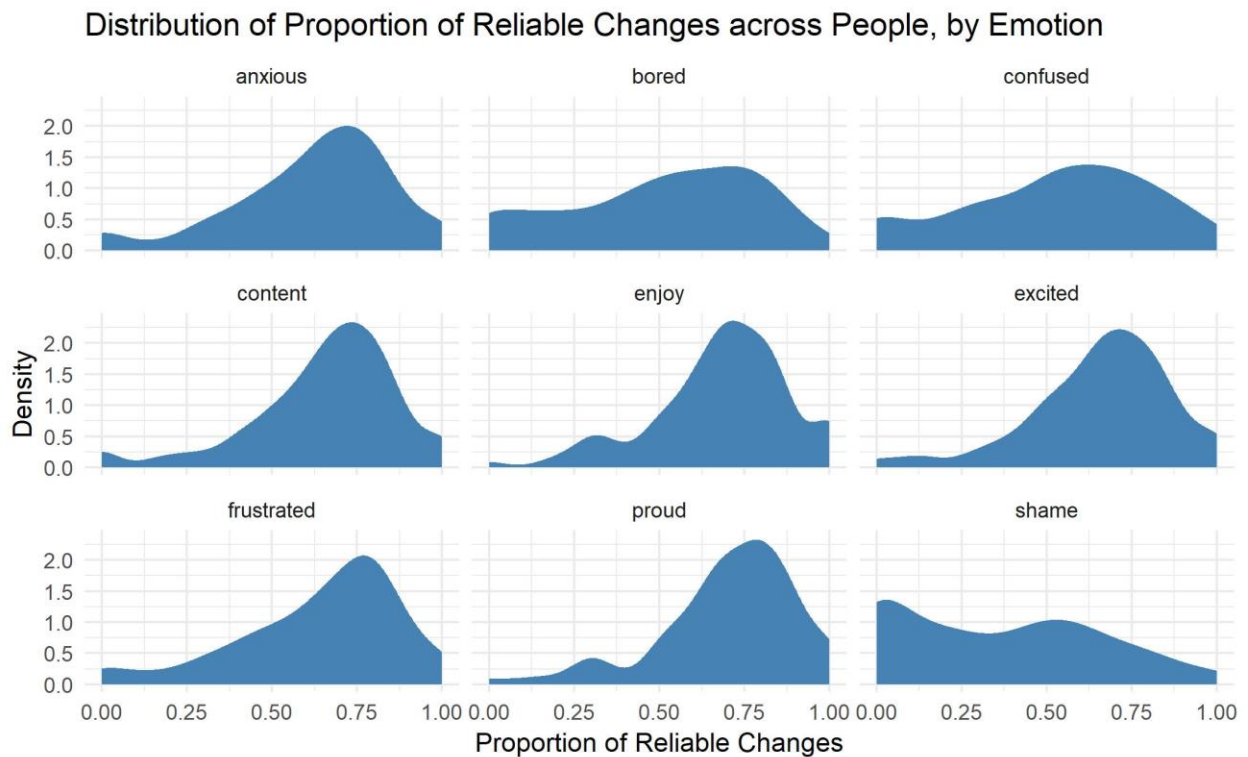
Figure 8.

Table 6. Reliable Change Indices by Person by Emotion.

Emotion	Mean RCI	SD RCI	Min RCI	Max RCI
Pride	0.703	0.203	0	1
Enjoyment	0.682	0.201	0	1
Excitement	0.660	0.208	0	1
Contentment	0.655	0.216	0	1
Frustration	0.639	0.240	0	1
Anxiety	0.622	0.234	0	1
Confusion	0.530	0.280	0	1
Boredom	0.506	0.281	0	1
Shame	0.354	0.302	0	1

Note. RCI = Reliable Change Indices.

Figure 8. Distribution of Proportion of RCIs across People, by Emotion.



Finally, I investigated potential trends in proportions of reliable changes by emotion over time. I investigated trends in terms of all reliable changes, reliable increases, and reliable decreases. Although I considered time to be random for participants in the study, I conducted these exploratory analyses to diagnose any potential time effects on the stability of writers'

emotions over the course of the study. As Figures 9 and 10 show, there do not appear to be any systematic relationship between time and the proportion of all reliable changes for any writing-related emotions. As Figures 11 and 12 (for positively-valenced emotions) as well as Figures 13 and 14 (for negatively-valenced emotions and boredom) suggest, there seem to be cyclical patterns between reliable increases and reliable decreases. If there was a particularly high proportion of reliable decreases for a given emotion at time t , there would often be a particularly low proportion of reliable decreases for that emotion at time $t+1$. For instance, nearly 50% of all writers reported a reliable decrease in pride on day 27, but then only about half of this many reported a reliable decrease in pride on day 28. Inversely, about 28% of writers reported a reliable increase in pride on day 27, and then roughly 37% reported a reliable increase in pride on day 28. Together, these patterns suggest that, on average, writers seem to return to their emotional baseline from day to day. Using Orin, one of our hypothetical writers, as an example, if Orin reported a reliable increase in pride one day, it is less likely that he would report another reliable increase in pride on the subsequent day. Instead, Orin would be more likely to report a reliable decrease in pride (or possibly no change). In other words, Orin would experience relatively little emotional inertia or day-to-day stability. Although findings of these RCI analyses hint at the notion that writers have little day-to-day emotional stability or inertia, I investigate this in another framework in the subsequent section.

Figure 9. Proportion of RCIs over Time for Positive Emotions, All Changes.

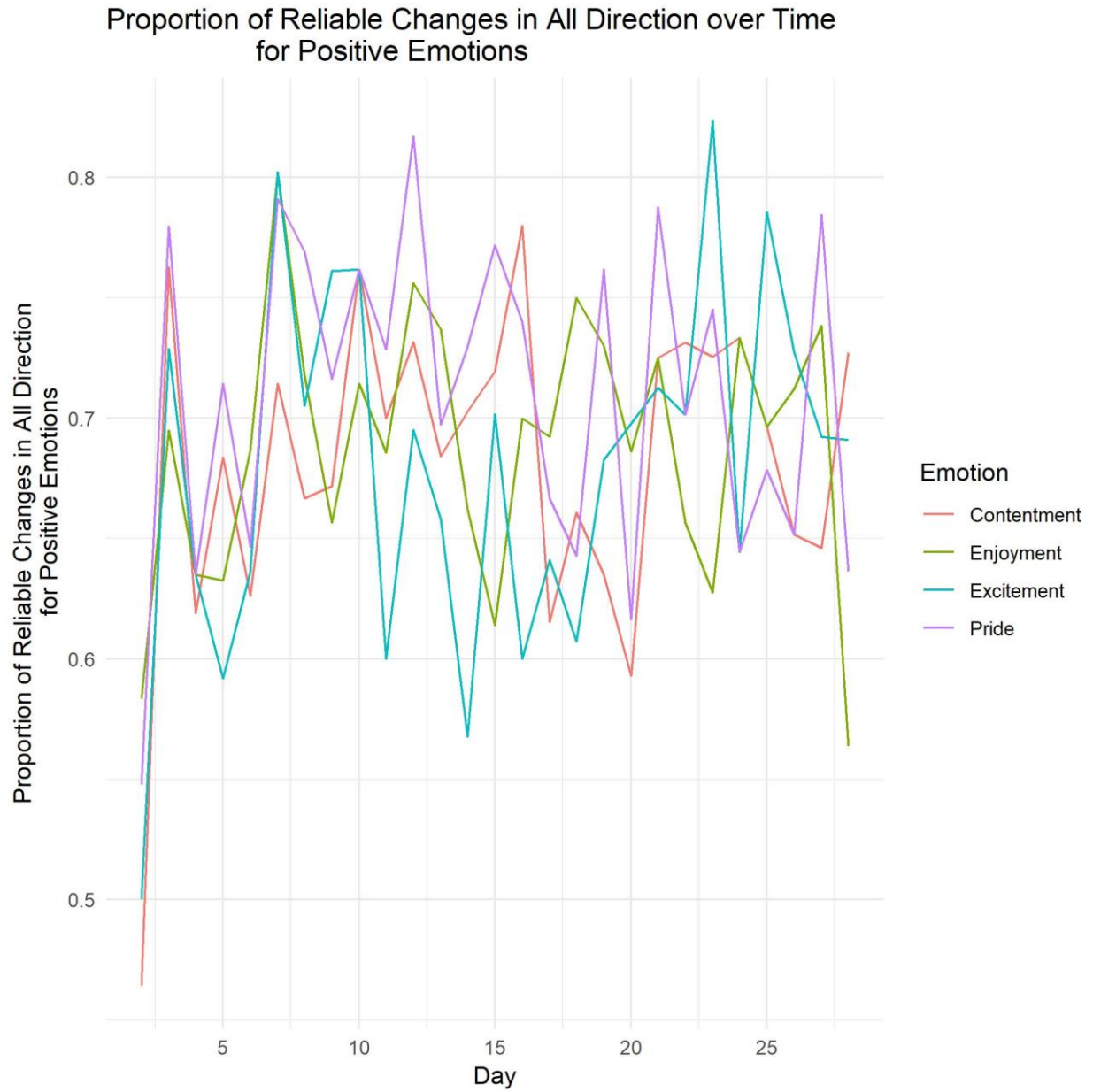


Figure 10. Proportion of RCIs over Time for Negative Emotions, All Changes.

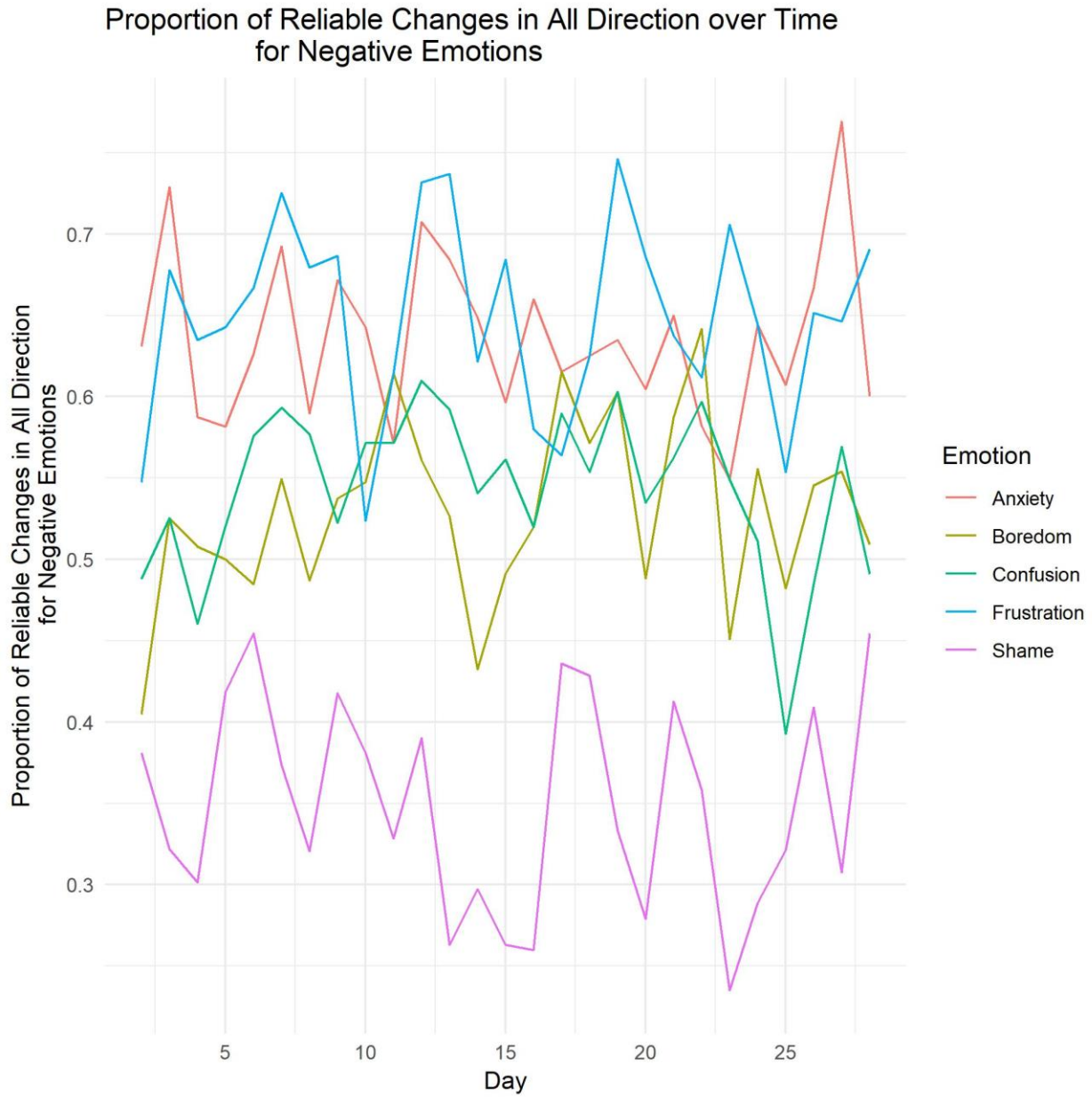


Figure 11. Proportion of RCIs over Time for Positive Emotions, Negative Changes.

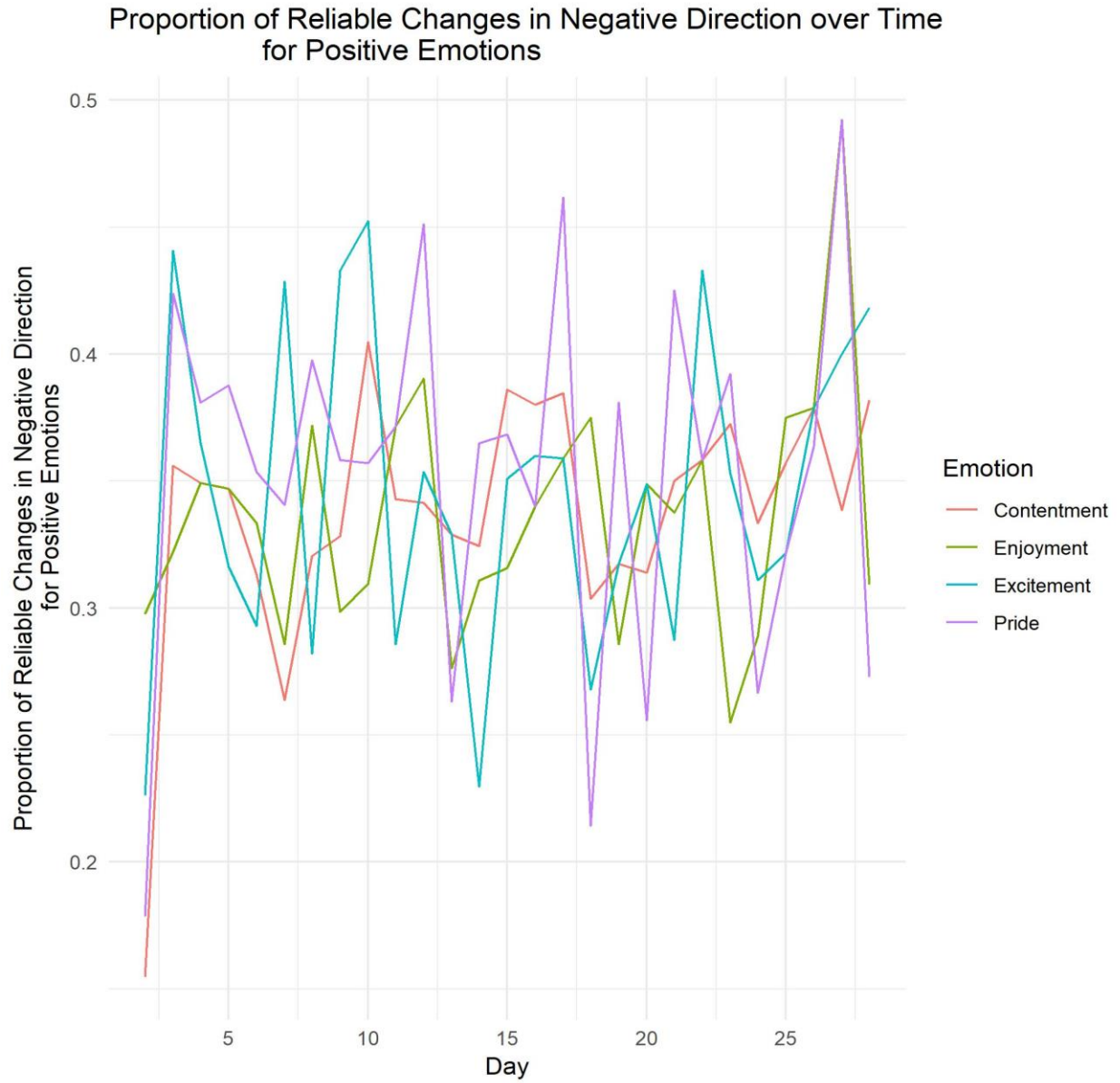


Figure 12. Proportion of RCIs over Time for Positive Emotions, Positive Changes.

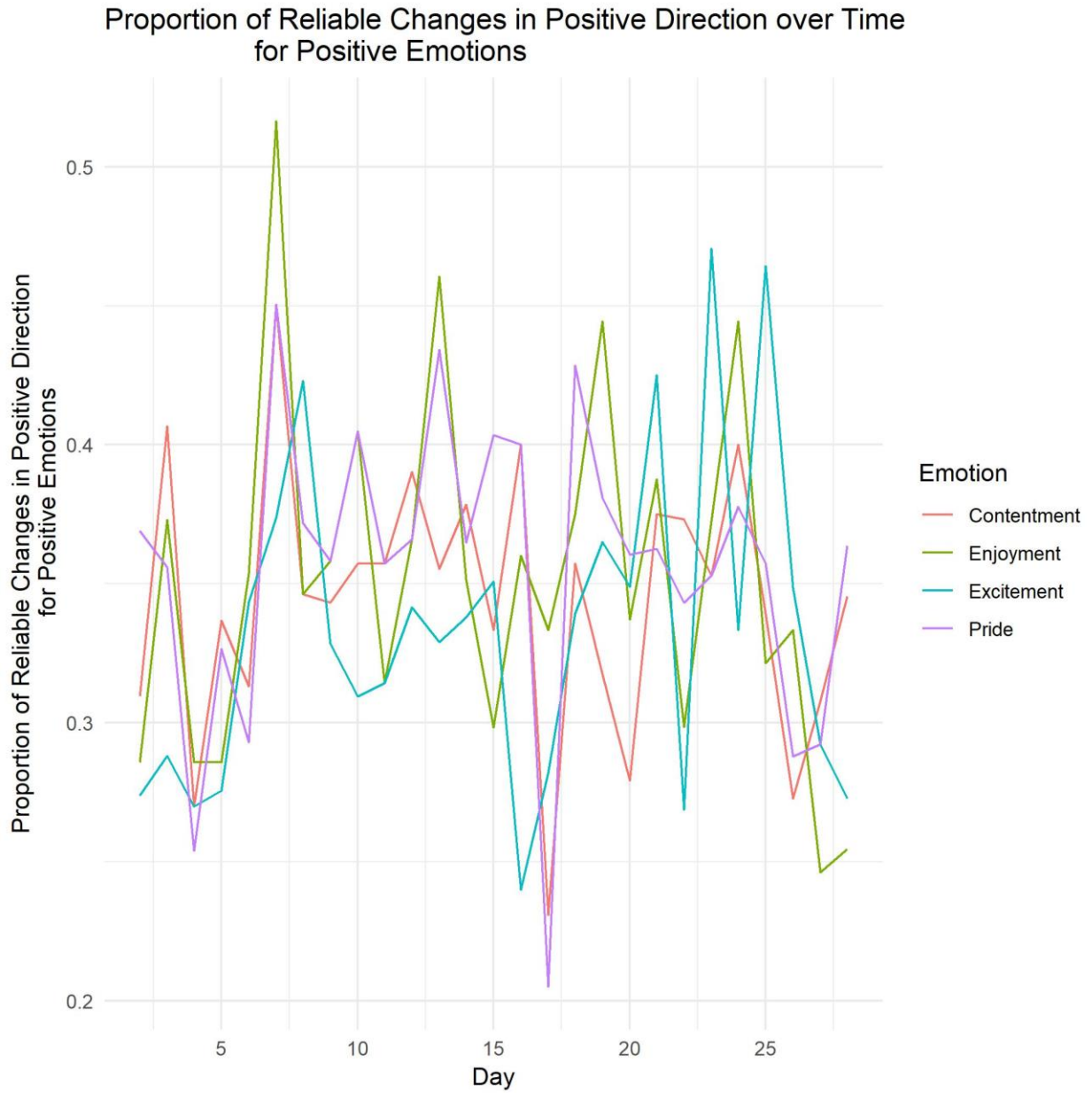


Figure 13. Proportion of RCIs over Time for Negative Emotions, Negative Changes.

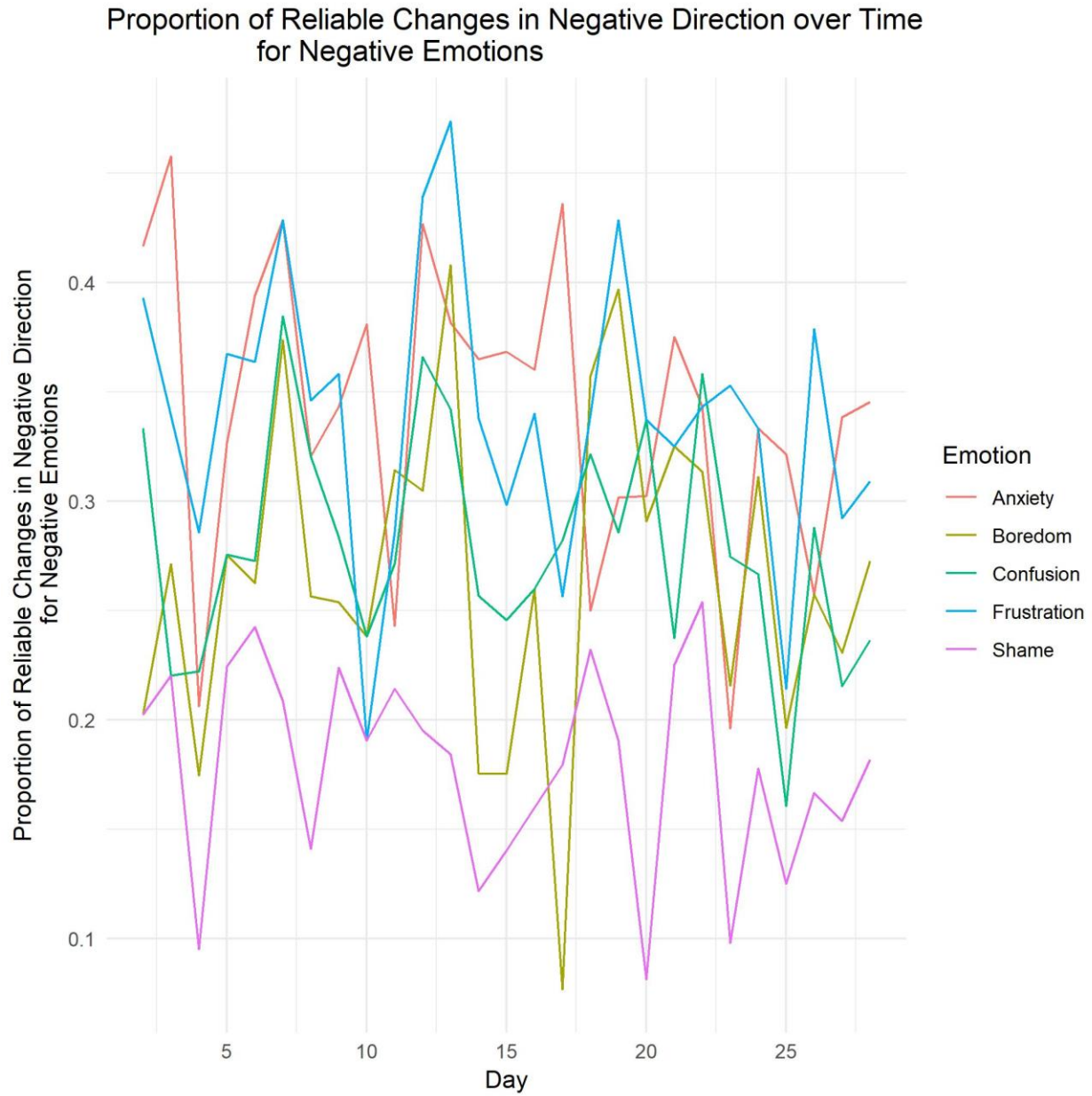
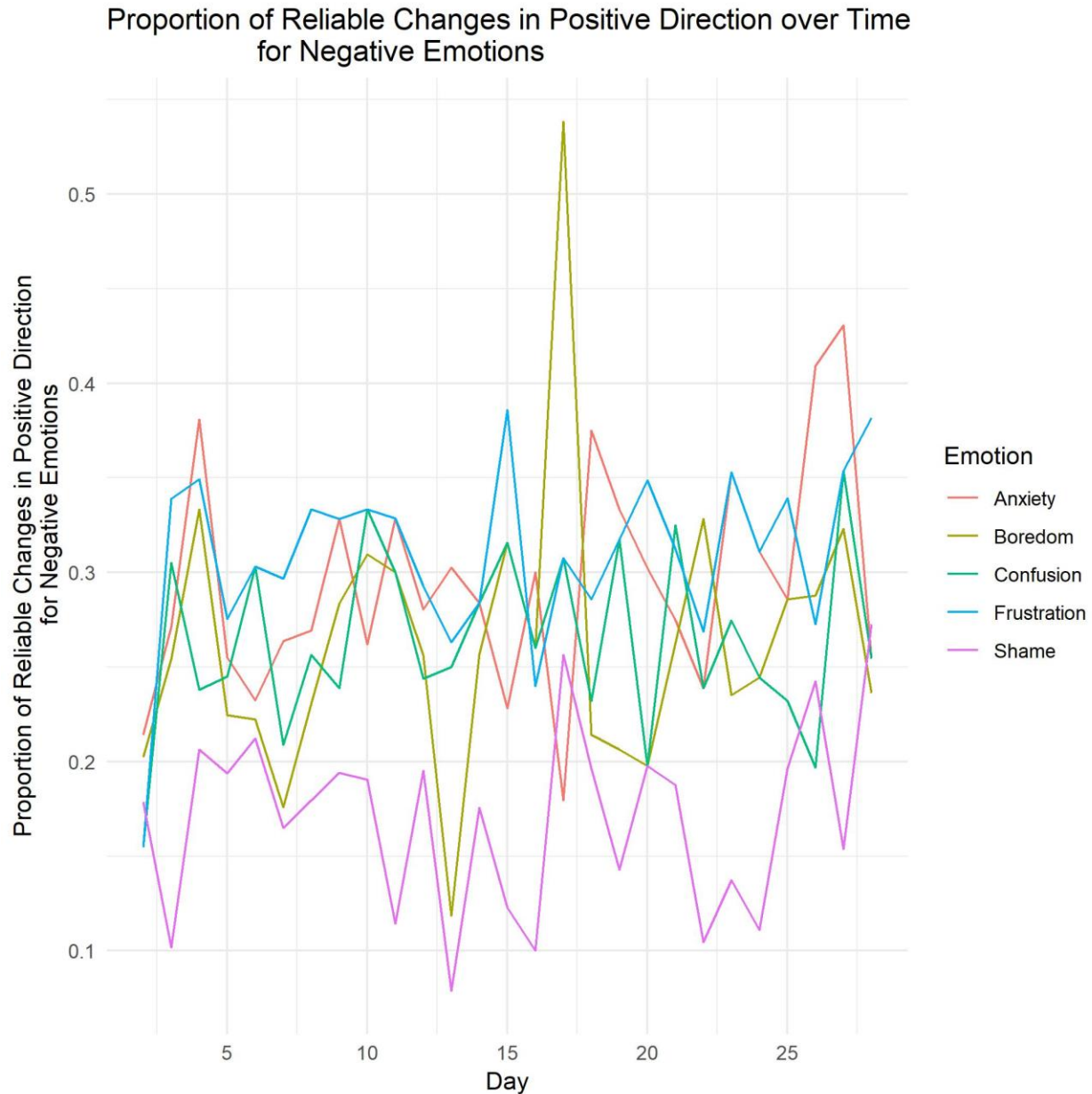


Figure 14. Proportion of RCIs over Time for Negative Emotions, Positive Changes.



Autoregression models. Next, to further investigate the day-to-day inertia of writer’s emotional experiences with writing, I fit several autoregression models in a GEE framework for each of the nine emotions measured in the current study. I present the results of these models in the sections below. To do so, I present the results sequentially according to the steps in the model building process described previously for all emotions. For instance, I present the results for the

first stage of model building for all emotions, then the second stage of model building for all emotions, etc. At the end of the section describing the results of all autoregression models in the process, I summarize the key findings.

Since it would be impractical to interpret each parameter from each estimated model, I limit my presentation of the results in text to the autoregressive parameters and any interaction effects involving the autoregressive parameters, since these are the primary concerns of the models. I do not interpret any day-level or person-level covariates in the models, although all estimates are presented in Tables 7 and 8. Some of these covariate effects are described in the discussion.

Additionally, I would like to remind readers that all emotion ratings – both the current day and the lagged ratings – are group-mean centered, and all estimates are unstandardized. Therefore, coefficients for autoregressive parameters should be interpreted as points above (or below) a person's average rating of that emotion on an 8-point rating scale.

Table 7. Results from Emotional Inertia Models 1-3.

Parameter	Model 1			Model 2			Model 3		
	B	SE	<i>p</i>	B	SE	<i>p</i>	B	SE	<i>p</i>
<i>Anxiety</i>									
<i>n</i>	1740			1726			1726		
Lagged Anxiety	0.080	0.030	0.008	0.076	0.030	0.012	0.093	0.071	0.188
Time	-0.017	0.006	0.003	-0.017	0.006	0.003	-0.016	0.006	0.004
Individual Project				0.127	0.068	0.062	0.127	0.069	0.065
Draft				0.077	0.068	0.260	0.077	0.069	0.260
Plan				0.076	0.068	0.260	0.077	0.068	0.260
Revise				0.215	0.071	0.002	0.216	0.071	0.002
Lagged Anxiety x Time							-0.002	0.005	0.730
<i>Boredom</i>									
<i>n</i>	1739			1726			1726		
Lagged Boredom	0.038	0.033	0.249	0.040	0.034	0.238	0.073	0.056	0.189
Time	-0.009	0.004	0.044	-0.010	0.005	0.036	-0.010	0.005	0.036
Individual Project				-0.033	0.064	0.612	-0.031	0.065	0.632
Draft				0.038	0.068	0.575	0.038	0.068	0.583
Plan				-0.085	0.055	0.126	-0.083	0.056	0.136
Revise				-0.033	0.064	0.602	-0.032	0.064	0.615
Lagged Boredom x Time							-0.003	0.003	0.379
<i>Confusion</i>									
<i>n</i>	1738			1724			1724		
Lagged Confusion	0.031	0.032	0.328	0.038	0.032	0.233	0.121	0.066	0.067
Time	-0.009	0.005	0.043	-0.009	0.005	0.047	-0.009	0.005	0.052
Individual Project				0.034	0.054	0.531	0.027	0.055	0.626
Draft				0.085	0.060	0.158	0.078	0.060	0.193
Plan				0.087	0.062	0.165	0.081	0.064	0.206
Revise				0.079	0.060	0.188	0.078	0.060	0.196

Lagged Confusion x Time							-0.008	0.004	0.026
<i>Contentment</i>									
<i>n</i>	1716			1702			1702		
Lagged Contentment	0.027	0.028	0.329	0.049	0.029	0.088	-0.028	0.061	0.642
Time	0.000	0.005	0.978	0.000	0.005	0.987	0.000	0.005	0.956
Individual Project				0.044	0.058	0.446	0.041	0.057	0.467
Draft				0.050	0.068	0.457	0.049	0.067	0.464
Plan				0.021	0.061	0.734	0.015	0.061	0.801
Revise				0.108	0.063	0.088	0.107	0.062	0.085
Lagged Contentment x Time							0.006	0.004	0.082
<i>Enjoyment</i>									
<i>n</i>	1744			1730			1730		
Lagged Enjoyment	0.062	0.030	0.036	0.055	0.030	0.067	0.016	0.051	0.749
Time	0.000	0.005	0.972	0.000	0.005	0.981	0.000	0.005	0.993
Individual Project				-0.006	0.071	0.933	-0.008	0.070	0.909
Draft				0.076	0.071	0.281	0.074	0.071	0.297
Plan				0.094	0.066	0.154	0.094	0.065	0.150
Revise				0.134	0.064	0.035	0.132	0.063	0.035
Lagged Enjoyment x Time							0.003	0.003	0.322
<i>Excitement</i>									
<i>n</i>	1736			1722			1722		
Lagged Excitement	0.036	0.034	0.299	0.040	0.035	0.256	-0.014	0.055	0.795
Time	-0.006	0.005	0.213	-0.006	0.005	0.222	-0.006	0.005	0.219
Individual Project				-0.022	0.071	0.762	-0.021	0.069	0.759
Draft				0.058	0.071	0.413	0.057	0.070	0.420
Plan				0.102	0.066	0.122	0.097	0.066	0.139
Revise				0.112	0.066	0.089	0.109	0.065	0.096
Lagged Excitement x Time							0.006	0.003	0.079

Frustration

<i>n</i>	1742			1728			1728		
Lagged Frustration	0.006	0.033	0.859	0.024	0.033	0.466	0.015	0.063	0.812
Time	-0.015	0.005	0.002	-0.015	0.005	0.002	-0.015	0.005	0.002
Individual Project				-0.002	0.070	0.972	-0.001	0.070	0.990
Draft				0.166	0.069	0.016	0.166	0.069	0.016
Plan				0.058	0.069	0.401	0.058	0.069	0.402
Revise				0.150	0.078	0.054	0.149	0.078	0.054
Lagged Frustration x Time							0.001	0.004	0.831

Pride

<i>n</i>	1739			1725			1725		
Lagged Pride	0.003	0.029	0.913	-0.011	0.029	0.692	-0.079	0.059	0.177
Time	-0.005	0.005	0.293	-0.007	0.005	0.210	-0.006	0.005	0.220
Individual Project				0.036	0.069	0.598	0.035	0.068	0.607
Draft				0.113	0.072	0.115	0.113	0.072	0.115
Plan				-0.054	0.070	0.440	-0.057	0.070	0.417
Revise				0.375	0.070	0.000	0.372	0.069	0.000
Lagged Pride x Time							0.005	0.004	0.146

Shame

<i>n</i>	1743			1729			1729		
Lagged Shame	0.001	0.033	0.978	-0.015	0.033	0.653	-0.033	0.066	0.617
Time	-0.007	0.004	0.059	-0.006	0.004	0.082	-0.006	0.004	0.080
Individual Project				0.146	0.043	0.001	0.146	0.043	0.001
Draft				0.063	0.058	0.273	0.064	0.058	0.266
Plan				0.063	0.042	0.134	0.062	0.042	0.140
Revise				0.074	0.054	0.168	0.075	0.054	0.168
Lagged Shame x Time							0.002	0.004	0.636

Note: *p* values of less than .05 are highlighted in green

Table 8. Results from Emotional Inertia Models 4-6.

Parameter	Model 4			Model 5			Model 6		
	B	SE	<i>p</i>	B	SE	<i>p</i>	B	SE	<i>p</i>
<i>Anxiety</i>									
<i>n</i>	1726			1726			1726		
Lagged Anxiety	0.076	0.030	0.011	0.106	0.030	0.000	0.122	0.040	0.002
Time	-0.017	0.006	0.003	-0.016	0.005	0.003	-0.017	0.006	0.002
Individual Project	0.128	0.069	0.064	0.119	0.068	0.081	0.133	0.069	0.055
Draft	0.077	0.068	0.261	0.074	0.068	0.277	0.079	0.069	0.247
Plan	0.075	0.068	0.275	0.071	0.067	0.288	0.074	0.069	0.282
Revise	0.212	0.071	0.003	0.208	0.070	0.003	0.210	0.071	0.003
Male	0.038	0.040	0.342	0.045	0.039	0.248	0.036	0.040	0.373
School of Education (SoE)	-0.013	0.031	0.683	-0.014	0.031	0.657	-0.011	0.031	0.719
Lagged Anxiety x Male				-0.217	0.085	0.010			
Lagged Anxiety x SoE							-0.097	0.057	0.090
<i>Boredom</i>									
<i>n</i>	1726			1726			1726		
Lagged Boredom	0.040	0.034	0.237	0.048	0.036	0.182	0.056	0.053	0.293
Time	-0.010	0.005	0.036	-0.010	0.005	0.036	-0.010	0.005	0.033
Individual Project	-0.033	0.065	0.615	-0.033	0.065	0.617	-0.032	0.065	0.629
Draft	0.038	0.068	0.574	0.037	0.069	0.593	0.039	0.068	0.564
Plan	-0.086	0.056	0.122	-0.085	0.056	0.125	-0.088	0.056	0.116
Revise	-0.034	0.064	0.591	-0.033	0.064	0.606	-0.035	0.064	0.587
Male	0.031	0.024	0.200	0.030	0.024	0.212	0.030	0.024	0.217
School of Education (SoE)	-0.004	0.022	0.857	-0.005	0.023	0.831	-0.004	0.022	0.856
Lagged Boredom x Male				-0.067	0.105	0.524			
Lagged Boredom x SoE							-0.029	0.067	0.664
<i>Confusion</i>									
<i>n</i>	1724			1724			1724		

Lagged Confusion	0.038	0.032	0.226	0.044	0.035	0.208	0.037	0.047	0.424
Time	-0.009	0.005	0.046	-0.009	0.005	0.046	-0.009	0.005	0.043
Individual Project	0.036	0.054	0.505	0.035	0.054	0.519	0.036	0.054	0.505
Draft	0.084	0.060	0.163	0.085	0.061	0.160	0.084	0.061	0.166
Plan	0.084	0.063	0.179	0.085	0.063	0.176	0.084	0.063	0.179
Revise	0.076	0.061	0.210	0.076	0.060	0.209	0.076	0.061	0.211
Male	0.032	0.032	0.315	0.032	0.032	0.309	0.032	0.032	0.315
School of Education (SoE)	-0.023	0.027	0.404	-0.023	0.027	0.405	-0.023	0.027	0.405
Lagged Confusion x Male				-0.046	0.070	0.514			
Lagged Confusion x SoE							0.002	0.064	0.974

Contentment

<i>n</i>	1702			1702			1702		
Lagged Contentment	0.049	0.029	0.088	0.050	0.032	0.119	0.095	0.051	0.060
Time	0.000	0.005	0.989	0.000	0.005	0.990	0.000	0.005	0.988
Individual Project	0.045	0.058	0.440	0.045	0.058	0.437	0.041	0.058	0.477
Draft	0.050	0.067	0.462	0.050	0.067	0.459	0.052	0.067	0.439
Plan	0.022	0.061	0.712	0.023	0.061	0.711	0.022	0.061	0.712
Revise	0.110	0.064	0.085	0.110	0.064	0.084	0.109	0.064	0.087
Male	-0.047	0.041	0.247	-0.047	0.041	0.251	-0.048	0.040	0.235
School of Education (SoE)	0.004	0.027	0.892	0.004	0.027	0.893	0.004	0.027	0.886
Lagged Contentment x Male				-0.006	0.069	0.933			
Lagged Contentment x SoE							-0.079	0.060	0.191

Enjoyment

<i>n</i>	1730			1730			1730		
Lagged Enjoyment	0.055	0.030	0.068	0.052	0.033	0.114	0.066	0.046	0.150
Time	0.000	0.005	0.984	0.000	0.005	0.974	0.000	0.005	0.991
Individual Project	-0.007	0.073	0.928	-0.007	0.072	0.921	-0.008	0.072	0.916
Draft	0.076	0.071	0.281	0.076	0.071	0.283	0.076	0.071	0.281
Plan	0.095	0.066	0.151	0.094	0.066	0.153	0.096	0.066	0.148
Revise	0.135	0.064	0.035	0.135	0.064	0.034	0.136	0.064	0.033

Male	-0.019	0.023	0.413	-0.018	0.023	0.425	-0.019	0.023	0.409
School of Education (SoE)	0.007	0.026	0.781	0.007	0.026	0.776	0.007	0.026	0.771
Lagged Enjoyment x Male				0.026	0.073	0.725			
Lagged Enjoyment x SoE							-0.018	0.060	0.760

Excitement

<i>n</i>	1722			1722			1722		
Lagged Excitement	0.040	0.035	0.256	0.033	0.039	0.410	0.089	0.065	0.166
Time	-0.006	0.005	0.223	-0.006	0.005	0.203	-0.006	0.005	0.236
Individual Project	-0.022	0.073	0.761	-0.024	0.072	0.735	-0.028	0.072	0.695
Draft	0.058	0.071	0.413	0.057	0.071	0.426	0.058	0.071	0.413
Plan	0.103	0.067	0.124	0.100	0.067	0.136	0.101	0.067	0.127
Revise	0.112	0.067	0.091	0.115	0.066	0.084	0.111	0.066	0.093
Male	-0.001	0.026	0.982	0.003	0.027	0.908	0.000	0.026	0.997
School of Education (SoE)	0.004	0.027	0.889	0.004	0.027	0.887	0.005	0.027	0.839
Lagged Excitement x Male				0.080	0.066	0.227			
Lagged Excitement x SoE							-0.079	0.072	0.271

Frustration

<i>n</i>	1728			1728			1728		
Lagged Frustration	0.026	0.033	0.444	0.023	0.036	0.532	0.000	0.053	0.994
Time	-0.015	0.005	0.002	-0.015	0.005	0.002	-0.015	0.005	0.002
Individual Project	0.001	0.071	0.994	0.001	0.070	0.985	0.000	0.070	0.995
Draft	0.165	0.068	0.016	0.166	0.068	0.015	0.164	0.068	0.016
Plan	0.054	0.069	0.437	0.054	0.069	0.437	0.054	0.069	0.431
Revise	0.145	0.078	0.065	0.147	0.078	0.060	0.146	0.078	0.062
Male	0.068	0.025	0.006	0.067	0.026	0.010	0.069	0.025	0.006
School of Education (SoE)	-0.031	0.029	0.288	-0.031	0.029	0.293	-0.032	0.030	0.279
Lagged Frustration x Male				0.041	0.088	0.640			
Lagged Frustration x SoE							0.048	0.067	0.475

Pride

<i>n</i>	1725			1725			1725		
Lagged Pride	-0.011	0.029	0.691	-0.021	0.031	0.504	0.019	0.048	0.698
Time	-0.007	0.005	0.215	-0.007	0.005	0.213	-0.007	0.005	0.220
Individual Project	0.032	0.070	0.647	0.027	0.069	0.698	0.029	0.070	0.676
Draft	0.114	0.072	0.111	0.114	0.071	0.111	0.111	0.071	0.117
Plan	-0.052	0.071	0.465	-0.052	0.071	0.464	-0.051	0.070	0.466
Revise	0.378	0.070	0.000	0.378	0.070	0.000	0.377	0.069	0.000
Male	-0.040	0.030	0.174	-0.036	0.030	0.225	-0.041	0.029	0.168
School of Education (SoE)	0.034	0.033	0.301	0.035	0.033	0.281	0.034	0.033	0.300
Lagged Pride x Male				0.126	0.072	0.080			
Lagged Pride x SoE							-0.049	0.059	0.409

Shame

<i>n</i>	1729			1729			1729		
Lagged Shame	-0.014	0.033	0.671	0.003	0.032	0.937	0.024	0.037	0.506
Time	-0.007	0.004	0.081	-0.006	0.004	0.112	-0.006	0.004	0.087
Individual Project	0.145	0.044	0.001	0.143	0.044	0.001	0.147	0.044	0.001
Draft	0.063	0.058	0.270	0.058	0.057	0.302	0.063	0.058	0.276
Plan	0.061	0.042	0.148	0.061	0.042	0.142	0.058	0.043	0.173
Revise	0.072	0.054	0.183	0.067	0.053	0.205	0.070	0.054	0.195
Male	0.053	0.020	0.006	0.050	0.019	0.009	0.053	0.019	0.006
School of Education (SoE)	-0.006	0.023	0.802	-0.007	0.023	0.756	-0.006	0.023	0.791
Lagged Shame x Male				-0.230	0.115	0.045			
Lagged Shame x SoE							-0.080	0.062	0.197

Note: p values of less than .05 are highlighted green

Model 1. To estimate the first model, I regressed the current day's emotion rating on the lagged emotion rating, and I also included time as a covariate. Across all emotions, the autoregressive parameters were significant only for anxiety ($B = .08, p = .008$) and enjoyment ($B = .062, p = .036$). For both anxiety and enjoyment, lagged ratings one point above a person's average levels of anxiety or enjoyment predicted current-day ratings of anxiety and enjoyment that were slightly higher than person-level averages. In other words, after experiencing higher (or lower) anxiety or enjoyment than usual, a writer would not completely return to baseline the next day.

Let's put this into the context of Joelle, one of our hypothetical average writers. Assuming Joelle's average writing-related anxiety rating is 3, if she rated her anxiety as a 7 yesterday, her predicted level of anxiety for today at a 3.28, which is still slightly above her baseline. Likewise, if we assume Joelle's average writing-related enjoyment is a 3 and she rated her enjoyment as a 7 yesterday, her predicted level of enjoyment for today would be a 3.25.

Model 2⁹. To estimate the second model, I retained the parameters from Model 1 and added daily covariates to control for the type of project the writer worked on (i.e. individual or collaborative) and the phases of the writing process the writer engaged in (i.e. planning, drafting, and revising). Across all emotions, the autoregressive parameter was significant only for anxiety ($B = .076, p = .012$), although it approached significance for enjoyment ($B = .055, p = .067$) and contentment ($B = .049, p = .088$). Once again, using Joelle to illustrate this, after controlling for the phases of the writing process Joelle engaged in as well as the type of project she worked on during a given day, feeling more anxious than usual about writing yesterday would have been associated with slightly increased feelings of anxiety today relative to her baseline.

⁹ Before estimating this model, I tested models with quadratic effects for the lagged variables. Because none of these quadratic effects were significant, I opted not to formally report the results of these models here.

Model 3. To estimate the third model, I retained all parameters from Model 2 and added a lagged emotion by time interaction effect. This effect represents the extent to which day-to-day emotional stability differed over the course of the four-week study. Across all emotions, this interaction effect was significant for only confusion ($B = -.008, p = .026$), although it approached significance for contentment ($B = .006, p = .082$) and excitement ($B = .006, p = .079$).

In the model for confusion, the main autoregressive effect was estimated at $B = .121$, although this effect was not significant ($p = .067$). Again, let's use Joelle to illustrate the interpretation of these effects. At the very beginning of the study, Joelle's confusion regarding writing on the previous day seemed to be modestly (but not significantly) and positively related to her confusion related to writing on the current day. As the study went on, however, the magnitude of this relation between decreased toward zero, became negative, and then became increasingly negative. By the end of the study, the autoregressive relationship between current day confusion and lagged confusion would have been negative (roughly $B = -.103$ on the final day of the study), indicating that greater confusion on day 27 would have been associated with less confusion on day 28.

Model 4. To estimate the fourth model for each emotion, I retained all parameters from Model 2 (i.e. I did not include the interaction effect from Model 3) and added in two person-level predictors: gender (dummy coded where male = 1) and academic affiliation (dummy coded where School/Department of Education affiliation = 1). This model allowed me to control for time-varying and time-invariant covariates. Parameter estimates for these models were nearly identical to those reported for Model 2; the autoregressive effect was significant only for anxiety ($B = .076, p = .011$), although it was nearly significant for contentment ($B = .049, p = .088$) as well as for enjoyment ($B = .055, p = .068$).

To situate these findings in our hypothetical writer, after accounting for the phases of the writing process Joelle engaged in on a given day, the type of project she worked on during a given day, her gender, and her academic affiliation, feelings of writing-related anxiety higher than her baseline levels of anxiety yesterday would have been associated with feelings of writing-related anxiety slightly higher than her baseline levels today.

Model 5. To estimate the fifth model for each emotion, I retained all parameters from Model 4 and added a gender-by-autoregressive effect interaction. This interaction captures the extent to which the autoregressive effect for each emotion differs between males and females. Across all emotions, the interaction effect was significant for anxiety ($B = -.217, p = .01$) and shame ($B = -.23, p = .045$), and the effect approached significance for pride ($B = .126, p = .08$).

Once again, it may help to situate these findings in our hypothetical writers, Orin and Joelle. With the interactions included in the models, the main autoregressive effects for anxiety and shame were estimated at $.106 (p < .001)$ and $.003 (p = .937)$, respectively. In other words, for Joelle, our hypothetical female writer, a rating of writing-related anxiety above baseline yesterday was modestly associated with a rating of anxiety above baseline today. For Orin (our hypothetical male writer), however, a rating of anxiety above baseline for yesterday would have been associated with a rating of anxiety below baseline today. In terms of writing-related shame, there was no relation between yesterday's shame and today's shame for Joelle; however, for Orin, a rating of shame above baseline yesterday was associated with a rating of shame modestly below baseline today.

Model 6. To estimate the sixth model for each emotion, I retained all parameters from Model 4 (i.e. I did not include the gender-by-autoregressive effect interaction from Model 5) and added an academic affiliation-by-autoregressive effect interaction. This interaction captures the

extent to which the autoregressive effect for each emotion differs between graduate students affiliated with schools (or departments) of education and those affiliated with other schools or departments. As a reminder, due to limited variability in responses, all academic affiliations that were not school/department of education were collapsed into an “other” category, which serves as the reference group for this analysis.

This interaction effect was not significant for any emotions, indicating that autoregressive effects did not differ between graduate students associated with schools of education and those associated with other academic school or departments.

Summary of autoregression models. Across all stages of the model-building process, I found the most robust autoregressive effects for writing-related anxiety. Departures from baseline anxiety at the previous measurement occasion were positively associated with departures from baseline anxiety at the current measurement occasion, indicating some degree of day-to-day stability or inertia in writers’ feelings of anxiety. These effects were significant in the initial model, which included only time as a covariate, as well as in later models that included other time-varying and time-invariant covariates. Furthermore, this autoregressive effect seems to be different for males and females; for females, previous anxiety was positively associated with current anxiety, whereas for males, previous anxiety was negatively associated with current anxiety.

No other emotions displayed consistently significant autoregressive effects across stages of model building. In the initial stage of model building, I found a significant and positive autoregressive effect for writing-related enjoyment, indicating that departures from baseline enjoyment at the previous measurement occasion were positively associated with departures from baseline enjoyment at the current measurement occasion. However, this effect was not

statistically significant in models that included time-varying and time-invariant covariates, although the effect did approach significance.

I found a statistically significant interaction between time and the autoregressive effect for confusion in stage 3 of the model building process. This interaction suggests that, as the study progressed, the autoregressive effect of confusion shifted from being modestly positive to modestly negative. In other words, at the beginning of the four weeks in which the study was conducted, departures from baseline confusion at the previous measurement occasion were positively associated with departures from baseline confusion at the current measurement occasion. However, by the end of the four-week period, this association was negative, indicating that a writer rating her confusion as above baseline at the previous measurement occasion would rate her confusion as below baseline at the current measurement occasion.

Finally, I also found a statistically significant interaction between gender and the autoregressive effect for shame. For females, there was no association between writing-related shame at the previous measurement occasion and shame at the current measurement occasion. However, for males, there was a negative association, indicating that a male writer who rated his shame as above baseline at the previous measurement occasion would rate his shame as below baseline at the current measurement occasion.

Another important consideration is that, across all of these models, all significant autoregressive effects and/or interaction effects were small. The largest effect I detected was the autoregressive effect for anxiety in Model 1, which included only time as a covariate. This effect was estimated at $B = .08$. To illustrate what this means, as well as the relatively magnitude of the effect, let's assume that Orin's baseline level of anxiety is a 3 on our 8 point scale (recall that the grand mean for anxiety is 3.22). If Orin rated his writing-related anxiety as an 8 – the highest

possible rating on the scale and 5 points higher than his baseline – yesterday, his estimated anxiety today would be roughly 3.4, which isn't even a full point above his baseline on the response scale.

These results somewhat aligned with my hypothesis. Contrary to my expectations, most emotions did not demonstrate significant day to day inertia. However, as I hypothesized, anxiety had the strongest day-to-day inertia, since it was the only emotion to demonstrate consistently significant autoregressive effects across the model building stages. The findings regarding enjoyment partially supported my hypotheses. Unlike all other emotions (except anxiety), writers' previous enjoyment did predict current enjoyment in Model 1, which provides some support for the day-to-day inertia of enjoyment. However, these effects were not significant once additional covariates were included in the models.

Relations between Writers' Emotions and Attention Regulation

To investigate the relations between writers' daily attention regulation while writing and their daily writing-related emotional experiences, I estimated several GEE models. As in the previous section, I present these results sequentially in terms of the steps of the model building process. Additionally, due to the large number of parameters in each model, I limit my in-text reporting to only significant parameters that are central to Research Question 3. After presenting these model-by-model results, I summarize the results across the entire model-building process. Full results are presented in Table 9.

Table 9. Results of Attention Regulation Models.

Parameter	Model 1 (n = 1698)			Model 2 (n = 1684)			Model 3 (n = 1684)			Model 4 (n = 1684)		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
Lagged Attention Regulation	0.007	0.031	0.831	0.001	0.031	0.978	0.001	0.031	0.975	0.003	0.031	0.910
Time	0.019	0.005	0.000	0.017	0.005	0.000	0.017	0.005	0.000	0.017	0.005	0.000
Anxiety	-0.061	0.029	0.035	-0.060	0.028	0.034	-0.060	0.028	0.034	-0.060	0.028	0.033
Boredom	-0.113	0.035	0.001	-0.116	0.035	0.001	-0.116	0.035	0.001	-0.117	0.035	0.001
Confusion	0.016	0.035	0.654	0.014	0.035	0.688	0.014	0.035	0.687	0.014	0.035	0.696
Contentment	0.143	0.034	0.000	0.144	0.034	0.000	0.144	0.034	0.000	0.144	0.034	0.000
Enjoyment	0.214	0.043	0.000	0.214	0.043	0.000	0.214	0.043	0.000	0.214	0.043	0.000
Excitement	-0.014	0.042	0.743	-0.010	0.041	0.801	-0.010	0.041	0.802	-0.011	0.041	0.795
Frustration	0.057	0.028	0.043	0.054	0.029	0.060	0.054	0.029	0.060	0.054	0.029	0.060
Pride	0.139	0.043	0.001	0.123	0.042	0.004	0.123	0.042	0.004	0.123	0.043	0.004
Shame	-0.032	0.044	0.462	-0.042	0.041	0.307	-0.042	0.041	0.306	-0.043	0.041	0.304
Individual Project				-0.022	0.065	0.738	-0.020	0.066	0.767	-0.015	0.067	0.819
Draft				0.278	0.073	0.000	0.277	0.073	0.000	0.280	0.074	0.000
Plan				-0.136	0.064	0.035	-0.136	0.064	0.033	-0.140	0.065	0.030
Revise				0.136	0.071	0.055	0.134	0.071	0.058	0.137	0.072	0.055
Male							0.005	0.033	0.887	-0.002	0.035	0.960
School of Education (SoE)							-0.014	0.029	0.628	-0.029	0.030	0.330
Anxiety (Person Avg)										-0.021	0.019	0.247
Boredom (Person Avg)										-0.005	0.014	0.701
Confusion (Person Avg)										0.041	0.022	0.059
Contentment (Person Avg)										0.001	0.018	0.968

Enjoyment (Person Avg)	0.038	0.021	0.069
Excitement (Person Avg)	-0.035	0.028	0.206
Frustration (Person Avg)	0.006	0.026	0.816
Pride (Person Avg)	-0.001	0.022	0.948
Shame (Person Avg)	-0.012	0.019	0.548

Note: p values of < .05 are highlighted light green.

Model 1. To estimate the first model, I regressed the current day's attention regulation scale score on the previous measurement occasion's attention regulation scale score, time, and all of the current day's emotion scores. In this model, anxiety ($B = -.06, p = .035$), boredom ($B = -.11, p = .001$), contentment ($B = .14, p < .001$), enjoyment ($B = .21, p < .001$), frustration ($B = .06, p = .043$), and pride ($B = .14, p = .001$) significantly predicted the current day's attention regulation.

Returning to our hypothetical writer, assuming Orin averages a score of 5 on the attention regulation scale, which ranges from 1-8, for each point of contentment, enjoyment, pride, and frustration above his personal averages for those emotions, he would experience slightly greater ability to regulate his attention during writing, whereas for each point of anxiety and boredom above his personal averages, he would experience slightly lesser ability to regulate his emotions. Assuming that Orin feels the positive emotions described previously (i.e. contentment, enjoyment, and pride) particularly strongly (3 points above his average) on a given day and the negatively-predictive (i.e. anxiety, boredom) emotions particularly weakly on a given day (3 points below his average), we would expect Orin to rate his attention regulation at a 7, only one point off the maximum level of agreement on the scale.

Model 2. To estimate Model 2, I retained all parameters from Model 1 and added daily covariates as controls, including whether the project was an individual project (as opposed to a collaborative project), and the phases of the writing process (i.e. planning, drafting, revising) that the writer reported engaging in. In terms of magnitude and significance of the parameters associated with emotions, the results of this model were nearly identical to those of the previous model, although frustration did not emerge as a significant predictor in this model. Once again,

current day's scores for anxiety ($B = -.06, p = .03$), boredom ($B = -.12, p = .001$), contentment ($B = .14, p < .001$), enjoyment ($B = .21, p < .001$), and pride ($B = .12, p = .004$) emerged as significant predictors of the current day's attention regulation during writing.

Model 3. To estimate Model 3, I retained all parameters from Model 2 and added person-level covariates as controls, including gender and academic affiliation. The magnitude and significance of the focal parameters (i.e. the current-day emotion terms) were identical in this model and in the previous model. These values are presented in Table 9.

Model 4. To estimate the final model, I retained all parameters from Model 3 and added in person-level averages for each of the nine emotion variables. Therefore, this model included both a daily rating for each emotion, representing the degree to which a person's rating of the current day's emotion departed from their average emotional experience, as well as a rating representing that person's average emotional experience over the course of the study, in addition to several covariates. This allowed me to examine the influence of both departures from average emotional experiences and the magnitude of average emotional experiences on writers' attention regulation. None of these average emotion terms were significant predictors of current day attention regulation in this model, although average confusion ($p = .06$) and average enjoyment ($p = .07$) approached significance. The magnitude and significance of the current day emotion terms in this model were identical to those in the previous two models. Once again, these values are presented in Table 9.

Summary of models predicting writing attention regulation. Across all models, I found that writers' daily feelings of anxiety, boredom, contentment, enjoyment, and pride consistently predicted their daily attention regulation while writing, even after controlling for several time varying and time invariant covariates. These effects were significant in the initial

model, which included only calendar time and the previous measurement occasion's attention regulation score as controls, as well as in the final model, which included numerous other controls. All of these predictive relations were in the expected direction, with daily anxiety and boredom demonstrating negative relations with attention regulation, and daily contentment, enjoyment, and pride demonstrating positive relations with attention regulation. Among these variables, writing-related enjoyment was consistently the strongest positive predictor of attention regulation, with a coefficient roughly 50% larger than that of contentment, the next-strongest positive predictor. Across all models, boredom was the strongest negative predictor, with a predictive magnitude nearly double that of anxiety, the only other consistently significant negative predictor.

The other daily emotions included in the models – confusion, excitement, frustration, and shame – demonstrated either inconsistent or non-significant relations with daily writing attention regulation. In the initial model, daily frustration emerged as a modest yet significant positive predictor of attention regulation; or, in other words, above-average ratings of frustration predicted above-average ratings of attention regulation on a given day. However, this effect was no longer significant once additional time varying and time invariant covariates were added to the models. Neither daily confusion nor excitement nor shame were significant predictors of daily attention regulation in any models.

Finally, none of the person-level averages of any of the emotions were significant predictors of daily attention regulation.

These results are in line with my hypotheses. I hypothesized that enjoyment would be the strongest positive predictor of attention regulation, which is what I found in my analyses. I also hypothesized that boredom would be the strongest negative predictor of attention regulation,

which was supported by my results. I further hypothesized that writers' daily writing-related emotional states would be more predictive of daily attention regulation than would writers' average emotional states. This hypothesis was mostly supported by these results, although some emotions were not significantly related to attention regulation at either the daily or the average level.

Relations between Writers' Emotions and Productivity

In this section, I describe the results of models investigating relations between two different measures of writing productivity – time spent writing and words written – and writers' daily writing-related emotional experiences. As described in the previous sections, I examined these relations by estimating several GEE models. In the current section, I first present results for the models where daily minutes spent writing is the outcome, and afterward I present results for the models where daily words written is the outcome. Once again, due to the large number of parameters in the models, I limit my in-text reporting to only significant parameters that are central to Research Question 4. After presenting the results for each outcome, I summarize the results for each outcome across all models. Full results for models with daily minutes spent writing as the outcome are presented in Table 10, and full results for models with daily words written as the outcome are presented in Table 11.

Daily minutes spent writing. In this section, I present results for all models predicting the current day's minutes spent writing.

Model 1. To estimate the first model, I regressed the current day's minutes spent writing on the previous measurement occasion's minutes spent writing, time, and all of the current day's emotion scores. In this model, writers' daily feelings of writing-related anxiety ($B = 5.84, p = .009$), confusion ($B = 4.95, p = .036$), enjoyment ($B = 5.33, p = .04$), frustration

Table 10. Results of Minutes Spent Writing Models.

Parameter	Model 1 (n = 1702)			Model 2 (n = 1702)			Model 3 (n = 1702)		
	B	SE	p	B	SE	p	B	SE	p
Lagged Minutes									
Writing	0.050	0.029	0.083	0.050	0.029	0.083	0.053	0.029	0.068
Time	0.601	0.338	0.076	0.602	0.338	0.075	0.606	0.339	0.074
Anxiety	5.841	2.248	0.009	5.841	2.247	0.009	5.841	2.245	0.009
Boredom	-0.851	2.152	0.692	-0.851	2.152	0.692	-0.849	2.157	0.694
Confusion	4.954	2.356	0.036	4.952	2.356	0.036	4.959	2.355	0.035
Contentment	2.859	2.085	0.170	2.858	2.085	0.170	2.862	2.090	0.171
Enjoyment	5.333	2.579	0.039	5.335	2.579	0.039	5.425	2.579	0.035
Excitement	-1.422	1.945	0.465	-1.422	1.945	0.465	-1.452	1.951	0.457
Frustration	6.142	2.097	0.003	6.145	2.097	0.003	6.187	2.105	0.003
Pride	9.883	2.292	0.000	9.883	2.292	0.000	9.875	2.286	0.000
Shame	-5.356	2.694	0.047	-5.352	2.695	0.047	-5.337	2.695	0.048
Male				-0.608	2.465	0.805	-0.213	2.506	0.932
School of Education (SoE)				0.137	1.598	0.932	0.128	1.684	0.939
Anxiety (Person Avg)							-1.331	1.458	0.361
Boredom (Person Avg)							-0.755	1.086	0.487
Confusion (Person Avg)							0.467	1.346	0.729
Contentment (Person Avg)							-0.065	0.832	0.938
Enjoyment (Person Avg)							-3.127	1.187	0.008
Excitement (Person Avg)							0.488	1.498	0.745

Frustration (Person Avg)	1.410	2.123	0.507
Pride (Person Avg)	1.455	1.489	0.328
Shame (Person Avg)	-0.082	1.385	0.953

Note: all p values less than .05 are highlighted in green

Table 11. Results of Number of Words Written Models.

Parameter	Model 1 (n = 1657)			Model 2 (n = 1657)			Model 3 (n = 1657)		
	B	SE	p	B	SE	p	B	SE	p
Lagged Words									
Written	-0.038	0.036	0.294	-0.037	0.036	0.297	-0.036	0.036	0.315
Time	-0.870	2.284	0.703	-0.843	2.289	0.713	-0.759	2.301	0.741
Anxiety	30.022	16.596	0.070	30.072	16.602	0.070	30.115	16.633	0.070
Boredom	12.149	13.189	0.357	12.171	13.187	0.356	12.202	13.203	0.355
Confusion	2.153	14.853	0.885	2.210	14.830	0.882	2.271	14.797	0.878
Contentment	31.269	14.903	0.036	31.238	14.907	0.036	31.194	14.925	0.037
Enjoyment	55.328	17.884	0.002	55.418	17.888	0.002	55.858	17.894	0.002
Excitement	-4.265	15.565	0.784	-4.264	15.569	0.784	-4.395	15.575	0.778
Frustration	33.661	13.557	0.013	33.692	13.558	0.013	33.884	13.586	0.013
Pride	26.855	15.624	0.086	26.869	15.623	0.085	26.926	15.631	0.085
Shame	-30.527	20.710	0.140	-30.550	20.717	0.140	-30.516	20.788	0.142
Male				4.462	10.482	0.670	6.823	11.011	0.536
School of Education (SoE)				11.488	10.253	0.263	11.198	12.822	0.382
Anxiety (Person Avg)							-1.306	7.320	0.858
Boredom (Person Avg)							-2.664	5.689	0.640
Confusion (Person Avg)							0.039	6.170	0.995
Contentment (Person Avg)							3.362	5.503	0.541
Enjoyment (Person Avg)							-13.138	8.176	0.108
Excitement (Person Avg)							0.348	9.829	0.972

Frustration (Person Avg)	12.921	9.029	0.152
Pride (Person Avg)	5.072	8.880	0.568
Shame (Person Avg)	-13.196	6.425	0.040

Note: all p values less than .05 are highlighted in green

($B = 6.14, p = .003$), pride ($B = 9.88, p < .001$), and shame ($B = -5.36, p = .047$) emerged as significant predictors of their daily minutes spent writing.

To illustrate this, let's assume that Joelle spends 135 minutes per day writing on average, which aligns with the grand mean of time spent writing per day. If Joelle experiences particularly high levels of enjoyment and pride when writing that day (i.e. 3 points higher than her average levels of these emotions), and average levels of all other emotions, we would expect her to write for approximately 180 minutes – 45 minutes more than her average. Likewise, if Joelle experiences particularly high levels of anxiety, confusion, and frustration, along with average levels of all other emotions, we would expect her to write for approximately 185 minutes, or 50 minutes more than her daily average. Finally, if Joelle experiences particularly high levels of shame, we would expect her to write for roughly 119 minutes, or 16 minutes less than her daily average.

Model 2. To estimate Model 2, I retained all predictors from Model 1 and added in time invariant covariates, including the writers' gender and their academic affiliation. In this model, the significance and magnitude of the focal parameters (i.e. the coefficients for the daily emotion variables) were nearly identical to those in Model 1, with differences in magnitude only at the thousandths decimal place. These values are presented in Table 10.

Model 3. To estimate Model 3, I retained all predictors from Model 2 and added person-level averages for each of the nine emotion variables. Once again, this model allowed me to investigate the influence both of writers' average emotional states on daily minutes spent writing as well as of departures from these average states.

The magnitudes of the predictive relationships between daily minutes spent writing and daily emotions were very similar in Model 3 and Model 2 across most of the daily writing-related emotion scores. However, the coefficient for daily enjoyment was slightly higher in the current model ($B = 5.425, p = .035$). Additionally, enjoyment was the only emotion for which the person-level average significantly predicted daily minutes spent writing, albeit in a negative direction ($B = -3.13, p = .008$).

Let's return again to Joelle to illustrate these findings. First, let's assume that Joelle's average enjoyment of writing is a 4 (on a scale of 1-8). Next, let's assume that, on average, she spends 135 minutes writing per day. If Orin, our other hypothetical writer, had an average enjoyment of writing that was a 3 (i.e. one point lower than Joelle's average), we would expect him to write for 138 minutes per day. If Joelle experienced particularly high enjoyment of writing on a given day (i.e. 3 points higher than her average), we would expect her to write for approximately 151 minutes that day, and likewise, we would expect Orin to write for approximately 154 minutes.

Summary of models predicting daily minutes spent writing. Across all models, daily writing-related anxiety, confusion, enjoyment, frustration, pride, and shame consistently predicted writers' daily minutes spent writing. These effects were significant in the initial model, which included only time and previous minutes spent writing as covariates, as well as in the final model, which included several other time invariant covariates. Of these emotions, shame was the only daily emotion that was negatively predictive of daily minutes spent writing; anxiety, confusion, enjoyment, frustration, and pride were all positively related to daily minutes spent writing. Among these positive predictors, pride consistently demonstrated the strongest

predictive relationship with daily minutes spent writing, with its predictive magnitude roughly 50% larger than that of frustration, the next-strongest predictor.

Across all models, neither daily boredom nor contentment nor excitement were significantly related to daily minutes spent writing.

In terms of contextual effects, only writers' average level of enjoyment was significantly related to daily minutes spent writing. Furthermore, this relationship was negative, such that writers who averaged higher levels of enjoyment tended to write for slightly less time per day than those who averaged lower levels of enjoyment.

Some of these results are in line with my hypotheses, whereas others are not. The significant positive associations between daily enjoyment and daily minutes spent writing as well as between daily pride and minutes spent writing aligned with my hypothesis; however, I predicted that enjoyment would be a stronger predictor than pride, which was not the case. Contrary to my hypotheses, anxiety, confusion, and frustration were all positively associated with daily minutes spent writing. Additionally, boredom was not associated with daily time spent writing, which was not in line with my hypothesis that it would be a negative predictor of time spent writing. Finally, the results of these analyses generally supported my hypothesis that daily emotional states would be more predictive of daily minutes spent writing than would average emotional states.

Daily number of words written. In this section, I present results for all models predicting the current day's number of words written.

Model 1. To estimate the first model, I regressed the current day's number of words written on the previous measurement occasion's number of words written, time, and all of the daily emotion scores. In this model, writers' daily feelings of contentment ($B = 31.27, p = .036$),

enjoyment ($B = 55.33, p = .002$), and frustration ($B = 33.66, p = .013$) were significantly related to daily number of words written.

To illustrate these results, let's assume that Orin writes 675 words per day on average, which is roughly in line with the grand mean of daily words written. If Orin feels particularly high levels of enjoyment and contentment (i.e. 3 points above his averages for these emotions), we would expect him to write approximately 935 words on that day. Inversely, if he felt particularly low levels of enjoyment and contentment related to writing that day (i.e. 3 points below his averages for these emotions), we would expect him to write approximately 415 words on that day. Furthermore, if Orin experienced particularly high levels of frustration, we might expect him to write roughly 776 words that day.

Model 2. To estimate the second model, I retained all parameters from the previous model and added time invariant covariates, including gender and academic affiliation. In this model, the significance and magnitude of the focal parameters (i.e. the coefficients for the daily emotion variables) were nearly identical to those in Model 1. These values are presented in Table 11.

Model 3. To estimate the final model, I retained all parameters from the previous model and added person-level averages of all nine emotion variables. As described previously, this model allowed me to investigate the influence of writers' average emotional states on daily number of words written as well as the influence of departures from these average states on daily words written.

In this model, the significance and magnitude of the predictive relationships between daily emotion scores and daily words written were similar to those found in Model 1 and Model 2. Additionally, writers' average levels of shame ($B = -13.2, p = .04$) emerged as a significant

and negative predictor of daily words written. To illustrate this, let's assume again that Orin writes 675 words on a given day and that his average level of writing-related shame throughout the entirety of the study is a 2 (on a scale of 1-8). If Joelle's average level of shame is a 4, we would expect her to write roughly 648 words on a given day, holding all other factors equal.

Summary of models predicting daily number of words written. Across all models, daily scores of writing-related contentment, enjoyment, and frustration consistently predicted writers' daily number of words written. The magnitude of these associations changed minimally even after controlling for several person-level covariates. Furthermore, all of these predictive associations were in the positive direction. Writing-related enjoyment was the strongest predictor of daily words written, with its predictive magnitude approximately 67% larger than that of frustration, the next strongest predictor. Across all models, anxiety, boredom, confusion, excitement, pride, and shame were not significantly associated with daily words written, although anxiety ($p = .07$ across all models) and pride ($p = .08$ across all models) approached significance.

Shame was the only emotion for which the person-level averages were associated with writers' daily words written. This relationship was negative, such that writers who, on average, felt more shame related to their writing tended to write fewer words per day than those who felt less shame on average.

Once again, some of these results are in line with my hypotheses, whereas other are not. As I hypothesized, daily enjoyment was the strongest predictor of daily words written. Contrary to my hypothesis, frustration emerged as a positive predictor of words written. Also contrary to my hypothesis, boredom was not significantly associated with the number of words written daily. Finally, although daily feelings of shame were not significantly associated with daily words

written, writers' average levels of shame were negatively associated with daily words written, which is not in line with my hypothesis that daily emotional states would generally be stronger predictors of daily words written than would average emotional states.

Chapter 5 – Discussion

In this chapter, I discuss the findings described in the previous chapter and connect these findings to relevant literature reviewed previously, including models of writing production, models of emotion elicitation, regulation, and influence in academic settings, literature describing connections between emotions and writing processes, and other pertinent literature as appropriate. I begin this discussion by providing a broad overview of the study's purpose(s) and methodology. Next, I divide the discussion into several sections, each aligning with a particular research question under investigation in the current study. In each of these sections, I briefly restate findings from the current study before connecting these findings to extant literature and describing the contribution of the current study. Finally, I discuss the limitations of the current study, provide recommendations for future research, and offer some brief concluding thoughts.

Overview of Current Study

This study sought to investigate graduate student writers' daily emotional experiences during writing as well as how these emotional experiences relate to proximal outcomes such as daily attention regulation and productivity. To do so, I recruited an international sample of graduate students enrolled in writing-intensive disciplines and asked them to complete a daily survey about their writing experiences each day over the course of four weeks, ranging from March 7, 2019 through April 3, 2019. After these data were collected, I conducted several analyses, the results of which were presented in the previous chapter, to answer the four research questions that guided the study. I discuss each of these below.

Discussion of Major Findings

Intensity of Writers' Average Emotional Experiences

Generally, the graduate student writers in this study reported low to moderate average emotional intensity for all writing-related emotions under investigation in the current study.

Across all participants and time points, emotion means ranged from 1.84 (for shame) and 4.38 (for enjoyment), where 8 was the maximum scale value. Additionally, writers tended to report higher levels of positively-valenced emotional experiences than negatively-valenced emotional experiences, with the lowest-intensity positively-valenced emotion (excitement, $M = 3.51$) being significantly greater than the highest-intensity negatively-valenced emotion (anxiety, $M = 3.22$). As mentioned previously, these results are somewhat in line with my hypothesis. I predicted that writers would experience enjoyment more strongly than other emotions, which was supported by the results. However, I also predicted that writers would experience similarly strong degrees of anxiety, which was not the case in the current study. Likewise, I predicted that boredom would be the least intense of the emotions writers experienced. Although boredom was among the lowest-intensity emotions on average, writers' experiences of shame were significantly weaker, and their experiences of confusion were comparable to their experiences of boredom.

These results are similar to those found in a series of studies conducted by Brand and colleagues (Brand, 1987; Brand & House, 1987; Brand & Leckie, 1988; Brand & Powell, 1986; Powell and Brand, 1987; see also Brand, 1990 for a review of these studies). The writers participating in these studies – who included undergraduate students majoring in various disciplines, academics, English teachers, and creative writers and are, therefore, similar to the sample of the current study – reported feeling consistently high levels of excitement and enjoyment before, during, and after writing sessions.

Likewise, writers in these studies conducted by Brand and colleagues reported feeling anxiety more strongly than other negative-valence emotions, which was the case in the current study, where the mean levels of all negative-valence emotions were significantly lower for confusion, frustration, shame, and boredom than for anxiety. Given that anxiety has long been

acknowledged as a critical emotion in academic situations, and one that affects students of all skill levels (e.g. Pekrun, 2006; Zeidner, 1998), it is not surprising that anxiety was the negative emotion that writers reported feeling most strongly in the current study. Additionally, writers in the studies conducted by Brand and colleagues reported feeling negative passive emotions, such as shame, infrequently and weakly, which was the case in the current study. Across all writers, shame was the least-intensely experienced emotion, with a mean score of just 1.84 on a scale of 1-8.

Multiple studies beyond those conducted by Brand, as well as broader theoretical frameworks of emotions in academic settings, also complement the findings of the current study. Although writers' attitudes toward writing differ somewhat from their writing-related emotions, there are nevertheless some overlaps between these constructs. A recent review by Ekholm and colleagues (2018) found that writers in the studies reviewed mostly tended to have positive attitudes toward writing, which provides some support for the findings here, where writers typically experienced stronger positive emotions than negative or neutral emotions. However, many of the studies reviewed by Ekholm and colleagues (2018) studied samples of K-12 writers rather than more advanced graduate student writers. Collie and colleagues (2016) found that male high school students reported somewhat stronger levels of enjoyment (4.17 on a scale 1-7) of writing than anxiety regarding writing (3.97 on a scale 1-7), and Pajares and colleagues (2007) found that K-12 students tended to feel low-to-moderate levels of writing-related anxiety (2.49 on a scale 1-6). Together, these findings provide some support for the notion that, on average, writing tends to evoke more positive emotional experiences than negative emotional experiences. Further, although anxiety has received much more attention than many other emotional experiences, writers seem not to experience intense levels of anxiety when writing.

When viewed through the lens of the control-value theory of achievement emotions (Pekrun, 2006), these results are perhaps not surprising. Recall that the control-value theory posits that a writer's control appraisals and value appraisals are antecedents to their emotional experiences during a writing session. All the positive-valence emotions in the current study are thought to result from high control appraisals (i.e. a writer feeling competent that he can successfully complete the task) along with high value appraisals (i.e. a writer placing subjective importance on the task). Anxiety, on the other hand, is thought to result from high value appraisals but low control appraisals. Given the stakes associated with writing well and frequently for graduate students – including job offers, awards, and grants – it is not surprising that the emotions associated with high value appraisals were the most strongly experienced emotions in the current study. In other words, since writing is important for graduate students, it makes sense that emotions associated with perceived importance had the highest mean values across time points and participants. Inversely, this also accounts for the low mean levels of boredom, which is associated with low value appraisals. That is, given how valued writing is in academia, we would expect writers to experience boredom fairly weakly and infrequently.

These descriptive findings have implications for both future research and, potentially, educational practice. One key implication is that many negatively-valenced emotional states tended to occur weakly and infrequently in the writers in the current study. Anecdotal accounts of writing – including the Hemingway quote presented at the beginning of this manuscript – may lead people to believe that writing is often a negative experience during which writers feel shame, frustration, and anxiety (see also Zumbrunn, Ekholm, Stringer, McKnight, & DeBusk-Lane, 2017). Based on the current data, that seems not to be the case. This is not to suggest that these emotional states do not matter when they do occur, but rather that their occurrence is less

frequent/intense than some might believe based on anecdotal accounts. In a practical sense, this suggests that researchers developing writing strategies or interventions may want to focus their efforts on maximizing the benefits of positive emotional states rather than on developing universal strategies that writers can employ to regulate negative emotions. Since negative emotional experiences tended to be less prevalent, particularly when considering feelings of shame, developing strategies to combat these feelings may be less critical. Or, researchers may consider developing adaptive interventions in digital environments that can accurately detect infrequent emotional states – such as shame – and deliver timely emotion regulation interventions in these critical windows (see e.g. Baker et al., 2010).

Stability, Inertia, and Change of Writers' Emotions

To examine writers' day-to-day emotional stability, inertia, and change, I conducted two different types of analyses. First, I examined reliable change indices (RCIs), which allowed me to measure the extent to which writers' emotional experiences differed from day to day. Second, for each of the nine emotions measured in the current study, I fit a series of modified AR(1) models to estimate writers' day-to-day emotional inertia, or the extent to which writers' previous emotional states were related to their subsequent emotional states.

Results of the RCI analyses indicate that, for the most part, writers' emotional states changed considerably from day to day. Over 60% of the total daily measurements of pride, enjoyment, contentment, excitement, and frustration indicated reliable change from the previous measurement, over 50% of the daily measures of anxiety and confusion indicated reliable change, and approximately 50% of the daily measures of boredom indicated reliable change. Writers' feelings of shame were the most stable from day to day, with only 33% of measurements indicating reliable change. For all emotions, the ratio of positive changes to

negative changes was roughly equal, which indicates that, on average, writers experienced about as many increases in emotional intensity as they did decreases in emotional intensity.

Furthermore, across the autoregression models, anxiety was the only writing-related emotion to consistently demonstrate significant autoregressive effects, where feelings of writing-related anxiety above one's typical level at the previous measurement occasion were associated with elevated writing-related anxiety at the subsequent measurement occasion. The autoregressive effect of enjoyment was significant and positive in one model; however, it was no longer significant once additional covariates were added.

Together, these results suggest that writers' emotional experiences vary considerably between days and that there is very little emotional carryover from one day to the next. Although these findings are at odds with my hypotheses regarding emotional inertia and stability, they do align with what we know about emotions and emotion regulation as well as with the likely characteristics of the current sample. Recall that emotions are brief, often intense, states that are elicited by a particular object or scenario (Gross, 2015a; Pekrun, 2006; Rosenberg, 1998). In the current study, this object in a very general sense is writing; however, the specific features of "writing" will likely change from day to day as writers progress through different parts or phases of a single project or even transition between various projects. For instance, Orin might spend Monday drafting the methods section of a conference proposal he's submitting on his own and Tuesday revising the literature review of a manuscript he's co-authoring with his peers. Given that academic emotions result from control and value appraisals specific to the task at hand, it seems natural that Orin's writing-related emotions on Tuesday would differ from his emotions on Monday since the writing tasks themselves are rather different. This supposition is in line with results described by Kahneman and colleagues (2004), who found that local circumstances

(i.e. what a person is currently doing and who they are with) were powerfully related to affective experiences, whereas previous circumstances had smaller influences. The predictive magnitude of some of the covariates included in the AR(1) models provides some additional support for this interpretation. Across several models, the phase of the writing process and the type of project emerged as significant predictors of writers' present-day emotional experiences (see Tables 7 and 8). For instance, when writers indicated that they were predominantly focused on revising during a given day, they tended to feel higher levels of pride, enjoyment, and anxiety. When writers indicated that they mostly focused on drafting, they tended to feel higher levels of frustration. And when they indicated working on an individual project (as opposed to a collaborative project), they tended to feel higher levels of shame. This suggests that features of the current day's writing task are more related to writers' current emotional experiences than are their past emotional experiences. However, it is worth noting that these findings contrast those reported by Kuppens and colleagues (2010), who found significant emotional inertia for all emotions in a sample of college students.

Similarly, this lack of emotional inertia may be due to the emotion regulation aptitude of the current sample. All participants in the current study were graduate students enrolled in writing intensive disciplines (e.g. psychology, education), and though they are not (yet) professional writers or academics, they are likely fairly proficient writers and learners who have developed, over their many years as students, systems for accomplishing academic tasks. As Boekaerts and Pekrun (2016) describe, "successful emotion regulation is an essential aspect of self-regulated learning," (p. 85), and so given the degree of self-regulation that is required to succeed as a graduate student and as a writer (Graham & Harris, 2000), we might expect that these students have some emotion regulation strategies in place and therefore experience less

day-to-day emotional inertia. Furthermore, higher levels of emotional inertia often accompany extremely intense emotional experiences (e.g. Kuppens et al., 2010), which were rarely reported in the current study.

The lack of significant autocorrelation between writers' daily emotions, along with the findings of the RCI analyses, which indicate considerable variability in day-to-day emotional experiences, further highlight the need for capturing emotions at a more nuanced level to better understand how they unfold moment to moment. For instance, a recent large, multiyear study conducted by Pekrun and colleagues (2017) examined autoregressive effects of trait emotions in secondary students over the course of several years. The authors reported large positive autoregressive effects for all emotions, with the standardized beta for all autoregressive effects greater than .5. The takeaway from the study conducted by Pekrun and colleagues (2017), then, is that learners' typical emotional experiences are relatively stable from year to year. However, in the current study, which investigated daily changes in emotions, we see much less stability from day to day. These findings further attest that, as other researchers have suggested, state and trait emotions ought to be considered distinctly (e.g. Goetz et al., 2016).

Based on these results, researchers may want to further develop models delineating writing-specific contextual factors relating to emotion elicitation as well as explanations regarding why these factors may differentially elicit emotions. In a broad sense, Graham (2018) posits that features of writing communities interact with intrapersonal factors (including emotions) to influence writing production; however, this model does not specify why certain features of writing contexts might lead to different emotional states. For instance, the current research suggests that drafting a text was more associated with increased levels of frustration, whereas revising was more associated with increased levels of pride. It is possible that these

differences align with domain-general explanations for emotion elicitation in learning contexts (e.g. Pekrun et al., 2007; D'Mello & Graesser, 2012), but it may be that there are specific aspects of writing experiences not present in other domains that differentially elicit emotions in writers. These writing-specific contextual factors might include the phase of the writing process (planning, drafting, or revising) and the genre of writing being produced (e.g. poetry, academic manuscript), among others. This suggestion that researchers ought to further investigate and explicitly model how time-varying contextual features specific to writing lead to emotional responses in writers is one key theoretical contribution of the current study.

That said, writers' daily levels of anxiety did demonstrate significant positive emotional inertia from day to day, where departures from one's typical levels of anxiety on the previous day were positively associated with departures from typical anxiety on the subsequent day. This suggests that, even after controlling for several other covariates, there was some degree of day-to-day carryover in writers' anxiety. This aligns with my hypothesis as well as with previous findings reported by Kuppens and colleagues (2010), who reported a significant and positive autoregressive effect for college students' daily anxiety. However, it is unclear why the effect for anxiety was significant in the current study whereas no other autoregressive effects were significant. It could be that anxiety in and of itself did not necessarily beget later anxiety, but rather that a mediating variable could account for this relationship. The control value theory (Pekrun, 2006) posits reciprocal causation between emotions and behaviors/outcomes whereby emotions influence learners behaviors, behaviors (and associated outcomes) influence subsequent control and value appraisals, and these appraisals in turn influence later emotional experiences. It is possible that a mediating behavior unique to anxiety not captured in the current study could explain why writers tended to experience emotional inertia for anxiety but not for

other emotional states. Given that anxiety was the only emotion to demonstrate day-to-day inertia, future research might investigate time-varying (e.g. contextual features) and time-invariant (e.g. personality traits) factors that are specifically related to anxiety and the carryover of anxiety from day to day. Some previous research indicates that inertia of anxiety from day to day is associated with psychological maladjustment (e.g. Peeters, Nicolson, Berkhof, Delespaul, & deVries, 2003; Suls, Green, and Hillis, 1998), and though writers' personality and other psychological constructs were not measured in the current study, they may be worth investigating alongside daily writing anxiety in future research.

Finally, although I have collapsed the discussion of writers' emotional inertia and variability in the current section, these are separate (albeit related) phenomena. For instance, the writers in the current study seem to be characterized by high variability and low inertia, which corresponds with sudden and frequent shifts between days in emotional experiences. To some extent, this pattern of sudden, frequent shifts is captured in the figures displaying RCIs over time (see Figures 9 through 14). However, other patterns of inertia and variability are possible. For instance, writers could theoretically have both high inertia and high variability, which would correspond to large but slow shifts in emotions (e.g. reporting extremely high anxiety for a few days and then reporting extremely low anxiety for a few days). Future research employing different modeling approaches, such as the sinusoidal and spin/pulse analyses described previously, might better capture patterns among stability and inertia between and within people. For the time being, the current study does provide evidence that these relationships may not be adequately captured by linear or quadratic models.

Relations between Writers' Emotions and Attention Regulation

To examine the relationships between graduate student writers' emotions and attention regulation, I fit several models in which writers' daily attention regulation was regressed on daily emotion scores, average emotion scores, and several covariates. Across these models, daily anxiety and boredom consistently emerged as negative predictors of daily attention regulation, whereas daily contentment, enjoyment, and pride emerged as positive predictors of attention regulation. Among these significant predictors, daily enjoyment was consistently the strongest positive predictor, and daily boredom was consistently the strongest negative predictor, with daily enjoyment having the overall strongest relationship with daily attention regulation, regardless of direction. Furthermore, none of the average scores for any emotions were significantly related to daily attention regulation.

Generally, these results are consistent with theories of achievement emotions and engagement (e.g. Csikszentmihalyi, 1990; D'Mello & Graesser, 2012; Pekrun, 2006; Pekrun et al., 2007), theories of self-regulation and cognition (e.g. Ashby & Isen, 1999; Boekaerts, 1997; Boekaerts & Corno, 2005; Cowan, 2014; Derakshan & Eysenck, 2009), and models of writing (e.g. Graham, 2018). These theories mostly agree that positively-valenced emotions are beneficial for learning, engagement, and self-regulation, although they differ in their explanations regarding the psychological and physiological mechanics at play. Dynamic models of engagement and emotions (e.g. Csikszentmihalyi, 1990; D'Mello & Graesser, 2012) suggest that positive emotional experiences interact with task challenge to produce states of flow or deep engagement with a task, which are characterized by intense concentration. In these states of flow, learners may feel like time is passing quickly and they may feel impervious to any distractions (Csikszentmihalyi, 1990). According to D'Mello and Graesser (2012), this intense concentration

is a result of learners coming across a specific learning challenge – or impasse – when working on a task, struggling with it briefly, and then resolving it. This resolution leads to feelings of pride and enjoyment, which plunge learners back into a state of flow. When considering the current study, it is possible that writers had very similar experiences. We know that writing can often be a challenging task, and anecdotally most writers are familiar with the feelings of pride and joy that accompany “figuring out” challenges that pop up, such as arriving at the right word or piecing together an argument fluidly. This seems to be one plausible explanation for the positive relationships between contentment, enjoyment, and pride and daily attention regulation found in the current study.

These positive associations are also consistent with propositions of the control-value theory (Pekrun, 2006) as well as the dual process model of self-regulation (Boekaerts, 1997). These models mostly suggest that positively-valenced emotions promote self-regulation, including attention regulation, in learners. Both theories suggest that positive emotions promote psychological well-being, and, in doing so, can serve to direct attention toward the writing task at hand because it is the object of these emotions. Put more simply, if writing is currently making Joelle feel happy, she will likely continue to focus her attention on it. Inversely, when writers experience negative emotions during writing, they often must regulate these negative emotions. Although there are several different types of emotion regulation strategies (e.g. Gross 2015a; 2015b), all require some appropriation of cognitive resources to enact. Or, in other words, if Joelle is feeling anxious while writing, she may have to divert some of her attention to regulate these emotions, perhaps by briefly distracting herself on the internet or by taking a few minutes to mentally reframe the writing task. Once again, the results of the current study are consistent with these propositions as well as with other studies. For instance, results of a study conducted

by Pekrun and colleagues (see Pekrun et al., 2002, Table 4) found that undergraduate students' experiences of enjoyment and hope were positively associated with enacting self-regulation strategies and negatively associated with task-irrelevant thought, whereas these students' experiences of anxiety and boredom displayed the opposite patterns, although it is worth noting that this study was not conducted specifically in the domain of writing. Furthermore, Stewart and colleagues (2015) found that anxiety was negatively related to undergraduate students' use of metacognitive strategies.

Graham's (2018) Writer within Community model also complements these findings. Although this model focuses on several intrapersonal, interpersonal, and social factors that influence writing – and therefore does not solely focus on emotions – it does nevertheless posit that emotions serve as modulators for writers' intrapersonal mechanisms. Among these are the control mechanisms, which include writers' attention and executive control (i.e. self-regulation). Therefore, the model suggests that positive emotional experiences with writing will focus writers' attention on the writing task at hand, whereas negative emotional experiences will diminish writers' attention, which is precisely what the current study finds.

The negative association between writers' daily boredom and daily attention regulation also aligns with these theoretical frameworks. In the control-value theory, boredom is thought to arise from low value appraisals (i.e. the writer believing the current writing task has little value), regardless of their control appraisals (Pekrun, 2006). These feelings of boredom then theoretically lead to disengagement and, perhaps more specifically, daydreaming, which diverts attention away from the writing task. Furthermore, although the overall mean level of boredom across all writers and timepoints was low ($M = 2.52$), the relationships modeled here used person-mean centered levels of daily boredom. In other words, even if Orin experiences boredom

relatively weakly on average, daily levels of boredom above this average would be associated with significant decreases in his ability to concentrate on his writing. Although some past research has suggested there may be benefits of boredom in that daydreaming can promote creative ideation (e.g. Singer, 1981), these potential benefits – which are beyond the scope of the current study to investigate – may come at the cost of attention.

In the current study, excitement was the only positively-valenced emotion that was not significantly associated with writers' attention regulation. Recall that emotions can be considered in terms of their degrees of arousal in addition to their valence, and excitement, more so than the other positively-valenced emotions studied here, is associated with high degrees of arousal. Higher levels of arousal are themselves associated with increased heart rate, alertness, and an overall sense of being on edge (Ashby & Isen, 1999). Since writing is not an activity that requires physical exertion or alertness, it could be that these sensations associated with increased arousal mitigate the potential benefits associated with the positive valence of excitement, which seem to manifest themselves through the other positive valence emotions with lower degrees of arousal (i.e. enjoyment, contentment, and pride).

Frustration was the only negatively-valenced emotion that was positively associated with daily attention regulation, albeit only in the first model before additional covariates were introduced. This was contrary to what I anticipated, but it is not completely unexpected given that some previous research has found links between frustration and positive learning behaviors and outcomes (Pardos et al., 2014; Sabourin et al., 2011). As Pardos and colleagues suggest, it is possible that writers will experience greater frustration when they value a certain task and when they reach impasses in that task. This association between frustration and attention regulation, then, may not suggest that frustration necessarily enhances attention focusing, but rather that

certain features of a writing task (e.g. its importance, its difficulty) may lead to frustration and increased attention requirements.

Finally, I found no relationships between writers' average emotional states and their daily attention regulation in the current study. In other words, between-person differences in typical writing-related emotions seem much less relevant to daily attention regulation than do within-person departures from typical emotional experiences. Given that emotions are short-lived and context-specific states, it is perhaps not surprising that averages of these states are less related to daily behaviors than are more nuanced measures of emotions. Writers' daily fluctuations in emotions – which results associated with the previous research question indicate occur quite frequently – are themselves associated with meaningful differences in their abilities to regulate their attention. When these daily fluctuations are averaged out, measures of emotions seem to lose their predictive potency, at least in relation to writers' ability to concentrate on their writing. Recruiting Joelle to illustrate a point once again, how Joelle typically feels during writing seems unrelated to how well she can focus on her writing today, whereas how she feels today seems to matter quite a bit.

Once again, these findings tend to be consistent with past research and theoretical propositions. They do suggest, though, that writing researchers ought to be mindful about which discrete emotions they choose to investigate as well as how they design interventions, since various emotions were differently related to attention regulation. For instance, although both are positively-valenced emotions, enjoyment and excitement are not interchangeable and relate differently to attention regulation. Those developing writing interventions may want to consider how to promote enjoyment rather than excitement. Similarly, teachers of writing should not balk if their students feel frustrated, since frustration seems to relate to increased focus (as well as

increased productivity, which I describe subsequently). In other words, different emotions seem to be associated with different cognitive processing approaches, different attentional demands, and (potentially) different emotion regulation strategies. The specifics of these patterns need to be investigated further, likely in more targeted contexts, but for the time being, this study does provide evidence to meaningfully distinguish discrete emotions in writing contexts.

Relations between Writers' Emotions and Productivity

In the current study, I examined two different measures of writers' productivity – their daily minutes spent writing and their daily number of words written. I intended to incorporate a third measure of writing productivity – a 4-item Likert-type scale in which writers rated the quality of their ideation and how much progress they felt they made on their writing – however, preliminary multilevel confirmatory factor analyses suggested that loading all items onto a single factor may not have appropriately represented the covariance among the items. Given this, I opted not to conduct any further analyses using that scale.

In models where daily minutes spent writing served as the outcome, daily measures of anxiety, confusion, enjoyment, frustration, pride, and shame consistently emerged as significant predictors, as did writers' average level of enjoyment. Of the significant daily measures, all but shame were positively associated with daily minutes spent writing. Furthermore, writers' average level of enjoyment was negatively associated with daily minutes spent writing, indicating that writers who typically enjoyed writing more tended to spend slightly less time writing than peers who enjoyed writing less.

In models where daily words written served as the outcome, daily measures of contentment, enjoyment, and frustration consistently emerged as significant predictors, as did writers' average levels of shame. All of the significant daily emotion measures were positively

associated with daily number of words written, whereas writers' average level of shame was negatively associated with daily number of words written.

The positive relationships that daily measures of pride and enjoyment demonstrated with minutes spent writing as well as the positive relationships that daily measures of enjoyment and contentment demonstrated with number of words written are consistent with many of the theoretical propositions and empirical findings described previously. For instance, the control-value theory posits that positive activating emotions – such as enjoyment, contentment, and pride – lead to greater engagement and academic achievement (Pekrun, 2007; Pekrun et al., 2007), and these theoretical propositions have been supported by the results of numerous studies (e.g. Beymer et al., 2018; Pekrun et al., 2002; Pekrun et al., 2017; Tomas & Ritchie, 2012). Illustrating this, in a study with high school seniors, Tomas and Ritchie (2012) found that writers' feelings of pride led them to want to engage more with future writing activities. Likewise, flow theory posits that positive emotional experiences are prerequisites for entering flow states characterized by deep engagement (e.g. Csikszentmihalyi, 2000; D'Mello & Graesser, 2012). In the current study, minutes spent writing as well as number of words written can be thought of as measures of engagement during writing, where more engaged writers would be expected to write longer and produce more words than less engaged writers. In this sense, enjoyment seems particularly beneficial to writers' engagement, since it was consistently related to both minutes spent writing and number of words written.

Although daily levels of enjoyment emerged as a consistently positive predictor of both daily minutes spent writing as well as daily words written (and daily attention regulation), writers' average feelings of enjoyment during writing were negatively associated with daily minutes spent writing. That is, writers who reported enjoying writing more tended to write for

slightly less time than those who reported enjoying writing less. Given that previous research has resoundingly found that enjoyment is beneficial in academic contexts generally (Boekaerts & Pekrun, 2016) and writing more specifically (e.g. Bohn-Gettler & Rapp, 2014), this was an unexpected finding. Furthermore, given that the grand mean of enjoyment was near the midpoint of the scale ($M = 4.38$ on a scale of 1-8), it seems unlikely that this result is due to a ceiling effect. One possible explanation is that there are other person-level confounds not captured in the current study that, if included in the models, would render this effect null.

These results also suggest that researchers ought to be cautious in how much value we place in minutes spent writing as a proxy for writers' engagement in and of itself. In addition to the curious relationship between average levels of enjoyment and time spent writing, daily measures of both confusion and anxiety were positively associated with minutes spent writing, which is at odds with most previous research suggesting that these emotions tend to be detrimental for learners (e.g. Boekaerts & Pekrun, 2016), although some research indicates that both can be beneficial in certain circumstances (e.g. D'Mello et al., 2014; Yerkes & Dodson, 1908; Zeidner, 1998). However, neither daily anxiety nor daily confusion were significantly associated with the number of words written on a given day. This means that, when experiencing levels of anxiety and confusion above their typical levels, writers spent more time on writing tasks but did not produce more words than they typically would. When we further consider that increased anxiety was negatively associated with writers' abilities to regulate their attention, a clearer picture emerges. Returning to Orin, if he feels more anxious than usual when writing, he will likely have more trouble focusing on his writing, which in turn leads him to spend more time on a writing task to produce the same number of words that he otherwise would when feeling less anxious. In contrast, deliberately taking small breaks (i.e. taking time off task) can lead to

more productivity and more adaptive learning behaviors in the long term, particularly when such breaks are used to regulate potentially maladaptive emotions (e.g. Sabourin et al., 2011).

In these models, writing-related shame emerged as a detrimental emotion, both at the daily level and at the person level, with daily shame negatively related to daily minutes spent writing and person-level average shame negatively related to number of words written. In a broad sense, these findings are not surprising. Conceptually, shame is a negative activating emotion that overlaps some with anxiety (e.g. Pekrun et al., 2002) and therefore likely displays many of the same (largely negative) relationships with academic outcomes that anxiety does. More specifically, however, the patterns of the relationships found in the current study are interesting. Daily increases in writers' experiences of shame above their typical levels were associated with slightly less time spent writing but were not associated with their daily number of words written. On the other hand, writers' average levels of writing-related shame were negatively associated with number of daily words written but not with daily minutes spent writing. In other words, if Orin experiences more shame about his writing on average than does Joelle, he will tend to write fewer words than her on a given day. However, if Joelle feels more shame about her writing on a given day than she usually does, she will likely spend less time writing on that day. It is unclear why these specific patterns emerged, and given that shame has not been extensively studied in general (Pekrun et al., 2002), more research is needed to better understand how shame influences writers.

The findings around writing-related frustration were somewhat unexpected. Writers' daily levels of frustration were consistently positively predictive of their daily minutes spent writing and their number of words written. Put differently, when writers felt more frustrated with their writing than usual, they spent more time writing and wrote more words. Frustration, like

anxiety and shame, is a negative activating emotion that is typically detrimental in academic contexts (e.g. Goetz & Hall, 2013; Goetz et al., 2016; Pekrun & Linnenbrink-Garcia, 2012), and, as such, I anticipated that it would be a predictor of all writing productivity outcomes. However, that was not the case here. One possible explanation for these benefits comes from Forgas (1995), who found that negatively valenced emotions may produce more analytic, detail-oriented thinking, which could lead to more engagement and productivity. This somewhat complements students' accounts of their feelings of anger described by Pekrun and colleagues (2002). In this study, students reported that anger was a "meta-emotion" (Pekrun et al., 2002, p. 93) that actually cued them to regulate their anxiety. Though frustration differs somewhat from anger, it is possible that the frustration writers in the current study experienced actually prompted them to regulate other emotions and helped them think more analytically about their writing. Additionally, as Pardos and colleagues (2014) suggest, frustration may co-occur with task importance, and so frustration may simply correlate with increased productivity due to this. That is, writers may tend to write more words, spend more time writing, and feel more frustrated on certain tasks that they find important. Future research would be needed to more explicitly investigate these propositions, though.

One consideration to keep in mind when interpreting these findings is that, due to the unacceptable fit of the MLCFA for the Writing Productivity Scale, the current study does not include a measure of the quality of writers' daily writing. Although writers themselves often do consider words written and time spent writing as informal measures of productivity (e.g. King, 2002; Mayrath, 2008), and text length can, in some instances, serve as one indicator of writing quality (e.g. Graham et al., 2015; Scott, 2009; Troia et al., 2013), these measures do not capture the quality or creativity of writers' ideas or written expression.

All in all, several emotional states were significantly related to measures of daily productivity. Additionally, some of these relationships were quite large – for instance, a one-point increase in daily enjoyment above one’s average levels of enjoyment was associated with 55 more words written, assuming all other emotional states are at their average levels. Practically, this suggests that educators could capitalize on these relationships and design writing assignments, contexts, or strategies to promote adaptive emotional experiences and (possibly) meaningfully increase writers’ productivity. Researchers might also further investigate the specific features of writing tasks or contexts that were associated with increases in adaptive emotions to develop interventions that can cue these emotional responses.

Summary

The overarching goal of the current study was to gain a better understanding of graduate student writers’ daily emotional experiences during writing, including the degree to which writers felt various emotions, how these emotions fluctuated or persisted over time, and how they related to proximal outcomes such as attention regulation and productivity. Results of this study indicate that these writers tended to feel positive valence emotions more strongly than negative valence emotions. Furthermore, the intensity with which writers felt these emotions varied considerably from day to day for all emotions other than shame, which writers tended to experience very weakly, and emotional experiences other than anxiety showed little to no day-to-day inertia. Finally, on a given day, several of these emotions were significantly related to key proximal processes, including attention regulation, minutes spent writing, and number of words written. The purpose of this current section is not to recap the results or discussions presented in previous sections, but rather to summarize key takeaways and highlight potential implications before describing limitations and recommendations for future research.

One key takeaway from the current study is that writers' emotional experiences matter. Anecdotally, we've known this for a long time. Stories abound of bored writers feeling their attention drift toward emails, the weather, or what they're planning to cook for dinner that night as well as of writers experiencing great joy and clicking into states of flow, emerging hours later with several pages written. Despite this anecdotal evidence, many popular models of writing production have not explicitly incorporated emotions into their frameworks (e.g. Flower & Hayes, 1981). Although Graham's recent Writer within Community model (2018) does explicitly include propositions related to writers' emotions, few if any empirical studies have tested these propositions due to the model's relative youth, and the exact mechanisms of these relationships are not precisely defined. Drawing from this model, domain-general models of emotions, cognition, and self-regulation, and anecdotal evidence describing the influence of emotions on writers, the current study provides quantitative evidence linking writers' emotions to key writing processes and outcomes.

Beyond affirming that writers' emotional experiences matter broadly, the current study also demonstrates that daily emotional experiences matter and that writers' emotional states often vary quite a bit from day to day. Once again, the propositions that emotions are short-lived experiences that can vary from moment to moment, and that trait-like "typical" emotions are fundamentally different from state-like "in the moment" emotions are not new (see e.g. Augustine & Larsen, 2012). Likewise, several studies have demonstrated that findings from interindividual analyses may not necessarily apply to intraindividual relationships (e.g. Hamaker, Dolan, & Molenaar, 2005; Nesselroade, 2001). The current study reaffirms these principles in the domain of writing. Across several types of analyses, I found that writers' emotions varied considerably from day to day and were generally not related to their emotional states on the

previous day. I also found that writers' typical emotional experiences were much less predictive of their daily behaviors than were their departures from these typical emotional experiences. In other words, if we want to predict how writers will behave in a given day, we ought to know how they feel on that day, rather than how they felt yesterday or how they typically feel.

This study also reiterates the academic benefits typically associated with positive emotional states (e.g. Boekaerts & Pekrun, 2016). Across all outcomes considered, positively-valenced emotions such as enjoyment, contentment, excitement, and pride were either positively associated with outcomes or, at worst, not associated with an outcome. Enjoyment emerged as a particularly beneficial daily state, demonstrating significant positive relationships with attention regulation, minutes spent writing, and words written. Inversely, negative emotional states tended to be detrimental, which also aligns with previous research, although this was not always the case. For instance, increases in both daily anxiety and boredom were associated with decreases in attention regulation. Anxiety and confusion were positively associated with time spent writing but not with words written, which suggests that increases in these states were associated with more time spent writing to produce the same number of words. Curiously, frustration seemed to be beneficial for writers – increased levels of daily frustration were associated with greater attention regulation, increased time spent writing, and more words written. This is something that future research should investigate, since these relations are largely at odds with most current theoretical propositions. In particular, future research might investigate the exact types of behaviors that frustration might cue in writers as well as how feelings of frustration relate to other features of writing tasks, such as the perceived importance of the writing task.

Finally, the current study extends previous theoretical propositions and empirical findings into the domain of writing, where they had, for the most part, not been tested. Writing differs

from other academic domains in many respects, and so researchers should test theories and findings from other domains in the domain of writing rather than simply assuming they hold. The current study did just that. As mentioned previously, many of the domain-general findings did seem to apply to the domain of writing. Given this baseline, future models of emotions in writing contexts might investigate how features specific to writing contexts – including the genre of writing a writer is working on or the phase of the writing process she is primarily engaged in – elicit certain emotions, since these writing-specific features are not elaborated upon in domain-general models of academic emotions.

Practical Implications

This study was an early exploration into quantitatively studying graduate student writers' day-to-day emotional experiences, writing behaviors, and writing productivity. My goals in conducting the study were to better understand relations over time between the constructs of interest. None of the models I estimated should be interpreted representing causal relationships. Given these goals and the observational design of the study, readers should be cautious about drawing too many practical implications from the current findings. That said, some of these findings may be of interest to educators, people who work with graduate student writers, and graduate student writers themselves.

First, educators who work with graduate student writers ought to be mindful of their emotional states as well as how the writing tasks and assignments they provide for these writers might elicit various emotional states. The findings of the current study indicate that writers' daily emotional states are meaningfully linked to proximal outcomes including attention regulation and productivity, and previous theoretical work indicates that emotional states in academic contexts arise as a result of task appraisals (Pekrun, 2006). Once again, although these findings

should not be interpreted as causal – that is, experiencing joy while writing may not necessarily cause writers to focus more on their writing – several emotions are nevertheless related to the outcomes studied here, and these emotions may provide visible clues that can prompt conversations or reflections. For instance, emotions can be inferred from facial expressions and other visible indicators (Baker et al., 2010; Pardos et al., 2014), so if an educator notices that a writer appears anxious while writing, the educator may want to talk to the writer to better discern why he or she might be feeling anxious. This conversation might reveal that certain features of the writing task or the writing environment are partially responsible for that students' anxiety. Likewise, if an educator notices that the majority of his students seem to be enjoying writing, and knowing that this enjoyment is linked to beneficial behaviors and outcomes, he might reflect on which features of the writing task or context might be contributing to these feelings. These conversations could lead the educator to modify the writing task or be mindful of how similar tasks might elicit various emotions in students.

Additionally, these findings further emphasize that educators and writers themselves should be wary about heuristically categorizing emotions as beneficial or detrimental based solely on their valence. Although daily ratings of enjoyment were positively associated with all outcome measures, other emotions showed differential patterns of relations with outcomes. Furthermore, daily ratings of frustration, which is a negatively valenced emotion, were positively associated with several outcomes. Practically, this suggests that writers should not be entirely averse to feeling frustrated while writing. In fact, feeling frustrated may be an indicator that the task is important and challenging. Likewise, educators creating writing tasks should not feel overly alarmed if their students feel frustrated during writing every so often. This is not to suggest that educators should create tasks in which writers will continuously feel frustrated, since

prolonged frustration may lead to task disengagement (D'Mello & Graesser, 2012), but rather that occasional states of frustration during writing seem to be associated with positive outcomes.

Limitations and Recommendations for Future Research

There are some limitations of this study. First, although the recruited sample did include participants from across the United States as well as some international participants, it was nevertheless a convenience sample comprising only graduate students who responded to an initial invitation to participate. Further, the vast majority of the participants were female, white, under age 30, and/or enrolled in education or psychology graduate programs. Therefore, the results I presented here may not generalize more broadly, although they may provide a starting point for research investigating similar phenomena in other populations. Future research should seek to replicate the methodology of the current study in other samples, particularly in samples of younger and less-experienced writers whose emotional experiences may differ considerably from those found here.

Second, the four weeks in which data were collected were not anchored to any specific event or timeline (e.g. the beginning of a semester or the four weeks before a project due date), and therefore time functions as random in the current study. In other words, participants in the study may have had highly individualized project timelines where some writers may have been exceptionally busy/productive whereas others may have been writing less due to other demands on their time. I believe that meeting writers where they were and allowing them this autonomy to work on their own writing projects was critical to recruiting and retaining an adequate sample; however, it also certainly introduced a confound into the study. For instance, one participant reached out to me via email and mentioned that she was writing “WAY more frequently and for longer duration than [she] typically would” because she needed to finish her dissertation.

Inversely, another participant emailed me to say that she was writing less than usual because she was in the data analysis phase of a research project. In theory, the randomness of time ought to average out, and participants who were less productive would be offset by those who were more productive; however, given the relatively small sample at the person level ($n = 183$), this may not be the case here. Therefore, it is worth keeping this limitation in mind when interpreting the results of this study. Additionally, future research might anchor the study timeline to a common event or timeline for participants. For instance, research conducted in a single classroom – or multiple classrooms that share syllabi or curricula – could examine writers’ emotional experiences in the weeks leading up to the due date of a lengthy writing project. This approach would add more relevance to any time effects included in models.

Additionally, participants may have altered their behavior due to participating in the study. For instance, knowing that they would be asked report their time spent writing and number of words produced each day, writers might have written more than they normally do, which could affect the results of the study. In fact, a few of the study’s participants whom I know personally mentioned to me in informal conversations that participating in the study was motivating them to write more. Once again, I believe that allowing writers as much autonomy as possible in terms of their writing behaviors was critical for maintaining a sample of participants throughout the study. Nevertheless, future research might address this by collecting variables that are not so readily manipulated by participants. For instance, asking participants to submit writing samples and then scoring these samples, though a time-consuming process, might provide researchers with a measure of writing quality that is less susceptible to an intervention effect resulting from participation in the study.

Another limitation of the current study is the large number of models and parameters that were estimated. For instance, in my model building process for investigating my second research question, I fit six different models for each of the nine emotions under investigation, which equates to at 54 models. Further, multiple parameters were estimated in each model. Although I chose this approach because it systematically builds models by increasing complexity at each step and follows advice from statisticians (e.g. Hox et al., 2017), it also increases the Type I error rate. In other words, some of the statistically significant parameters in these models are potentially a byproduct of chance and the sheer number of parameters being estimated. Therefore, readers ought to consider the practical significance of the magnitude and direction of the parameter estimates in addition to the statistical significance when interpreting these results.

Additionally, the manner in which I lagged the variables may affect some of the results from the RCI analyses as well as the emotional stability/inertia models. To accommodate missing data and maximize the number of responses I could use, I operationalized a “lagged response” as the response at the previous measurement occasion. In many cases, this was the previous day; however, if a participant did not complete a survey on the previous day, the lag could be the day before that, or the day before that, etc. Theoretically, this is a valid approach because it retains the same object focus and general time referent (i.e. the last time the person wrote), but it does mean that lags will represent different periods of time. In the future, researchers might conduct a similar study in classrooms with relatively prescribed writing schedules. For instance, researchers might locate a high school English classroom where students write every day of the week. This explicit schedule would help ensure that lags are consistent across participants.

Furthermore, as a way to maximize the number of total participants as well as the number of surveys included in my analyses, I retained any participants who responded to at least 14 surveys. However, these participants could have responded that they did not write on a given day, and so responding to a survey did not necessarily lead to usable data from that survey. As a result, some participants contributed relatively few usable data points to the current analyses, whereas other participants contributed many. The sparsity and imbalance in these cluster sizes precluded my ability to fit multilevel models with random effects, so I could not model randomness in any of the parameters in the stability, attention regulation, and productivity models. As described previously, recruiting a sample with a relatively fixed and known writing schedule (e.g. students in a high school English classroom) could help researchers create a data structure where all participants contribute the same (or nearly the same) number of daily responses, which would in turn be more amenable to multilevel modeling approaches.

Finally, the amount and type of data I collected each day from participants in this study was fairly limited. Particularly when designing daily diary surveys, researchers need to be careful to keep daily surveys short to avoid overburdening participants (Gunthert & Wenzel, 2012). Following this advice, I collected relatively little data that contextualized participants' daily writing sessions. Perhaps most notably, although I collected Likert-style measures of writers' emotional experiences, I did not ask writers to explain why they chose any of these responses or, more broadly, to describe how they felt their writing sessions went. Collecting this type of rich qualitative data could provide a more nuanced understanding of contextual features associated with writers' daily emotional states as well as of the dynamics of emotional states before, during, and after writing tasks. I also did not collect much information about the type of task they were working on, how important it was to them, or where/with whom they were

working. Although providing such responses would undoubtedly require more time from participants, some past research indicates that participants may be willing to complete quite lengthy daily surveys (e.g. Kahneman et al., 2004). Similarly, in the initial survey, I only collected general demographic data about participants. Future research in this area might collect deeper daily responses, including open-ended survey responses, writing samples, or more contextual indicators. Likewise, future research might capture more person-level data, including data on writers' personalities, mental health, and beliefs about writing (e.g. self-efficacy and implicit beliefs). Capturing this data could allow for a more nuanced understanding of the contextual and person-level factors associated with daily emotional states, including correlates of changing emotional states.

Furthermore, the current study raises several additional questions that future research might seek to address. First, future research might seek to employ different approaches to tease out more about writers' affective dynamics. For instance, using facial recognition software and keystroke analytics to record writers during writing tasks and then inferring information such as their affective states and when they reached an impasse during writing might lead to a more detailed understanding of how emotions transition and how such transitions might coincide with keystroke patterns. Additionally, future research using daily data – such as the data collected in the current study – might employ different analytical approaches and treatments of time to discern more about day-to-day emotional inertia and variability. For example, including a variable that represents the number of days since writing last and interacting this with the autoregressive effect could provide information about how writing – or not writing – regularly might moderate emotional inertia. Similarly, including additional autoregressive terms or cubic terms could also lead to a deeper understanding of these time effects. Estimating different types

of models, such as regression splines, might also provide more data about potential thresholds at which inertia is more likely, since some previous research indicates that inertia is most common after intense emotional states (Kuppens et al., 2010).

Second, after replicating these findings in other populations, researchers might consider how to support writers experiencing deleterious emotional states and, inversely, how to prolong beneficial emotional states. This might entail developing interventions that teach writers how and when to employ effective emotion regulation strategies that ultimately lead to greater engagement during writing and psychological wellbeing. For example, when writers feel shame, teaching them to employ cognitive change strategies (Gross, 2015a) to consider the experience as an opportunity to learn might mitigate these feelings of shame. Another option might be to leverage facial recognition technology and develop computer-based interventions that can infer detrimental emotional states in learners and deliver targeted emotion-regulation interventions in the form of short text-based pop ups or brief videos. Once again, more observational work would be needed to inform such interventions, but they seem to be a promising opportunity to work toward, with the current study serving as an early step in that direction.

Future research might also explore different how different types of emotions relate to writers' behaviors and outcomes. As described in the literature review, writer might feel the same emotion (e.g. enjoyment) during writing for various reasons, and epistemic enjoyment might relate differently to behaviors and outcomes than does topic enjoyment. Capturing these different types of emotions might require the use of different scale items or of open-ended responses.

Finally, scholars devoted to studying writing might build upon this research to advance models that more explicitly describe writers' emotional states, including why writers might feel

various emotions, how these emotions might relate to writing behaviors, processes, and outcomes, and how these emotional states change (or don't) during and between writing tasks. As the findings of this study indicates, some of the propositions of such models may mirror domain-general propositions describing emotional states during achievement tasks (e.g. Pekrun, 2006); however, such models should also capture behaviors and outcomes specific to writing that do not have analogs in other domains. For instance, writing is often evaluated for stylistic elements that extend beyond the quality of an idea or whether it is "right" or "wrong." Additionally, the number of words produced as an indicator of quality or of productivity is certainly more applicable to writing tasks than to math tasks. In addition to including outcomes and behaviors specific to writing, these future theoretical models ought to include propositions describing how specific discrete emotions relate to various behaviors and outcomes. Such theoretical propositions specific to writing would provide an invaluable lens through which researchers could advance our understanding of how writers write.

Conclusion

*"Sometimes my feelings get in the way
Of what I really feel I needed to say"*

-Isaac Brock

The findings of the current study indicate that sometimes writers' feelings really do seem to get in the way. At other times, these feelings facilitate writing. And these feelings change considerably from day to day. Hopefully, the current study serves as an early step in a longer journey toward better understanding writers' emotions, how they relate to writing outcomes, and how researchers and practitioners can promote adaptive emotional experiences and emotion regulation strategies in writers of all ages and abilities.

References

- Amabile, T. M., Barsade, S. G., Mueller, J. S., & Staw, B. M. (2005). Affect and creativity at work. *Administrative Science Quarterly*, 50(3), 367-403.
- Ashby, F., & Isen, A. (1999). A neuropsychological theory of positive affect and its influence on cognition. *The Psychological Review*, 106(3), 529-550.
- Aspinwall, L. G. (1998). Rethinking the role of positive affect in self-regulation. *Motivation and Emotion*, 22(1), 1-32.
- Augustine, A., & Larsen, R. (2012). Emotion research. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 497-510). New York: Guilford Press.
- Baas, M., De Dreu, C. K., & Nijstad, B. A. (2008). A meta-analysis of 25 years of mood-creativity research: Hedonic tone, activation, or regulatory focus?. *Psychological Bulletin*, 134(6), 779-806.
- Baddeley, A. (2000). The episodic buffer: a new component of working memory?. *Trends in Cognitive Sciences*, 4(11), 417-423.
- Baker, R. S., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive-affective states during interactions with three different computer-based learning environments. *International Journal of Human-Computer Studies*, 68(4), 223-241.
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. Macmillan.
- Bates, D., Maechler, M. Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1-48.doi:10.18637/jss.v067.i01.
- Bazerman, C. (2016). What do sociocultural studies of writing tell us about learning to write? In C. A. MacArthur, S. Graham, & J. Fitzgerald (Eds.), *Handbook of writing research* (2nd ed., pp. 11-23). New York: Guilford Press.
- Bazerman, C. (2018). What does a model model? And for whom? *Educational Psychologist*, doi: 10.1080/00461520.2018.1496022.
- Becker, H. S. (2007). *Writing for social scientists: How to start and finish your thesis, book, or article*. Chicago: University of Chicago Press.
- Bell, G. (2011). The value of boredom. TEDxSydney Conference. Retrieved from http://www.youtube.com/watch?v=Ps_YUEIM2EQ

- Bereiter, C., & Scardamalia, M. (1987). *The psychology of written composition*. Hillsdale, NJ: Erlbaum.
- Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, 44(2), 175-184.
- Bernacki, M. L., Nokes-Malach, T. J., & Aleven, V. (2013). Fine-grained assessment of motivation over long periods of learning with an intelligent tutoring system: Methodology, advantages, and preliminary results. In R. Azevedo & V. Aleven, (Eds.) *International handbook of metacognition and learning technologies* (pp. 629-644). Springer New York.
- Bernacki, M. L., Nokes-Malach, T. J., & Aleven, V. (2015). Examining self-efficacy during learning: variability and relations to behavior, performance, and learning. *Metacognition and Learning*, 10(1), 99-117.
- Berninger, V. W., Fuller, F., & Whitaker, D. (1996). A process model of writing development across the lifespan. *Educational Psychology Review*, 8(3), 193-218.
- Beymer, P. N., Rosenberg, J. M., Schmidt, J. A., & Naftzger, N. J. (2018). Examining relationships among choice, affect, and engagement in summer STEM programs. *Journal of Youth and Adolescence*, 47(6), 1178-1191.
- Bjornebekk, G. (2008). Positive affect and negative affect as modulators of cognition and motivation: The rediscovery of affect in achievement goal theory. *Scandinavian Journal of Educational Research*, 52(2), 153-170.
- Boekaerts, M. (1997). Self-regulated learning: A new concept embraced by researchers, policy makers, educators, teachers, and students. *Learning and Instruction*, 7(2), 161-186.
- Boekaerts, M. (2007). Understanding students' affective processes in the classroom. In P. A. Schutz & R. Pekrun (Eds.), *Emotion in education* (pp. 37-56). San Diego: Academic Press.
- Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: A perspective on assessment and intervention. *Applied Psychology*, 54(2), 199-231.
- Boekaerts, M., & Niemivirta, M. (2000). Self-regulated learning: Finding a balance between learning goals and ego-protective goals. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 417 - 450): San Diego, CA: Academic Press.
- Boekaerts, M., & Pekrun, R. (2016). Emotions and emotion regulation in academic settings. In L. Corno & E.M. Anderman (Eds.), *Handbook of educational psychology* (pp. 76-90). Abingdon: Routledge.

- Bohn-Gettler, C.M., & Rapp, D.N. (2014). Emotion during reading and writing. In L. Linnenbrink-Garcia & R. Pekrun (Eds.), *International handbook of emotions in education*. (pp. 437-457). Routledge.
- Boice, B. (1997). Which is more productive, writing in binge patterns of creative illness or in moderation? *Written Communication, 14*(4), 435-459.
- Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology, 54*(1), 579-616.
- Brand, A. G. (1990). Writing and feelings: Checking our vital signs. *Rhetoric Review, 8*(2), 290-308.
- Brand, A. (1987). The why of cognition: Emotion and the writing process. *College Composition and Communication, 38*(4), 436-443.
- Brand, A. G., & House, G. (1987). Relationships between types of assignments, writer variables, and emotions of college composition students. *Alberta Journal of Educational Research, 33*(1), 21-32.
- Brand, A. G., & Leckie, P. A. (1988). The emotions of professional writers. *The Journal of Psychology, 122*(5), 421-439.
- Brand, A. G., & Powell, J. L. (1986). Emotions and the writing process: A description of apprentice writers. *The Journal of Educational Research, 79*(5), 280-285.
- Bruning, R., Dempsey, M., Kauffman, D. F., McKim, C., & Zumbrunn, S. (2013). Examining dimensions of self-efficacy for writing. *Journal of Educational Psychology, 105*(1), 25-38.
- Bruning, R., & Horn, C. (2000). Developing motivation to write. *Educational Psychologist, 35*(1), 25-37.
- Calkins, L. (1986). *The art of teaching writing* (1st ed.). Portsmouth, N.H.: Heinemann.
- Chenoweth, N. A., & Hayes, J. R. (2001). Fluency in writing: Generating text in L1 and L2. *Written Communication, 18*(1), 80-98.
- Chang, W., Cheng, J., Allaire, J. J., Xie, Y., & McPherson, J. (2018). shiny: Web application framework for R. R package version 1.1.0. <https://CRAN.R-project.org/package=shiny>
- Christensen, T. C., Barrett, L. F., Bliss-Moreau, E., Lebo, K., & Kaschub, C. (2003). A practical guide to experience-sampling procedures. *Journal of Happiness Studies, 4*(1), 53-78.
- Christensen, L., & Mendoza, J. L. (1986). A method of assessing change in a single subject: An alteration of the RC index. *Behavior Therapy, 17*, 305-308.

- Citron, F. M. (2012). Neural correlates of written emotion word processing: a review of recent electrophysiological and hemodynamic neuroimaging studies. *Brain and Language*, 122(3), 211-226.
- Cleary, L. M. (1991). Affect and cognition in the writing processes of eleventh graders: A study of concentration and motivation. *Written Communication*, 8(4), 473-508.
- Clore, G. L., & Huntsinger, J. R. (2009). How the object of affect guides its impact. *Emotion Review*, 1(1), 39-54.
- Collie, R. J., Martin, A. J., & Curwood, J. S. (2016). Multidimensional motivation and engagement for writing: Construct validation with a sample of boys. *Educational Psychology*, 36(4), 771-791.
- Cowan, N. (2014). Working memory underpins cognitive development, learning, and education. *Educational Psychology Review*, 26(2), 197-223.
- Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal performance*. New York: Harper & Row.
- Csikszentmihalyi, M., & Larson, R. (1987). Validity and Reliability of the Experience-Sampling Method. *The Journal of Nervous and Mental Disease*, 175(9), 526-536.
- Cranford, J. A., Shrout, P. E., Iida, M., Rafaeli, E., Yip, T., & Bolger, N. (2006). A procedure for evaluating sensitivity to within-person change: Can mood measures in diary studies detect change reliably?. *Personality and Social Psychology Bulletin*, 32(7), 917-929.
- Cuisinier, F., Sanguin-Bruckert, C., Bruckert, JP, & Clavel, C. (2010). Do emotions affect orthographic performance in dictation? *The Psychological Year*, 110 (1), 3-48.
- Delespaul, P. A., Reis, H. T., & DeVries, M. W. (2004). Ecological and motivational determinants of activation: Studying compared to sports and watching TV. *Social Indicators Research*, 67(1-2), 129-143.
- Derakshan, N., & Eysenck, M. W. (2009). Anxiety, processing efficiency, and cognitive performance: New developments from attentional control theory. *European Psychologist*, 14(2), 168-176.
- Derakshan, N., & Eysenck, M. W. (2010). Introduction to the special issue: Emotional states, attention, and working memory. *Cognition and Emotion*, 24(2), 189-199.
- De Smedt, F., Merchie, E., Barendse, M., Rosseel, Y., De Naeghel, J., & Van Keer, H. (2018). Cognitive and motivational challenges in writing: Studying the relation with writing performance across students' gender and achievement level. *Reading Research Quarterly*, 53(2), 249-272.

- De Smedt, F., Van Keer, H., & Merchie, E. (2016). Student, teacher and class-level correlates of Flemish late elementary school children's writing performance. *Reading and Writing*, 29(5), 833-868.
- D'Mello, S., & Graesser, A. (2011). The half-life of cognitive-affective states during complex learning. *Cognition & Emotion*, 25(7), 1299-1308.
- D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, 22(2), 145-157.
- D'Mello, S., Lehman, B., Pekrun, R., & Graesser, A. (2014). Confusion can be beneficial for learning. *Learning and Instruction*, 29, 153-170.
- Eccles, J. S. (2005). Subjective task value and the Eccles et al. model of achievement-related choices. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105–21). New York: Guilford Press.
- Ekholm, E., Zumbunn, S., & DeBusk-Lane, M. (2018). Clarifying an elusive construct: A systematic review of writing attitudes. *Educational Psychology Review*, 30(3), 827-856.
- Elliott, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist*, 34(3), 169–89.
- Ellis, H. C., & Ashbrook, P. W. (1988). Resource allocation model of the effects of depressed mood states on memory. In K. Fiedler & J. Forgas (Eds.), *Affect, cognition and social behaviour* (pp. 25–43). Toronto, Canada: Hogrefe
- Ellis, H. C., & Moore, B. A. (1999). Mood and memory. In T. Dalgleish & M. J. Power (Eds.), *Handbook of cognition and emotion* (pp. 193-210). Chichester, UK: Wiley.
- Enders, C. K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, 12(2), 121-138.
- Enders, W. (2008). *Applied econometric time series*. John Wiley & Sons.
- Engle, R. W., & Kane, M. J. (2004). Executive attention, working memory capacity, and a two-factor theory of cognitive control. In B. Ross (Ed.), *The psychology of learning and motivation* (pp. 145–199). New York: Academic Press.
- Ericsson, K. A. (2006). The influence of experience and deliberate practice on the development of superior expert performance. *The Cambridge handbook of expertise and expert performance*, 38, 685-705.
- Fartoukh, M., Chanquoy, L., & Piolat, A. (2012). Effects of emotion on writing processes in children. *Written Communication*, 29(4), 391-411.

- Fitzgerald, J., & Shanahan, T. (2000). Reading and writing relations and their development. *Educational Psychologist, 35*(1), 39-50.
- Flanigan, A. E., Kiewra, K. A., & Luo, L. (2018). Conversations with four highly productive German educational psychologists: Frank Fischer, Hans Gruber, Heinz Mandl, and Alexander Renkl. *Educational Psychology Review, 30*(1), 303-330.
- Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication, 32*(4), 365-387.
- Forand, N. R., Gunthert, K. C., German, R. E., & Wenzel, S. J. (2010). Appearance investment and everyday interpersonal functioning: An experience sampling study. *Psychology of Women Quarterly, 34*(3), 380-393.
- Forgas, J. P. (1992). On mood and peculiar people: Affect and person typicality in impression formation. *Journal of Personality and Social Psychology, 62*(5), 863-875.
- Forgas, J. P. (1995). Mood and judgment: the affect infusion model (AIM). *Psychological Bulletin, 117*(1), 39-66.
- Franzen, J. (2002). Why bother. *How to be alone: Essays* (pp. 55-97). New York: Farrar, Straus and Giroux.
- Frijda, N. H. (1986). *The emotions*. Cambridge University Press.
- Gaylin, W. (1979). Feeling bored. In W. Gaylin (Ed.), *Feelings: Our vital signs* (pp. 113-129). New York, NY: Harper and Row.
- Gilbert, J., & Graham, S. (2010). Teaching writing to elementary students in grades 4-6: A national survey. *The Elementary School Journal, 110*(4), 494-518.
- Gillespie, A., & Graham, S. (2014). A meta-analysis of writing interventions for students with learning disabilities. *Exceptional Children, 80*(4), 454-473.
- Goetz, T., & Hall, N. C. (2013). Emotion and achievement in the classroom. In J. Hattie & E. M. Anderman (Eds.), *International guide to student achievement* (pp. 192-195). New York, NY: Routledge.
- Goetz, T., Sticca, F., Pekrun, R., Murayama, K., & Elliot, A. J. (2016). Intraindividual relations between achievement goals and discrete achievement emotions: an experience sampling approach. *Learning and Instruction, 41*(1), 115-125.
- Gogol, K., Brunner, M., Goetz, T., Martin, R., Ugen, S., Keller, U., ... & Preckel, F. (2014). "My Questionnaire is Too Long!" The assessments of motivational-affective constructs with

- three-item and single-item measures. *Contemporary Educational Psychology*, 39(3), 188-205.
- Goodson, P. (2016). *Becoming an academic writer: 50 exercises for paced, productive, and powerful writing*. Sage Publications.
- Graham, S. (2018). A writer(s) within community model of writing. In C. Bazerman, V. Berninger, D. Brandt, S. Graham, J. Langer, S. Murphy, P. Matsuda, D. Rowe, & M. Schleppegrell,(Eds.), *The lifespan development of writing* (pp. 271-325). Urbana, IL: National Council of English.
- Graham, S., & Harris, K. R. (2000). The role of self-regulation and transcription skills in writing and writing development. *Educational Psychologist*, 35(1), 3-12.
- Graham, S., Harris, K. R., & Mason, L. (2005). Improving the writing performance, knowledge, and self-efficacy of struggling young writers: The effects of self-regulated strategy development. *Contemporary Educational Psychology*, 30(2), 207-241.
- Graham, S., Harris, K. R., & Santangelo, T. (2015). Research-based writing practices and the Common Core: Meta-analysis and meta-synthesis. *The Elementary School Journal*, 115(4), 498-522.
- Graham, S., McKeown, D., Kiuahara, S., & Harris, K. R. (2012). A meta-analysis of writing instruction for students in the elementary grades. *Journal of Educational Psychology*, 104(4), 879-896.
- Graham, S., & Perin, D. (2007). A meta-analysis of writing instruction for adolescent students. *Journal of Educational Psychology*, 99(3), 445-476.
- Graves, D. (1983). *Writing: Teachers and children at work*. Exeter, N.H.: Heinemann Educational Books.
- Greeno, J. G. (1998). The situativity of knowing, learning, and research. *American Psychologist*, 53(1), 5-26.
- Gross, J. J. (1998). The emerging field of emotion regulation: an integrative review. *Review of General Psychology*, 2(3), 271-299.
- Gross, J. J. (2015a). Emotion regulation: Current status and future prospects. *Psychological Inquiry*, 26(1), 1-26.
- Gross, J. J. (2015b). The extended process model of emotion regulation: Elaborations, applications, and future directions. *Psychological Inquiry*, 26(1), 130-137.
- Gross, J. J., & Jazaieri, H. (2014). Emotion, emotion regulation, and psychopathology: An affective science perspective. *Clinical Psychological Science*, 2(4), 387-401.

- Gross, J. J., Sheppes, G., & Urry, H. L. (2011). Cognition and emotion lecture at the 2010 SPSP Emotion Preconference: Emotion generation and emotion regulation: A distinction we should make (carefully). *Cognition & Emotion*, 25(5), 765-781.
- Gunthert, K. C., & Wenzel, S. J. (2012). Daily diary methods. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 144-159). New York: Guilford Press.
- Hacker, D. J. (2018). A metacognitive model of writing: An update from a developmental perspective. *Educational Psychologist*, <https://doi.org/10.1080/00461520.2018.1480373>
- Halekoh, U., Højsgaard, S., & Yan, J. (2006). The R package geepack for generalized estimating equations. *Journal of Statistical Software*, 15(2), 1-11.
- Hamaker, E. L. (2012). Why researchers should think “within-person”: A paradigmatic rationale. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 43-61). New York: Guilford Press.
- Hamaker, E. L., Dolan, C. V., & Molenaar, P. C. (2005). Statistical modeling of the individual: Rationale and application of multivariate stationary time series analysis. *Multivariate Behavioral Research*, 40(2), 207-233.
- Harris, K. R., Graham, S., & Mason, L. H. (2006). Improving the writing, knowledge, and motivation of struggling young writers: Effects of self-regulated strategy development with and without peer support. *American Educational Research Journal*, 43(2), 295-340.
- Harris, M. B. (2000). Correlates and characteristics of boredom proneness and boredom. *Journal of Applied Social Psychology*, 30(3), 576-598.
- Hayes, J. (1996). A new framework for understanding cognition and affect in writing. In C.M. Levy and S. Randell (Eds.), *The science of writing: Theories, methods, individual differences, and applications* (pp. 1-27). Mahwah, NJ: Lawrence Erlbaum.
- Hayes, J. R. (2012). Modeling and remodeling writing. *Written Communication*, 29(3), 369-388.
- Hayes, J. R., & Flower, L. S. (1986). Writing research and the writer. *American Psychologist*, 41(10), 1106-1113.
- Hektner, J. M., Schmidt, J. A., & Csikszentmihalyi, M. (2007). *Experience sampling method: Measuring the quality of everyday life*. Sage.
- Hidi, S., Berndorff, D., & Ainley, M. (2002). Children's argument writing, interest and self-efficacy: An intervention study. *Learning and Instruction*, 12(4), 429-446.

- Holland, R. (2013). Writing experiences of community college students with self-reported writing anxieties and linguistic insecurity: A perspective for college counselors. *Community College Journal of Research and Practice*, 37(4), 278-295.
- Hox, J. J., Moerbeek, M., & Van de Schoot, R. (2017). *Multilevel analysis: Techniques and applications*. Routledge.
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55.
- Isen, A. M., Daubman, K. A., & Nowicki, G. P. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology*, 52(6), 1122-1131.
- Kahneman, D. (1999). Objective happiness. In D. Kahneman, E. Diener, and N. Schwarz, (Eds.) *Well-being: The foundations of hedonic psychology*, (pp. 3-25). New York: Russell Sage Foundation.
- Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702), 1776-1780.
- Kane, M. J., Poole, B. J., Tuholski, S. W., & Engle, R. W. (2006). Working memory capacity and the top-down control of visual search: Exploring the boundaries of " executive attention". *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 32(4), 749-777.
- Kaplan, S., & Berman, M. G. (2010). Directed attention as a common resource for executive functioning and self-regulation. *Perspectives on Psychological Science*, 5(1), 43-57.
- Kaplan, A., Lichtinger, E., & Gorodetsky, M. (2009). Achievement goal orientations and self-regulation in writing: An integrative perspective. *Journal of Educational Psychology*, 101(1), 51-69.
- Kellogg, R. T. (2008). Training writing skills: A cognitive developmental perspective. *Journal of Writing Research*, 1(1), 1-26.
- Kelsky, K. (2015). *The professor is in: The essential guide to turning your Ph. D. into a job*. Three Rivers Press (CA).
- King, S. (2002). *On writing*. Simon and Schuster.
- Kopcsó, K., & Láng, A. (2017). Regulated divergence: Textual patterns, creativity and cognitive emotion regulation. *Creativity Research Journal*, 29(2), 218-223.

- Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science, 21*(7), 984-991.
- Kuppens, P., Van Mechelen, I., Nezlek, J. B., Dossche, D., & Timmermans, T. (2007). Individual differences in core affect variability and their relationship to personality and psychological adjustment. *Emotion, 7*(2), 262-274.
- Kreft, I. G., de Leeuw, J., & Aiken, L. S. (1995). The effect of different forms of centering in hierarchical linear models. *Multivariate Behavioral Research, 30*, 1-21.
http://dx.doi.org/10.1207/s15327906mbr3001_1
- Lane, K. L., Harris, K. R., Graham, S., Weisenbach, J. L., Brindle, M., & Morphy, P. (2008). The effects of self-regulated strategy development on the writing performance of second-grade students with behavioral and writing difficulties. *The Journal of Special Education, 41*(4), 234-253.
- Larsen, R. J., & Kasimatis, M. (1990). Individual differences in entrainment of mood to the weekly calendar. *Journal of Personality and Social Psychology, 58*(1), 164-171.
- Larson, R. W. (1990). Emotions and the creative process; anxiety, boredom, and enjoyment as predictors of creative writing. *Imagination, Cognition and Personality, 9*(4), 275-292.
- Lennartsson, A. K., Horwitz, E. B., Theorell, T., & Ullén, F. (2017). Creative artistic achievement is related to lower levels of alexithymia. *Creativity Research Journal, 29*(1), 29-36.
- Liang, K. Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika, 73*(1), 13-22.
- Lichtenfeld, S., Pekrun, R., Stupnisky, R. H., Reiss, K., & Murayama, K. (2012). Measuring students' emotions in the early years: the achievement emotions questionnaire-elementary school (AEQ-ES). *Learning and Individual Differences, 22*(2), 190-201.
- Lischetzke, T., Angelova, R., & Eid, M. (2011). Validating an indirect measure of clarity of feelings: Evidence from laboratory and naturalistic settings. *Psychological Assessment, 23*(2), 447-455.
- Lüdecke, D. (2019). *_sjstats: Statistical functions for regression models (Version 0.17.4)_*. doi: 10.5281/zenodo.1284472
- Lüdtke, O., Trautwein, U., Kunter, M., & Baumert, J. (2007). Reliability and agreement of student ratings of the classroom environment: a reanalysis of TIMSS data. *Learning Environments Research, 9*(3), 215e230. <http://dx.doi.org/10.1007/S10984-006-9014-8>.
- Lynton, H., & Salovey, P. (1997). The effects of mood on expository writing. *Imagination, Cognition and Personality, 17*(2), 95-110.

- Mann, S., & Cadman, R. (2014). Does being bored make us more creative?. *Creativity Research Journal*, 26(2), 165-173.
- Martinez, C. T., Kock, N., & Cass, J. (2011). Pain and pleasure in short essay writing: Factors predicting university students' writing anxiety and writing self-efficacy. *Journal of Adolescent & Adult Literacy*, 54(5), 351-360.
- Mayrath, M. C. (2008). Attributions of productive authors in educational psychology journals. *Educational Psychology Review*, 20(1), 41-56.
- McCutchen, D. (1996). A capacity theory of writing: Working memory in composition. *Educational Psychology Review*, 8(3), 299-325.
- McGrail, M. R., Rickard, C. M., & Jones, R. (2006). Publish or perish: a systematic review of interventions to increase academic publication rates. *Higher Education Research & Development*, 25(1), 19-35.
- McNeish, D. M. (2014). Modeling sparsely clustered data: Design-based, model-based, and single-level methods. *Psychological Methods*, 19(4), 552-563.
- McNeish, D., Stapleton, L. M., & Silverman, R. D. (2017). On the unnecessary ubiquity of hierarchical linear modeling. *Psychological Methods*, 22(1), 114-140.
- Mehl, M., & Conner, T. S. (2012). *Handbook of research methods for studying daily life*. New York: Guilford Press.
- Meyer, D. K., & Turner, J. C. (2002). Discovering emotion in classroom motivation research. *Educational Psychologist*, 37(2), 107-114.
- Miedijensky, S., & Lichtinger, E. (2016). Seminar for master's thesis projects: Promoting students' self-regulation. *International Journal of Higher Education*, 5(4), 13-26.
- Miller, D. J., Vachon, D. D., & Lynam, D. R. (2009). Neuroticism, negative affect, and negative affect instability: Establishing convergent and discriminant validity using ecological momentary assessment. *Personality and individual differences*, 47(8), 873-877.
- Monette, S., Bigras, M., & Guay, M. C. (2011). The role of the executive functions in school achievement at the end of Grade 1. *Journal of Experimental Child Psychology*, 109(2), 158-173.
- Morris, M., Kathawala, Q., Leen, T., Gorenstein, E., Guilak, F., Labhard, M., & Deleeuw, W. (2010). Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness. *Journal of Medical Internet Research*, 12(2), E10.

- Moskowitz, D. S. & Sadikaj, G. (2012) Event-contingent recording. In M. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life*. (pp. 160-175). New York: Guilford Press.
- Muis, K. R. (2007). The role of epistemic beliefs in self-regulated learning. *Educational Psychologist*, 42(3), 173-190.
- Muis, K., Chevrier, M., & Singh, C. (2018). The role of epistemic emotions in personal epistemology and self-regulated learning. *Educational Psychologist*, 53(3), 165-184.
- National Commission on Writing. (2003, April). *The neglected "R": The need for a writing revolution*. Retrieved March 23, 2017, from http://www.collegeboard.com/prod_downloads/writingcom/neglectedr.pdf
- Nesselrode, J. R. (2001). Intraindividual variability in development within and between individuals. *European Psychologist*, 6(3), 187-193.
- Nezlek, J. B. (2001). Multilevel random coefficient analyses of event-and interval-contingent data in social and personality psychology research. *Personality and Social Psychology Bulletin*, 27(7), 771-785.
- Nezlek, J. B. (2012). Multilevel modeling analyses of diary-style data. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 357-383). New York: Guilford Press.
- Olthouse, J. M. (2013). MFA Writers' relationships with writing. *Journal of Advanced Academics*, 24(4), 259-274.
- Olthouse, J. M. (2014). Gifted children's relationships with writing. *Journal for the Education of the Gifted*, 37(2), 171-188.
- Paas, F. G. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology*, 84(4), 429-434.
- Paas, F., & Sweller, J. (2014). Implications of cognitive load theory for multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 27-42). Cambridge, UK: Cambridge University Press.
- Pajares, F. (2003). Self-efficacy beliefs, motivation, and achievement in writing: A review of the literature. *Reading & Writing Quarterly*, 19(2), 139-158.
- Pajares, F., Johnson, M., & Usher, E. (2007). Sources of writing self-efficacy beliefs of elementary, middle, and high school students. *Research in the Teaching of English*, 42(1), 104-20.

- Pardos, Z. A., Baker, R. S., San Pedro, M. O., Gowda, S. M., & Gowda, S. M. (2014). Affective states and state tests: Investigating how affect and engagement during the school year predict end-of-year learning outcomes. *Journal of Learning Analytics, 1*(1), 107-128.
- Patall, E. A., Vasquez, A. C., Steingut, R. R., Trimble, S. S., & Pituch, K. A. (2016). Daily interest, engagement, and autonomy support in the high school science classroom. *Contemporary Educational Psychology, 46*, 180-194.
- Patterson-Hazley, M., & Kiewra, K. A. (2013). Conversations with four highly productive educational psychologists: Patricia Alexander, Richard Mayer, Dale Schunk, and Barry Zimmerman. *Educational Psychology Review, 25*(1), 19-45.
- Peeters, F., Nicolson, N. A., Berkhof, J., Delespaul, P., & deVries, M. (2003). Effects of daily events on mood states in major depressive disorder. *Journal of Abnormal Psychology, 112*(2), 203-211.
- Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review, 18*(4), 315-341.
- Pekrun, R., Frenzel, A. C., Goetz, T., & Perry, R. P. (2007). The control-value theory of achievement emotions: An integrative approach to emotions in education. In *Emotion in education* (pp. 13-36).
- Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology, 36*(1), 36-48.
- Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., & Goetz, T. (2017). Achievement emotions and academic performance: Longitudinal models of reciprocal effects. *Child Development, 88*(5), 1653-1670.
- Pekrun, R., & Linnenbrink-Garcia, L. (2012). Academic emotions and student engagement. In S. L. Christensen, A. L. Reschly & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 259–282). New York, NY: Springer US.
- Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)* (Tech. Report No. 91-B-004). Board of Regents, University of Michigan, Ann Arbor, MI.
- Pollak, J. P., Adams, P., & Gay, G. (2011, May). PAM: a photographic affect meter for frequent, in situ measurement of affect. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 725-734). ACM.
- Powell, J. L., & Brand, A. G. (1987). The development of an emotions scale for writers. *Educational and Psychological Measurement, 47*(2), 329-338.

- Prebel, J. (2016). Engaging a " pedagogy of discomfort": Emotion as critical inquiry in community-based writing courses. In *Composition Forum* (Vol. 34). Association of Teachers of Advanced Composition.
- R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>.
- Randall, J. G., Oswald, F. L., & Beier, M. E. (2014). Mind-wandering, cognition, and performance: A theory-driven meta-analysis of attention regulation. *Psychological Bulletin*, 140(6), 1411-1431.
- Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). Sage.
- Rawat, S. & Meena, S. (2014). Publish or perish: Where are we heading? *Journal of Research in Medical Sciences*, 19(2), 87-89.
- Reis, H. T., Sheldon, K. M., Gable, S. L., Roscoe, J., & Ryan, R. M. (2000). Daily well-being: The role of autonomy, competence, and relatedness. *Personality and Social Psychology Bulletin*, 26(4), 419-435.
- Revelle, W. (2018) psych: Procedures for personality and psychological research, Northwestern University, Evanston, Illinois, USA, <https://CRAN.R-project.org/package=psych> Version = 1.8.12.
- Rosenberg, E. L. (1998). Levels of analysis and the organization of affect. *Review of General Psychology*, 2(3), 247-270.
- Ross, P. M., Burgin, S., Aitchison, C., & Catterall, J. (2011). Research writing in the Sciences: Liminal territory and high emotion. *Journal of Learning Design*, 4(3), 14-27.
- Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, 48(2), 1-36.
- RStudio Team (2016). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL <http://www.rstudio.com/>.
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161-1178.
- Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). Affect grid: A single-item scale of pleasure and arousal. *Journal of Personality and Social Psychology*, 57(3), 493-502.
- Sabourin, J., Rowe, J. P., Mott, B. W., & Lester, J. C. (2011, June). When off-task is on-task: The affective role of off-task behavior in narrative-centered learning environments. In

- International Conference on Artificial Intelligence in Education* (pp. 534-536). Springer, Berlin, Heidelberg.
- Sala-Bubaré, A., & Castelló, M. (2018). Writing regulation processes in higher education: a review of two decades of empirical research. *Reading and Writing, 31*(4), 757-777.
- Schmeichel, B. J. (2007). Attention control, memory updating, and emotion regulation temporarily reduce the capacity for executive control. *Journal of Experimental Psychology: General, 136*(2), 241-255.
- Shrout, P. E., & Lane, S. P. (2012). Psychometrics. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 302-320). New York: Guilford Press.
- Schunk, D. H. (2012). Social cognitive theory. In K. R. Harris, S. Graham, & T. C. Urdan (Eds.), *APA educational psychology handbook: Vol. 1. Theories, constructs, and critical issues* (pp. 101-23). Washington, DC: American Psychological Association.
- Schutz, P. A., & Lanehart, S. L. (2002). Introduction: Emotions in education. *Educational Psychologist, 37*(2), 67-68.
- Scott, C. M. (2009). Language-based assessment of written expression. In G. A. Troia (Ed.), *Instruction and assessment for struggling writers: Evidence-based practices*, (pp. 358 - 386). New York: Guilford Press.
- Sharples, M. (1996). An account of writing as creative design. In C. M. Levy & S. Ransdell (Eds.), *The Science of Writing—Theories, Methods, Individual Differences and Applications* (pp. 9-28). Mahwah, NJ: Lawrence Erlbaum Associates.
- Shoda, Y., Mischel, W., & Wright, J. C. (1994). Intraindividual stability in the organization and patterning of behavior: Incorporating psychological situations into the idiographic analysis of personality. *Journal of Personality and Social Psychology, 67*(4), 674-687.
- Sikes, P. (2006). Working in a 'new' university: In the shadow of the Research Assessment Exercise?. *Studies in Higher Education, 31*(5), 555-568.
- Silvia, P. J. (2007). *How to write a lot: A practical guide to productive academic writing*. American Psychological Association.
- Singer, J. L. (1981). Towards the scientific study of imagination. *Imagination, Cognition and Personality, 1*(1), 5-28.
- Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European Journal of Operational Research, 177*(3), 1333-1352.

- Stewart, G., Seifert, T. A., & Rolheiser, C. (2015). Anxiety and self-efficacy's relationship with undergraduate students' perceptions of the use of metacognitive writing strategies. *Canadian Journal for the Scholarship of Teaching and Learning*, 6(1), 4-17.
- Suls, J., Green, P., & Hillis, S. (1998). Emotional reactivity to everyday problems, affective inertia, and neuroticism. *Personality and Social Psychology Bulletin*, 24(2), 127-136.
- Theall, K. P., Scribner, R., Broyles, S., Yu, Q., Chotalia, J., Simonsen, N., ... & Carlin, B. P. (2011). Impact of small group size on neighbourhood influences in multilevel models. *Journal of Epidemiology & Community Health*, 65(8), 688-695.
- Tomas, L., & Ritchie, S. M. (2012). Positive emotional responses to hybridised writing about a socio-scientific issue. *Research in Science Education*, 42(1), 25-49.
- Trnka, R., Zahradnik, M., & Kuška, M. (2016). Emotional creativity and real-life involvement in different types of creative leisure activities. *Creativity Research Journal*, 28(3), 348-356.
- Troia, G. A., Harbaugh, A. G., Shankland, R. K., Wolbers, K. A., & Lawrence, A. M. (2013). Relationships between writing motivation, writing activity, and writing performance: Effects of grade, sex, and ability. *Reading and Writing*, 26(1), 17-44.
- Troia, G. A., Shankland, R. K., & Wolbers, K. A. (2012). Motivation research in writing: Theoretical and empirical considerations. *Reading & Writing Quarterly*, 28(1), 5-28.
- Turner, J. E., & Schallert, D. L. (2001). Expectancy–value relationships of shame reactions and shame resiliency. *Journal of Educational Psychology*, 93(2), 320-329.
- Usher, E. L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of Educational Research*, 78(4), 751-796.
- Vass, E. (2007). Exploring processes of collaborative creativity—The role of emotions in children's joint creative writing. *Thinking Skills and Creativity*, 2(2), 107-117.
- Wang, Z., Lukowski, S. L., Hart, S. A., Lyons, I. M., Thompson, L. A., Kovas, Y., ... & Petrill, S. A. (2015). Is math anxiety always bad for math learning? The role of math motivation. *Psychological Science*, 26(12), 1863-1876.
- Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: How good are single-item measures?. *Journal of Applied Psychology*, 82(2), 247-252.
- Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063-1070.
- Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review*, 92(4), 548-573.

- West, C. P., Dyrbye, L. N., Sloan, J. A., & Shanafelt, T. D. (2009). Single item measures of emotional exhaustion and depersonalization are useful for assessing burnout in medical professionals. *Journal of General Internal Medicine*, 24(12), 1318-1321.
- Wigfield, A. (1997). Reading motivation: A domain-specific approach to motivation. *Educational Psychologist*, 32(2), 59-68.
- Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, 25(1), 68-81.
- Wigfield, A., Tonks, S., & Klauda, S. L. (2009). Expectancy-value theory. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of motivation at school* (pp. 55–75). New York: Routledge.
- Winne, P. H. (1995). Inherent details in self-regulated learning. *Educational Psychologist*, 30(4), 173-187.
- Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. *Metacognition in educational theory and practice*, 93, 27-30.
- Ye, S., Ngan, R. Y. L., & Hui, A. N. (2013). The state, not the trait, of nostalgia increases creativity. *Creativity Research Journal*, 25(3), 317-323.
- Yeo, G., & Neal, A. (2008). Subjective cognitive effort: A model of states, traits, and time. *Journal of Applied Psychology*, 93(3), 617-631.
- Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, 18(5), 459-482.
- Zeger, S. L., Liang, K. Y., & Albert, P. S. (1988). Models for longitudinal data: a generalized estimating equation approach. *Biometrics*, 1049-1060.
- Zeidner, M. (1998). *Test anxiety: The state of the art*. Springer Science & Business Media.
- Zenasni, F., & Lubart, T. (2011). Pleasantness of creative tasks and creative performance. *Thinking Skills and Creativity*, 6(1), 49-56.
- Zimmerman, B. J. (2013). Theories of self-regulated learning and academic achievement: An overview and analysis. In *Self-regulated learning and academic achievement* (pp. 10-45). Routledge.
- Zimmerman, B. J., & Risemberg, R. (1997). Becoming a self-regulated writer: A social cognitive perspective. *Contemporary Educational Psychology*, 22(1), 73–101.

- Zimmerman, B. J., & Schunk, D. H. (2011). *Handbook of self-regulated learning and performance*. New York: Routledge.
- Zirkel, S., Garcia, J. A., & Murphy, M. C. (2015). Experience-sampling research methods and their potential for education research. *Educational Researcher*, 44(1), 7-16.
- Zumbrunn, S., Broda, M., Conklin, S., Varier, D., Larsen, R., Walsh, M., & Love, S. (2017). *Examining the role of self-efficacy for writing on writing achievement and self-regulation*. Paper presented at the international meeting of the Writing Research Across Borders Conference, Bogota, Columbia.
- Zumbrunn, S., Ekholm, E., Stringer, J. K., McKnight, K., & DeBusk-Lane, M. (2017). Student experiences with writing: Taking the temperature of the classroom. *The Reading Teacher*, 70(6), 667-677. <https://doi.org/10.1002/trtr.1574>

APPENDIX A – Email Invitation to Participate in the Study

Dear graduate student writer,

You are invited to participate in a research study seeking to better understand graduate student writers' daily writing-related emotional experiences and writing behaviors. You are being invited to participate because you are currently a graduate student in a writing-intensive discipline. Participation in the study is completely optional and will entail answering a few demographic questions as well as responding to a brief survey regarding writing experiences each day over the course of 4 weeks, ranging from March 7th to April 3rd. The initial demographic questions should take less than 5 minutes to complete, and each daily survey should take approximately 5 minutes to complete.

People who complete at least 50% of the daily surveys in the study will be entered into a modified raffle. Participants will earn 1 point per each daily survey completed, and all participants who complete at least 50% of the daily surveys will be entered into a raffle with their number of entries corresponding to the number of points earned. Eight winners will be selected from this raffle, and each winner will receive a \$100 Amazon gift card. Participants will also be provided with individualized reports of their data in preliminary form at multiple occasions during the study and in a finalized form after the completion of the study.

If you are willing to participate, please view the attached information sheet and then click the link below, which will take you to an online demographic questionnaire. Please only complete the demographics questionnaire if you are interested in responding to the daily surveys. If you have any other questions or concerns, please feel free to reach out to me via email at ekholmeh@vcu.edu.

Thank you for your consideration!

<LINK TO SURVEY HERE>

Eric Ekholm, M.T.
Graduate Research Assistant
Educational Psychology
Virginia Commonwealth University
(703)434-9689

APPENDIX B – Participant Information Form

Research Participant Information Form

Title:

Investigating Daily Writing Emotions, Self-Regulation, and Productivity: An Intensive Longitudinal Study

VCU IRB NO: HM20015129

Purpose of the study:

The purpose of this research study is to learn more about writers' daily emotional experiences, including the stability of these experiences over time as well as how they relate to writing behaviors and productivity. You are invited to participate in this study because you are a graduate student in a writing-intensive discipline. You must be at least 18 years old to participate in this study.

Description of the study and your involvement:

This study is being conducted by researchers in Virginia Commonwealth University's School of Education. Participants in the study are expected to write on a daily or near-daily basis and are therefore being recruited from writing-intensive disciplines. If you decide to participate in the study, you will be asked to first complete a brief demographics survey. Additionally, you will be asked to complete a brief daily survey regarding your writing-related emotions, behaviors, and productivity each day over the course of four weeks, between March 7th and April 3rd. Daily surveys should take approximately 5 minutes to complete each day. Daily surveys will be emailed to participants each morning at 8 a.m., and daily reminders will be emailed at 5 p.m. Personally identifiable information will not be shared with anyone outside of the research study. Only aggregated, de-identified, and/or anonymized data will be shared.

Risks and discomforts:

We do not anticipate greater than minimal risks or discomforts resulting from participation in this study.

Benefits to you and others:

You will be given access to a web app that provides individualized reports of your data in preliminary form at multiple occasions through the study. After the study has concluded, you will receive access to an app that provides a finalized personalized report illustrating trends in your data, which may help you think about your own approach to writing. Additionally, information gained from this study will contribute to the scholarly understanding of writers' emotional experiences and behaviors. This information may be used to help design writing strategies and tools in the future.

Costs:

There are no costs for participating in this study other than the time you will spend each day completing the daily surveys.

Compensation:

All participants who complete at least 50% of the daily surveys will be entered into a modified raffle. Participants will earn 1 point per each daily survey completed, and all participants will be entered into the raffle with their number of entries corresponding to the number of points earned. Eight winners will be selected from this raffle, and each winner will receive a \$100 Amazon gift card. The raffle drawing will be held after the completion of the study. Participants will also be provided with a finalized, individualized report of their data after the study is completed.

Confidentiality:

Your name, email address, and potentially identifying demographic information will be collected for this study. This information, along with data from daily surveys, will be maintained in a password-protected drive accessible only by the researchers.

Aggregated data from all participants will be included in the write-up of the study, but no identifying information will be included. Identifying information will only be used to match data to participants during data analysis.

What is learned from this study may be presented at conferences, published in journals, or used to inform subsequent research. Your identifying information will not be included in any of these uses.

Voluntary participation and withdrawal:

You are not required to participate in this study. If you choose to participate, you may withdraw at any time without penalty. You may also choose not to answer questions that are included in each daily survey. If you choose to withdraw from the study, you may do so at any time by emailing the researcher. If you choose to withdraw from the study, you will no longer be entered into the raffle and your information will not be included in the final study.

Your participation in this study may be stopped at any time by the researchers without your consent due to administrative reasons. Participants who are removed from the study by the researcher will be withdrawn from the raffle and will not receive a data report.

Questions:

If you have any questions, complaints, or concerns about your participation in the study, please do not hesitate to contact me.

Eric Ekholm
ekholmeh@vcu.edu

703-434-9689

VCU School of Education

The researcher named above is the best person to contact with questions about your participation in this study.

If you have questions about your rights as a participant in this or any other research, you may contact:

Office of Research
Virginia Commonwealth University
800 East Leigh Street, Suite 3000
P. O. Box 980568
Richmond, VA 23298
Telephone: 804-827-2157

APPENDIX C – Demographic Questions

Q1: Please provide your first and last name.

Q2: Please provide your email address.

Q3: What gender do you identify as? (Response options will include Male, Female, Other - please specify, and Choose not to answer)

Q4: What race do you identify as? (Response options will include White, African American, Latinx, Asian, Two or More, Native American, Other - please specify, and Choose not to answer)

Q5: How old are you? (Open-ended response)

Q6: Which academic school or department are you primarily affiliated with? (Response options will include Education, English, Psychology, Sociology, History, Other – Humanities, Other – Social Sciences, Other – Hard Sciences)

Q7: During what time of the day do you typically write? (Open-ended)

APPENDIX D – “Gatekeeper” Email Template

Dear [NAME],

I am conducting a study investigating graduate student writers’ day-to-day writing behaviors and emotional experiences related to writing. You are receiving this email because you hold an academic position and are likely to have connections to several graduate students in writing-intensive disciplines. If possible, I would greatly appreciate it if you could forward the message below to any of your students or advisees who meet the following criteria:

- 1) the person is currently a graduate student,
- 2) the person is over the age of 18,
- 3) the person is enrolled in a writing-intensive discipline.

Alternatively, if you would be willing to send me the email addresses of potential participants who fit these criteria, I can send them the recruitment email directly.

Thank you for your assistance. If you have any questions about the project or would like more information, please feel free to reach out to me via email at ekholmeh@vcu.edu.

Best,

Eric Ekholm
ekholmeh@vcu.edu
703-434-9689

[INSERT TEXT OF APPENDIX A HERE]

APPENDIX E – Screenshots of Shiny App

Figure 15. Preliminary View of Shiny App.

Daily Writing Emotions, Attention, and Productivity Study

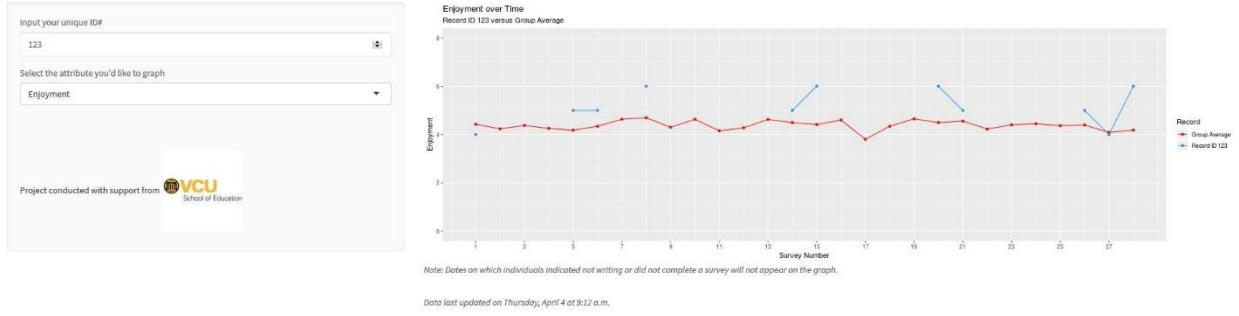


Figure 16. Final View of Shiny App, Screen 1.

Daily Writing Emotions, Attention, and Productivity Study

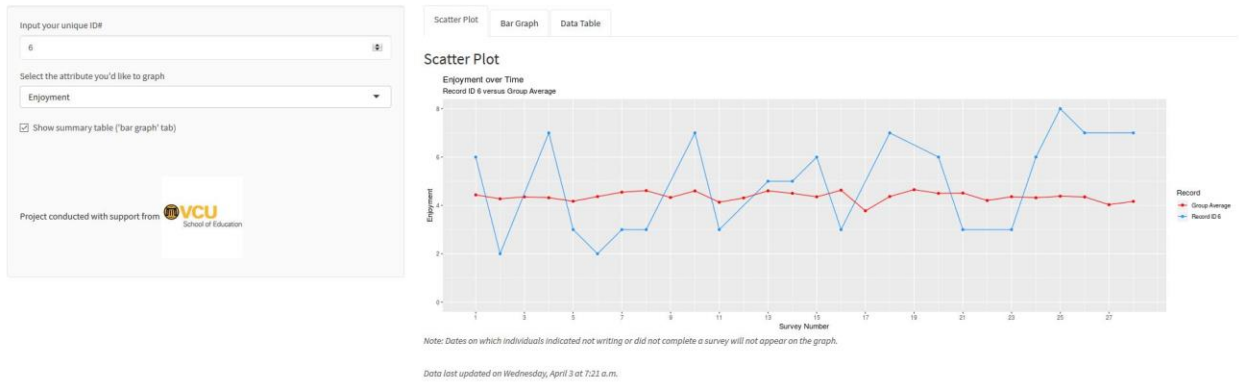


Figure 17. Final View of Shiny App, Screen 2.

Daily Writing Emotions, Attention, and Productivity Study

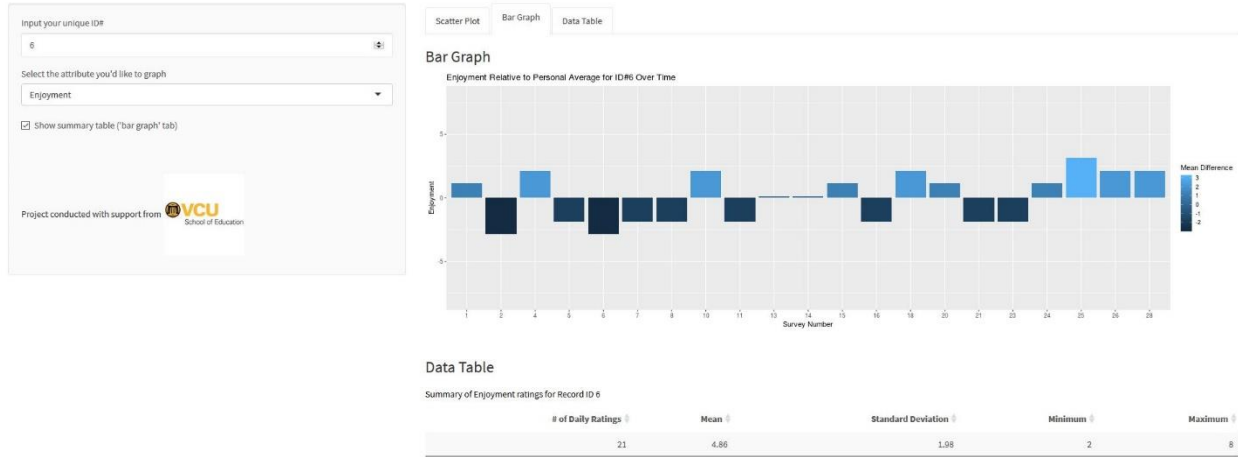
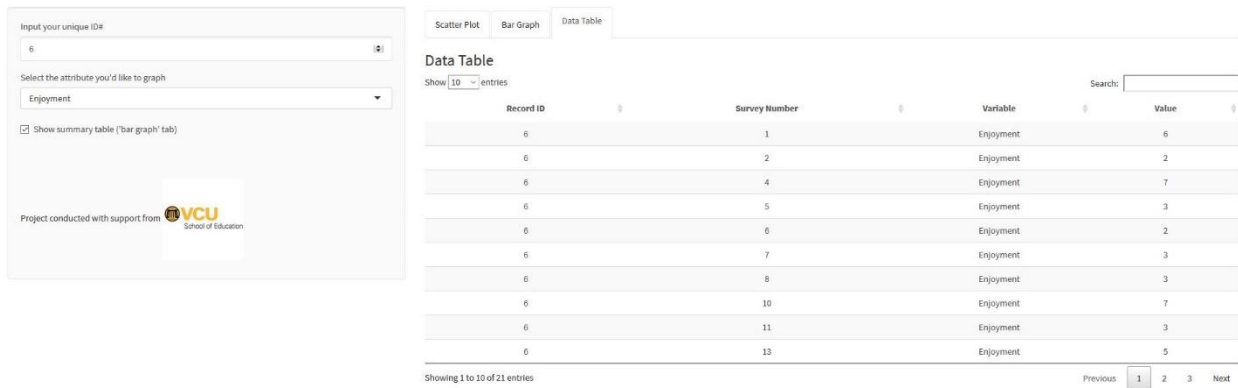


Figure 18. Final View of Shiny App, Screen 3.

Daily Writing Emotions, Attention, and Productivity Study



APPENDIX F – Daily Survey Questions

The following survey will ask you about your experiences and behaviors writing today. For the purposes of this study, writing refers to producing or revising a text that could be submitted for publication or as part of a class or work project. Writing in a journal would also qualify as writing in this study. Activities such as responding to emails, texting, or creating to-do lists would not qualify as writing.

Initial Items

1. Please provide your first and last name.
2. Please provide your email address.
3. Did you write today? (Response options: yes, no)
 - a. *Note that only participants who response “yes” to this question will be able to complete the remaining questions on the survey

Types of Writing Activities

Directions: Please indicate the types of writing activities you engaged in today. You may select as many options as apply.

1. Planning, including generating ideas and organizing ideas into a coherent structure.
2. Drafting, including generating new sections of text.
3. Revising, including considerably altering or rewriting previously drafted text.

Writing Context

1. Is the writing activity you worked on today an individual project or a collaborative project? (Response options binary: individual, collaborative)
2. Relative to your average, how much time did you have available to write today? (Response options: less time than usual, about as much time as usual, more time than usual)
3. When did you write today? Check all that apply. (early morning, late morning, afternoon, evening, night)

Emotion Items

Directions: Please indicate the degree to which you felt the following emotions while writing today, ranging from 1 (not at all) to 8 (very strongly)

1. Today when writing, I felt enjoyment.
2. Today when writing, I felt ashamed.
3. Today when writing, I felt anxious.
4. Today when writing, I felt proud.
5. Today when writing, I felt frustrated.
6. Today when writing, I felt bored.
7. Today when writing, I felt excited.
8. Today when writing, I felt confused.
9. Today when writing, I felt contentment.

Attention Regulation Items

Directions: Please indicate the degree to which you agree or disagree with the following statements, ranging from 1 (strongly disagree) to 8 (strongly agree)

1. While writing today, I made sure to concentrate on my work and not think about other things.
2. I managed to stay focused during my writing today.
3. While writing today, I avoided mental distractions.
4. While writing today, I was able to focus my attention on my writing tasks.

Productivity Items

Directions: Please indicate the degree to which you agree or disagree with the following statements, ranging from 1 (strongly disagree) to 8 (strongly agree)

1. Today was a productive writing day.
2. I was able to generate good ideas while writing today.
3. I was able to generate unique, creative ideas while writing today.
4. I made meaningful progress on my writing tasks today.

Open-Ended Productivity Items

1. Please indicate approximately how many **minutes** you spent writing today. You may include time spent revising or outlining in this estimate, but please do not include time spent doing background reading or other activities. (Open-ended response).
2. Please indicate approximately how many **words** you wrote today. If possible, please use your word processor's "word count" feature to help you make this estimate.

APPENDIX G – Writing Self-Regulation Scale Items Piloted

1. When writing today, I quit before I finished what I planned to do.
2. I worked hard to do well on my writing today even when I didn't like what I was doing.
3. When writing was difficult today, I gave up or only worked on an easy part.
4. I managed to keep writing today until I met my goals.
5. While writing today, I made sure to concentrate on my work and not think about other things.
6. I managed to sustain a high level of effort during my writing today.
7. While writing today, I was able to focus my effort on my writing tasks.
8. While writing today, I avoided mental distractions.
9. While writing today, I was able to focus my attention on my writing tasks.

APPENDIX H - Email Message Template for Daily Surveys

Dear [NAME],

Please complete the survey below regarding your writing experiences for [DATE]. Please complete the survey after you have finished writing for the day.

You may open the survey in your web browser by clicking the link below:

<LINK>

If the link above does not work, try copying the link below into your web browser:

<LINK>

Thank you for participating in this study of graduate student writers' daily experiences with writing. Your participation in the study is helping to advance our understanding of this area, and this knowledge will help support graduate student writers in the future.