

# Measuring Distributed Mentoring in an Online Fanfiction Community

Jenna Frens

A dissertation presented in partial fulfillment of the degree of

Doctor of Philosophy

University of Washington

2023

**Reading Committee:**

Cecilia Aragon

Benjamin Mako Hill

Sucheta Ghoshal

Katie Davis

**Program Authorized to Offer Degree:**

Human Centered Design & Engineering

© Copyright 2023

Jenna Frens

University of Washington

## Abstract

Measuring Distributed Mentoring in an Online Fanfiction Community

Jenna Frens

Chair of the Supervisory Committee:

Cecilia Aragon

Human Centered Design & Engineering

This dissertation approaches questions about how creators informally learn from their online networks using a human-centered data science perspective. Over the past few decades, participation in online communities has become a staple piece of how people engage with mainstream media, produce narratives, and develop creative skills. Informal exchanges of knowledge, feedback and support across networked spaces are key in the creative process and growth of today's creators. Distributed Mentoring provides a theoretical framework for how individually brief exchanges among a network of media producers and consumers may sum to a greater whole of mentorship. This dissertation expands on the rich lineage of ethnographic research in this area by contributing new quantitative analyses that model distributed mentoring in a large fanfiction community where millions of writers have participated for decades. In addition to contributing new findings about the structure and effects of distributed mentoring in the fanfiction community, this work demonstrates an interdisciplinary, human-centered approach to conducting data science for the purpose of studying online informal learning. I conclude with

implications for effective feedback exchange and network growth in creative communities, such as addressing socio-emotional needs, signaling interests and identities, supporting authentic relationships and designing inclusive and safe feedback environments.

## Acknowledgments

In my time working on this dissertation, I had the privilege of being around so many great people: collaborators, mentees, supporters, family and friends. To my advisor Cecilia Aragon, thank you for everything: for all of your support and mentorship, for accepting me as I am and for standing up for me during the difficult times. Thank you to my committee members, Mako, Sucheta Ghoshal and Katie Davis for supporting me through to the end of this journey. Thanks Pat Reilly for your warm encouragement—I don't think I'd be graduating without you. Thanks to senior students who showed me the way forward: Elena, Mia, Lucas, Rafal, Kristen and Mar. I would also like to thank my co-first-authors: Ruby Davis, Regina Cheng, John Fowler and Linda Wu. And to so many others who collaborated with me in the fanfiction data science research group: Jihyun, Nanchen, Niamh, G, Andrea, Kush, Mahir, Arthur, Isabella, Keri, Meena, Murtaza, Netra, Niharika, Rouxi, Sarah, Wei, Miaoxin, Matt, Trais and Zealer. I am incredibly honored to have worked with all of you! And an extra big thanks to Alyse Allred for nudging me to the finish line. Thanks Destination Toast for your support, encouragement and deep thoughts. Thanks to the folks at work who have been cheering me on: Vicky Springer, Lindsey Rasie, Victoria Hollis, Mark Nichoson, Alpa Dave, Chris Chapman, Samantha West and so many others. Thanks to my lovely chosen family, Andy, Lauren, Dani, Alyssa, Tony, Alec, Dave and Siah. Thank you to my parents, and my sister Leigh and her family Alex, Jack, and the yet-to-be-named baby due the same week as my graduation. Thank you Sara Cannon, my love. And last but not least, I wish to acknowledge and thank the anonymous members of the fanfiction community who participated in this research and made all of this dissertation possible.

# Contents

## Measuring Distributed Mentoring in an Online Fanfiction Community

Abstract

Acknowledgments

Contents

### Chapter 1: Dissertation Introduction

1.1 Chapter Overview

1.2 Motivation

1.3 Positionality

1.4 Research Questions

1.5 Methods

1.6 Contributions

1.7 Dissertation Overview

### Chapter 2: Related Literature

2.1 Chapter Introduction

2.2 Fanfiction and Distributed Mentoring

2.2.1 What is Fanfiction?

2.2.2 What Fanfiction Writers Learn

2.2.3 Distributed Mentoring in Online Fanfiction Communities

2.3 Affinity in Communities

2.3.1 What is a Community?

2.3.2 Participatory Culture

2.3.3 Discourse, Affinity and Networking

2.4 Feedback, Learning, and Human Centered Data-Science

2.4.1 Online Feedback Exchange Systems

2.4.2 Epistemological Divides in Feedback and Learning

2.4.3 A Human-Centered Data Science Approach

2.5 Chapter Conclusion

### Chapter 3: Reviews vs Lexical Development

3.1 Chapter Introduction

3.2 Do Fanfiction Reviews Lead to Writing Improvement?

3.3 The Fanfiction.net Dataset

3.3.1 Prior Research Contributions and the Web Scraper

3.3.2 Addressing Data Ethics

3.3.3 The Measure of Textual Lexical Diversity (MTLD)

3.3.4 Chapter Timestamps, Outliers and Language Detection

3.4 Models and Findings: The Abundance Effect of Distributed Mentoring

- 3.4.1 Profile Parsing and Computing Author Age
  - 3.4.2 Mixed Linear Modeling
  - 3.4.3 MTLT Increases During Late Adolescence
  - 3.4.4 MTLT Increases Over Time in the Fanfiction.net Dataset
  - 3.4.5 The (Negative) Immediate Effect of Increased Reviews on Lexical Diversity
  - 3.4.6 The Cumulative Effect of Reviews on Lexical Diversity
  - 3.5 Discussion
    - 3.5.1 Implications for Distributed Mentoring Theory
    - 3.5.2 Limitations
    - 3.5.3 A Look Ahead
  - 3.6 Chapter Summary
- Chapter 4: Deepening the Analysis
- 4.1 Chapter Introduction
    - 4.1.1 The Reverse Causation Hypothesis
    - 4.1.2 Modeling Different Types of Reviews
    - 4.1.3 The Effect of Sending Reviews
    - 4.1.4 Methodological Contribution of this Chapter
  - 4.2 Building a Machine Classifier for Fanfiction Reviews
    - 4.2.1 Qualitative-to-Quantitative Transformation
    - 4.2.2 Review Categories
    - 4.2.3 Coding Reviews
    - 4.2.4 Training the Classifier
    - 4.2.5 Author Sampling
  - 4.3 Expanded Model and Findings
    - 4.3.1 Autoregressive Linear Mixed Effect Models
    - 4.3.2 Model Constructs
    - 4.3.3 The Effect of Receiving Different Types of Reviews
    - 4.3.4 The Effect of Sending Different Types of Reviews
  - 4.4 Discussion
    - 4.4.1 Interpretation of Analysis Findings
    - 4.4.2 Implications for Distributed Mentoring Theory
    - 4.4.3 Methodological Contribution
    - 4.4.4 Limitations
    - 4.4.5 Looking Ahead
  - 4.5 Chapter Summary
- Chapter 5: Mentorship Network Structure
- 5.1 Chapter Introduction
  - 5.2 Dunbar's Layered Network Theory

## 5.3 Relationship Hierarchy in Distributed Mentoring networks

### 5.3.1 Research Questions

### 5.3.2 The Fanfiction.net Relationship Network Dataset

### 5.3.3 Categorizing Reviews Exchanged in Each Network Layer

### 5.3.4 The Optimal Value of K

### 5.3.5 Describing the 2- to 3-Layer Network Structure of Fanfiction Reviewing

### 5.3.6 Types of Reviews Exchanged by Layer

## 5.4 Written Interviews

### 5.4.1 Research Questions

### 5.4.2 Distributing the Written Interview

### 5.4.3 Survey Demographics and Mentorship Participation

### 5.4.4 The Value of Relationship Networks

### 5.4.5 Motivations and Networking Patterns

## 5.5 Discussion & Conclusion

### 5.5.1 Quantitative Discussion

### 5.5.2 Comparison with Facebook & Twitter

### 5.5.3 Contribution to Distributed Mentoring Theory

### 5.5.4 Design Implications

### 5.5.5 Looking Ahead

## 5.6 Chapter Summary

## Chapter 6: How Reviews Predict Continued Participation on FanFiction.net

### 6.1 Chapter Introduction

#### 6.1.1 The Effect of Affect

#### 6.1.2 Methodological Contribution of this Chapter

### 6.2 Methodology

#### 6.2.1 Survival Modeling in Social Computing

#### 6.2.2 Determining the Appropriate Model

#### 6.2.3 Visualizing Kaplan-Meier Curves

#### 6.3.4 Significance Testing with the Peto-Peto-Prentice Test

#### 6.3.5 Building a Parametric Model

#### 6.3.6 The Weibull Distribution

#### 6.3.7 Building an Analysis Dataset

#### 6.3.8 Description of Analysis Dataset

### 6.4 Conducting Survival Analysis

#### 6.4.1 Checking Assumptions

#### 6.4.2 Kaplan-Meier Curves and Peto-Peto-Prentice Significance Testing.

#### 6.4.3 Parametric Weibull Modeling.

### 6.5 Findings

- 6.5.1 Model Specification and Validation
  - 6.5.2 Checking Assumptions
  - 6.5.3 Kaplan-Meier Curves and Peto-Peto-Prentice Significance Testing
  - 6.5.4 Parametric Weibull Modeling
  - 6.6 Discussion
    - 6.6.1 Interpretation of Findings
    - 6.6.2 Implications for Distributed Mentoring Theory
    - 6.6.4 Limitations & Looking Ahead
  - 6.7 Chapter Summary
- Chapter 7: Fanfiction Writer Interviews: A Case Study of Online Fanfiction Writers
- 7.1 Chapter Introduction
    - 7.1.1 Seeking Feedback: How Writers Build Connections
    - 7.1.2 Online Feedback Exchange
    - 7.1.3 Online Affinity and Fanfiction Writers
  - 7.2 Method: Interviewing Writers
    - 7.2.1 Participants and Recruitment
    - 7.2.2 Semi-Structured Interviews
    - 7.2.3 Qualitative Data analysis
    - 7.2.4 Researcher Positionality
  - 7.3 Findings
    - 7.3.1 How do fanfiction writers seek feedback in online affinity networks?
      - 7.3.1.1 “Throw Ideas at Each Other”
      - 7.3.1.2 “Give My Friends a Little Snippet”
      - 7.3.1.3 “Beta Reading”
      - 7.3.1.4 “All I Want for Christmas are Reviews”
    - 7.3.2 How do fanfiction writers identify affinity and build online connections for feedback?
      - 7.3.2.1 Connecting Through Public Comments
      - 7.3.2.2 Participating in Social Events
      - 7.3.2.3 Just Reaching Out
      - 7.3.2.4 Engaging in Small Private Communities
      - 7.3.2.5 Disclosing Identities
  - 7.4 Discussion
    - 7.4.1 Social needs in feedback exchange throughout the creative process
    - 7.4.2 Feedback and Relationships From Public to Private Spaces
    - 7.4.3 Feedback and the ecology of online spaces
    - 7.4.4 Design Considerations For Supporting Online Feedback
      - 7.4.4.1 Address a range of social needs in feedback

- 7.4.4.2 Help feedback seekers signal interests and identity
- 7.4.4.3 Support authentic relationships in feedback exchanges
- 7.4.4.4 Build inclusive, safe spaces for feedback
- 7.4.4.5 Implications for Fanfiction Writers

#### 7.5 Chapter Summary

### Chapter 8: Dissertation Conclusion

#### 8.1 Chapter Introduction

#### 8.2 The Importance of Distributed Mentoring Fanfiction Communities

#### 8.3 Review of Findings

#### 8.4 Contributions to Theory and Practice

#### 8.5 Conclusion

### Contribution Statement for Coauthored Chapters

### References

# Chapter 1: Dissertation Introduction

## 1.1 Chapter Overview

This dissertation explores mentoring among fanfiction writers using a human-centered data science approach. Fanfiction communities provide space for people to express themselves creatively, connect with others who share their interests and grow into themselves. This powerful phenomenon of connection over the internet warrants exploration. In particular, this dissertation will focus on the mentoring networks that support writers. Can we measure the effects of distributed mentoring on writers? How do writers build their networks? And how might we facilitate the connection and feedback we have observed in the fanfiction community? In this chapter, I will start by describing the motivation for studying fanfiction communities, as well as my own positionality within this work. Then, I will introduce the key research questions that this dissertation will answer, followed by an overview of the mixed-method approach and description of the methods of each chapter. Finally, I will summarize the contributions of the body of research presented throughout this dissertation's chapters, and outline what's ahead in the remainder of the document.

## 1.2 Motivation

Our world is in panic. I conducted the research of this dissertation at a time when the culture around me was hyperfocused on pandemics of misinformation, facism, racism, transphobia and, of course, COVID-19. At times like these, it is important not only to understand societal failures and disrupt the power structures that create them, but also to envision and create alternative spaces that model the world we wish to see. Fandom communities are lasting alternative spaces

that have been around on the internet since the very beginning [36,62]. These communities have undermined commercial dynamics that centralize media production [110] and transformed mainstream narratives to fill gaps in representation and imagine new worlds [188], making visible narratives from historically underrepresented perspectives [253]. In addition to this cultural impact, fanfiction communities have provided space for millions of people to develop literacy practices. Fanfiction communities are interesting to study because they can give us insight about human connection, learning, and creative development as they are mediated over the internet today.

Research in fanfiction, especially early on, has needed to respond to a disparaging academic culture by establishing legitimacy [33]. I personally have had the experience of being laughed at by an entire statistics classroom in response to stating that I study fanfiction, and I have received plenty of non-constructive anonymous comments from academic conference reviewers. On the other hand, I have also met researchers who jump up and down when they learn what this dissertation is about, I have received effortful academic conference reviews and I've presented to filled rooms at fan conventions. To a certain extent, I feel that my audience either intuitively understands why fanfiction research is valuable, or refuses to listen in the first place. In any case, one of the primary motivations of this research is to continue to extend the legitimacy of research in this space by contributing to the body of evidence that shows how fanfiction positively impacts millions of people.

This dissertation in particular focuses on developing the theory of distributed mentoring, which accounts for how people informally learn in online networks [6]. Understanding how people

develop creative practices through informal, networked interactions is important because increasingly, this is how literacy skills and domain expertise are learned [242]. Educational institutions learned the hard way during the COVID-19 pandemic that face-to-face modes of learning do not simply translate to distributed settings. More infrastructure in support of distributed learning might have helped to mitigate the disastrous consequences of the COVID-19 lockdown for schools worldwide [32]. In any case, younger generations are not waiting for institutions to adapt to rapidly changing technologies – increasingly, they are learning the skills needed to participate in 21st-century society by participating in online communities.

Our work is situated in fanfiction because these communities are well-established as exemplary spaces for studying media engagement, literacy development and informal learning [23,143,145,149,154]. Additionally, Fanfiction.net is a suitable choice for extending the theory of distributed mentoring because this enables us to directly build on the prior work by Evans et al. [2017], which qualitatively analyzed reviews from three Fanfiction.net sub-communities. Fanfiction.net [185] was also the longest-standing, largest archive of fanfiction at the time of our analysis, which enabled us to conduct longitudinal analyses of writing development at an unprecedented scale.

Finally, an important piece of the motivation for this research is to give back to the fanfiction community. Throughout the years, we have communicated our findings back to the spaces where we recruit fanfiction writers, we have presented at GeekGirlCon panels about fandom and statistics, and we have striven to conduct work that has useful implications for writers and researchers alike. We wish to encourage media fans to engage with data science, and scientists to

engage more with fandom. To that end, I hope this dissertation is interesting and useful to readers at this intersection.

### 1.3 Positionality

*Positionality* is a term “that describes how individuals come to knowledge-making processes from multiple positions, including race, gender, geography, class, ability and more” [78].

Researchers disclose their positionality so that research can be considered in context, a part of transparency that is especially important in data science [78]. Considering one’s own positionality is an important piece of *reflexivity*, the ability to reflect on and take responsibility for one’s own position, which in turn, promotes fairness in data science [78]. In this section, I will disclose my positionality with respect to the research presented in this dissertation.

These are some of the words I use to describe my identity today: I am white, trans, autistic, a PhD student, a professional data scientist, a gamer and a pole dance instructor. I cannot help but reflect on my self-discovery over the past few years. My identity has changed over the course of this research as I have come out as transgender and transitioned, and come out as autistic and unmasked. Trans identities and neurodivergent special interests are more accepted in fanfiction communities than in the communities I experienced growing up. Conducting research in a space where it was safe to be me, and where my participants made me feel at home, was a positive influence that helped me to grow in my own identity. In the course of this development I built a sense of deep connection to this research and to the fanfiction community.

Other aspects of my position have also influenced my approach to this research. I was a computer nerd from a young age, and became a self-taught programmer and hacker as a teenager.

My first involvements in online affinity spaces were also at this time in my youth. My love for independent learning, online communities and computer science culminated in a double-major in Computer Science and Psychology with a Human-Computer Interaction minor at Carnegie Mellon University, which is where I was also exposed to research in learning technologies and first met researchers in the field. In addition to motivating my PhD in the space, there are clear influences from my undergraduate education in the literature framing this dissertation. When I initially became involved in the Human-Centered Data Science Lab, I was an outsider to fanfiction, but I jumped into the research because of my experiences of online community and informal learning. In becoming a part of the fanfiction community, I learned I was not just studying learning, but connection, identity and belongingness.

#### 1.4 Research Questions

The research questions of this dissertation call for different approaches to describing distributed mentoring, with the goal of triangulating quantitative and qualitative knowledge. We ask the following:

1. Can we measure the effects of distributed mentoring on writers?
2. How do writers build their networks?
3. How might we facilitate the connection and feedback we have observed in the fanfiction community?

In the following section, I will introduce the methodological approach behind these questions – why we have started with quantitative questions and moved to qualitative questions, and how this reflects an human-centered approach.

## 1.5 Methods

This dissertation approaches the research questions we've described above with a *human-centered data science* approach [9], drawing from methods in human-computer interaction, social science, statistics and computational techniques to better inform data science practice [9]. We will answer our research questions with an interdisciplinary mixed-method approach that incorporates qualitative research methods and computational analysis of the fanfiction community. In the early chapters of this dissertation, we focus on integrating prior ethnographic research conducted by Evans et al. [2017] into quantitative models of distributed mentoring. To do this, we collected a massive dataset of fanfiction text and review data, manually categorized thousands of fanfiction reviews using Evans et al.'s [2017] taxonomy, and trained a machine classifier to automate the classification of millions of reviews. The strength of this *qualitative-to-quantitative transformation* [65] is that we preserve contextual knowledge about the types of reviews understood by ethnographic research, while scaling our ability to analyze reviews to a level only attainable through computation. In addition, we introduced new dependent variables to measure the effects of reviews on developmental changes in fanfiction text as well as continuing participation in writing. As a result, we were able to build longitudinal models that measure the impact of distributed mentoring on writers.

This dissertation introduces innovative machine learning methods in order to study distributed mentoring and informal learning. In addition to building a machine classifier for fanfiction reviews, we adapted statistical models from other fields to our data, including: autoregressive linear mixed modeling [12], survival modeling [181,208,221,272], and relationship network modeling [85,192]. Each analysis is groundbreaking in this field, and to the knowledge of the

authors, is differentiated from prior research both by the model's use in informal learning, and by our integration of qualitative research into each statistical model. We describe these methods in depth in the methods section of each chapter in order to promote more use of data science in informal learning research. Later in the dissertation, we turn towards *quantitative-to-qualitative explanatory designs* [65], which connect insights from our large-scale analyses back to the experiences of fanfiction writers. Explaining why we observed patterns in lexical development, participation, and network building is important for contributing strategies that designers and community members can use to facilitate distributed mentoring. By using a human-centered approach, we are able to not only uncover evidence that builds the theory, but implications that we can contribute back to the community. We outline the contributions of this dissertation next.

## 1.6 Contributions

In answering our research questions with innovative mixed-methods research, this dissertation contributes interdisciplinary research to the fields of informal learning, human-centered data science, and computer-supported collaborative work. I have summarized our contributions here:

1. We contribute novel mixed-method analyses and quantitative models of distributed mentoring that uncover new evidence in support of the theory.
  - a. We measured longitudinal changes in fanfiction, showing how distributed mentoring together with maturation contribute to lexical development in adolescent writers. Our model predicts that an adolescent writer who has accumulated roughly 700 reviews will write at the same level as if they had aged (matured) by one year. To the knowledge of the authors, this longitudinal investigation of lexical development in over 1 million people is the first of its kind.

- b. We categorized reviews into three types and measured corresponding changes in lexical diversity, contrasting shallow positive, targeted, and update encouragement reviews in terms of effects on lexical development. We triangulate this new evidence with prior ethnographic research regarding writers' perceptions of the different types of reviews, finding support for the notion that large numbers of shallow reviews can provide developmental support.
- c. We tested the hypothesis that fanfiction writers learn from reading and reviewing others' fics by modeling the effect of sending reviews, adding another previously-unexplored dimension to our model. We found that sending targeted reviews is predictive of more rapid increases in lexical diversity in comparison to sending update encouragement and shallow positive reviews, contributing new data in support of predictions made by distributed mentoring theory.
- d. We contribute a network structure analysis of distributed mentoring networks, showing how connections between writers and reviewers are organized into layers. Highly active fanfiction writers tend to have a small, inner group of reviewers who review almost everything the writers publish, and larger outer groups that review on a less frequent basis. We describe the types of reviews exchanged in each layer, and complement the analysis with perspectives from writer interviews.
- e. We measured the motivational effect of distributed mentoring on fanfiction writing using survival modeling. Our parametric model makes predictions about how likely authors are to continue writing, and measures the extent to which

receiving more reviews can influence this probability. This quantifies the affect attribute of distributed mentoring on Fanfiction.net.

- f. We contribute a new grounded theory of strategies for building mentoring connections and gathering creative feedback, which we developed from a series of 29 interviews with fanfiction writers. In addition to deepening knowledge about how distributed mentoring occurs across an ecosystem of online platforms, we connect our observations about writers' feedback practices with stages in their creative processes, revealing differences in how writers solicit feedback for ideation, early work, high-fidelity drafts and complete stories.
  - g. We identified key social barriers to building effective feedback networks, outlined strategies that fanfiction authors use to build their networks and contributed implications for design researchers to facilitate better feedback. We also pass on advice from our interviews about how new writers can build connections.
2. We contributed to human-centered data science methodology by expanding prior methods through the incorporation of new machine learning and statistical analysis techniques, many of which are also novel in online informal learning research.
- a. We trained a machine learning classifier to categorize fanfiction reviews by qualitative types so that they could be used to model the effects of feedback. This is a novel technique built on the qualitative-to-quantitative transformation method proposed by Scott et al. [2010] In the process, we improved on ALOE [34] by using a neural network algorithm to achieve greater accuracy in short-text classification. The prior implementation for ALOE classified texts using a simple

Support Vector Machine (SVM) [250] solution, whereas we used Bidirectional Encoder Representations from Transformers (BERT) [77].

- b. We introduced a novel use of autoregressive linear mixed modeling to study online informal learning, contributing an approach to understanding the effects of feedback on writing development situated in a space where pre-post experiments are not possible. This method may help to generate quantitative findings in informal settings that can be compared to experimental designs used more frequently in learning sciences.
- c. We adapted Dunbar et al's social network structure analysis method to uncover the layered structure of distributed mentoring on Fanfiction.net. In addition to being the first such application of k-means clustering method to understand relationship networks in a learning context, we incorporated the method into an quantitative to qualitative explanatory mixed methods design, demonstrating how rich contextual insight can complement this data science technique.
- d. We conducted survival model analysis on the Fanfiction.net dataset, which was a novel application of this class of models in the space of studying online informal learning. In particular, we demonstrated the first use of the weighted-residuals score test and the Peto-Peto-Prentice significance in this field. The weighted-residuals score test is crucial to determining the type of survival model to use, and Peto-Peto-Prentice significance testing enables hypothesis testing across categorical groups. We wish to encourage more use of these fundamental survival analysis techniques in human-computer interaction research.

- e. Throughout the dissertation, we contribute in-depth explanations of our methods.

Although we cannot share the dataset used across much of our analyses due to our ethical obligation to preserve fanfiction writers' right to remove their data from the public internet, we hope that the high detail enables the data science techniques we used to be replicated in future research.

## 1.7 Dissertation Overview

To conclude this chapter, I will look ahead to each of the remaining chapters in this dissertation and summarize the contents with respect to the overarching research questions and methodology.

Chapter 2 situates the research of this dissertation in prior lineages of research about fanfiction, learning communities and data science. I will describe theories and methodologies emerging from each of these fields and their relevance to the phenomena under study in this dissertation. This chapter also examines distributed mentoring theory in depth to drive research questions that will be approached throughout the document. I also discuss our methodology, and how a human-centered data science approach to studying fanfiction communities has unique potential to contribute new knowledge to the space. Finally, I overview the particular machine learning and data analysis techniques used in our work.

Chapter 3 is about developing an approach to measuring the effect of distributed mentoring on writing. We examine the question of how much the accumulation of reviews by fanfiction writers can affect their writing development. Additionally, this chapter describes the key dependent variable of lexical diversity as well as outlining mixed linear models we used to longitudinally measure lexical development. Our findings reveal measurable differences in writing over time as

writers accumulate reviews from their audiences. The discussion of this chapter poses implications for distributed mentoring theory and sets the stage for continuing analysis throughout the remainder of the dissertation.

Chapter 4 significantly expands on our initial approach to measuring the effect of distributed mentoring on writing by asking and answering new research questions about how reviewing behaviors on Fanfiction.net affect lexical development. I describe in depth how we trained a machine classifier for fanfiction reviews. We also use autoregressive mixed linear modeling in order to address the reverse causality limitation (i.e., we eliminate the claim that our findings can be explained by lexical development causing increased reviews). Fitting our model to the Fanfiction.net dataset, we show how different types of reviews affect lexical development, and measure how the act of writing reviews can impact authors' writing. We discuss implications for distributed mentoring theory, such as how encouraging specific reviews and reciprocal interactions can facilitate a better learning environment.

Chapter 5 describes the network structure of communities that support writers. By *mentorship network structure*, we mean the layers of socially cohesive groups involved in mentoring. This structure is defined by the closeness and number of people's relationships, which can be organized into layers. We ask how many layers are typical in a distributed mentoring network, and how reviewing behaviors differ in each layer. In addition to using machine learning techniques to cluster and describe the network structure of the Fanfiction.net dataset, we integrate author interviews for additional depth, explaining the value of different relationships and the strategies writers use to build their distributed mentoring networks.

In Chapter 6, we examine the question of whether reviews have a motivational effect on fanfiction writing. In particular, we introduce survival analysis as a method for quantifying the effect of feedback on the probability of continued chapter publication. We find that differences in the amounts of reviews are correlated with dramatic changes in participation rates. Our model establishes the size of that relationship on a large, longitudinal sample, supporting the distributed mentoring theory claim that reviews motivate and provide direction to authors. Our result provides insight into the benefit of affective support writers receive from reviewers by showing how much support is needed to have an influence on writer behavior.

Chapter 7 explores fanfiction writers' feedback practices through interviews with writers in order to unpack social and psychological challenges that writers face as they build connections and seek feedback from their networks. We highlight the strategies writers have used to overcome these difficulties, as well as the community practices among writers that help to facilitate connection and support. In particular, we identify four distinct practices throughout the creative process that writers use to get feedback corresponding to their needs. Our findings surface the importance of affinity and trust in online feedback exchange, holding key implications for feedback exchange systems across creative domains. We pass on advice from our interviewees to other writers and outline design considerations that address a range of social needs in feedback, including helping feedback seekers signal interests and identities, supporting authentic relationship-building during feedback exchange, and building inclusive, safe community spaces for feedback.

Finally Chapter 8 concludes this dissertation with a discussion of the implications and contributions of research presented throughout the previous chapters. To contextualize this discussion, in the first section of this chapter I overview the motivations and research questions pursued in this line of research. Then, I review the primary findings of each chapter, and how they contribute to distributed mentoring theory. Finally, I discuss this work's contributions to the methodology of human-centered data science, as well as implications for designing human-centered systems that support creative growth and feedback exchange.

## Chapter 2: Related Literature

### 2.1 Chapter Introduction

This chapter situates the research of this dissertation as a set of cross-disciplinary, mixed-method analyses that intersects with lineages of study centered on fanfiction, learning communities and human-centered data science. In this chapter, I will describe theories and methodologies emerging from each of these fields, their relevance to the phenomenon of mass youth participation in transformative writing, and how the chapters that follow in this dissertation will contribute evidence and elaborate on theories. Then, I will discuss our methodology: a human-centered data science approach to studying fanfiction communities, and its potential to unlock knowledge about how future generations of people will grow their skills and identities in creative online communities.

### 2.2 Fanfiction and Distributed Mentoring

In this section, I will delve into the rich body of research surrounding fanfiction. By interrogating the very definition of fanfiction, I will tie different views of what fanfiction *is* with academic topics of interest to researchers who study fanfiction and fandom. Next, I'll focus more specifically on the study of learning in fanfiction communities, reviewing prominent work in the area and key findings that will inform discussions throughout this dissertation. Finally, I'll introduce distributed mentoring theory, the focal point of this dissertation's work, its theoretical underpinnings and prior research that has developed important aspects of the theory.

### 2.2.1 What is Fanfiction?

To begin unpacking perspectives of fanfiction (sometimes called “fanfic” or “fic”), I will start by interrogating its definition. My simple definition of fanfiction is that it is a type of written work, produced by fans, that borrows elements such as concepts, characters, or settings from popular media. Although simple enough at a surface level, this definition raises questions. Who counts as a fan [37]? Do literary classics that reference other text, such as John Milton’s *Paradise Lost*, fit within the definition of fanfiction [255]? What constitutes the difference between a fanfic and an original piece of “popular media”? The answers to these questions are socially negotiated, and therefore the boundaries of what can be considered a work of fanfiction are blurry. Arguably, “fanfiction” is a lens for looking at remixing, transformation and affect in creative work, rather than a strict ontological category [266]. Therefore, rather than strictly define fanfiction, I’ll enumerate conceptualizations of fanfiction from the field of fan studies that will be useful in the context of this dissertation and its work within fanfiction communities.

In many ways, fanfiction is defined by its contextualization within fandom communities tracing back to Trekkies of the 1960s [62]. Fandom describes the emotional connection people feel towards a media universe and the community that forms around it. The participants of a fandom are fans. By etymology, “fan” is short for “fanatic,” someone who is zealously devoted to and energized by the subject of their fanaticism [152]. This is historically rooted in an assumption that fans are disproportionately interested, and therefore socially deviant, invoking stereotypes and judgments that are rooted in patriarchal (and neurotypical, I would add) values [255]. Within fan studies, a more widely accepted definition of “fans” positions them as people of deep passion who engage in fannish practices and culture – that is, they partake in fandom by consuming and

producing language, knowledge, art, and history (e.g. fanlore) that is specific to their particular fan community [50,81]. One fannish practice of particular relevance to this dissertation is the practice of reworking published media to create fan content that has new meaning [152]. With the caveat that not all self-identified fans participate in fandom, and fannish activities fall along a wide spectrum [37], we may view fanfiction as a type of written fanwork produced by a fan for an audience of others in the fandom.

Fanfiction together with other fanworks may also be viewed by their legal status (in the United States, Canada and Europe) as transformative works [257]. Transformativeness describes the extent to which a new work has meaning distinct from the original, contributing societal benefit and differentiating copyright infringement from fair use. From this perspective, research demonstrating the educational and cultural benefits of fanworks is essential to upholding their legal protection [182,258]. Additionally, commercial impact is both a legal consideration during cases and often the motivation for copyright holders to pursue legal cases in the first place. One of the strongest ways fanfiction writers can protect themselves in a world where a few powerful businesses own most copyrighted work is to keep their work non-commercial [14]. And fanfiction writers who do wish to commercialize their work may remove copyrighted elements, turning fanfiction into fiction. Most famously, *Fifty Shades of Grey* writer E. L. James rose to popularity writing *Twilight* fanfiction, decided to commercialize, and made changes such as rewriting the fic's version of teenage vampire Edward Cullen into the wealthy CEO Christian Grey. Changing 11% of the fic's text, she transformed her fanfiction into original copyrighted fiction, and not without controversy [156]. The extent of transformativeness from *Twilight* copyright was not disputed, rather, this high-profile case of pulling-to-publish elevated questions

about the commercialization of fanwork, and in particular, the exploitation of communal fan labor for profit [205].

Non-commerciality is widely considered to be a defining characteristic of fanfiction, not only because fanfiction writers need to protect their work as fair use under copyright law, but because the fan community has developed their own value system for creative ownership that is alternative to commercial and legal systems. For many fans, the non-commercial exchange of creative work in fandom is participation in a gift economy [160]. This aspect of fannish culture was solidified even in pre-internet fan convention culture, where fanzines and other fanworks were distributed at-cost or in trading circuits [11]. In the decades since, fanfiction communities have butted heads with commercial entities which have sought to exploit fan labor for profit. In one prominent case, controversy surrounded FanLib, a website that held fanfiction writing contests requiring writers to forfeit their rights in order to participate [74]. Beyond labor issues, censorship and content deletions have contributed to a history of repeated community migrations from one fanfiction website to the next [99]. As a result, fans self-organized to create the non-profit website Archive of Our Own (AO3) in order to build a free exchange and protect writers' content, as well as to instill their values in the design of the site [100]. These are feminist values that trace back to the decades of women-led fandom predating the internet, such as inclusivity and non-censorship, protection of identities, attribution of remixed content and the preservation of community history [100]. However, in naming non-commerciality as a defining characteristic of fanfiction, I am not claiming that all fans have a singular position within the gift economy, or full agreement with the values of Archive of Our Own. For example, women fanfiction writers who have built careers in publishing have expressed viewpoints of the gift

economy ranging from a restrictive obligation to a nurturing developmental space, revealing a more fluid, liminal role for fan spaces in career development [103]. And beyond fanfiction, fanworks that have material costs such as print fanzines continue to face legal threats and production barriers as fan creators try to recoup expenses [3]. Works that are sold at-cost fall somewhere between commerciality and gift, again showing that there is not a clear binary. Nonetheless, viewing fan works as non-commercial provides a useful lens for articulating the educational and developmental benefits resulting from gift culture.

Fanfiction creates opportunities for people who are marginalized to tell their own stories, reimagining and subverting mainstream narratives [253]. Fanfiction has been studied as part of constructing queer female space [188], and creating discourse that subverts heterosexuality and gender [39]. In a (cis)heteropatriarchal society where media largely centered on male characters, male gaze, and heterosexual relationships throughout the 1960s, 70s and 80s, female fans of *Star Trek* and *Sherlock Holmes* wrote fanfiction exploring homoerotic relationships between the lead characters, developing the genre known as slash [11]. Much of the organizing behind fan conventions, zines and cosplays happened inside people's homes, in small, tight-knit communities [11]. By the 1990's, at a time during the internet's early days when the vast majority of internet users were men, women began creating private cyberspaces in the form of email distribution lists, where they could, for example, safely host discussions applying a female gaze to David Duchovny of *The X-Files* without interference from the show's male audience [36].

Fanfiction gives transgender people the opportunity to challenge cissexism by reimagining cisgender characters as trans [87,235]. This contributes to important discourse that helps trans people to feel less alienated and to navigate their own identity development in a world where even children's book authors politicize trans bodies [82,83]. In the process, LGBTQ people construct safe online spaces where this recovery work can take place [88]. Fandom also attracts neurodivergent people, who, seeing characters in media that are coded as neurodivergent (but rarely explicitly stated as so), reinterpret them as such [194,207]. Autistic people cast autistic characters in their fics, diversifying the available representations of autistic characters and disrupting common tropes about autism [19]. And despite fandom's (and moreover, the fan studies field's) predominant whiteness [216,249], fans of color have been present in fan communities since they were first studied [36]. Fans have engaged in discourse with white-centered media by "racebending" – creating fanart and fanfiction that recasts popular media introducing racial diversity [107,122,220].

In summary, fanfiction is a practice contextualized by participation in fandom, that remixes content from copyrighted media, transforming it. Fanfiction is most often produced as a gift to the community, and is part of constructing social bonds between people in fandom. Fanfiction provides opportunities for people who are marginalized to challenge narratives where they are misrepresented or completely left out, developing their own identities and building communities in the process. Over the last two decades, massive groups of fans have gathered in online platforms such as Geocities, LiveJournal, Fanfiction.net, Tumblr, Wattpad and Archive of Our Own. However, we will find in our own investigations that follow in the chapters of this dissertation, that fanfiction communities today are tied to the cultural lineage outlined by fan

studies pioneers such as Bacon-Smith, Jenkins and Bury, as predominantly queer and female spaces where writers collaborate to transform mainstream narratives. Today's fanfiction is primarily published and distributed online within fanfiction communities and archives, such as Fanfiction.net and ArchiveOfOurOwn. These sites are particularly popular among young people and represent part of a greater movement of youth participation in online digital media.

### 2.2.2 What Fanfiction Writers Learn

In the course of writing and participating in fandom, fanfiction writers develop important skills that will serve them throughout their lives, including language development, identity development, and media literacy skills [21,24,25,167]. What fanfiction writers and other participants in fandom learn goes beyond traditional media literacy (e.g. reading comprehension, descriptive writing) into expansive forms of literacy such as networked and collaborative information gathering, shaping media distribution through social media, integration of information across modalities and critically evaluating information sources [61,151,242]. And in the course of interacting with their fan communities, writers learn the knowledge and practices needed to navigate the community, develop their practices and grow in their identities – in other words, they learn how to present themselves as individuals to their audiences [24,118].

Researchers have approached the study of learning in fanfiction primarily from two angles: understanding how fandom and fanfiction communities support learning naturalistically (e.g., Ito 2012), and developing practices that support learning by integrating fandom and fanfiction activities into classroom and extra-curricular settings (e.g., Howell [2018] [136]). In either case, this research underscores the powerful, positive impact of participation in fanfiction on learning.

One of the most prominent effects of participation in fanfiction practices on writers is language development. This connection is well-demonstrated in case studies of multilingual English language learners who read and write fanfiction: they get connected with a supportive community, build confidence, break through social isolation, establish a writing practice, and continuously receive feedback [20,183,236]. These learners attribute the English language skills they've built to participation in writing fanfiction in English, as well as reading fanfiction and interacting with other fans. Additional case studies show students develop literacy practices outside of school while participating in fanfiction [49]. This happens because the affordances of participating in fandom are more expansive than the affordances of an English class (e.g., continuing a story that was well-received by an authentic audience) [178]. Fanfiction writers build interactive language skills as they engage in discussion with other fans. The community's culture of encouragement, constructive feedback, and collaboration provides focused and individualized grounds for improvement, and affords writers the opportunity to ask specific questions of reviewers, receive grammar corrections, and get feedback [23]. The growing body of evidence built on studies of fanfiction writers stands in direct contrast with mainstream media narratives that purport literacy is declining among younger generations due to the internet and social media [17,48], scholars have observed that literacy has been fundamentally revolutionized in the last two decades.

Fanfiction has stood at the forefront of radical changes to how literacy is both learned and practiced in the 21st century. In one analysis, the practices of middle-school fanfiction writers were observed to be demonstrative of multiliteracies [61]: characterized by multimodal blending of visual and textual content, intertextual connections to both the original media and discourse

within fandom, and hybrid genres [49]. Over time, the term “new media literacies” came to describe a variety of activities observed in the consumption and production of content seen in fandom and across media culture [151]. For instance, fan producers of all kinds acquire unique, contextualized vocabularies as well as skills in creating, editing and remixing hybrid media types as they learn to participate in niche communities [142]. Additionally, fanfiction writers learn to engage with media critically, disputing cultural representations of their identities by inserting their own voices into their texts and engaging in discourse with their readers [24]. And in addition to this, fanfiction writers learn to produce and engage in creating in a way that is deeply collaborative, promoting shared authorship and a sense of community as authors negotiate meaning together with fans [38,153]. The fanfiction-writer-driven development of Archive of Our Own stands as an example of how the community has built technical literacy in coding among its members [101].

Crucially, identity development and lexical development are inexorably linked. Identity work is a process whereby they construct their sense of self through narrative-building and position themselves within their communities [88,262]. Building identity is socially negotiated, and involves building knowledge and learning the activities and language of the identity a person wants to take on [118]. For instance, in a study of One Direction fanfiction writers, “being and being recognized as a true fan or fangirl carried with it the liability of knowing specific facts about the band, writing in an emotional cadence, and leveraging certain symbols and texts” [167]. In another case, as a multilingual learner began writing fanfiction in English, she positioned herself as an English language learner in her author notes, prompting her audience to respond with social support and gentle language-related feedback. She additionally adopted

language to establish herself within adolescent popular culture, and further repositioned her identity to emphasize her heritage as she began writing multilingual narratives [21]. In doing identity work, Queer people also pick up new language as they connect with others and re-construct narratives. For example, 14 out of 31 queer participants interviewed by Dym et al. [2019] first encountered the words they today use to describe their gender identities or sexual orientations from fandom.

Education researchers have argued that fan practices could be transferred into classroom practice in order to enhance learning, by leveraging the motivational benefits of interacting with a live audience, remixing and transforming existing content and creating multimodal content [6,67,187]. And there is a growing body of research about this potential pedagogical development. For instance, in one high school class inspired and modeled after fanfiction, students collaboratively co-authored a fantasy world, reading fantasy classics, sharing their own writing and commenting on each-others' work [229]. In a first-year university course for future English teachers, students worked in role-play groups to co-write missing scenes from *The Hobbit*, a task leading to lexical development as students strove to replicate J.R.R. Tolkien's writing style [238,239]. In an assessment of fanfiction-writing tasks assigned directly to Italian high school students, they self-reported the experience as an opportunity to improve their English, practice real communication, make connections and make class more lively and interesting [125]. Although these explorations are promising, the slow-changing nature of institutional infrastructure resists widespread replication of informal learning communities within schools [151]. The key to translating the learning and literacies of fandom and other interest-driven communities into equitable opportunities, then, arguably lies in meeting learners

where they are at and building points of connection between informal communities and formal institutions [143].

In conclusion, fanfiction communities stand on their own as rich and mature informal learning spaces, as well as sites of literary innovation. As people participate, they draw on linguistic resources to position themselves within the community, often developing these identities over time as they begin to participate in fan activities, which are themselves practices in multiliteracies [23]. The connection participants feel with other readers and writers motivate them to continue participating and learning, fueling deep interest-driven learning [143]. This learning is observable in their knowledge, their language, and their reported feelings of self-efficacy.

### 2.2.3 Distributed Mentoring in Online Fanfiction Communities

*Distributed mentoring* is a theoretical framework that describes the way people mentor each other in online fanfiction communities [6,42]. At a high level, the theory of distributed mentoring explains how many small interactions over the internet can promote literacy development by fulfilling writers' needs for social support, encouragement, and constructive feedback. To do so, distributed mentoring theory synthesizes Hutchins' theory of distributed cognition [140] with Dawson's [2014] framework of mentoring [73]. A key takeaway is that technology can mediate mentoring, and in addition, as a result of this mediation, mentoring is augmented in interesting ways. In an ethnographic investigation where researchers analyzed stories, author notes and reviews, and conducted interviews with writers across across multiple fandoms, Campbell et al. [2016] observed that mentoring behaviors were distributed across one-to-one, one-to-many and many-to-many networking channels, and diverse in both content and relationship dynamics. In

addition to beta reading, a semi-formalized practice where writers request explicit feedback on a draft of their fic prior to posting [25], mentoring interactions were observed in forums, group discussions, and reviews [42].

Just as distributed cognition reorients the locus of cognition from the individual to the group, prompting researchers to examine human-computer interaction from a networked perspective [134], distributed mentoring is rooted in an examination of learning as a socially embedded process. This has important implications for studying how fanfiction authors interact. The key contribution of distributed cognition theory is the idea that cognition is embedded in artifacts [140] – crucially, the tools people use in sensemaking and communication influence cognition. For example, the tagging system of Archive of Our Own is designed to embed a community-created taxonomy into the site, reflecting community values and augmenting both how authors describe their work to potential readers and how readers search and filter to find stories [100]. This idea can be extended to mentoring as well – instead of an individual mentoring a learner 1:1 in a traditional model, distributed mentoring offers the view of a whole system of individuals and technology doing mentoring. This is why comments are so important from a distributed mentoring perspective: these little public asynchronous statements represent units of mentoring, as well as a potential design space for mediating feedback and mentoring within the community. And, from a distributed mentoring perspective, mentoring is not just constructive feedback. Dawson's [2014] Mentoring Framework introduces a flexible concept of mentoring that includes different dimensions to describe how mentoring interactions may occur. Mentoring includes a range of activities with the purpose of supporting learners, including

sharing domain knowledge, helping the learner set goals, offering encouragement, connecting the mentee with others, and sharing experiences.

Campbell et al. [2016] identify seven aspects underpinning their observations of distributed mentoring: aggregation, accretion, acceleration, abundance, availability, asynchronicity, and affect. I've briefly described each of these in the Table 2.2.3 below.

**Table 2.2.3: Attributes of distributed mentoring described by Campbell et al. [2016].**

<b>Attribute</b>	<b>Description</b>
Aggregation	Small individual pieces of feedback sum to a greater whole as authors interpret reader responses together.
Accretion	Feedback-givers collaboratively build knowledge as they respond to each other's comments.
Acceleration	Conflicting opinions and active discussion yield a more complex, nuanced body of feedback.
Abundance	Authors have access to a large volume of feedback from a massive network of potential feedback providers.
Availability	Public, persistently viewable comments allow authors to learn from feedback on others' work.
Asynchronicity	Conversations are facilitated between people living in different time zones and schedules.
Affect	Authors receive emotional support that contributes to their self-efficacy and motivation to continue writing.

These attributes highlight the ways that fandom networks as experienced by writers can provide or even enhance the elements of traditional mentoring. For instance, asynchronicity describes how the temporal persistence of fanfiction reviews affords writers with the opportunity to learn from feedback at whatever moment they wish to access them or by engaging in asynchronous conversations with multiple reviewers.

Among the seven attributes, *abundance* is a key driver of the powerful impact distributed mentoring can have on literacy development. Abundance, which describes the amount of

feedback an author can receive from their network, moderates aggregation, accretion and acceleration, because the amount of collaborative knowledge-building, active discussion and cumulatively available feedback overall is driven by the strength and size of the network. The central claim relating the abundance of feedback to writing development is that although single interactions between writers and reviewers may seem too minute to amount to mentorship when considered in isolation, the sum experience of accumulating reviews and conversing with feedback providers can provide enough support to promote literacy development at a large scale. In particular, fanfiction writers were reportedly able to derive directional support for the continued development of their stories from bodies of feedback that are individually composed of relatively shallow, positive comments [42,93].

However, some researchers such as Magnifico et al. [2015] have raised questions regarding whether the feedback environments facilitated by fanfiction communities are generally conducive to literacy development. Because much of the research demonstrating informal literacy development within fanfiction communities is built on individual cases, it is arguably questionable that the phenomenon is really occurring at a large scale. To better understand the contribution that fanfiction reviews may have, Magnifico et al. [2015] conducted a linguistic analysis of reviews on two *Hunger Games* fics, one on Fanfiction.net and one on Figment.com, that received 69 and 49 reviews respectively, which were analyzed as 646 idea units. Across the reviews, about 80% of idea units communicated general reactions to the story, while about 8% directed the author to take any action. Within the Fanfiction.net dataset, only 1.9% of idea units explicitly identified problems in the text. Magnifico et al. [2015] conclude that “few reviewers write in-depth reviews, but social validation and presence are important to fanfiction authors.”

Certainly, *affect* is central in distributed mentoring as the emotional support embedded in the reviews authors receive from their communities helps motivate continued participation in writing, especially because sharing creative work is an act of emotional vulnerability [42]. Additionally, the role of each review varies, and the effect of reviews overall depends on the author's interpretation of them. Evans et al. [2017] categorized 4,500 reviews into 13 overlapping categories. 35.1% of reviews were shallow and positive, 46.6% specifically targeted aspects of the text, and 27.6% encouraged updates. In contrast with Magnifico et al.'s [2015] analysis, Evans et al. [2017] found that 16.6% of reviews contained constructive or corrective feedback. On top of analyzing a larger sample of reviews, Evans et al. [2017] additionally interviewed fanfiction authors, finding that authors develop strategies to incorporate them into their writing, compiling feedback together, and finding solutions that work for them. However, this labor could be emotionally difficult, and the overwhelming presence of positive comments helped offset the difficulty of receiving critical feedback by offsetting it with affective support.

While prior ethnographic investigation of feedback in fanfiction communities has revealed how mentoring networks can contribute to authors' development through distributed mentoring, there are unresolved questions: how much impact do reviews have on lexical development? Do the effects observed in case studies and reported in interviews scale to millions of writers? To empirically evaluate distributed mentoring theory, this dissertation tackles the challenge of quantifying distributed mentoring on a large scale. This requires a different methodology than prior examinations of learning in the fanfiction community; I will describe our mixed-methods approach and its underpinnings in the remainder of this chapter. By quantifying the impact of

distributed mentoring, we will contribute evidence that helps settle questions of scale and impact. In addition, this dissertation will go further by investigating the formation of networks around authors, and the strategies that they use to obtain the feedback and support needed to continue developing in their writing. But first, I will situate the study of learning in fanfiction communities in a broader discussion of informal learning, community, and networking in the next section.

### 2.3 Affinity in Communities

The purpose of this section is to situate fandom and fanfiction specifically as practices within communities studied at the forefront of research about media, literacy and informal learning. As fans produce fanfiction, fanart, fanvids and other content, they engage critically with media, often transforming existing narratives and creating new ones that draw on their personal experiences and identities. By sharing their work, these creators are actively designing their own media landscapes, and contributing discourse to spaces where others will engage with them. These spaces are communities. Because they are central in developing the skills to engage critically with media, which is crucial for anyone living in the political and economic climate of the 21st century, it is important to understand how modern communities function and what drives people to participate in them. For decades, fandom has been at the forefront of research that drives understanding how communities shape culture, media literacy and learning. In this section, I will trace the lineage of research surrounding community through fanfiction, and describe how the concept of affinity has been identified as the key driver of community.

### 2.3.1 What is a Community?

*Communities* are groups of people who share a place (real or virtual, such as a social communication channel), engage in common activities, and share identities or interests. In this subsection, I will review high level concepts from the past three decades regarding communities and how people informally learn within them. During this time period, there have been historic changes to how communities can interact because of widespread internet adoption and continued technology developments such as Web 2.0 [214] and social media [158]. People are more connected and face fewer barriers to contributing discourse, which fundamentally changes and accelerates learning: both how people learn and what they need to learn in order to participate fully in their communities [241]. Ethnographic studies of communities, virtual and IRL (“in real life”) have helped develop theories of learning and community that are robust to these changes, accounting for how people come to share places, activities, identities and interests in our present interconnected world [117,142,143,149].

In the late 1980s and early 1990s, Lave and Wenger were looking for alternative models of learning to individualist cognitivist approaches, and in particular, to “rescue the idea of apprenticeship” [180] and build on sociocultural theories of learning (e.g. Vygotsky & Cole [1981] [259]). Drawing on anthropological perspectives, they observed *in situ* the activities of apprenticeship across four professions. Lave and Wenger coined the term *legitimate peripheral participation* to describe the process by which beginners join a community and move from its periphery towards its center, learning the activities of that community in the process [180]. Learners built relationships with more established members of the community, but rather than formal instruction, newcomers started out with small, low-risk tasks that allowed them to

develop familiarity with the community's goals, structure, and principles. Lave and Wenger emphasized that this did not always occur through formal apprenticeship relationships between beginners and mentors, rather, learning was an informal part of participating as a peripheral community member.

This perspective defines a *community of practice*, “formed by people who engage in a process of collective learning in a shared domain of human endeavor [264].”

As the internet became more widespread, human-computer interaction scholars have adapted this perspective of community to understand online communities across many domains, such as professional practice [206], knowledge-sharing communities such as Wikipedia [263], and open-source software communities [10]. The community of practice concept orients on a domain of expertise – often focusing on communities with hierarchies based on domain expertise. Those with deep expertise in the domain, who work to define and teach its practices, are at the center of the community. People who are just beginning to learn the domain practices are on the periphery. This concept is reflected in the “reader to leader” framework by Preece and Shneiderman [2009] [223], which outlines design considerations to help promote engagement and move community members from “lurkers” to commenters to contributors.

Despite the wide applicability of the community of practice framework across internet communities, new concepts became necessary to describe some of the unique phenomena seen in media fandom and gaming communities. For example, a single-domain-focused approach makes less sense in an online world where anyone can engage in any domain at any time, and

communities often center multiple intersecting domains [116]. Another criticism of the communities of practice framework is that it assumes more static membership than is often present in the communities under study, where modes of engagement are more fluid [22]. It is worth noting that these criticisms are not exclusive to fandom and gaming and are also found in examinations of informal learning in workplace contexts (see e.g., Boud & Middleton [2003] [29]). Furthermore, because of its wide applicability, Jenkins et al. found that communities of practice itself as a concept began to feel like a “buzzword” that had been “watered down” because of its use in describing so many different things [154]. As a result, scholars have developed concepts to frame people’s activities, participation and learning, particularly in fandom. Rather than conflict with communities of practice theory, these concepts bridge and expand the theory to account for how people interact and build identities within their communities [1].

### 2.3.2 Participatory Culture

One expansive theoretical framework that accounts for macro-level changes in online interactions between people, where fandom has been at the forefront, is the concept of a *participatory culture*. As discussed in the previous section, fanfiction and fandom more broadly has been observed as a phenomenon of changing media engagement, wherein fans are no longer viewed solely as consumers, but as producers of their own content in response to mainstream narratives. Media scholar Henry Jenkins contrasted this view of media engagement with widespread stereotypes at the time that marginalized fandom participants as “obsessed,” “brainless consumers” who cultivate “worthless knowledge.” Contemporarily with Rhiannon Bury, Jenkins observed that fans were reclaiming and remaking media by, for instance, telling gay narratives about Kirk and Spock of *Star Trek*.

*“The irony, of course, is that fans have found the very forces that work to isolate us from each other to be the ideal foundation for creating connections across traditional boundaries; that fans have found the very forces that transform many Americans into spectators to provide the resources for creating a more participatory culture; that fans have found the very forces that reinforce patriarchal authority to contain tools by which to critique that authority.” (Jenkins, *Textual Poachers* [2013] pg. 284)*

Participatory culture is a flexible concept that Jenkins initially introduced to describe fandom communities and the conditions that produced transformative media, but over time, came to describe large-scale cultural changes in media engagement at a societal level. In its earlier form, as a descriptor of a community, participatory culture is defined by the following characteristics: relatively low barriers to engagement, strong support for creation, informal mentorship, social connection, and a shared belief that contributions matter [151]. This idea is inspired by the constructivist learning theory of Papert [1980] [217], who, after observing how spontaneous learning groups formed and dissolved among Samba dancers, predicted a technology-mediated future where situated, informal learning could also occur. Similarly to communities of practice theory, the focus is on learning by participating, but in contrast, while groups are not stable, culture is shared across groups. In fanfiction communities, writers learn cultural norms and practices that are shared widely, such as beta reading, but they also create and dissolve groups that are fleeting as they engage in different events and move across fandoms. In some cases, the community of practice provides a framework useful for examining apprenticeship in a specific subgroup of writers (e.g. Fiesler [2017]), while at other times, participatory culture provides a

framework for examining writing as participation in fan culture [21], with learning a key outcome in either framework.

As Web 2.0 and social media saw widespread adoption, participatory culture came to be theorized as part of a more general convergence between media consumption and production [150]. As this technological and cultural shift in engagement with media grew beyond fandom, the concept of participatory culture itself became more expansive, as scholars discussed implications not only for literacy and learning, but for civic engagement and participation in democratic society [154]. While literacy and learning are essential in democracy especially in contemporary media culture [197], and participation in fandom demonstrably builds multiliteracies necessary for critical engagement with media beyond classroom learning [2,24,47,177], the lens of participatory culture offers a community-based learning paradigm without necessarily providing a deep explanation of how this form of learning functions, or how the communities that make up a participatory culture are held together. Indeed, participatory culture is a call to research these topics more than an answer to the challenges of 21st century society [76,151,154].

### 2.3.3 Discourse, Affinity and Networking

Discourse theory provides a perspective that ties together ideas of community, literacy, identity and learning with research situated in fandom. From this perspective put forward by James Gee, community is centered on a semiotic domain, or a distinctive set of messages shared by a group of people [116]. Participation within a community requires some degree of fluency in its discourse, which can involve multiple modalities, and mastery of a domain is defined as the capability to recruit its grammar in order to understand and produce messages in a socially

accepted and understood manner. This socially-situated sense of expertise is driven by a socially-situated sense of identity – in other words, *being* leads to *doing*, which in turn leads to learning [118].

This model of mastery lends itself to examining lifelong learning outside of school and is simultaneously critical of in-school learning, because in-school domain learning may not be associated with participation in outside activities and discourse [117]. In contrast, Gee observed that not only were video games excellent tools for learning, but that fans of popular games were developing terms, knowledge, activities and markers of social status. All of this contrasted with stereotypes of gaming as a “waste of time” [115]. Case studies of this theory centered around gaming communities such as *World of Warcraft* [215] and *The Sims* [120], finding connection between activities, language, knowledge and social relationships that directly overlaps with other fanish phenomena.

The concept of *affinity space* places this identity-driven conceptualization of learning within social spaces where people share a passionate interest. Affinity spaces are sites of distributed knowledge, and support multiple domains of expertise within a single semiotic domain, as well as a more fluid model of peer-to-peer mentoring (rather than expert-to-beginner apprenticeship) [115]. For instance, *Dota 2* fans might engage in different activities such as playing the game, learning popular strategies, following professional teams and creating articles, posts, streams and videos. In participating in these activities, gamers learn to seek out credible information and communicate with others on the internet [18]. In describing how fanfiction writers learn the same, Black [2008] recruited the multiliteracy term *procedural knowledge* [179], which

“involves the acquisition of skills and strategies for how to learn and continue learning via networks,” to contrast with propositional knowledge (“that primarily involves the learning content area of facts and figures”) learned in classrooms. This makes Fanfiction.net an exemplar of an affinity space, and an excellent site to understand multiliteracy and lifelong learning. However, selecting an affinity space as a site for research poses the limitation that for any individual participant of that space, their learning is not isolated to the site. In understanding the role of affinity in the lives of learners, it is important to situate them in activities and relationships that cross multiple spaces.

The concept of *affinity network* helps to capture an experience of informal learning in communities that integrates the world of social networking and intersecting online platforms surrounding people’s shared passions. Affinity networks are made up of relationships that are specialized in an interest area, intentionally affiliated and openly networked online. Although open networking and a lack of institutional gatekeeping are distinguishing characteristics in contrast with communities of practice, the concept is flexible to include face-to-face encounters and private communication [143]. Unlike social networks, which reflect social connections built in daily life, affinity networks are primarily formed by shared affiliations with media and technology. This is not to say that affinity networks do not cross social media platforms like Twitter and Facebook.

The conceptual expansion from affinity spaces to affinity networks comes from the Digital Youth Project [142], which set out to uncover how young people were informally learning and engaging with technology and media with a series of ethnographic investigations. The resulting

model of learning included both social- and interest-motivated engagement with media across online and offline life [141]. In this model, “hanging out” is socially-driven, motivated by teens’ need for connection with their local peers. They may adopt social technology or talk about media in order to connect with their friends. “Messing around” as a mode of engagement is characterized by socially seeking out information, experimenting with technology, tinkering with media and sharing with friends. “Geeking out” is driven by deep interest in a particular area, and exploring core interests, and developing social connections with others of shared interest. Like prior theories, Ito’s research in affinity emphasizes youth media engagement as crucial to building the skills needed to thrive in 21st century society, and offers multiple case studies from fandom. But unlike prior theories, Ito’s theory offers a broad picture of learning and captures the role of media literacy in participatory culture, while also detailing an individual-level process of how and why people engage in self-directed learning.

In the studies of this dissertation’s chapters, we will draw from theories of affinity-driven learning in our analysis of mentoring among fanfiction writers. While Fanfiction.net may be conceptualized as a community of practice, we leverage the affinity space model in characterizing mentoring as many-to-many peer interactions. Later, in the final two chapters of this dissertation, we model the affinity network, exploring both how writers form reviewing networks on Fanfiction.net, and interviewing writers to understand the broader set of technology platforms they recruit throughout the ecosystem in order to build their mentoring networks, and the strategies they undertake in doing so. This contributes to validation of the prior literature by quantifying it with data science, and deeper exploration into the activities underlying network development in this prototypical space for literacy learning. For the remainder of this chapter, I’ll

discuss why this quantitative and mixed-method approach is an important complement to the decades of ethnographic research examining this broadly impactful phenomenon.

## 2.4 Feedback, Learning, and Human Centered Data-Science

In this section, I will discuss why a new methodological approach is needed to address divided ontological and epistemological perspectives, especially in the study of feedback in online communities. To contextualize the argument of this section, I will introduce research in *Massive Open Online Courses (MOOCs)* and *Online Feedback Exchange (OFE)* systems as well as open problem areas in those spaces. Then, I will discuss how the underlying perspective of self-regulated learning theory does not address these gaps, and argue for the integration of learning theories that center affinity and community. However, to integrate cognitive and sociocultural learning theories, differences in their methodological and epistemological perspectives must first be addressed. It follows that by combining ethnographic investigation with at-scale data analysis, the mixed-method perspective of human-centered data science is a suitable approach to bridge learning theories from informal online communities with theories of feedback developed in formalized educational settings.

### 2.4.1 Online Feedback Exchange Systems

The potential to create scalable systems that provide people with feedback from distributed networks of their peers has energized research about learning. Outside of the literature surrounding informal online communities that I've described in the previous sections, the last two decades have seen an explosion of innovative research about MOOCs and OFE systems. MOOCs are learning platforms that offer education that is low cost, geographically distributed, and potentially unlimited in the number of students [200]. OFEs describe a more broad set of

feedback systems that support feedback exchange among creatives, students and professionals, including crowdsourcing platforms, social networks and online communities [105]. Undoubtedly, feedback is a crucial support for learning [40,130,237] as well as creative expression [123,251,281]. Although there are motivational differences between why different populations seek feedback [45,121], it is possible that principles for effective large-scale feedback exchange could transfer across learning domains – and where they do not transfer, researchers should investigate why and uncover differences. Therefore, the integration of findings across OFEs holds potential for broad impact on creative support.

Research on MOOCs have explored the use of peer feedback in order to support learning at a scale larger than instructor feedback could possibly support [175,252]. The demonstrated benefits of peer feedback in instructional settings are very promising: peer feedback helps students interpret assignments, learn from others' work, become more confident, and achieve higher grades [175,247,261]. Well-designed peer assessment correlates with instructor assessment, which marks it as a potentially useful grading tool [176,184]. However, MOOCs that support peer interaction are challenged by low engagement and low completion rates, which tend to be correlated in individual behavior [157,196]. Qualitative research has shown that students who disengage are dissatisfied with peer interactions in MOOCs due to issues such as rudeness, irrelevant information, and superficial, inconsistent feedback [133], although MOOC students who do engage in peer feedback find the experience to be valuable [161]. Motivating increased engagement and encouraging quality interaction is crucial to supporting learning.

*“these findings raise questions regarding the extent to which the social learning potential of MOOCs is realized, as well as regarding the feasibility of holding effective discussions in a course that contains thousands of participants. There is a need to consider the development of social learning mechanisms, which are more adapted for massive courses.” (Kahan [2017] [157]).*

Today, the vast majority of MOOCs have moved away from formative peer assessments due to these historical challenges with engagement and quality in feedback exchange, while a modest amount of research in the field has improved the review process, driving quality and credibility [278]. For instance, feedback is improved when peer evaluators are given comparison answers during evaluation [41] and when they are prompted with guidelines and suggestions [209].

Regarding further research, a systematic review of peer assessment research in MOOCs found that one of the most promising directions for peer assessment is consideration for social factors and integration of interaction with peer assessment [113]. Researchers who wish to innovate in this space may consider looking across fields to examine how peer interaction supports learning, and how feedback systems work outside of educational settings.

Crowdworker-based systems have also been explored as opportunities to leverage crowdworkers in order to compose feedback as a creative support for learners and professionals [79,271].

Researchers have explored how interfaces provided to crowdworkers can help facilitate quality feedback that designers and other creators find helpful [190,213]. Carefully-designed rubrics can yield useful critique from the crowd that approaches the quality of feedback provided by experts [279]. Designs may also facilitate feedback interactions between individual crowdworkers to

coordinate efforts and produce creative work [163]. However, there are ethical issues to address in crowd work such as imbalanced power dynamics, under \$6 per hour pay, and additional, unpaid invisibilized labor [135,202,256].

People also leverage social platforms as informal spaces to seek feedback and contribute knowledge. Recently, social computing researchers have examined community interactions in social platforms [171], competitive communities [56], gig-worker communities [168] and entrepreneurial crowd-funding communities [139]. These studies have identified strategies people use in seeking feedback in informal communities, and interestingly, several socio-psychological challenges of feedback exchange, such as feelings of vulnerability, discomfort, and distrust, cut across communities [105]. People feel uncomfortable and vulnerable in sharing early-stage work to strangers in the first place [168]. They also face challenges with summarizing their context and feedback needs in a short text blurb to someone unfamiliar with their work [57]. Additionally, people are often uncertain about the extent to which they can trust feedback from feedback providers without knowing their expertise and background [139]. And further questions remain regarding naturalistic online feedback exchange. People informally engaging in content creation face challenges with identifying high-quality and stable sources of feedback [63]. New creators are especially vulnerable to being left out, as they often feel self-conscious and hesitant to put their creative work out for critique [195]. Despite a growing amount of research on online feedback systems, more research is needed to understand the dynamics between feedback seekers and providers [105].

One of the most pressing issues in online feedback exchange is addressing social factors: motivating participation, building trust, easing anxiety and facilitating effortful feedback. As discussed throughout this section, these issues are observable in massive open online courses (MOOCs), crowdworker-based feedback systems, and in informal online communities. Although some of the same human needs and issues come up across different feedback systems, prior research has greatly differed in methodological approaches to supporting feedback, from design experiments to quantitative analysis to ethnography. With these issues in mind, this dissertation will examine feedback practices among fanfiction writers from both a quantitative and qualitative perspective, measuring outcomes on a quantitative scale and learning from individual writers about community strategies for overcoming barriers to feedback. In the next section, I will dive deeper into the epistemological divide between these approaches, as well as in theoretical frameworks for understanding the role of feedback in learning.

#### 2.4.2 Epistemological Divides in Feedback and Learning

Learning scientists who study feedback exchange from a design perspective occupy a different position in comparison to scholars who study learning using ethnography and discourse analysis. Namely, feedback systems built by researchers are centered on design experiments (Cobb 2003). Researchers have learning goals, metrics, and experimental parameters in mind, and they use these systems to set up design experiments and test theories regarding feedback and learning [248]. Because of the potential to systematically run experiments and gather individualized data within MOOCs, learning researchers have been called to study peer feedback using data in the growing field of learning analytics [268]. This research field has seen massive growth over the past decade [231]. This deeply contrasts with how learning has been studied in fandom (e.g. Black [2009], Ito et al. [2012]) and in community-based learning theories (e.g. Campbell et al.

[2016], Gee [2008], Ito et al. [2019]) I've described previously. In these settings, learners adopted whatever systems were available to them in order to achieve their own goals: pursuing interests, social connection and creative expression. Researchers studied learning wherever it occurred naturalistically, developing theories by making observations and conducting case studies and discourse analysis. Because these methodological differences are rooted in epistemological differences about what it means to observe and measure learning, it's important to outline the learning theories that underpin this type of feedback design research.

*Self-regulated learning theory* is a widely influential theory of learning that describes the cognitive processes underlying how students “become masters of their own learning” [282]. This theory sets the focus of classroom learning to supporting students' self-motivating, goal-setting, and self-monitoring behaviors. From this perspective, feedback is modeled as a key factor influencing self-perception and metacognition as well as task-level cognition and domain knowledge [40,130,165]. A major implication of self-regulated learning theory is that to become effective learners, students should proactively generate feedback, and therefore, cultivating effective classroom feedback practices can help students succeed [43,211]. These *sustainable feedback* practices are described as “dialogic processes and activities which can support and inform the student on the current task, whilst also developing the ability to self-regulate performance on future tasks” [43]. Facilitating these practices in class can look like building in structured self-reflection tasks, providing expert and peer examples for self-comparison, and facilitating scaffolded peer feedback activities [30]. Ultimately, the goal is to equip students with the skills to set goals, identify learning needs, and proactively seek feedback in their lives and careers beyond graduation [30].

With more peer feedback and collaborative group tasks in instructional design, as well as the introduction of computing to the classroom, self-regulated learning theory has expanded with the addition of *co-regulated learning* theory to describe the influence of interpersonal interactions on cognitive processes, and *socially shared regulation* to describe group cognition as a dialogic process [267]. After early calls to increase the use of learning theory in learning technology [16], this expanded cognitive framework for learning has been used to study the design of computer-based learning tools that facilitate peer interaction [53]. Each of these perspectives brings new dimensions to how learning researchers study social factors in learning [128]. In addition to enhancing learning for students in class, computer-supported collaborative learning tools promise the scalability to facilitate feedback among large numbers of learners and the granular depth of data to support learning analytics and personalization [218]. Additionally, design experiments within feedback exchange tools have been shown to yield promising design innovations that address social factors [137]. However, differences between classroom and informal learning require an expansion of the self-regulated learning model. Learning that is self-regulated is not always self-directed, i.e., the learner is bringing their own goals rather than responding to tasks set by an instructor [189]. This has important implications for feedback. Instead of interpreting and understanding criteria, and seeking task clarity, learners must begin to self-reflect and develop their own objectives in a socially negotiated process. Additionally, with the wealth of information available online, self-directed learning behaviors such as discovering resources and seeking help from others is increasingly mediated by technology [226].

Cognitivist perspectives are well-represented in learning science, and most often, are at the root of methodologies that measure learning by test outcomes [102]. Broadly speaking, this is the dominant epistemological and methodological approach in the study of computer-mediated learning [46,127,147]. On the other hand, informal learning studies are most often rooted in social constructivist and sociocultural perspectives, which emphasize views of learning as authentic participation in a practice [126,244]. If the goal in either case is to support human development and build an engaged, literate society, shouldn't researchers share insights across formal and informal learning domains? Certainly, researchers have made incredible efforts towards recognizing student achievement outside of school [71] and building touchpoints between in- and out-of-school learning to create economic opportunities for young people [141]. However, I would argue that reconciling methodological differences in how learning is understood and measured will also be integral for bridging research. I call on the example of feedback exchange as an example in making this case: while feedback systems in more formalized settings face challenging social factors, we can look to informal communities with well-developed practices to understand how they have been solved. For example, a problem facing MOOCs is that feedback efforts are anti-reciprocal – the more effort someone puts into giving feedback, the less they receive [113,169]. We replicated the analysis to demonstrate reciprocity on Fanfiction.net [111,245]. Using a similar methodology was essential in making this comparison, however, we have more to do to explain this difference and outline design implications. In the next section, I will outline our methodological approach, and why it is well-suited to putting research from different theoretical perspectives in conversation.

### 2.4.3 A Human-Centered Data Science Approach

Human-centered data science (HCDS) is an interdisciplinary field of study that draws from human-computer interaction, social science, statistics and computational techniques to better inform data science practice [9]. Human-centered data scientists approach the human side of data by examining context – the conditions under which the data was generated and collected, the relationship of data scientists to people who produced the data, and the process of data analysis. As a methodology, HCDS bridges human sensemaking with exponentially growing data by mixing qualitative and quantitative methods to approach research questions from multiple perspectives. Data science gives us the potential to build scalable models, driving understanding of data that would be impossibly large to fully grasp qualitatively. We can quantify *how frequently* a phenomenon occurs in the data and *how much* effect it has on dependent variables, as well as build models to predict outcomes based on independent variables. However, in curating data for computational processing, it is abstracted from the original setting in which it was generated, which risks a loss of knowledge about the data. Ethnographic and qualitative methods uncover rich, contextual knowledge that often has explanatory power in terms of answering questions about *why* we're seeing patterns in the data, *how* those patterns emerge and *what* patterns we should be looking for in future analyses.

A human-centered approach is ethically important for research in the fanfiction community because we are working with potentially sensitive data. Only the qualitative research in this dissertation was subject to review by the University of Washington IRB, (such as surveys we distributed and the interviews conducted for Chapter 7). However, the data analyses of Chapters 3 to 6 were all exempt from being considered as human-subjects research because the datasets

were built on publicly available data from Fanfiction.net. As human-centered data scientists, we have an obligation to address ethics questions in an ongoing reflexive dialogue during our research [9]. Autonomy and identity are key issues here – we strive to do no harm by protecting writers’ right to delete their data from the internet, and to remain pseudonymous. As a result, we did not make our dataset available publicly. All of the data we present is in aggregate. We do not deanonymize any writers, or quote any of the text we mined from Fanfiction.net. And throughout our research we were careful to handle the data as we would any other sensitive PII (personally identifiable information). Our research is in line with contemporary ethical principles outlined for online fandom data by Dym & Fiesler [2020], which were established from interviews and surveys with fans. By conducting data science in conjunction with ethnographic methods, we were better able to respect the values and norms of the fanfiction community.

Mixed-method research is also suited to this dissertation’s research because multiple perspectives are needed to address open questions in feedback exchange. As I’ve discussed previously, where feedback exchange has been studied at scale and quantified, motivational and socio-psychological factors arise as key issues to resolve in the field [105]. However, in research that has studied affinity, motivation, social connection and feedback seeking in online communities, case studies are often the focus, and outcomes are reported by learners, rather than measured and quantified [42,143]. This divide results from theoretical differences in what the role of feedback in learning *is*, and epistemological differences in *how to understand* the impact of feedback on learners. Researchers share the larger goal of supporting people with feedback and connection in order to grow literacy. In order to share learnings across fields, it is important to bridge this epistemological divide. Mixed-method research can put different perspectives in

dialogue by studying the same phenomena from multiple perspectives, triangulating knowledge – we can learn what fanfiction authors are saying about their experiences, and measure hypotheses using fanfiction data in order to scale and quantify findings [65]. As a result, this dissertation provides both at-scale findings about feedback exchange on Fanfiction.net, as well as rich, deep data about the experiences of writers.

The method used in our research builds on a growing body of literature that applies computational and mixed methods to understand informal learning spaces [8]. For instance, qualitative description and quantitative analysis have been important in studying informal learning in the Scratch Community, a programming language and learning space designed by the MIT Media Lab [228,284]. Scratch has characteristics in parallel with Fanfiction.net, such as the intentional culture of remixing [69]. Prior research has worked to strengthen the connection between youth participation in the Scratch community and data literacy [70,131] and civic engagement [232]. Researchers identified common programming patterns in projects shared within the Scratch community and used the diversity of programming concepts as a longitudinal measure of programming sophistication [97,198]. After identifying gender differences in participation and programming sophistication [98], this line of research further modeled the effect of feedback as a mediating factor, finding increased numbers of comments help close the gender participation gap among inexperienced users [114]. Further mixed-method research has explored the social feedback loop in community-based learning research in Scratch, identifying new paths for innovating in community-based learning design and equitably serving the needs of learners [54]. Converging together quantitative outcomes with qualitative explanation can help to

drive data-informed design implications [65] such as breaking down barriers to participation [54].

This dissertation contributes an applied demonstration of the human-centered data science principles and methodology by triangulating machine learning modeling on a large dataset with qualitative analysis. For example, we employ a mixed-method study design known as *qualitative-to-quantitative transformation* [65]. Qual-to-quant transformations re-encode qualitative data into a quantitative format in order to support scalable statistical analyses. For example, in a qualitative analysis, researchers may manually label text samples. The labeled data may be re-encoded as quantitative data by producing a table where each row represents an individual sample of text, and each column contains values of zero or one corresponding to the absence or presence of a given label. The resulting matrix of binary data can then be used computationally in statistical analysis and predictive modeling.

As described in Chapter 4, we built a machine classifier to quantify types of reviews in the Fanfiction.net dataset based on categories that resulted from Evans et al's [2017] grounded, interactive qualitative coding of fanfiction reviews. The design builds on previous methods used in the Human-Centered Data Science Lab [283] to transform a grounded theory taxonomy to a machine learning classifier for short informal texts [35,243]. After manually labeling the affect of text chat communications between geographically distributed scientists, members of the HCDS Lab transformed the qualitative data to a matrix of binary data, and built a model that could predict the affect labels that best correspond to a new text chat message [35,243].

Underlying their model was a support vector machine [250], which is a relatively simple type of

machine classifier that works by treating each row of data as a vector in multidimensional space, and finding a hyperplane function that best separates the data into two categories. The hyperplane function is a linear combination of coefficients multiplied by ones and zeros that indicate the presence or absence of words. For example, if the classifier was built to differentiate positive from negative affect, words like “wow,” “fantastic” and “OMG” would likely have large positive coefficients associated with them, while words like “ugh” and “terrible” would have negative coefficients in the model. The more positive words that are present in a chat message, the more likely it would be to be classified as a message with positive affect.

We improved short-text classification accuracy for our qual-to-quant transformation to near-human accuracy using BERT (Bidirectional Encoder Representations from Transformers) [77]. BERT is a neural network model that is pre-trained on a large text dataset, in other words, before training on our manually coded dataset, the algorithm has already ingested a vast text corpus and built associations between words. After learning these latent word associations, we then train the model on our data. Unlike a support vector machine classifier, BERT is able to make classifications based on the context of words used in combination.

In addition to improving classifier accuracy, we built on the method by incorporating machine learning models into the analysis that followed the qual-to-quant transformation, building predictive models using autoregressive linear mixed models [12] in Chapter 4 and survival modeling [181,208,221,272] in Chapter 6. Beyond understanding the presence or absence of different types of fanfiction reviews across the Fanfiction.net dataset, we wanted to use the classified data to predict behavioral outcomes. Autoregressive linear mixed modeling predicts

change in a dependent variable based on inputs over time. In our case, we used this class of modeling to predict outcomes in lexical development as a result of receiving and sending different types of reviews. Survival modeling is used to predict the occurrence of events based on inputs over time, and we were able to build a predictive model to demonstrate how receiving different amounts of reviews correlates with the likelihood someone will publish a new chapter of their fic. In addition to using mixed methods to make predictions, we also used qualitative methods for explanatory purposes in Chapter 5 and Chapter 7 to complement our k-clustering [192] model of the relationship network structure [85]. Ultimately, this mixed methodology helped us expand theory about how distributed mentoring works, particularly with respect to the strategies used by fanfiction writers to build their mentoring networks.

Throughout the chapters in this dissertation, we are deeply descriptive in the quantitative methods, because each of our models are state-of-the-art in the application of machine learning to informal learning. We wish to encourage the continuation of this methodology in the study of fanfiction sites and other informal online communities where people create and learn.

## 2.5 Chapter Conclusion

In this chapter, I introduced the body of research surrounding fanfiction by exploring its definition. I discussed its relevance in academic topics across fields, situating this massive creative phenomenon in interdisciplinary research about transformative media, literacy, learning, communities and mentoring. I reviewed key findings about what fanfiction writers learn as they create and share their work online. As writers transform their favorite stories from media into new narratives, the feedback and affective support they receive from their networks helps to support their growth in identity and literacy. Based on ethnographic research with fanfiction

writers, distributed mentoring theory [42] describes the aspects of this technologically-mediated informal learning process. As I've highlighted in this chapter, abundance and affect are two key components that drive distributed mentoring. An abundance of feedback provides writers with diverse perspectives that enable them to derive insights about their audience's relationship to their work. Receiving affective support helps writers to build confidence and motivation to continue posting. As writers engage with audience members, they build knowledge about fandom and fannish practices – which helps with building their identities.

Because fanfiction and fandom communities were at the forefront of internet communities during broader developments in how people consume media and develop literacy in the information era, fan culture has been influential in the research lineages that trace these changes. Case studies of fanfiction and other fandom activities have shaped theory about what a community is and how communities function and support learning, especially youth development of critical media literacy and multiliteracies. Fan activities melted the barriers between media consumption and production because of its participatory and creative nature. As fans actively design their own media landscapes, pursuing their interests and connecting with others, they build networks that are distributed across the open internet. I introduced affinity as a key concept – driving the formation of communities, interactions between people who share interests, and transformative engagement with popular media. This represents an important shift in how communities are viewed – rather than centering community on domain expertise within a practice, I explore perspectives that view communities as multi-domain networks centered on shared practices, identities and interests.

Fanfiction writers have developed innovative ways of mentoring and learning from each other that may hold key insights to challenges found in online feedback exchange research. Across research in massive open online courses and other feedback systems, researchers have found psychological, social and cultural barriers to producing sustainable feedback practices in learners. In this chapter, I have discussed some of the key gaps, including motivating participation, building trust, easing anxiety and facilitating high-quality feedback. This dissertation will answer how fanfiction writers overcome these issues as they seek feedback from their networks. However, differences in methodological and epistemological perspectives must be addressed in order for there to be a stronger integration of insights across disciplines, especially across informal and formal learning studies. I argue that by combining ethnographic investigation with at-scale data analysis, the mixed-method perspective of human-centered data science is a suitable approach to bridge learning theories from informal online communities with theories of feedback developed in formalized educational settings.

In addition to contributing findings that may inform researchers across disciplines about overcoming social barriers to supporting creators with network-based feedback, this dissertation contributes novel findings about fanfiction writers that are interesting in their own right. We explore the developmental and motivational effects of reviews, contributing quantitative evidence to the corresponding abundance and affect aspects of distributed mentoring theory. We study the effects of different kinds of reviews, settling questions about the unique values of shallow positive reviews, targeted feedback, and update encouragement. We describe the network formation of reviewers around writers, and crucially, our analysis is complemented by our discussions with fandom writers. We actively engaged with the community over the years of

this research, incorporating community input and feedback, ensuring we represented fan values, and highlighting voices of writers in this document.

## Chapter 3: Reviews vs Lexical Development

Co-authors: Ruby Davis, Jihyun Lee, Diana Zhang, Cecilia Aragon

### 3.1 Chapter Introduction

This chapter is about developing an approach to measuring the effect of distributed mentoring on writing, and supporting a key claim of distributed mentoring theory – that an abundance of reviews can influence writing development [42] – with quantitative evidence. In the upcoming sections of this chapter, I will describe the chapter’s research question, the collection of the Fanfiction.net dataset, the selection of lexical diversity as a suitable dependent variable, and the set of mixed linear models we fit to the data. Finally, I will discuss how our findings reveal measurable differences in writing over time as writers accumulate reviews from their audiences, and the implications for distributed mentoring theory. This work sets a foundation for extended analysis throughout the remainder of the dissertation by building a dataset, establishing key variables and opening new avenues for research regarding distributed mentoring on Fanfiction.net that we will approach later in Chapters 4, 5, and 6.

### 3.2 Do Fanfiction Reviews Lead to Writing Improvement?

The question of this chapter, and a central question to distributed mentoring theory, regards the impact of distributed mentoring on writers, and in particular, the effect of reviews on lexical development. This question is interesting because it addresses an area of contention in prior literature [193] and because it is methodologically challenging to answer. Distributed mentoring theory claims that distributed mentoring *is* mentoring, i.e., the loosely tied, asynchronous communications of Fanfiction.net are intended to improve writing skills. This is supported by

ethnographic evidence including writers' own stories about how they experienced growth as a result of their interactions with readers through reviews, and reviewers' discussion of their motivations for reviewing [42]. On the other hand, Magnifico et al. [2015] investigated whether the content of reviews on Fanfiction.net, finding that while reviews contribute social validation, "few readers write real points of criticism or ask questions that might help the author to revise his or her work." They suggest that without the involvement of teachers, peer feedback exchange in these types of informal settings falls short of what is needed to improve writing. Clarifying evidence would support or refute these conflicting claims about whether reviews on Fanfiction.net can lead to writing improvements. Thus, we ask:

**RQ: Does distributed mentoring on Fanfiction.net affect writing development?**

The question is methodologically challenging because of the informal setting under study. Proof of causality is best established in controlled settings, but fanfiction writing and reviewing is self-selected and interest-motivated. Instructing teenagers to write and review fanfiction in a randomized controlled study would result in a loss of external validity, because the interactions under study must be with an authentically interested audience in order to be motivating for writers [67]. However, Campbell et al.'s [2016] ethnographic approach was unsuitable for making quantitative claims about the effect of distributed mentoring. They state:

*"We are not able to claim for certain that distributed mentoring directly affects writing ability. We set out to understand and describe the type of mentoring present in online fanfiction communities, leaving the verification of its effect to later research."*

A quantitative investigation of naturalistically-generated data can uncover additional evidence, either supporting or refuting the claim that reviews affect writing ability. Although we are also not able to make causal claims about relationships between variables in the Fanfiction.net dataset, correlative evidence can complement prior ethnographic evidence by measuring the size of the effect, and showing the extent to which the claim generalizes across the population. Our approach is a bit different from an experiment: instead of simulating distributed mentoring in a lab to isolate the causal effect, we're analyzing naturalistically generated data to observe the effect and get ever-closer to causality. The remainder of this chapter will describe how we correlated changes in writing with distributed mentoring while controlling for the effect of maturation. And in Chapter 4, I will describe how we took this analysis two steps further, temporally isolating the effect and measuring the effect of different types of reviews.

### 3.3 The Fanfiction.net Dataset

To study the relationship between feedback exchange and writing development on Fanfiction.net, we gathered a massive content archive of reviews, profiles and fanfiction. In this section, I will describe how prior research contributed both research questions and tools for building the Fanfiction.net dataset that ultimately answered them, and the ethical issues we addressed with collecting and conducting research on this dataset. I will also discuss how I selected and operationalized the independent variable under study, the Measure of Textual Lexical Diversity, how I addressed data quality issues, and how I transformed the archive into an analysis table for conducting longitudinal analysis.



This yearly spike in publications during times when school was on break led to the hypothesis that the majority of fanfiction writers were school-aged, raising the question: could we determine the self-reported age of the Fanfiction.net writer population from author profiles? The new questions generated from metadata observations would need to be answered by analyzing content. This called for a new round of collection, to gather content in addition to metadata.

In addition to raising questions, prior research gave us a head start on the tools needed to answer them. Kodlee Yin architected the metadata database and web scraper with the potential need for content scraping in mind. When Jihyun Lee joined the lab, Yin handed over the Java-based web-scraper he developed, as well as the MySQL server used to store the metadata. The architecture was in place to model the fanfiction website as closely as possible, meaning that rather than create a new architecture from scratch, Lee modified the existing architecture with additional tables to store chapter, profile and review content (see Figure 3.3.1B). Lee implemented a new iteration of the web scraper and used it to crawl Fanfiction.net, building a MySQL database on our lab server containing a massive collection of content. The Fanfiction.net archive contains nearly 7 million stories, posted in chapters, covering approximately 10,000 different fandoms (fandoms refer to the fictional universe or characters borrowed by the fanfiction author, e.g. Harry Potter). Each story contains an average of 4.17 chapters (SD: 8.12). The dataset included 672.8 GB of data, with 28,493,311 chapters from 6,828,943 stories, as well as 8,492,507 users and 176,715,206 reviews. The dataset represents sixteen years of stories published to Fanfiction.net, from 2001 to 2017.

### 3.3.2 Addressing Data Ethics

Our lab made several notable ethics-related decisions regarding the fanfiction data. We consulted with the internal review board (IRB) at University of Washington regarding the collection of the data, and although our ethnographic, survey and interview research was subject to review, data gathered from public websites did not qualify as “human subjects research,” and therefore was not subject to the same oversight. It was our responsibility to do the right thing without oversight, and we felt a strong ethical obligation to protect fanfiction writers from any possibility of harm. In particular, we wanted to protect writers’ right to delete their stories if they so desired, without us publicly resurfacing that data. For this reason, we treated user profiles, story titles, story content and review content with the same set of data practices as PII (Personally Identifiable Information), carefully controlling data access, never publishing usernames, quotes from stories or story titles in our papers. The team also reviewed Fanfiction.net’s terms of service and determined that scraping was okay as long as traffic was throttled. When Yin et al. published the metadata archive, they anonymized PII and implemented a group-differential privacy mechanism so that deleted stories would not be identifiable. We also felt that it was important to share findings back to the community under study, and did so via our lab Tumblr blog, and by presenting research at GeekGirlCon. Although it would be years before best practices for research using online fandom data would emerge, our practices were fully in-line with the recommendations outlined by Dym & Fiesler [89]: obtaining permission where appropriate, obscuring data, attribution where appropriate, presenting findings back to the community, and ethnographically studying the community to learn community norms.

### 3.3.3 The Measure of Textual Lexical Diversity (MTLD)

One of my first contributions to the group was to find a suitable outcome measure for the effect of distributed mentoring on fanfiction writing. There were a number of requirements for this measure. First, the measure would need to be correlated with the development of writing skills in teenagers and young adults. We want to be able to tell if writers are improving over time based on changes in the outcome variable. Second, it would need to be applicable to the type of text we were analyzing: narrative fiction. As it turns out, many measures of writing have been developed for structured, argumentative prose, the type of writing requested by standardized tests, and much fewer have been developed for fiction. Third, the measure would need to work well for comparing variable-length text, since chapters of fanfiction can range from hundreds to thousands of words. If the score changed simply because the chapters got longer, our analysis would be confounded. And lastly, the measure would need to be efficiently computable, so we could run it on billions of words of text.

The *Measure of Textual Lexical Diversity (MTLD)* was the most suitable, non-proprietary text measure we could find that met all of the above requirements. MTLD in writing has been correlated with lexical development in teens and young adults. In a longitudinal study by White (2014), MTLD increased significantly from grade 11 to grade 13 among New Zealand students aged 15-18. Expert evaluations of undergraduate student essays differed significantly in MTLD between low- and high-proficiency argumentative essays, with mean scores of 72.64 and 78.71 respectively. MTLD is also suitable for narrative text [95](Fergadiotis, Wright, & Green, 2015). and correlated with expert assessments of narrative quality [212](Olinghouse and Wilson, 2013). Students who worked on their writing also demonstrated increased MTLD in their essays

[199](Mazgutova and Kormos, 2015). In addition to being a suitable operationalization of lexical development in fiction writing, MTL D is length-independent, meaning that scores do not correlate with the number of words in the text being measured [148]. The properties of MTL D matched our need for an efficient automated comparison between fanfiction texts of varied length for a longitudinal analysis of writing.

MTL D is a relatively simple, linear complexity algorithm, making it suitable for running on billions of words of text. MTL D is defined as the average length of substrings within a text that maintain a given ratio of unique words to total words. The algorithm keeps track of a running type-token ratio (TTR) as each word is processed sequentially; the running TTR increases when new words are found and decreases when word repetitions occur. The algorithm maintains a count of “factors,” defined as a sequential group of words with a TTR of 0.72 or below [201]. Each time a factor is found, the running TTR is reset and a count of factors is incremented by one. When the algorithm completes, any remaining words become a partial factor, which is 0 if the running TTR is 1.00 and approaches 1 as the running TTR approaches 0.72. The output unit of MTL D is the mean length in words of factors within the given text. We chose to use the 0.72 threshold provided by McCarthy and Jarvis [2010], which was calibrated using a corpus containing fiction and nonfiction texts. We implemented MTL D in Python (see code below) and processed 28,493,311 fanfiction chapters with a minimum length of 100 words. In total, 61,560,528,896 words were processed.

```

import string

# Global transform for removing punctuation from words
remove_punctuation = str.maketrans('', '', string.punctuation)

# MTLT internal implementation
def mtld_calc(word_array, ttr_threshold):
    current_ttr = 1.0
    token_count = 0
    type_count = 0
    types = set()
    factors = 0.0

    for token in word_array:
        token = token.translate(remove_punctuation).lower() # trim punctuation, make lowercase
        token_count += 1
        if token not in types:
            type_count += 1
            types.add(token)
        current_ttr = type_count / token_count
        if current_ttr <= ttr_threshold:
            factors += 1
            token_count = 0
            type_count = 0
            types = set()
            current_ttr = 1.0

    excess = 1.0 - current_ttr
    excess_val = 1.0 - ttr_threshold
    factors += excess / excess_val
    if factors != 0:
        return len(word_array) / factors
    return -1

# MTLT implementation
def mtld(word_array, ttr_threshold=0.72):
    if isinstance(word_array, str):
        raise ValueError("Input should be a list of strings, rather than a string. Try using string.split()")
    if len(word_array) < 50:
        raise ValueError("Input word list should be at least 50 in length")
    return (mtld_calc(word_array, ttr_threshold) + mtld_calc(word_array[::-1], ttr_threshold)) / 2

```

**Figure 3.3.3: Python code for computing MTLT.**

In case any readers are interested in computing MTLT on their own text datasets, I've made code from this study available on GitHub (see: [lexical\\_diversity \[108\]](#)).

### 3.3.4 Chapter Timestamps, Outliers and Language Detection

Chapter publication times are not directly accessible on the website, thus we made estimates using story and review metadata. We took the story publication time as the time for the first chapter. For subsequent chapters, we used the time of the first review as an estimate of its time of

publication. To verify the accuracy of this estimate, we compared story publication time with first review time for first chapters, and found that the median time to review a first chapter was 3 days, and 42% of first chapters received their first review within 24 hours. Chapters with zero reviews were assigned publication times equal to the nearest known chapter times. We obtained story languages from metadata available on Fanfiction.net. We verified the accuracy of this data using the Python library langdetect. Overall, the metadata matched with langdetect when finding English vs non-English for 99.5% of chapters. MTLN varies with language, and previous studies utilized lemmatization with MTLN while working with non-English languages [204]. Our study included English texts, 25,266,230 of 28,493,311 chapters, and did not use lemmatization.

While most fanfiction chapters had MTLN between 50 and 150, a few texts had extremely low or high scores. We reviewed a sample of texts with MTLN below 5 and found that almost all of these low-scoring texts are non-narrative word repetitions. A sample of texts above MTLN 300 were mostly non-narrative, including number sequences, lists of random words, tables of contents, glossaries, and random typing. We eliminated 2,678 outlier chapters with MTLN below 5 or above 300 from the analysis. We also eliminated 22 chapters with erroneous data, and 427,662 chapters containing fewer than 100 words. The dataset used for our analysis of lexical diversity includes 53,185,524,320 words contained in 24,835,868 chapters of fanfiction from 5,906,217 stories. Chapter MTLN scores in this set were normally distributed around the mean of 97.35, with a standard deviation of 21.96.

### 3.4 Models and Findings: The Abundance Effect of Distributed Mentoring

In this section, I'll outline our first longitudinal analysis, designed to meet the challenge of quantitatively measuring the *abundance effect* of distributed mentoring on fanfiction writing.

Abundance is a single aspect of distributed mentoring that represents the sheer volume of feedback; this provides direction to the writer even though the individual comments may be shallow [93]. We measured abundance by counting the cumulative number of reviews an author has received when they post a new fanfiction chapter. To study its effect, we use the Measure of Textual Lexical Diversity (MTLD). Since teens and young adults see lexical development as they age, we expect to find changes in lexical diversity in correlation with both distributed mentoring and maturation. This leads to our hypotheses:

H1: Lexical diversity will increase during late adolescence across the Fanfiction.net population.

H2: Lexical diversity will increase longitudinally as authors continue to post chapters.

H3: Lexical diversity will increase between subsequent chapters after increased reviews.

H4: Lexical diversity will be greater as an author has cumulatively received more reviews.

Testing these hypotheses contributes new quantitative evidence of distributed mentoring in fanfiction. In this analysis, we find correlative evidence of the relationship between lexical diversity in fanfiction stories and distributed mentoring. We replicate prior findings that lexical development occurs during late adolescence [265], and measure the maturation effect with a large-scale longitudinal analysis of the Fanfiction.net dataset. We contradict H3, finding that more reviews does not correlate with an immediate increase in the next chapter (although, later in this chapter we will show this effect depends on the type of review). Finally, we present a mixed linear model of lexical diversity with respect to reviews and maturation, showing that the effect of receiving 700 reviews roughly equates to 1 year of maturation.

### 3.4.1 Profile Parsing and Computing Author Age

To examine the relationship between lexical diversity and age, we gathered the ages of Fanfiction.net users from their profiles. Jihyun parsed biography text from the entire set of 8,492,273 user profiles, and extracted self-reported age information using regular expressions, finding 284,448 profiles containing self-reported ages (M: 16.80, SD: 8.32). 62.3% of them were aged 13 to 19, indicating that a majority of Fanfiction.net users were adolescents. This is supported by data from previous work [276]. We computed author age approximations for each fanfiction chapter by adding their self-reported age to the difference between the chapter publication and user profile update times. For instance, a user who updated their profile in January 2010 stating they were 21, and published a story in June 2011, would be estimated at 22.5 years old for that story. Profile-parsed ages have obvious limitations; for example, we parsed ages that ranged from 0 to 99 years old, but it is unlikely a 1-year-old would be able to write a profile description. We mitigated this by examining outliers and setting inclusion criteria. 105,184 users were excluded from the analysis because they did not author any English fanfiction, we excluded 24,792 authors who reported ages that placed their adjusted age below 10, and 21 were eliminated because their profile update time could not be found.

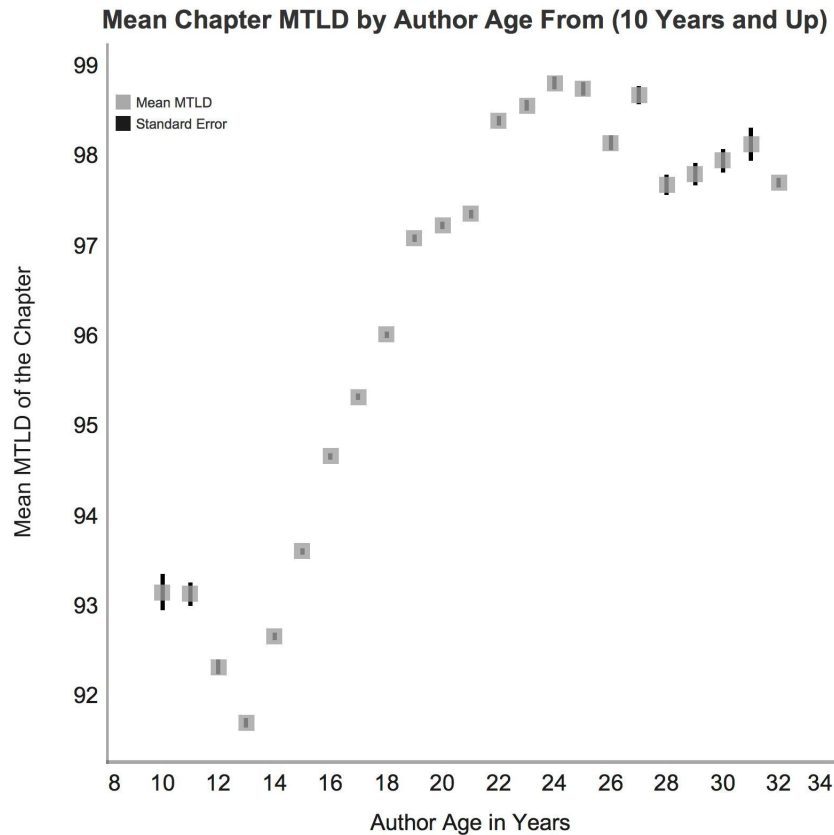
### 3.4.2 Mixed Linear Modeling

Mixed linear models are a class of regression models suited to testing longitudinal differences on a continuous dependent variable. In a mixed model, fixed effects represent independent variables of interest. Random effects typically account for individual differences, such as between students, and group differences, such as between classrooms. In our regression analyses, fixed effects were used to model our independent measures: cumulative reviews and time. Random effects were used to group data by user and by fandom. A random effect for user statistically

accounts for individual differences between writers. Adding fandom as an additional random effect controls the potential confound that lexical diversity differs by fandom. Kodlee Yin et al. [2017] previously found that the number of reviews exchanged varies by fandom, and we also found in exploratory descriptive analysis that MTLN varies by fandom.

### 3.4.3 MTLN Increases During Late Adolescence

We examined the relationship between age and MTLN for English speaking Fanfiction.net authors (see Figure 1 below). We observed statistically significant changes in text during late adolescence. The average MTLN score was 93.6 for fanfiction written by 15-year-olds. By age 19, this number increased to 97.1. People writing fanfiction in their early-to-mid 20s had slightly higher lexical diversity in their text than their teenage and late 20s counterparts. Overall, the trend was upwards and leveled off by age 32, where we start to see higher standard error due to lower counts of fanfiction chapters written by authors at those ages.



**Figure 3.4.3: A scatter plot of mean MTLD of fanfiction by author age by Diana Zhang. The plot includes 154,451 authors and lexical diversity for 3,696,107 fanfiction chapters.**

This supports our first hypothesis, that there is an overall, population-wide increase in lexical diversity that is observable during late adolescence, the majority age of fanfiction writers. To statistically validate our remaining hypotheses, we built mixed linear models, which will be described next.

### 3.4.4 MTLD Increases Over Time in the Fanfiction.net Dataset

To test H2, we built a simple linear model to determine whether MTLD increases longitudinally. The model is built to calculate the line of best fit predicting MTLD based on the number of years someone has spent participating on Fanfiction.net.

$$MTLD = A\beta_1 + A/Uu_1 + \varepsilon$$

In this model, age is the single fixed effect, while user and fandom are random effects. Our sample of this analysis included 1,608,824 chapters by 71,983 authors with estimated ages from 15.0 to 20.0 years old. See the results below in Table 3.4.4.

**Table 3.4.4: Results of Age vs MTL D**

Effect	$\beta$ Coefficient	Standard Error	$p$ -value	Cohen's $F^2$
Age (Years)	1.66	<0.001	<0.001	.007

Table 3.4.4 shows the fixed effect coefficients predicting MTL D based on maturation (days) and distributed mentoring abundance (cumulative reviews). Age was significantly ( $p < 0.001$ ) and positively linked with MTL D—for each year in age, MTL D increased by 1.66. Note that Cohen's  $F^2$  is 0.007, indicating the effect of age is small relative to overall variance in MTL D. The result supports our hypothesis, replicating findings from other settings that show lexical development in adolescence.

In this model, Age is the only fixed effect, while user and fandom are modeled as random effects. The significant ( $p < 0.001$ ) and positive coefficient of 1.66 indicates that MTL D substantially increases each year during late adolescence. Cohen's  $F^2$  is 0.007, indicating the effect size is small relative to variance. This result supports H2, replicating previous findings that show adolescence to be a significant period of lexical development [265].

### 3.4.5 The (Negative) Immediate Effect of Increased Reviews on Lexical Diversity

To test H3, we examined MTLTD change between subsequent chapters written within a one-month window with respect to reviews. We calculated 19,709,160 MTLTD differences for this analysis, with a mean increase of .019 (SD=20.69). We determined the number of reviews received by the author between chapter publications (Mean=4.51, SD=6.67). We used reviews and days as fixed effects and user as a random effect in our mixed linear model. The fixed effects were weakly correlated ( $r=0.30$ ).

$$\Delta MTLTD = R\beta_1 + D\beta_2 + D/Uu_1 + \varepsilon$$

We built a model in order to compute coefficients to predict change in MTLTD between chapters in a linear relationship with days and reviews between chapters.

**Table 3.4.5: Results of Reviews vs subsequent MTLTD change**

<b>Effect</b>	<b><math>\beta</math> Coefficient</b>	<b>Standard Error</b>	<b><math>p</math>-value</b>	<b>Cohen's <math>F^2</math></b>
Reviews Between	-0.007	<0.001	<0.001	<0.001
Days Between	0.024	<0.001	<0.001	<0.001

The resulting coefficient for reviews (see Table 3.4.5) indicates that each additional review predicted a decrease in MTLTD of 0.007, while the coefficient for days indicates that each day between chapters was associated an increased MTLTD of 0.024. Cohen's  $F^2$  for both variables was <0.001, indicating the effect sizes were nominal. The results contradict H3, showing that

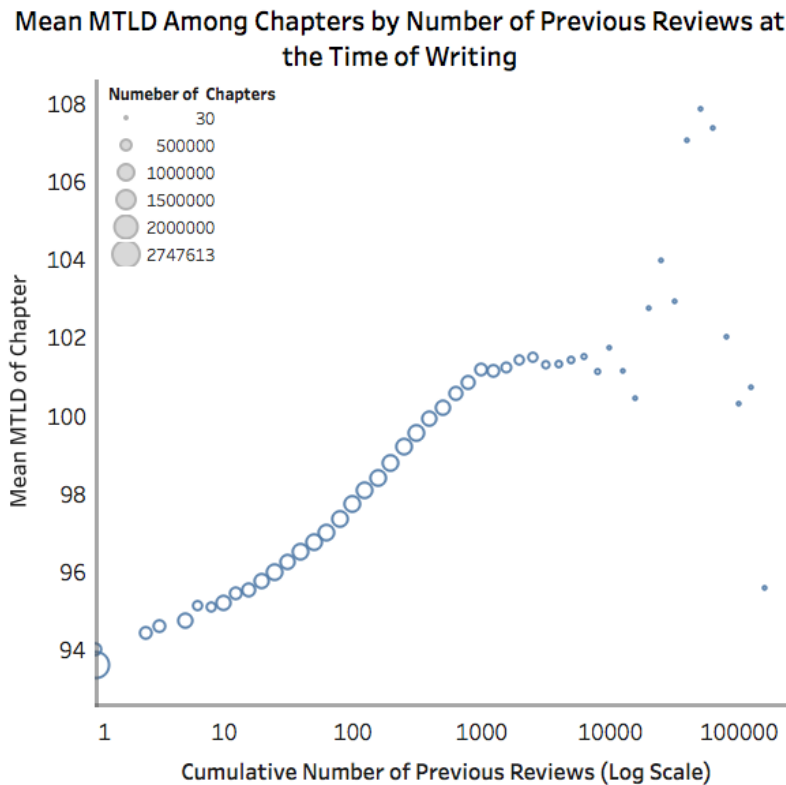
increased numbers of reviews do not predict an immediate increase on the subsequently written chapter.

### 3.4.6 The Cumulative Effect of Reviews on Lexical Diversity

We performed a mixed linear regression to test H3 (maturation predicts increased lexical diversity) and H4 (accumulating reviews predicts increased lexical diversity). This analysis tracks MTLTD changes during authors' first 50 chapters. 1,065,606 authors wrote at least two chapters, and 16,658,721 chapters were analyzed in total. The two fixed effects are weakly correlated ( $r=0.27$ ). Cumulative reviews and days each significantly predicted chapter lexical diversity (see Table 3.4.6). For each day of maturation, MTLTD increased by .0032. For each review received, MTLTD increased by .0018. This supports H3 and H4 and indicates that distributed mentoring and maturation uniquely contribute to authors' development.

To operationalize the abundance of distributed mentoring, we counted, for each chapter in the English dataset ( $N=24,835,868$ ), the cumulative number of previously received reviews by the same author. The median number of reviews was 59, with a right skew (Mean=420.38, SD=1741.70), and a maximum of 128,870 reviews. Next, to visually examine the relationship between cumulative reviews and lexical diversity, we created logarithmic groups of chapters by the number of previously received reviews and computed the mean MTLTD score among chapters in each bucket. As shown in Figure 3.4.6, the mean lexical diversity (MTLTD) increases with reviews, from 93.22 when reviews are absent to 102.33 when over 10,000 reviews have been accumulated by the author.

To visualize the relationship between cumulative reviews and lexical diversity, we grouped chapters by cumulatively received reviews at the time of writing, and computed mean MTLD for chapters in each group (see Figure 3.4.6).



**Figure 3.4.6: Mean fanfiction MTLD by author’s number of reviews received. Figure created by Diana Zhang.**

As shown in Figure 3.4.6, mean MTLD increases with reviews, from 93.22 for chapters written by authors with 0 reviews, to 102.33 when 10,000 or more reviews have been accumulated by the author. Cumulative reviews and aging are correlated ( $r=0.27$ ), so to measure the effect of

reviews, maturation must be a control in the model. We created a mixed linear model to measure how maturation and cumulative reviews predict fanfiction lexical diversity.

$$MTLD = A\beta_1 + R\beta_2 + A/Uu_1 + \varepsilon$$

We used this model to measure the abundance effect of distributed mentoring, as operationalized by cumulatively received reviews, on fanfiction MTL D. Our regression analysis modeled MTL D change in 16,658,721 chapters written by 1,065,606 authors. The findings of this model are reported in Table 3.4.6.

**Table 3.4.6: Results of Age and Cumulative Reviews vs MTL D**

<b>Effect</b>	<b><math>\beta</math> Coefficient</b>	<b>Standard Error</b>	<b><i>p</i>-value</b>	<b>Cohen's <math>F^2</math></b>
Age (Days)	0.0032	<0.001	<0.001	.004
Cumulative Reviews	0.0018	<0.001	<0.001	<0.001

Cumulative reviews and days each significantly predicted chapter lexical diversity. For each day of maturation, MTL D increased by .0032. For each review received, MTL D increased by .0018. This indicates that distributed mentoring and maturation uniquely contributed to authors' lexical development. In interpreting this model, note that overall variance in MTL D explained by the model was small. MTL D of fanfiction is a noisy measure. However, comparing the two coefficients, we can estimate that about 700 reviews predicted the same amount of change as one year of maturation.

## 3.5 Discussion

In this section, I will interpret the findings with respect to distributed mentoring theory, in particular, the abundance effect. Then, I'll point out some of the limitations of the analysis in this chapter. Finally, I'll look ahead to later chapters, where distributed mentoring is further explored.

### 3.5.1 Implications for Distributed Mentoring Theory

We found that an abundance of distributed mentoring predicts increased lexical diversity among fanfiction chapters. This was robust when we accounted for maturation and fandom differences. Effect sizes (Cohen's  $F_2$ ) were very small, indicating variance in MTLTD is mostly predicted by factors other than distributed mentoring or maturation. It is unsurprising to find this high degree of noise in an automated learning measure. The results imply that reviews exchanged on Fanfiction.net shape authors' writing. Lexical diversity trends with narrative quality [95,212] and language ability [199,204,265]. Our findings contribute behavioral evidence in support of claims by young authors interviewed by Evans et al. [2017], that the community contributed to their development as writers. While reviews did not immediately increase lexical diversity on the subsequent chapter, the effect occurred over time as reviews accumulated. Receiving roughly 650 reviews predicted the same increase in lexical diversity as one year of maturation. This underscores the significance of informal writing communities in the lives of young writers and the importance of affordances for distributed mentoring in such communities.

Several implications follow from our analysis of the abundance of distributed mentoring, particularly for members of learning communities like Fanfiction.net. Participants in informal learning communities should be encouraged to embrace and interact with those who have not yet received feedback on their work. This type of community support can occur spontaneously, such

as the “Review Revolution” on Fanfiction.net [42], but the creation of affordances by community developers to facilitate review encouragement would likely yield a significant dividend for new writers. There are fundamental implications for stakeholders such as parents, teachers, designers and researchers. We need to recognize the role of fanfiction in shaping the development of today’s connected youth. The type of feedback given through distributed mentoring has been discounted by researchers as shallow and therefore not valuable [193] Our results contribute behavioral evidence to the growing number of ethnographic and qualitative studies demonstrating the importance of fanfiction for shaping the identities [23], expression [149], and literacy [49,145] of young people. We should honor what young people are doing. Our findings support calls to acknowledge that this is a valid learning experience and incorporate it into formal education [4]. Involved adults should encourage adolescent participation in informal writing communities so young writers can engage in and benefit from distributed mentoring.

### 3.5.2 Limitations

Limitations and validity threats should be considered. First, there could be other causes for lexical diversity increase that correlate with distributed mentoring as operationalized by reviews. Second, our finding does not imply any causal relationship. Third, we do not know the degree to which stories were edited. Moreover, lexical diversity does not capture all aspects of narrative writing quality, nor does it represent all learning that occurs among fanfiction writers. More broadly, no algorithm assesses text like a human evaluator, and no behavioral measure can peek into minds to see what is learned.

### 3.5.3 A Look Ahead

This work opens areas for exploration in the study of connected learning in fanfiction communities, which we explore in the remaining chapters of this dissertation. First, Evans et al.'s [2017] aspects of distributed mentoring provide a framework for understanding how different types of reviews provide mentorship. In chapter 4, we extend the analysis by quantitatively examining how different kinds of mentoring impact changes in MTLD. We also isolate the distributed mentoring effect temporally, showing that changes occur directly after receiving reviews. In chapter 5, we conduct a social network analysis exploring the social layers that exist in the fanfiction community, and how different types of feedback relationships impact authors. Chapter 6 explores the motivational effect of reviews, and models how reviews affect continued participation in writing. These additional quantitative analyses, built on the same dataset, test principles of distributed mentoring and lend additional support to the theory.

### 3.6 Chapter Summary

Young adults at an age critical to lexical development represent the majority of Fanfiction.net users. This co-occurrence of development with fanfiction authorship, along with our found association between reviews and lexical diversity, underscore the importance of distributed mentoring in online writing communities for the growth of young authors. The study presented in this chapter was the largest application of MTLD to a public corpus at the time of writing, as well as the first longitudinal analysis of writing at such a massive scale. Our findings support calls to promote reviewing behavior and incorporate fanfiction into formal learning. In upcoming chapters, we will examine aspects of distributed mentoring beyond the sheer abundance of

reviews, explore the network of reader-reviewer relationships, and assess how best to support mentorship in informal online learning communities.

## Chapter 4: Deepening the Analysis

Co-authors: Linda Wu\*, Kush Tekriwal, Miaoxin Wang, Zealer Xiao, Wei Fan, Netra Pathak, Cecilia Aragon

\*Linda Wu is a co-first-author of this chapter

### 4.1 Chapter Introduction

This chapter significantly expands on the previous chapter's approach to measuring the effect of distributed mentoring on writing. We'll examine the immediate next-chapter effect of reviews, the effect of different types of reviews, and the effect of reviewing others' fics with respect to writing development. After introducing this chapter's research questions, I will describe the lab's effort to train a machine classifier for fanfiction reviews so we could account for different review types in the model. Then I will introduce the autoregressive models we used to overcome a key limitation from the previous chapter. Our findings uncover how different types of reviews affect the author's next chapter, and how the act of writing reviews also has a measurable impact on authors' writing. The findings contribute evidence to the causal claim of distributed mentoring by temporally isolating its effect, and reveal how different reviewing behaviors contribute (or do not contribute) to writing development.

#### 4.1.1 The Reverse Causation Hypothesis

Although we found evidence in support of the link between distributed mentoring and writing development, our correlative model from Chapter 3 is susceptible to the possibility of reverse causation. The converse to our theory that reviews cause writing development is the hypothesis

that writers' developmental growth may actually be the cause of accumulating more reviews. That explanation could account for the correlation between reviews and lexical diversity even if reviews did not have any impact in terms of helping writers improve. To confirm the direction of the link between reviews and MTLTD, we need to look more carefully at the sequence of events, placing reviews strictly *before* changes in MTLTD, accounting for this in our model. This leads us to this chapter's first research question:

**RQ1: Do MTLTD increases happen after reviews are received?**

In this chapter, we will expand on the previous mixed linear regression model by adding an autoregressive term, which allows us to measure the temporally isolated effect of reviews on the immediately following chapter. In longitudinal analysis, an autoregressive term is a variable that represents the previous measure of the dependent variable, which in our model is the MTLTD of the previous chapter. The remaining independent variables, reviews and time, represent only events that occurred between the previous chapter and the current chapter instead of cumulative counts. This essentially measures the effect of reviews by comparing MTLTD between chapters as a series of pre-post tests. By controlling the sequence of events and isolating the pre-post effect of reviews in our model, we can confirm that MTLTD increases happen directly after reviews are received, and reject the reverse causation hypothesis.

#### 4.1.2 Modeling Different Types of Reviews

We also found an opportunity to significantly expand our model and explore another aspect of distributed mentoring by examining the types of reviews being received by authors. Prior work [42,93] established a taxonomy of fanfiction reviews by iteratively coding thousands of reviews

in a grounded analysis. The three largest categories of reviews were shallow positive, targeted, and update encouragement, and different types of reviews were associated with different aspects of mentoring and impacts on the author. Shallow positive comments, although primarily affective, were believed to give directional support en masse. Targeted reviews provided both affective support and specific information writers could use to improve [93]. Update encouragement reviews ask the author to post another chapter, and there is much discussion about their effect in the fanfiction community, with some authors claiming they have a negative impact.

In their post “The Importance of Feedback on Fanfiction,” Tumblr user booksandgalore discusses a common experience in the community: feeling stressed and unsupported by update encouragement reviews [28]. This may be a point of conflicting motivation and effort between readers and writers, as readers want to see what happens next in their favorite fics, but they are not matching the writing effort with supportive feedback, and may not be recognizing any circumstances the writer may be experiencing outside of posting fic.

*“please update, I NEED MOAR!!, and any variant of an update comment, really... Authors get discouraged by this, not encouraged... The lack of feedback is the same as commenting that ‘update soon’ sentence. Wait. Is it even a sentence? It’s just two words. There’s no meaning, no thoughtfulness behind it.”*

*-booksandgalore [28]*

If update encouragement is as isolating and demotivating as receiving no feedback at all, and therefore has a negative impact on MTLT, this may explain why we found a negative result for

hypothesis 3 in Chapter 3. In that analysis, we associated receiving higher overall numbers of reviews with a negative immediate effect on MTLD. To unpack that result further, we need to understand how different types of reviews may have different impacts on writers. This leads us to our second research question for this chapter:

**RQ2: How do shallow positive, update encouragement, and targeted reviews affect MTLD?**

Accounting for different types of reviews in our model allowed us to separately measure the differences in effect between types of reviews. To enable this, we needed to build a large-scale analysis dataset and categorize each review received by thousands of authors over many chapters of fanfiction. By developing a machine classifier from human-coded fanfiction reviews, we were able to accurately classify millions of reviews by type: shallow positive, update encouragement, and targeted. Upon introducing review type to the model, we find that indeed update encouragement is associated with a negative change in MTLD for the subsequent chapter, while shallow positive and targeted reviews are associated with increased MTLD. This confirms a sentiment in the community, and highlights the importance of providing the right kind of feedback to support authors' growth.

#### 4.1.3 The Effect of Sending Reviews

As an additional expansion to our model, we explored the effect of sending reviews. The *acceleration* aspect of the theory of distributed mentoring places authors in an active role. Rather than passively receiving reviews and improving their writing, authors are actively engaging in ongoing discussions about fandom, consuming others' content and reciprocally interacting with their reviewers. Reading and reviewing others' fics is a key activity that may promote writing

development for fanfiction authors. This is analogous to the *tutoring effect* uncovered in classroom learning, whereby students assigned to tutor their peers improved their understanding of class materials by explaining and elaborating on their knowledge [233]. In our analysis, we will model the “tutoring effect” of sending reviews, testing the notion that fanfiction writers can develop their own writing by reviewing others’ fics. We raise the following question:

**RQ3: Does reviewing others’ fanfiction increase MTLN?**

In our model examining the effect of both sending and receiving reviews, we uncover that authors do indeed demonstrate lexical development after reviewing others’ work. Pairing this work together with the prior effort of separating reviews by type, we further find that the effect is positive only for targeted reviews. In other words, authors who reviewed others’ work with targeted, specific feedback tended to see increased MTLN on their next chapter. When authors sent shallow positive or update encouragement reviews, we observed small but statistically significant decreases in MTLN on subsequently written chapters. These findings support distributed mentoring theory by demonstrating the importance of active engagement in the community for continued writing development.

4.1.4 Methodological Contribution of this Chapter

In order to assess the reverse causation hypothesis for reviews and lexical diversity, uncover the effects of different kinds of reviews, and measure the effect of sending reviews, we needed to innovate by combining together methods in a way that has not previously been seen in the study of online informal learning. This work directly builds on Evans et al. [2017] and Davis et al. [2021] by qualitative to quantitative transformation. Our method involved transforming a

grounded theory coding set, and manually classified reviews, into a large-scale machine classification of reviews in the Fanfiction.net dataset. This is a substantial section and described in detail below. From there, we built a sample of texts and classified reviews, finally performing a mixed linear regression on the sample to test our research questions. We discuss the strengths and limitations of this ambitious mixed-method undertaking and its contribution to the methodology of understanding connection and development in online communities.

## 4.2 Building a Machine Classifier for Fanfiction Reviews

In this section, I will discuss our efforts in building a machine classifier for fanfiction reviews, which we used to answer our research question about the effects that different kinds of reviews have on writers. I will describe the methodological innovations of this qualitative-to-quantitative mixed method transformation, account the efforts to build a human-coded training dataset, and explain how we selected and fine-tuned the classifier algorithm. The following section on autoregressive modeling will describe the incorporation of classified reviews into our model of distributed mentoring.

### 4.2.1 Qualitative-to-Quantitative Transformation

This chapter contributes a methodological case study of qualitative-to-quantitative transformation in addition to the study's implications for distributed mentoring theory. *Mixed methods research* as an umbrella term describes methods that integrate qualitative analysis of content and meaning with computational and statistical analyses [64]. This type of methodology is central in the Human-Centered Data Science Lab because it generates understanding of data both broadly and deeply. *Qualitative-to-quantitative transformations* are a subset of mixed methods used to expand qualitative findings by generalizing them to a broader context [65].

This methodology is particularly suitable for working with large datasets of informal short-text data, because human coding can yield rich insights that may be limited in scale. Supervised machine learning techniques, such as text classification, can bridge this gap in scalability by using human-generated ground truth data to train models to accurately interpret data en masse [66,146,234]. Our transformation builds directly on prior work [35,243] by employing a text classifier trained on qualitative coding data. This yields a large-scale, accurate classification of reviews that we will utilize in regression modeling.

Our contribution to this method builds on Scott et al.'s [243] qualitative-to-quantitative transformation of a grounded theory in two important ways. First, we improve on the quality of the text classification. By using BERT [77], we improved accuracy and recall for the targeted review category in comparison with the SVM classifier used by Brooks et al. [2013]. Second, we extended the method by modeling the effect of different review categories on a dependent variable, the lexical diversity of fanfiction text, in a regression analysis. Additionally, since our independent and dependent variables are correlated with time, and there could be differences in this correlation between individual writers, we accounted for the temporal correlation of responses and the individual longitudinal changes by adding autocorrelation terms to the analysis [27]. This combined approach is highly flexible in its use and has broad applicability in the study of online collaboration over text communication.

#### 4.2.2 Review Categories

Evans et al. [2017] qualitatively coded a sample of 4,500 Fanfiction.net reviews and constructed a taxonomy of 13 types of reviews. The most common types of reviews in their sample were

*shallow positive, update encouragement, and targeted positive and/or constructive* reviews.

Shallow positive reviews are quick responses that offer non-specific, positive feedback. Update encouragement reviews encourage (or plead with) the author to post another chapter. Targeted reviews substantively call out specific aspects of the text, providing feedback that may be positive or critical. Reviews could be coded as both shallow positive and update encouragement, or both targeted and update encouragement. However, shallow positive and targeted were mutually exclusive categories.

Can the difference in impact between reviews of different categories be measured? In interviews with fanfiction writers, we've found that there is a perceived difference in writing improvement between shallow positive and targeted reviews. Because targeted reviews carry more affect and directive weight than shallow positive and update encouragement reviews, we predict that we will see larger subsequent increases in lexical diversity. There is also an open question about whether shallow positive reviews alone could have an effect on writing development. We examine the motivational aspect of reviews in Chapter 6. Here, we deepen our examination of the *abundance* effect from Chapter 3, which is the idea that the presence of positive feedback can directionally influence writing by letting the author know when they're doing well. Therefore, we predict that shallow positive reviews will be followed by non-zero increases in lexical diversity. Finally, we expect update encouragement reviews to have a motivational effect, but no effect on the writing itself.

Writers may also learn from reading others' fics, reviewing fics, and viewing feedback from other reviewers. This is the *acceleration* effect in distributed mentoring [93]. We therefore

predict that the act of sending reviews will have a separate measurable effect on MTLD. There is also an opportunity to examine the effect of sending different types of reviews. Do authors who consistently write targeted reviews see larger subsequent increases in the lexical diversity of their writing? This additional piece of the model contributes quantitative support to another aspect of the theory of distributed mentoring, and deepens the theory accounting for different types of reviews sent.

#### 4.2.3 Coding Reviews

In order to build an accurate, generalized machine classifier for Fanfiction.net reviews, we needed to resolve two key issues by expanding the ground truth dataset produced by Evans et al. The first issue was that the prior dataset sampled from just three fandoms. While this was suitable for the qualitative study, which also focused on those same fandoms, training on this sample could cause an overfitting issue. For example, since one third of the sample was *Harry Potter* reviews, a machine classifier built and tested on that data alone would be more accurate for reviews in the *Harry Potter* fandom than other fandoms. Additionally, more training data in general was needed to achieve a machine classifier accuracy score close to human accuracy. Therefore, to expand the original dataset, two separate student researcher teams coded an additional 4,945 reviews across six months.

We randomly selected additional English-language reviews to add to the dataset, using a pre-trained fastText language identification model to remove non-English reviews. The members of our lab who conducted coding were trained using Evans et al.'s [2017] coding guidelines, and regularly met to discuss and resolve coding conflicts. We used Fleiss' Kappa to measure inter-rater reliability [104]. For each review, the team recorded whether or not it contained each

of the individual codes, using a Boolean notation system. The Fleiss' Kappa values were between 0.72 and 0.94, that is a moderate-to-high agreement. These agreement levels were similar to those reported by Evans et al. [2017]. As the next step, the team further reviewed the data to ensure the best possible training data in support of an accurate machine learning model.

The team performed an additional audit to secure the quality of the training dataset in regards to its accuracy and consistency. To start, all reviews with codes were exported to a shared spreadsheet. Three students from different teams picked out reviews with disagreements and provided detailed accounts to explain the reasoning. Following this, a team discussion was held to align and calibrate the understanding of codes and resolve the discrepancies. After three iterations of this process, student auditors were ensured to have a thorough understanding of codes and identify the dataset's inconsistency with confidence. Auditors then manually examined all the reviews and checked obscure ones with the team, leading to a 22.90% change in review codes. Our final ground truth dataset consisted of 9,445 reviews along with the category codes for each review.

#### 4.2.4 Training the Classifier

After building the ground truth dataset, we were ready to develop a machine learning classification model. Based on recent machine learning literature, we identified BERT (Bidirectional Encoder Representations from Transformers) as a suitable tool to classify the reviews in our archive [77]. BERT is a method of pre-training language representations, meaning that it trains a general-purpose "language understanding" model on a large text corpus (such as Wikipedia), and then uses that model for downstream natural language processing (NLP) tasks that we care about. BERT is the first contextual, unsupervised, deeply bidirectional system for

pre-training NLP. BERT leverages two pre-training tasks: Masked Language Model and next sentence prediction. BERT obtained state of the art results on a wide variety of NLP tasks, which is why we decided to use it to classify fanfiction reviews.

Once we downloaded BERT's pre-trained language representations, we used this model for our downstream task, classifying fanfiction reviews. Since BERT is pre-trained on BookCorpus and English Wikipedia text, the word embeddings are not representative of fanfiction text. We adjusted these word embeddings on our dataset using a neural network. Specifically, we fed the outputs of BERT to a dense layer followed by a softmax layer to generate the predictions. We added dropout regularization to avoid overfitting and used categorical cross entropy as our loss. The word embeddings were, consequently, fine tuned by training end to end until convergence. This process is also referred to as transfer learning. The code and BERT training implementation can be found on our Github [260]. To assess the effectiveness of BERT for review classification, we split the manually coded reviews into a training and testing set, and computed the accuracy, precision, recall and F1 scores for the model. Table 4.2.4A below displays the results.

<b>Review Category</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>	<b>F1</b>
Shallow Positive	0.82	0.74	0.73	0.73
Combined Targeted	0.80	0.81	0.79	0.80
Update Encouragement	0.88	0.74	0.70	0.72

**Table 4.2.4A: Accuracy, Precision, Recall and F1 for BERT review classification.**

Accuracy is the proportion of correct predictions. This measure, however, can be misleading in classification problems. In the field of data science, we call a positive value true and a negative value false. In this case the value is positive if the review corresponds to the category in question and false otherwise. For example, if a dataset has 99 positive data points and 1 negative data

points, a model that predicts only positive would receive a 0.99 accuracy. Therefore, we also used precision and recall to provide a holistic perspective. Precision represents how many negative data points the model included in its list of positively predicted examples, and recall measures how many positive data points were missed. An acceptable range for precision and recall is 0.6 - 0.7. Scores below 0.6 may signify that the results are not valid, while scores above 0.7 are considered a reliable validation of our accuracy. The BERT model scores represent a model that is highly accurate and reliable. Recall that Fleiss Kappa for human coders ranged from between 0.72 and 0.94. The BERT review classification model achieved a similar range of agreement with the dataset in comparison with human agreement.

Before we settled on BERT, we tested eight other models, establishing baseline accuracy, precision and recall scores. The models include: ALOE [34], logistic regression, GaussianNB, BernoulliNB, MultinomialNB, Default SVM, Linear SVM, and Optimal SVM [13]. We conducted a detailed comparative study [28], the results of which we report below in Tables 4.2.4B, 4.2.4C, and 4.2.4D.

**Table 4.2.4B: Model performance results for classifying shallow positive reviews.**

<b>Model</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>
ALOE	0.78	0.70	0.64
Logistic Regression	0.75	0.64	0.68
GaussianNB	0.71	0.68	0.70
BernoulliNB	0.64	0.68	0.69
MultinomialNB	0.73	0.68	0.70
Default SVM	0.65	0.32	0.50
Linear SVM	0.75	0.73	0.74
Optimal SVM	0.76	0.74	0.75
BERT	0.82	0.74	0.73

**Table 4.2.4C: Model performance results for classifying targeted reviews.**

<b>Model</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>
ALOE	0.75	0.76	0.75
Logistic Regression	0.74	0.79	0.68
GaussianNB	0.69	0.69	0.69
BernoulliNB	0.68	0.72	0.69
MultinomialNB	0.70	0.71	0.70
Default SVM	0.62	0.69	0.63
Linear SVM	0.73	0.73	0.73
Optimal SVM	0.74	0.74	0.74
BERT	0.80	0.81	0.79

**Table 4.2.4D: Model performance results for classifying update encouragement reviews.**

<b>Model</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>
ALOE	0.87	0.75	0.61
Logistic Regression	0.87	0.75	0.61
GaussianNB	0.58	0.57	0.60
BernoulliNB	0.76	0.59	0.55
MultinomialNB	0.83	0.75	0.73
Default SVM	0.78	0.39	0.50
Linear SVM	0.85	0.78	0.77
Optimal SVM	0.86	0.80	0.77
BERT	0.88	0.74	0.70

Tables 4.2.4B (Top), 4.2.4C (Middle) and 4.2.4D (Bottom) catalog the accuracy, precision and recall for various classifiers tested on shallow positive, targeted, and update encouragement reviews from the Fanfiction.net review dataset. Overall, BERT scored higher than Optimal SVM and ALOE, which is ultimately why we decided to use BERT as our final model. In comparison with support vector machines, BERT is able to better represent long, complex reviews that vary drastically. After training our machine learning classifier on the ground truth labels dataset, the final step was to use the model to predict the category for all reviews in our sample so that they could be included in our autoregressive linear mixed effects model.

#### 4.2.5 Author Sampling

Due to processing constraints with running the autoregressive linear mixed effects model, We opted to run our analysis on a randomly selected subset of authors in the Fanfiction.net archive. We randomly sampled without replacement 100,000 authors. Of these, about 37% of authors never received any reviews on their fics – meaning within-subjects differences for these authors

cannot be measured. Because of this, we excluded the subset of authors who did not receive any reviews, keeping the remaining 63,264 authors for our analysis. In total, these authors wrote 169,137 stories divided into 431,588 chapters of fanfiction, and received 2,843,048 reviews. We computed MTLD scores for each chapter of fanfiction, and used our BERT classifier to classify the type of each review.

### 4.3 Expanded Model and Findings

In this section, I will introduce our hypotheses and present the models that we used to understand the impact of fanfiction reviewing on writing development. I will discuss how autoregressive modeling helps us temporally isolate the correlation between reviews and writing development, confirming that, in fact, measurable changes in writing occur after the reviews have been received. Then, I'll introduce our autoregressive linear mixed effect models that uncover the effects of receiving different types of reviews, and the effect of sending different types of reviews, on subsequently written fanfiction as measured by lexical diversity. Finally, I'll report and interpret the coefficients of these models in the context of our research questions.

#### 4.3.1 Autoregressive Linear Mixed Effect Models

In this analysis, we will use autoregressive linear mixed effect models to measure the effects of distributed mentoring on changes in lexical diversity. The particular autoregression structure we use is of 1st order, in other words, we look back to the lexical diversity of the author's previous chapter of fanfiction to predict the lexical diversity of their next chapter [222]. Higher order autoregressions look back to multiple previous chapters – we did not use a higher order because the particular purpose of our autoregression coefficient is to control the effect of previously

accumulated reviews, and 1st order autoregression is well-suited for this purpose. Our model fitting strategy was restricted maximum likelihood (REML) with autocorrelation structures [12].

Mixed effect models have two types of effects: fixed effects and random effects. The fixed effect coefficients in our model are used to measure the effects of our independent variables: reviews received and reviews sent, which we separated by review type. In addition, we included age as a fixed effect to account for the maturation over the timespan between fanfiction chapters. Each fixed effect has a beta coefficient that accounts for the direction and strength of that effect in terms of change in lexical diversity. Our model also uses random effects to group data by user and by fandom. Random effects control for individual differences in the rate of change in lexical diversity from the same amount of independent measures. For instance, different authors may have different rates of maturation over time, and authors writing in different fandoms may have differences in lexical diversity due to the content differences of the fandom. Random effects account for these differences by modeling differences in authors and fandoms as normally distributed random variables, so that we can assume the fixed effect findings are due to reviews, rather than individual or fandom differences.

#### 4.3.2 Model Constructs

This analysis represents effects in distributed mentoring as operationalized by variables in the Fanfiction.net dataset, focusing specifically on the attributes of abundance and acceleration in relation to lexical development. *Abundance* in distributed mentoring is defined by access to large amounts of feedback by writers [42,109]. We previously operationalized abundance as the number of fanfiction reviews cumulatively received by writers [109], but in this analysis, where we're carefully controlling the temporal order of reviews followed by writing changes,

abundance will be operationalized by the amount of feedback received in-between chapters. Aside from the sheer number of reviews, qualitative research has also shown that certain categories of reviews can have a greater impact on writing quality [93]. Therefore, in this study, we differentiate the three largest categories of reviews with different coefficients: shallow positive, targeted, and update encouragement. *Acceleration* describes how the interwoven back-and-forth discussion of fanfiction stories can accelerate the process of learning [93]. The operationalization of acceleration we explore in this study is the extent to which authors review others' work in-between their own written chapters. By sending reviews to other writers, they participate in the community discussion that accelerates their own learning [42]. Reviews sent are also differentiated with a coefficient for each type of review. *Maturation* is the effect of development over time, which we model as the number of days passed in between written chapters of fanfiction. Finally, our dependent variable of lexical development is measured by change in lexical diversity (MTLD) from one chapter to the next.

#### 4.3.3 The Effect of Receiving Different Types of Reviews

In addition to modeling the cumulative effect of reviews, we used an autocorrelation structure of order 1 to model the effect of reviews on MTLD from one chapter to the next. We also separated the effects of shallow positive, update encouragement, and targeted reviews. This enabled us to see the difference between types of reviews in their effect on MTLD. See Model 1.

**Model 1: Autoregressive model of fanfiction MTLD by reviews received, categorized by review type.**

$$MTLD = \rho MTLD_{(t-1)} + P\beta_1 + E\beta_2 + T\beta_3 + A\beta_4 + A/Uu_1 + \varepsilon$$

In this model,  $\rho$  is the autoregressive coefficient of the previous chapter's MTLD.  $P$  is the number of shallow positive reviews received since last response,  $E$  is the number of update encouragement reviews, and  $T$  is the number of targeted reviews.  $A$  is the number of days since the 1st chapter,  $U$  is a random effect to group data by user. The model measures the effect of three types of reviews on lexical diversity (MTLD). We analyzed a sample that included 63,264 authors and 431,588 fanfiction chapters, and 2,843,048 reviews. See Table 4.3.3 below for findings.

**Table 4.3.3: Results of autoregressive model. Fixed effect coefficients, p-values, standard errors, and F2 to test RQ 1. \*Significant  $p < 0.01$ .**

Effect	$\beta$ Coefficient	p-value	Standard Error	Cohen's $F^2$
Shallow Positive Reviews Received	<b>0.027</b>	0.0027	0.0091	1.87e-5
Update Encouragement Reviews Received	<b>-0.029</b>	0.0004	0.0081	1.39e-5
Targeted Reviews Received	<b>0.014</b>	0.0075	0.0053	0.0001
Age (days)	<b>0.0037</b>	1.3e-10	0.00024	0.00316

Targeted reviews, shallow positive reviews, and maturation significantly predicted increased MTLD. For each targeted review an author received, their next chapter was predicted to increase in MTLD by 0.014. For each shallow positive review, it increased by 0.027. For each day that passed, MTLD increased by 0.0037. The results of this model imply that targeted reviews and

shallow positive reviews contribute to lexical development to a greater degree than update encouragement reviews. Nominal effect sizes as measured by Cohen's F2 indicate that reviews and maturation account for a small amount of the overall variability of MTL D.

#### 4.3.4 The Effect of Sending Different Types of Reviews

We were interested in the effect of reviewing others' fanfics on lexical diversity. To expand our autoregressive mixed linear model, we added coefficients for reviews sent. We again classified the reviews by category, resulting in the following model (Model 2).

**Model 2: Autoregressive model of MTL D by reviews sent, categorized by review type.**

$$MTLD = \rho MTLD_{(t-1)} + R\beta_1 + P\beta_2 + E\beta_3 + T\beta_4 + A\beta_5 + A/Uu_1 + \varepsilon$$

In this model,  $\rho$  is the autoregression coefficient of the previous MTL D, R is the number of reviews received since last chapter, P is the number of shallow positive reviews sent, E is the number of update encouragement reviews sent, T is the number of targeted reviews sent, A is the number of days since the 1st chapter, and U is the user. We list the resulting coefficients in Table 4.3.4 below.

**Table 4.3.4: Results of autoregressive model. Fixed effect coefficients, p-values, standard errors, and F2 to test RQ 3.**

Effect	$\beta$ Coefficient	$p$ -value	Standard Error	Cohen's $F^2$
Reviews received	<b>0.0038</b>	0.0007	0.0011	0.0012
Shallow positive reviews given	<b>-0.0087</b>	0.0063	0.0032	7.57e-5
Update encouragement reviews given	<b>-0.013</b>	0.0001	0.0033	5.33e-5
Targeted reviews given	<b>0.018</b>	0.00001	0.0024	0.00028
Age	<b>0.0037</b>	2.9e-10	0.00024	0.00295

This analysis finds that sending shallow positive and update encouragement reviews predicted lower subsequent MTLT. For each shallow positive or update encouragement review sent, MTLT decreased by -0.0087 and -0.013 respectively. Sending targeted reviews predicted increased subsequent MTLT. The finding suggests that in addition to receiving reviews, sending reviews is an important factor in lexical development.

#### 4.4 Discussion

This Chapter's autoregressive analysis of thousands of authors' and reviewers' metadata supports key assumptions of distributed mentoring theory. In this section, I'll interpret the findings of our two regression models, and clarify the meaning of the model coefficients with respect to our research questions. We'll discuss implications for distributed mentoring theory, and the methodological contribution of this chapter for the science of informal learning.

##### 4.4.1 Interpretation of Analysis Findings

Model 1 addresses our first two research questions by controlling reverse causation and by separating reviews into type: shallow positive, targeted, and update encouragement. We found not only that the effect of receiving reviews is measurable in the next chapter posted by the author, but that the direction of the effect on lexical diversity depends on the type of review

being received. We were also able to model the effect of maturation on MTLT, and assess the model's capacity to account for overall variability in MTLT.

The beta coefficients for shallow positive reviews and targeted reviews were both significant and positive, meaning that our regression model predicts an increase in subsequently written chapters after an author receives one of these kinds of reviews. Interestingly, the shallow positive coefficient ( $\beta=0.027$ ) appears to be larger than the targeted coefficient ( $\beta=0.014$ ). In other words, Model 1 predicts that an author who posts every 30 days and receives 8 shallow positive reviews (and no other reviews) in between chapters would see 49.3% more MTLT improvement than if that same author received only 4 shallow positive reviews (+0.327 vs +0.219 MTLT). For 8 vs 4 targeted reviews over 30 days this would be 33.5% more MTLT improvement (+0.223 vs +0.167 MTLT). However, the coefficients for shallow positive and targeted reviews are slightly overlapping in standard error, meaning there is not a strong statistical claim that shallow positive reviews result in more MTLT increase than targeted reviews. The overall finding supports claims about the positive effect of reviews on writing development, however, we do not see an expected larger effect of receiving targeted reviews. Therefore, we can neither support nor reject any hypothesized differences between the effect of shallow positive versus targeted reviews as measured by MTLT.

In contrast with shallow positive and targeted reviews, update encouragement reviews were associated negatively ( $\beta=-0.029$ ) with subsequent MTLT. Model 1 roughly equates the effect of an update encouragement review to the inverse of a shallow positive review, and predicts that 4 update encouragement reviews in a 30 day period would be enough to completely negate an

author's improvement due to maturation. This finding supports the hypothesis that update encouragement reviews are not conducive to writing development, and deepens our understanding of the Chapter 4 H3 finding, where we found larger numbers of reviews overall to predict a negative immediate outcome on MTLT. In the updated model, update encouragement reviews appear to cancel the effect of shallow positive and targeted reviews in the short term growth of lexical diversity. However, over the long term, as measured in the previous chapter, reviews retain the cumulative effect of increasing MTLT as measured by lexical diversity. The negative coefficient for update encouragement in the autoregression model encouragement does not refute this claim.

Model 2 differentiates the effect of sending reviews from receiving them, addressing the question of whether authors learn by reading and reviewing others' fics. As with Model 1, we were interested in types of reviews: shallow positive, targeted and update encouragement. We found that there are significant effects for each type of reviews sent, and that Model 2 accounts for more variation in MTLT than Model 1. Overall, both autoregressive models provide confirmatory evidence that immediate changes in writing follow directly after mentoring engagements with the community.

The model 2 coefficient for sending targeted reviews was significant and positive ( $\beta=0.014$ ), indicating that authors who read others' fics and gave specific feedback saw subsequent increases in the lexical diversity of their writing. This finding supports the hypothesis that fanfiction authors develop their writing as they mentor others in the community. On the contrary, the coefficients for sending shallow positive reviews and update encouragement reviews were

both significant and negative ( $\beta=-0.0087$  and  $\beta=-0.013$  respectively). To illustrate this difference, imagine an author who posts two chapters of fanfiction 30 days apart, receiving 8 reviews over that time and sending 8 reviews. If the 8 reviews they sent over the month were shallow positive, model 2 predicts an increase of 0.0718 MTLTD on their next chapter. If the 8 reviews they sent over that month were targeted, model 2 predicts an increase of 0.2854 MTLTD between chapters, which is about four times the improvement predicted by sending 8 shallow positive reviews. If those 8 reviews were update encouragement, the model predicts an increase of 0.0374 MTLTD for that author's next chapter, which is about half the improvement predicted by 8 sending shallow positive reviews.

By including an autoregression term in the model, we are able to more clearly differentiate the immediate effects of reviews from their cumulative effects over time. This is because the previous cumulative effects of independent variables is accounted for by the previous chapter's MTLTD. One remarkable similarity between our autoregressive model and the prior cumulative model is that the effect of time itself was similar across both analyses. In Chapter 3 H4, we found that each day that passed after the publication of a writer's first chapter predicted a MTLTD increase of 0.0032. In this chapter, we found a similar positive age coefficient at  $\beta=0.0037$ . Therefore, we can state that the cumulative effect of time was similar to the immediate effect measured between chapters. In contrast, the immediate effect of receiving reviews (0.0038 in Model 2) appears to be larger than the cumulative effect (0.0018). However, overlapping standard errors mean we do not find conclusive statistical support for this observed difference. This suggests, but does not confirm, that there may be both a temporary and permanent boost to writing development after authors receive reviews. Finally, similar to our analysis in Chapter 3,

small effect sizes as measured by Cohen's  $F_2$  indicate that reviews and maturation account for only a small amount of the overall variability of MTL. Most of MTL variability overall is accounted for by other factors, such as the particular fandom, genre, and content of the fic. In any case, the sum of Cohen's  $F_2$  for model 2 was an increase over model 1, which indicates that the best model to account for the effects of distributed mentoring on lexical diversity includes maturation, reviews received and reviews sent.

#### 4.4.2 Implications for Distributed Mentoring Theory

This chapter explored the effects of distributed mentoring on writing development using autoregressive mixed linear models to predict the growth of lexical diversity in fanfiction writing. In addition to addressing the reverse-causation limitation of the previous model from Chapter 3, we deepened the analysis by categorizing the type of reviews, and by examining the effect of sending reviews in addition to receiving them. We found that each type of review authors sent or received was significantly predictive of MTL (Measure of Textual Lexical Diversity) change in their subsequent writing. This expanded analysis generates confirmatory evidence as well as new insights about the theory of distributed mentoring.

The *abundance* aspect of distributed mentoring describes how receiving reviews in large numbers can provide authors with both motivational and directional support in their writing (Campbell et al, Evans et al). In our analysis, we were able to separately examine the role of receiving different types of reviews in terms of the developmental outcome of changing lexical diversity in subsequently written text. Receiving shallow positive reviews and targeted reviews was linked with increased MTL in subsequent fanfiction chapters, while receiving update encouragement reviews predicted decreased MTL. We found inconclusive evidence about the

difference between shallow positive and targeted reviews, with a larger coefficient for shallow positive reviews but overlapping standard error ranges in our model. If shallow positive reviews were more impactful, this would be surprising because it would contradict observed connections between specificity in feedback and learning outcomes in other settings, such as classrooms [165,254], massive open online courses (MOOCs) and crowdsourcing platforms [80,172,209,279]. Interviews with fanfiction writers have also shown that these specific, positive reviews are highly valued [55,93]. One fanfiction author interviewed by Evans et al. [2017] stated the following:

*"The brief positive reviews probably make up the majority, and I don't tend to dwell on them very much, though obviously they're very nice reviews to receive. The more specific ones make a little more of an impact, they usually refer to something I was particularly pleased with or something I felt was harder to convey... (Author 16, Harry Potter)." - Evans et al. [2017]*

Although authors perceive specific interviews to be more impactful (a topic we will further explore in Chapter 7), and we did find a positive effect of targeted reviews, our findings did not support that they were more impactful than shallow reviews on lexical development. Therefore, there is an open question regarding our model versus the literature and qualitative evidence. One potential explanation is that a third, uncontrolled variable correlates with both shallow positive reviews and immediate increase in MTL. For example, shallow positive reviews could be associated with receiving additional feedback in private channels (and therefore not controlled in our analysis), while targeted reviews would not be associated with receiving this additional feedback. Another possibility is that the stronger impact of targeted reviews that authors report is

not measurable by MTLD, and some other dependent variable would better capture this difference.

Another interesting result we found was that receiving update encouragement predicted subsequent *decreases* in MTLD, which challenges our current understanding of the abundance aspect of distributed mentoring theory. Although update encouragement reviews are most often positive in affect, and generally not intended to harm writers in the way that non-constructive negative reviews (a.k.a. flaming) can be, they are not associated with writing development. This evidence contradicts the idea that all positive feedback is part of a whole of mentoring, and instead shows that some feedback that is meant to encourage writing can actually be detrimental. This supports a sentiment present in the community about update encouragement, that it puts pressure on authors to post fic faster, causing them to feel stressed and isolated.

Despite these challenges, our model strengthens quantitative support overall for the abundance effect by measuring the extent to which reviews impact lexical development while controlling for reverse causation. Shallow positive and targeted reviews were associated with subsequent increases in lexical diversity. With the autoregression term in our model controlling the temporal ordering of the events, we can more confidently claim that increases in lexical diversity did not cause increases in reviews. This is because in our model, the increases in lexical diversity are placed subsequently to the reception of reviews. This strengthens the prior work that connected the abundance of reviews in general with growth in lexical diversity in a mixed linear model, extending the previous quantitative modeling of distributed mentoring on the Fanfiction.net dataset through the lens of immediate pre-post changes instead of cumulative growth.

We also found correlations between *sending* reviews and subsequent changes in lexical diversity, and in particular, there was a strong positive association between sending targeted reviews and subsequent increases in MTL. In distributed mentoring theory, the practice of sending fanfiction reviews is viewed as a key component of *acceleration* [42], the learning effect that occurs when individuals engage in a dialogue with the community. This is an important complement to the observed culture of reciprocal exchange on Fanfiction.net [111,245] because the new evidence uncovered in our study shows that this cultural norm underpins lexical development in writers.

Our findings may also be viewed from a cognitive learning perspective, where peer tutors learn by elaborating, clarifying and extending knowledge through formulating explanations [233]. However, reviewing has a dialogic component: writing a targeted review is not only a demonstration of an individual's pre-existing knowledge but also a demonstration that the person has read and meaningfully engaged with the content they are responding to before formulating a response. Prior theory regarding literacy development through media engagement also predicts this learning effect from active consumption of fanfiction [151]. Therefore, the more specific reviews may be indicative of a more active consumption of the content, and thus more conducive to lexical development. Our finding supports distributed mentoring theory and aligns with the existing body of evidence from ethnographic work in online affinity spaces.

Interestingly, sending shallow positive and update encouragement reviews were associated with *negative* subsequent changes in MTL. This finding hints at an important behavior that authors

can directly control to promote their own growth as writers – deeply engaging in the content that they read, and writing more substantive reviews. This is not to say that sending certain types of reviews *cause* the subsequent MTLTD changes, because the type of reviews authors elect to send may be just one component of a greater set of associated practices that promote development. For instance, both interviews and analysis of authors’ social networks underscore the importance of developing close relationships with others in the community [55,72]. Only targeted reviews had a positive impact on subsequent writing both when being sent and received, and as we will find in the next chapter, targeted reviews are more prevalent in close relationships [72]. Therefore, the coefficient in Model 2 may be explained by the development of close relationships, rather than the reviews themselves. On the other hand, we will find in Chapter 7 that writing substantive reviews is also a relationship development strategy. Alongside this result, Chapter 6 will examine the motivational effect of reviews in a separate analysis. It will be interesting to explore the effects of update encouragement reviews on participation. Future explorations aside, the finding supports prior theory about the *acceleration* aspect of distributed mentoring [93] by showing how deeper engagement in dialogue with others is associated with faster writing development.

#### 4.4.3 Methodological Contribution

The model presented in this chapter stands out methodologically from prior literature in the learning sciences and computer supported collaborative work spaces. By developing a machine learning classifier for feedback text and conducting longitudinal autoregression analysis on metadata from a corpus of millions of writing samples, we demonstrated a novel method for operationalizing and modeling informal learning at a large scale in an online affinity space. This differs from mainstream learning science approaches, which more often focus on MOOCS

(massive open online courses) [155]. In comparison with massive open online courses and crowdsourcing platforms that are designed and controlled by researchers, informal online learning spaces may not afford researchers the ability to change the design of feedback exchange and implement A/B testing and pre-post experiments. We see a similar trend in the field of computer supported collaborative work, where experimental methods have been used to improve designs for feedback in MOOCs and crowdsourcing [80,279]. In contrast, in fields of research that have approached questions of informal online learning spaces, and have studied fanfiction communities in particular, ethnographic methods are predominant [11,23,42,101,120,141,144].

A human-centered data science approach can bridge this methodological gap in the study of large-scale online communities [7]. This is especially important for the study of learning from the viewpoint that it is situated in a cultural context [180], because it may not be possible to re-create the culture under controlled settings. Our approach of analyzing metadata left behind by online interactions enables a scalable analysis while preserving the context of the phenomenon under study. By building a machine learning classifier for fanfiction reviews, we demonstrated how a grounded coding of data can be generalized to a large dataset. Because of this qualitative-to-quantitative transformation, we were able to test predictions from prior ethnographic theory in order to generalize to the larger-scale community. The method of this chapter stands apart as a contribution on its own to show how we can empirically study learning at a massive scale, outside of researcher-controlled settings.

#### 4.4.4 Limitations

Certain limitations should be considered when contextualizing the findings and discussion of this chapter, especially regarding construct operationalization, the uncontrolled setting under study,

and the scope of interaction we were able to include in our analysis. In this section, I will discuss each of these limitations, how they affect the analysis, and what we will address in the latter chapters of this dissertation.

Construct validity describes the extent to which a measured variable is aligned with the theoretical construct under study. In the instance of this chapter of research, we used the variables of reviews received, reviews sent, time and MTL D change to measure the respective constructs of abundance, acceleration, maturation and writing development. The most crucial construct limitation to consider in this line of research, as I've outlined in Chapter 3, is that of our dependent variable, MTL D. While lexical diversity has been shown to be correlated with writing development across many settings, and we were able to show in Chapter 3 that longitudinal changes in written MTL D in fanfiction text especially among adolescents, I must again stress that *MTL D does not measure the quality of a fic*. In fact, most variation in fanfiction MTL D is unrelated to our independent variables. MTL D is a simple proxy for learning and captures only one aspect of change in fanfiction writing: the extent to which authors maintain a certain type-token ratio in their texts. It is crucial to triangulate this study with the qualitative evidence outlined by Campbell et al. [2016], Evans et al. [2017], Rebecca Black [2008] and others. Authors' statements about the perceived impact of distributed mentoring on their writing go beyond simple metrics to describe how they develop fandom knowledge, writing skills, and even their personal identities. On top of that, this study did not explore the motivational outcome of distributed mentoring, a topic we will address in Chapter 6.

In addition to the dependent variable construct operationalization limitations, it is worth noting the limitations of reviews received and sent as measures of abundance and acceleration, as part of a more general limitation in studying an uncontrolled, informal setting. The Fanfiction.net review dataset does not fully capture the mentoring between authors and reviewers, because some of that interaction happens in private messages, and on other platforms. We will address this with further qualitative exploration of the platform ecosystem and private feedback interactions in Chapter 7. In addition, our operationalization of the distributed mentoring concept of acceleration is limited to the phenomenon of sending reviews, whereas the concept describes a broader set of dialogue with the community, which includes author notes, replies to reviews, and participation in other fan spaces. This underscores the importance of ethnographic and qualitative work for building deep and contextual understandings of phenomena. Lastly, the classification of reviews in this analysis was limited to shallow positive, update encouragement, and targeted. Smaller categories of reviews outlined by Evans et al. [2017] such as non-constructive negative reviews could not be modeled because they were too small to build an accurate classifier. Therefore, we were not able to measure the effects of these categories of reviews.

Finally, and perhaps most importantly, this analysis, and indeed any observational analysis of an uncontrolled setting, cannot demonstrate causality between variables. Although we were able to use autoregression to eliminate the reverse causality limitation of Chapter 3, that does not equate with demonstrating forward causality. Our analysis does not rule out a third variable that may cause both reviews and lexical diversity. To better understand the role of reviews in relation to

the holistic experience of writing in the fanfiction community, we will explore the topic with interviews in Chapter 7.

#### 4.4.5 Looking Ahead

Although this chapter concludes our longitudinal modeling of the effects of review exchange on lexical development, there is much more to the distributed mentoring theory that we can explore in the Fanfiction.net dataset. We envisioned several exciting avenues for future research in the study of distributed mentoring and collaborative online learning in fanfiction communities. First, in Chapter 5, we begin to explore the relationships behind the reviews. We use social network analysis to understand the layered network structure of mentoring, establishing how stronger writer-reviewer relationships are more likely to contain targeted reviews. We follow up this analysis with written interviews where authors explain the impact of different kinds of relationships on their writing practices. Next, in Chapter 6, we explore the motivational outcomes of distributed mentoring with survival analysis, showing how the rate at which authors receive reviews can make or break patterns of continued participation in writing in the Fanfiction.net dataset. Finally, in Chapter 7, we'll explore how authors find feedback providers and build relationships in the fanfiction community, contextualizing the exchange of reviews with a wider view of interactions across platforms.

#### 4.5 Chapter Summary

In this chapter, we used an autoregressive linear mixed effect model to examine distributed mentoring, measuring the effects of receiving and sending different types of reviews on lexical diversity in fanfiction writing. In addition to triangulating with ethnographic research in the fanfiction community, our analysis contributes methodologically to the field by providing an

example of how a grounded theory and its associated qualitative coding set can be translated into large-scale quantitative analysis using a human-centered data science approach. By machine classifying reviews and modeling changes in writing, we were able to test predictions made from deep ethnographic investigation of a few fandoms, generalizing across the entire fanfiction.net author population. We found evidence upholding the powerful effects that an abundance of feedback can have on development, uncovered an interesting caveat surrounding update encouragement, and highlighted how sending targeted reviews can be as impactful as receiving them. Fanfiction communities stand as an example of how online affinity can promote literacy development, and this transformative impact on generations of youth warrants expansive research and analysis. With this foundational analysis, we begin to quantify this impact, and open up new lines of research for the theory of distributed mentoring.

## Chapter 5: Mentorship Network Structure

Co-authors of this Chapter: Ruby Davis\*, Niharika Sharma, Meena Devii Muralikumar, Cecilia Aragon, and Sarah Evans

\*Ruby Davis is a co-first-author of this chapter

### 5.1 Chapter Introduction

This chapter is about describing the network structure of communities that support writers. By *mentorship network structure*, we mean the layers of socially cohesive groups involved in mentoring. How many close relationships does an author have? What is the size of their online clique? How many group levels can be identified, from close connected circles to large supergroups? This structure is defined by the closeness and number of people's relationships, and the resulting networks formed. Understanding the size and closeness of communities, sub-communities and social cliques that form around authors can help to distinguish the types of interactions that make up distributed mentoring theory. After all, distributed mentoring is the result of a network of people providing support to a fanfiction writer, leading to continued activity and development. Describing the network layers helps us characterize how distributed mentoring works. In particular, our analysis in this chapter describes the composition of review types in each layer, and to complement this, we ask authors to characterize their experiences in a written interview. We examine the following research question:

**RQ: How are distributed mentoring networks structured?**

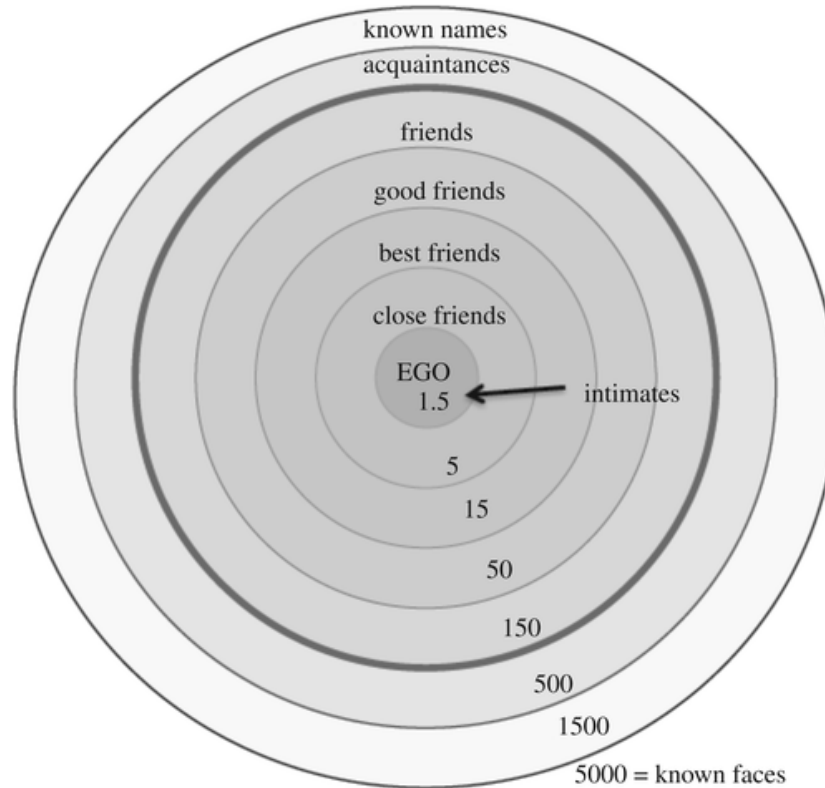
Between 2001 and 2018, 53 million relationships emerged between Fanfiction.net reviewers and writers. In some cases, these relationships extended over a long duration, where reviewers read and left reviews continuously as writers published their fics. In other cases, reviewers interacted with writers just a few times on a less frequent basis. In this chapter, we apply social network analysis methods to uncover the layered network structure of relationships among Fanfiction.net writers and reviewers. We use a clustering analysis on the relationship networks of authors to determine the overall layered structure of distributed mentoring on Fanfiction.net. We describe the number and size of each layer in the network surrounding writers, as well as the type of reviews exchanged in each layer. Our findings show that the relationships where reviews are exchanged most frequently are most likely to contain substantive reviews.

In addition to quantifying these relationship network patterns, it is interesting to understand how fanfiction writers personally experienced their mentoring networks. By distributing a written interview, we were able to get a view into what value people are able to derive from their interactions with their networks, how they experience close and distant relationships in the fanfiction community, what motivated their networking, and how their interaction strategies may explain the layered structure we see in our analysis. This type of mixed-method research design is known as a quantitative-to-qualitative explanatory study [65]. In our interview findings, we describe characteristic differences between close and distant mentoring network layers and why both types of relationships are valuable to writers. We also discuss how networking strategies like replying to every review, reviewing every chapter, and reciprocal reviewing may explain the layered networking pattern we see in our analysis.

In generalizing previous theory to an interest-driven affinity network, we reveal differences between socially-driven and interest-driven network structures. This work extends the theory of distributed mentoring [42] by linking the type of reviews being exchanged to different social layers. We integrate these findings and discuss implications for the theory of Distributed Mentoring as well as the design of spaces that support online affinity networks. This knowledge can aid in the construction of more effective mentorship communities whose affordances encourage and enhance distributed mentoring structures.

## 5.2 Dunbar's Layered Network Theory

Dunbar's theory posits that the number of quality relationships a person can maintain is finite, and that human social networks are characterized by distinct layers of closeness [85]. The smallest circle consists of about five people (or alters) with whom the individual (or ego) has a very close relationship. Every subsequent circle increases in size and decreases in closeness, with the outermost layer being acquaintances. Figure 5.2 below depicts the layered structure of human social networking found in face-to-face relationship networks.



**Figure 5.2: Structure of human ego networks (Source: Dunbar [2020] [84]).**

Although the outermost layer may be greatly expanded by features of social networking sites, the overall layered relationship structure observable on Twitter and Facebook datasets is similar to face-to-face relationship networks. Prior work by Dunbar et al. introduced a method for examining this structure by k-means clustering on relationship contact frequencies [85]. K-means clustering [192] is an unsupervised machine learning technique that divides data into “clusters,” or categories, based on their distance from each other. The technique computes cluster centroids, which are values that describe the center position of each cluster. In using k-means to describe network structure, the value of each cluster centroid describes the strength of relationships in each layer, as measured by how frequently people interact with each other. Additionally, the amount of data points in each cluster is a descriptive statistic that tells us the average number of relationships a person has in each social network layer. K is the number of clusters. By

computing the optimal number of cluster centroids for describing the network,  $k^*$ , we can determine the number of layers that characterize mentoring network structure.

### 5.3 Relationship Hierarchy in Distributed Mentoring networks

This section describes the quantitative investigation of this chapter, where we will explore how Dunbar's relationship hierarchy manifests in distributed mentoring networks. In particular, we replicate the method outlined by Dunbar et al.'s [2015] by transforming the Fanfiction.net dataset into a relationship graph, and using k-means clustering analysis to determine the number of layers that best describes ego networks on Fanfiction.net. After posing our quantitative research questions, we will describe how we adapted our dataset for this purpose, closely describe how we determined the optimal number of clusters  $k^*$ , and outline descriptive statistics for each layer in the 2-layer and 3-layer solution. Finally, we describe the makeup of reviews in each layer by their proportion of update encouragement and targeted reviews as classified by a machine learning algorithm.

#### 5.3.1 Research Questions

To describe the structure of distributed mentoring networks, we focus our analysis on determining the optimal number of layers to describe the network overall, and following that, to describe each layer. Beyond the number of reviewers in each layer, and the frequency with which they are reviewing, we are interested in understanding the type of reviews in each layer. As we find in Chapter 4 and Chapter 6, update encouragement reviews represent the lowest amount of effort and affective support, while targeted reviews require the most effort and carry the most affective weight for authors. Therefore, by describing the types of reviews in each layer, we also

gain understanding about the role distant versus close relationships have in providing support to writers. Therefore, we ask the following quantitative research questions:

**RQ1: How many layers are in a Fanfiction.net user's ego network structure?**

**RQ2: What kinds of reviews are exchanged in each layer?**

Answering these questions gives us key insights for describing what's happening in the mentoring networks formed around writers. By replicating prior analysis of social networks [85], we can compare our findings about distributed mentoring networks on Fanfiction.net with the more general relationship network structure found elsewhere. Additionally, we flip the direction of the analysis to describe reviewer ego networks, showing how the outward relationships that reviewers maintain are also organized in a layered network structure. Understanding how many authors an active reviewer is likely to be able to maintain regular connections with can inform better understanding of distributed mentoring through the lens of the mentors. Similarly, we look at the composition of reviews in reviewer ego network layers to understand how likely they are to write more effortful targeted reviews as a proportion of each layer.

### 5.3.2 The Fanfiction.net Relationship Network Dataset

We constructed a social graph from the metadata of reviews exchanged on Fanfiction.net between January 2001 and January 2017. To do this, we collected the metadata for all 173 million reviews we scraped from Fanfiction.net as described in Chapter 3. Each review in the dataset is associated with a timestamp from when it was posted to Fanfiction.net, and IDs of the reviewer and author in the exchange. Anonymous reviews were excluded from our analysis. In order to transform the review metadata into a relationship graph, we generated for each review a

pair of user identifiers, with the first identifier being the reviewer, and the second being the author who received the review. Grouping reviews by reviewer-author pair, we defined a *relationship* as any reviewer-author pair with at least two reviews exchanged over a duration of at least one month. For each relationship, we defined the *contact frequency* of a relationship as the number of times per month that reviews occurred over the duration of the relationship. The relationship network dataset contains 53,202,307 relationships between 2,580,411 reviewers and 1,373,910 authors.

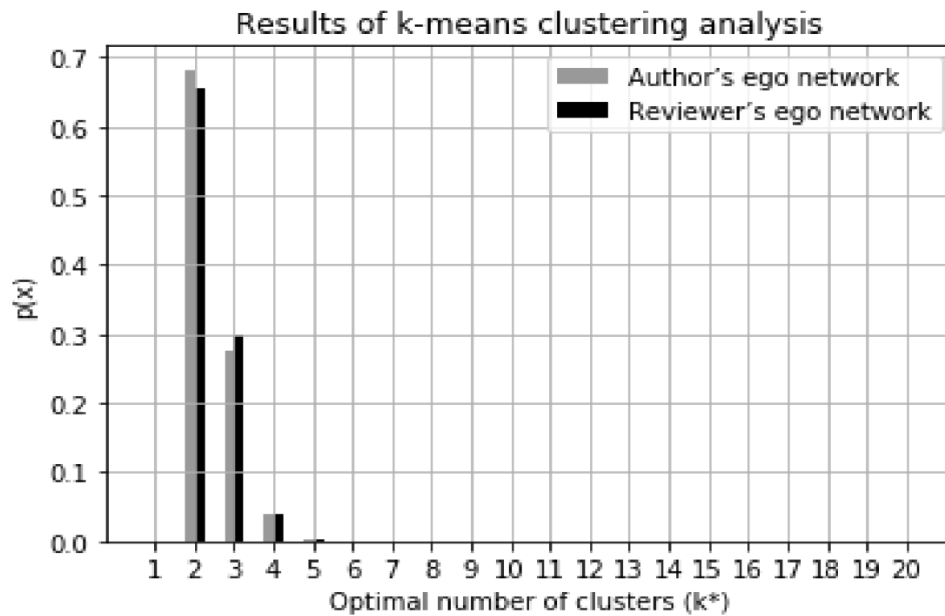
Next, for the purpose of our analysis, we needed to associate each relationship with its corresponding ego network. We define an author's *ego network* as a subgraph containing all relationships associated with the author's id as the recipient of reviews. Likewise, a reviewer's ego network is the subgraph containing all relationships the reviewer participated in. Next, we built a sample of ego networks such that each has enough relationships to be clustered, which we call regularly active authors or regularly active reviewers. We defined *regularly active* as giving or receiving at least 10 total reviews per month on average, and having at least 25 connections over the duration of their participation on Fanfiction.net. We analyzed the data from both the author and reviewer perspective, depending on whether we were looking at receiving or giving reviews in the FFN social graph. The resulting author-as-ego sample contained 66,798 authors (or 4.9% of all authors), and 747,502 reviewers, accounting for 73% of all reviews exchanged on FFN. In our second analysis, we looked at the ego networks of reviewers; the reviewer-as-ego sample contained 62,869 reviewers (2.4% of the reviewer population) and 458,286 authors, accounting for 31.4% of all reviews on Fanfiction.net.

### 5.3.3 Categorizing Reviews Exchanged in Each Network Layer

We trained a machine classifier on the human-coded dataset to classify all reviews in the Fanfiction.net dataset. We leveraged a dataset classified by members of the Human-Centered Data Science Lab research group, which contained roughly 8000 manually classified reviews at the time this analysis was conducted. Using the tool ALOE, outlined in detail by Michael Brooks [2013], we classified the reviews in the Fanfiction.net dataset with 87% accuracy for update encouragement and 75% accuracy for targeted reviews [13]. Using this classifier, we generated a binary prediction for each review included in the relationship network analysis dataset, flagging whether it contained update encouragement, or targeted feedback. After clustering relationships into layers as described below, we used this classification to examine the proportion of each type of review exchanged in each network layer.

### 5.3.4 The Optimal Value of K

We replicated Dunbar et al.'s k-means clustering approach [85] to examine the structure of social relationships on FFN. Given some value of k, the k-means algorithm chooses k cluster centers that best partition the ego network (i.e., grouping an author's reviewers into k different levels of reviewing frequency) [192]. We varied k from 1 to 20 and computed the value of k that best fits each ego network, which we call x. Figure 5.3.4 shows the proportion of x values,  $p(x)$ , for reviewer-as-ego and author-as-ego samples.



**Figure 5.3.4:  $p(x)$  for each value of  $k^*$ . About two thirds of ego networks, both reviewers and authors, were optimally clustered into two layers, while about 30% were optimally clustered into three layers. By Niharika Sharma.**

As seen in Figure 5.3.4, we found that most authors' ego networks are optimally clustered at  $k=2$  or  $k=3$  for both the author-as-ego and reviewer-as-ego samples. The mean optimal number of clusters,  $k^*$ , were 2.36 and 2.39 respectively. A mean silhouette score of  $s(x)=0.70$  indicated that the clusters were distinct and fit the sample well. This finding implies that there is a 2- to 3- layer social structure in Fanfiction.net reviewing networks—a close and distant set of relationships, or for some, a close, middle, and distant set (in addition to anonymous and one-off reviews, which were not included in the analysis).

### 5.3.5 Describing the 2- to 3-Layer Network Structure of Fanfiction Reviewing

To better understand the 2- to 3- layer network structure of Fanfiction.net reviewing networks from the author perspective, we examined the number of reviewers and frequency of reviewing in each layer. The mean and standard deviations of reviewing frequency across close and distant layers are shown in Table 5.3.5A below.

**Table 5.3.5A: Author as ego, 2-layer solution.**

<b>Layer (k=2)</b>	<b>Mean Alters</b>	<b>SE Alters</b>	<b>Freq. (Reviews/Month)</b>	<b>SE Freq.</b>
Inner	11.48	12.39	6.77	8.36
Outer	59.40	89.79	1.26	0.72

Next, we look at the 3-layer network structure from the author-as-ego perspective.

**Table 5.3.5B: Author as ego, 3-layer solution.**

<b>Layer (k=3)</b>	<b>Mean Alters</b>	<b>SE Alters</b>	<b>Freq. (Reviews/Month)</b>	<b>SE Freq.</b>
Inner	4.72	4.57	8.38	8.82
Middle	18.00	19.45	3.11	3.32
Outer	48.16	78.86	1.02	0.70

In these tables, we get a look at the structure of an author's reviewer network. Authors have a small inner circle who review them on a frequent basis. In the 2-layer solution, this looks like 11 people sending reviews twice per week. Note that this frequency varied widely. In the outer layer, a larger, widely varying number of people are reviewing about 1 time per month. The

3-layer solution splits the inner layer into roughly weekly and biweekly reviewing, and results in a smaller inner layer of about 5 people.

We similarly mapped out these numbers from the reviewer perspective, where mean alters is the number of authors the average reviewer in this analysis reviewed for that layer, and again we look at the mean frequency of reviews per month. See Tables 5.3.5C and 5.3.5D.

**Table 5.3.5C: Reviewer as ego, 2-layer solution.**

<b>Layer (k=2)</b>	<b>Mean Alters</b>	<b>SE Alters</b>	<b>Freq. (Reviews/Month)</b>	<b>SE Freq.</b>
Inner	9.08	9.10	7.01	7.50
Outer	50.30	59.34	1.26	0.65

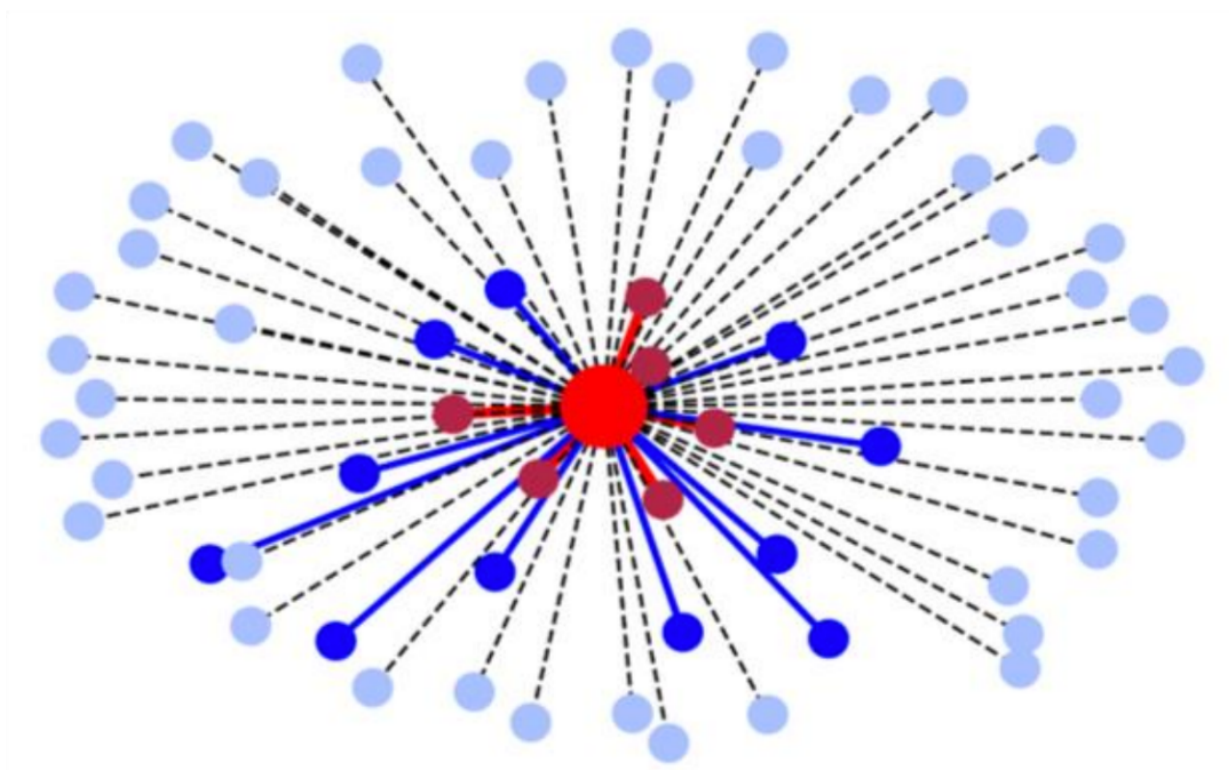
**Table 5.3.5D: Reviewer as ego, 3-layer solution.**

<b>Layer (k=3)</b>	<b>Mean Alters</b>	<b>SE Alters</b>	<b>Freq. (Reviews/Month)</b>	<b>SE Freq.</b>
Inner	3.89	3.52	8.66	8.04
Middle	14.76	13.98	3.25	2.92
Outer	40.73	51.82	0.97	0.58

Here, we're able to see that reviewers have a similar network structure to authors. They review a small number of people on a frequent basis, and a larger number on an infrequent basis. While the review frequencies are fairly similar to author-as-ego networks. The most notable differentiation between receiving reviews and giving reviews is the standard error of the number

of alters. This indicates that there is a longer tail of authors with high numbers of outer layer reviewers. The most prolific reviewers do not review as many authors in comparison to the number of reviewers that popular authors can retain.

Next we visualize a selected example from the author-as-ego dataset. Figure 5.3.5 visualizes this author's 3-layer ego network, with reviewers colored by layer and review frequency rendered as a distance from the ego.



**Figure 5.3.5: Visualization of an author's relationships, colored by layer and weighted by contact frequency.** By Niharika Sharma.

Figure 5.3.5 depicts a Fanfiction.net author's ego network. For the particular author in Figure 5.3.5, (Red Node), we can see the connected reviewers (blue nodes) and the corresponding layers they fit in. The red edges signify the closest layer, the blue edges signify the middle layer, and the dashed black edges the final layer. This graph is weighted according to the frequency of contact for a given author-reviewer pair.

### 5.3.6 Types of Reviews Exchanged by Layer

We computed a count of update encouragement and targeted reviews in each layer of the reviewer-as-ego dataset. Update encouragement reviews contain statements to the author that they should continue publishing work. Targeted reviews contain substantive commentary about the writing. These categories are not exclusive. The counts for each layer are shown in Table 5.3.6 below.

**Table 5.3.6. Percentage of update encouragement and targeted reviews in the reviewer 3-layer network structure.**

<b>Layer (k=3)</b>	<b>% Update Encouragement</b>	<b>% Targeted</b>
Inner	17.6%	55.3%
Middle	24.3%	53.1%
Outer	27.9%	49.8%

As shown in Table 5.3.6, the proportion of update encouragement increases from inner to outer layer, while the proportion of targeted reviews decreases. This indicates that reviewers spend more effort on substantive reviews in relationships with frequent contact.

Overall, our analysis revealed that active authors and reviewers tended to maintain a small number of close relationships (4 to 12) with both high frequency of contact (7 to 9 times a month) and higher likelihood of exchanging effortful and substantive reviews (55.7%). Authors and reviewers also had a larger number of relationships (40 to 60) that were infrequent (1 to 3 times a month) and more likely to contain less effortful reviews such as update encouragement (27.9%). These findings suggest that fanfiction participants tend to saturate their mentoring networks up to similar cognitive limits theorized by Dunbar et al. for more generalized social networks (Dunbar, et al., 2016).

## 5.4 Written Interviews

For our qualitative analysis, we distributed surveys with a combination of multiple choice and long response questions. We later contacted a smaller group of survey participants to complete follow-up questions in the form of online interviews via email.

### 5.4.1 Research Questions

We ask the following about writers' relationship networks, as followups to our quantitative questions posed previously in section 5.3.1.

**RQ3: What are these relationships like, and how are they meaningful?**

**RQ4: Why do readers and authors seek out these relationships?**

These questions are designed to derive meaningful insights about writers' perspectives of their mentoring networks, uncovering the characteristics and values of mentoring relationships, as well as motivations and strategies for network building. This builds depth in our findings beyond the numeric descriptions of mentoring networks contributed earlier in this chapter.

#### 5.4.2 Distributing the Written Interview

Our initial survey was distributed in November of 2017. Participants were enthusiastic in their responses and we received over 1.8 thousand completed questionnaires. Participants represented a wide range of ages, genders, and communities and answered questions about why and how they interact with their community. To recruit participants, we relied on snowball sampling [203] based on the researchers' personal contacts and a Tumblr account created for the study. The survey link was distributed through Tumblr, Twitter, fan groups on Facebook, email listservs, and fan Discord servers.

Survey participants were asked both multiple choice and long answer questions. In addition to our demographic questions, we asked participants to indicate which communities they participated in, which activities they engaged in, and how often they engaged in those activities. We also asked participants to explain in a long-answer question what motivated them to participate in fanfiction communities.

In August 2018, we sent a smaller group of survey participants additional long-response follow-up questions. This group consisted of people who had indicated in the initial survey that they frequently reviewed or commented on fanfiction. Nine interviews were conducted in total.

A set of five questions were sent to each interview participant. The questions differed slightly between interviewees who were authors and those who were reviewers.

#### 5.4.3 Survey Demographics and Mentorship Participation

Our survey participants represented a wide range of ages, genders, and experience. Of those we surveyed, 10% had been in fandom for two or less years, 28% had participated for 3 to 5 years, 30% had participated for 6 to 10 years, and 32% had participated for over 11 years. The age demographics of participants were consistent with findings from other fandom censuses; approximately 21% were 18 or under, 54% were between 19 and 29, and 25% were 30 or older. Gender was also consistent with prior research [42,96,285]—79% of our participants were women, 4.5% were men, and 20% were not strictly men or women. 2% of participants preferred not to disclose their gender. Note that these percentages are not additive, as participants were asked to select all identities that applied to them. In accordance with the terms of our IRB-approved protocol, we did not survey children under 13 years old.

Our survey results showed that most participants had experience on Fanfiction.Net, Archive of Our Own, and Tumblr. Over 95% of participants were current users of Archive of Our Own, while more than 75% were current or past users of FanFiction.Net. More than 80% were current Tumblr users.

Participants were asked to describe how often they do various activities in fandom. The vast majority of our participants were regular readers; we found that 66% of participants read fanfiction daily or almost daily, and 88% read fanfiction at least once a week. Many participants were also frequent reviewers; 46% indicated that they wrote comments at least once a week,

while 42% wrote reviews a couple times a month or less. Almost half of participants (48%) also direct or private messaged authors at least on an occasional basis. In addition, 62% of participants were currently fanfiction writers, and 30% wrote fanfiction once a week or more.

#### 5.4.4 The Value of Relationship Networks

In general, our survey participants emphasized the importance of community with “like minded” individuals as a key motivator for their participation in fanfiction communities. Many participants viewed fanfiction as a means of building and maintaining friendships, highlighting social networking as a core aspect of these communities. The development of writing skills was also continually referenced by participants as a key reason for their engagement with the community. Participants also noted a number of other reasons for their participation in fanfiction communities, including extended interest in source materials, stress relief, validation and encouragement from reviewers, exploration of queer themes and non-white characters, and a love for reading.

The survey and interview participants provided us with insight into the definition and significance of the different types of relationships fans build with one another in fanfiction communities. Participants associated different feelings and behaviors with different relationship categories. The participant’s closest relationships were people they engaged with both through fanfiction comments as well as other private platforms, like Twitter, Tumblr, Discord, or Google Chat. Most participants referred to these relationships as friendships. In online follow-up interviews to the initial survey, interview participants described using other platforms to go back and forth on fan theories, discuss more personal subjects, “beta” (or provide editing advice for) one another’s work, and share fan content. Writers indicated that the people they share these

close relationships with are typically also writers, and in addition to their other social behaviors, they regularly leave comments or reviews on each other's work. The support they received from fellow authors was critical in helping them improve their own craft.

Similar to our findings in the survey long-response questions, interview participants emphasized support, kinship, and social catharsis as key attributes of their cross-platform friendships that brought significant meaning to these relationships. One interviewee appreciated “the ability to talk about things I'm interested in without scaring others.” Another participant valued the ability to share thoughts on source material and “expect a gleeful, engaged response”. In addition, interviewees and survey participants alike emphasized fanfiction as a critical vehicle for friendship and community that may not be readily available offline—particularly for queer individuals. Being involved communities that, for one survey participant, can involve “queerness that's nearly ubiquitous” provides opportunities for relationships that are not always accessible in a fan's area of residence. One survey participant wrote, “For those of us who don't have the option of seeing our identities reflected back to us by the media, our families, our neighbors etc., the people in fandom become our friends--people who validate our experiences, our sexuality, our creativity. The stories we tell ourselves are deeply ingrained in who we are. Fandom gives us new narratives, which is empowering.”

#### 5.4.5 Motivations and Networking Patterns

A second category of relationships were contained within fanfiction platforms, and were not usually depicted as close as the cross-platform relationships. These relationships consisted primarily of regular reviews on an author's work and, if the platform afforded it, author responses to these reviews. In addition, most survey and interview participants described some

degree of positive emotional bond. One reader explained, “There was not really a relationship to speak of, but I like to think that after many consecutive reviews the author appreciated my effort in making reviews, and was capable of recognising my name when I left a review.” An author provided a similar perspective, writing, “Even just the brief, positive reviews make it so that I have positive connotations whenever I see their name.” One reader explained that when authors respond to their comments in a significant or regular way, the reader, “start to think of them as someone I “know”, and I might consider, for example, tagging them in stuff with a quick RTYI note if I follow them on Tumblr.” However, unlike the close multiplatform relationships, most participants did not describe these single-platform relationships as “friendships”. The only interview participant who did use the word “friendship” when characterizing their relationship with a regular reviewer further clarified the relationship as, “friendly colleagues”.

For other interview participants, regular reviewing was described as a step that sometimes leads to friendship, but is not necessarily friendship on its own. One author said, “I have a few regular reviewers who have since become friends, because their reviews lead to other conversations.” Another author explained, “I wouldn't say someone who comments often is automatically a friend, but that's definitely how I've made friends before!” One participant noted that while they haven't personally developed friendships through reviews, others they knew in the community had built extremely close relationships that began on fanfiction platforms. “Two of my good fandom friends met that way and are now getting married, so I know it happens.”

Regular reviewer-author relationships were meaningful to both parties. Reviewers sought to provide authors with continuous encouragement and support, as well as to express appreciation

for the enjoyment they'd gained from the author's work. Writers found regular reviewers to be, in general, deeply encouraging and motivational. "A regular reviewer becomes the star you wish to impress," one interviewee wrote. "I would say that the few regular reviewers I get always make me grin when I see them. It is so heartwarming to know they have stuck around AND are so happy to talk about what they liked and disliked."

A third category of relationships were reviewer-author relationships where a reviewer may only leave one or two reviews. These relationships are usually temporary and do not extend beyond the short interaction taking place on a writer's story. However, these interactions were still described as valuable to both writers and readers. Similar to the other two categories of relationships, readers from the survey and interviews appreciated the opportunity to let authors know that they "value their work and time" and to ensure that authors "got at least some positive feedback." One interview participant also described how leaving even one review can encourage the creation of desired content and influence a work's position in the context of the greater fanfiction community. "Commenting and reblogging and reviewing on its own changes what fic looks like in your corner of the fandom. ... So you're not just changing your relationship to the community when you review, you're feeding your corner of it."

Most writers valued their interactions with the majority of their one-off reviewers. They emphasized the importance of reviews as a source of validation and proof of an engaged and enthusiastic audience. "Knowing people like my writing sometimes motivates me to push past a finicky bit," one writer said. Another writer told us, "I keep a copy of my most loved comment in my wallet... They give me a boost when I'm feeling down. No matter what, sometime,

somewhere, I brought joy to someone else.” Although long reviews garnered an especially large amount of excitement, most participants valued short reviews as well. Another writer said, “Even if all the reader says is 'good job' it gets me more motivated to write than staring at a blank review box.” However, some writers were mostly indifferent to reviews; one writer when describing the experience of receiving reviews said, “If I don’t know them, I’m like thanks rando, and move on.” Some participants described a few rare negative review experiences. Multiple interviewees expressed annoyance at certain kinds of demanding “update soon!” reviews or unwanted criticism. One interviewee did describe an especially negative “draining and painful” experience where a reviewer attacked them for historical inaccuracies. Still, the interviewee did note many positive experiences with reviewers and on the whole considered reviews to be a positive experience.

## 5.5 Discussion & Conclusion

Our analysis revealed that inner circle relationships were more likely to contain targeted reviews, while outer circle connections were more likely to contain less effortful reviews such as update encouragement. Our findings regarding the size of each layer also suggest that fanfiction participants tended to saturate their mentoring networks up to cognitive limits in line with those theorized by Dunbar et al. [2015] for more generalized social networks. In this section, we contextualize these findings within prior literature and discuss implications for the design of online affinity spaces.

### 5.5.1 Quantitative Discussion

Our analyses revealed Fanfiction.net's layered structure, which is distinct from the layered structure described by Dunbar's research on other social networks. Where our analysis

determined the optimal number of layers to be 2 or 3, Dunbar et al. [2015] described 4 or 5 in their analysis of their Facebook and Twitter datasets. The dataset's lack of infrequent contact lower than once per two months shows that active reviewers do not typically maintain low-contact relationships. We only excluded relationships with contact frequencies of less than once a year, so this behavior cannot be explained by our exclusion criteria. One possible explanation for the lack of low-frequency layers emerges from the affordances of Fanfiction.net and the data we were able to collect. Reviewer-author relationships are reliant on an author's story update schedule, and readers are unlikely to leave public reviews without the catalyst of a story being published or updated. If an author does not update, it is unlikely that a steady flow of reviews will be posted on their story.

Although our qualitative research did point to different categories of relationships that correlate with contact frequency, these categories do not necessarily correspond directly with the layers discovered by our quantitative analysis. The third relationship category noted by interview participants represented relationships that were excluded from our quantitative analysis due to the low contact frequency existing in those relationships. The remaining two relationship categories noted by participants—multi-platform friendships and single-platform frequent reviewer relationships—may occur in any of the relationship layers uncovered by the quantitative analysis.

That said, we do expect many of the close multi-platform friendships described by interview and survey participants to fall within an ego's closest layer. Survey and interview participants reported near-daily interaction with those in fandom who they considered to be close friends.

There may be far more community interactions among these relationships than we were able to capture in our analysis of Fanfiction.net alone.

Other fan behaviors—particularly some observed in single-platform frequent reviewer-author relationships—may also correspond with different relationship layers uncovered by our analysis. As seen in our survey as well as the interviews conducted by Campbell et al. [2016], reviewers understand the value of their feedback and may seek out inexperienced authors to review, actively choose to nurture a particular author, and commit to leaving reviews on most fanfiction they read. If a reviewer commits to leaving reviews on as many works as they read, the relationships they build through this behavior may populate their outermost circle, maintaining low contact frequency but a high number of alters. If a reviewer has expressed interest in fostering talent, they may have high contact frequency relationships with a small number of authors. The middle circle of reviewer-author relationships may correspond to stories an author reviews after weekly or biweekly updates.

We observed a lack of contact frequencies lower than once every two months. Some author-reviewer relationships may simply be of short duration. Throughout the course of a reviewer-author relationship, a reviewer may lose interest in the story, unsubscribe from the author, or migrate to other “fandoms” to read fanfiction derived from different source material. The “nomadic behavior” of fans, where fans hop from source material to source material, is described in fanfiction researcher Henry Jenkin’s paper “Textual Poachers” [152] and was also noted by fans in their responses to our survey.

More research remains to be done on the fluidity of these different relationship layers. How often does a relationship shift from one category to another? Some survey participants described reviewer-author relationships growing closer or more distant, while others had not experienced changes in relationships built upon reviews.

Due to high individual variation, the ranges in number of alters per layer are large. This indicates a diversity of behavior among active reviewers on Fanfics.com. Although the mean number of alters does increase from layer to layer in our dataset, this may not be the case for every ego in the network. Some reviewers may have a handful of very close and frequent relationships and very few infrequent relationships. Similarly, some reviewers may have no close layer-zero relationships and over a hundred infrequent layer-two relationships.

This high variance in distributed mentoring styles shows that platforms for distributed mentoring must accommodate a variety of behaviors from reviewers to cater to a wide range of user activities. Fanfiction websites may increase contact frequency among reviewers and authors by implementing features such as more advanced subscription options for stories, easily accessible comment sections, threaded replies to reviews, and forum-based writing groups.

#### 5.5.2 Comparison with Facebook & Twitter

Although the social network structures are similar, there are fewer layers in the ego networks of active Fanfiction.net users in comparison with Facebook and Twitter users (2 and 3 versus 4 and 5 respectively [85]). The closest layer seen on Twitter, with alters contacting approximately at least once every 1 to 2 days, did not exist on Fanfiction.net. This may be explained by the affordances of reviewing fanfiction: reviewer-author relationships are reliant on an author's story

update schedule, and readers are unlikely to leave reviews without the catalyst of a new chapter being published. Twitter users may simply be able to create content more frequently because tweets are typically shorter than fanfiction chapters, resulting in more frequent exchanges. Additionally, Fanfiction.net lacked the middle layer seen on Facebook and Twitter, showcasing the two types of reviewers on the platform: frequent or infrequent. The outermost layer of the fanfiction.net dataset and the Facebook and Twitter dataset demonstrated similar behavior with some active reviewers typically maintaining low-contact relationships (the frequency of the outermost layer on Fanfiction.net was 1.26/month; on Facebook it was 1.37 and on Twitter 2.54).

### 5.5.3 Contribution to Distributed Mentoring Theory

These results suggest a difference between interest-driven and socially driven online communities, or “hanging out” versus “geeking out” [143]. Fans behave in a “nomadic” fashion, hopping from source material to source material as their interests change [152]. Throughout the course of a reviewer-author relationship, a reviewer may lose interest in the story, unsubscribe from the author, or migrate to a new fandom. We also found high individual variation; the ranges in number of alters per layer were larger than Facebook and Twitter. This indicates a diversity of behavior among active reviewers on Fanfiction.net. Some of this variation may be a result of differences between fandoms —particularly small and large fandoms. Interest and participation in a smaller fandom may lead to fewer and closer connections than a large fandom [6].

The theory of distributed mentoring [42] provides a framework for understanding the value and contribution of different feedback relationships. A large outer circle of reviewers helps to provide an abundance of feedback in the form of shallow positive reviews and update encouragement which in turn are linked to continued participation [13] and language

development [109]. The inner circle provides specific, directive feedback, which authors value highly and reciprocate, leading to stronger relationships, shared context, and better feedback in a virtuous cycle. The closer the relationship, the more effort is invested in feedback exchange, oftentimes going beyond the reviewing platform to beta reading, in-progress feedback and ideation feedback [6].

#### 5.5.4 Design Implications

Our findings imply that fanfiction websites and other online affinity spaces could be designed to optimize distributed mentoring by considering Dunbar's theory in the implementation of affordances for connection, feedback, exposure and recommendation. For instance, Fanfiction.net and Archive of Our Own both default to sorting works by their publication date—the most recently updated fanfiction are most likely to be seen. The result is that authors who publish frequently are most likely to receive exposure. However, based on our findings, these authors are less likely to need additional exposure in comparison with new authors who are posting for the first time in that fandom. There is potential for designing a different default which grants new authors more exposure until their networks are close to saturation. Likewise, for users with saturated networks, designs could focus on deepening their current relationships over exposure to more connections. Furthermore, we find that readers who frequently review an author are more likely to give substantive feedback. Platforms could further encourage this behavior by reminding frequent readers to do so, while prompting less frequent readers to give low-effort reviews like update encouragement.

### 5.5.5 Looking Ahead

Our work poses new questions about distributed mentoring and uncovers areas for additional research in the study of reviewer-author relationships in digital learning communities. Future research could compare the types of distributed mentoring performed in each layer. Comparing review content in each layer could reveal additional behavior differences between close frequent reviewer-author relationships and distant infrequent reviewer-author relationships. Further research could also explore the length of distributed mentoring relationships from layer to layer. Fans' nomadic behavior could limit the duration of reviewer-author relationships, thus explaining the lack of any layer with contact frequencies lower than once every two months. Both qualitative and empirical methods could be used to study this aspect of distributed mentoring relationships.

Our research focused only on substantive reviews and update encouragement, but further research could examine the occurrence of additional review types in a reviewer-author network. Examining how the bidirectionality of communication may differ between layers could also bolster our understanding of what each layer represents. Furthermore, the reviews that are exchanged on Fanfiction.net represent a small portion of the many interactions that occur in fandoms across the net. Examining how fans engage with one another across many different platforms could provide a more holistic view of this affinity network and its structure. This research could also be extended to explore networks beyond fan communities by comparing Fanfiction.net's structure to that of other networks, such as in-person mentorship networks.

## 5.6 Chapter Summary

Our large-scale analysis revealed the relationship structures within a distributed mentoring network. We characterized different layers of reviewer and author relationships and showcased the number, size, and distribution of relationship layers on Fanfiction.net. The findings show that targeted feedback is most likely to occur in the innermost layers, while less targeted feedback occurs more frequently in the outermost layers. To facilitate an ideal environment for distributed mentoring, sites must encourage the development of close relationships, where targeted feedback is exchanged, without oversaturating an individual's network beyond the limited number of relationships they can maintain. Future research can explore this design space to ensure the optimal balance of exposure and connection that allows individuals to build networks that facilitate mentoring. Designs that actively foster distributed mentoring networks can help millions of young people build their writing skills and share their voices.

Our research has empirically revealed previously unstudied structures within distributed mentoring communities and showcases the number, size, and distribution of relationship layers on Fanfics.com. An understanding of the structure of distributed mentoring communities can lead to improved affordances on sites that host distributed mentoring to better facilitate mentorship. For example, the size of layer 0 or 1 may be ideal for small collaborative group-based mentorship projects, while the size of layer 2 may be more suited to situations where participants provide feedback to any given individual only once or twice. Through our results, it is clear that distributed mentoring takes on a unique structure with a rich variety of behaviors from its participants. Work remains to further explore the implications of Fanfics.com's layers and illuminate the differences between them.

# Chapter 6: How Reviews Predict Continued Participation on FanFiction.net

Co-authors: John Fowler, Niharika Sharma, Matt Davidson, Wei Fan

\*John Fowler is a co-first-author of this chapter

## 6.1 Chapter Introduction

In this chapter, we will measure the effect of affective support on authors' motivation to continue posting to Fanfiction.net using a statistical modeling technique called survival analysis. Survival analysis can quantify the effect of feedback by differences in the probability of chapter publication. This type of analysis is new in the quantitative study of informal learning. We find that differences in the amounts of reviews are correlated with dramatic changes in participation rates. Our model establishes the size of that relationship on a large, longitudinal sample, demonstrating the measurability of findings suggested by previous ethnographic studies of FanFiction.net, which claim that reviews motivate and provide direction to authors. Our result provides insight into the benefit of affective support writers receive from reviewers in a large-scale community.

### 6.1.1 The Effect of Affect

Fanfiction.net reviews offer fanfiction writers an opportunity to connect with their audiences and receive feedback and encouragement. In general, reviews on Fanfiction.net are overwhelmingly positive in nature, with only about 1% of reviews being antagonistic [93]. The *affect* aspect of distributed mentoring describes the emotional support writers receive from their feedback providers, and the motivational effect this has on their writing [42]. Although each single

engagement between writers and readers may be limited to only a few words, prior participant observation and interviews with fanfiction writers have shown that encouraging reviews can be crucial for motivating authors to persevere [42]. In turn, this continued participation translates to measurable improvements in authors' writing [109].

Fanfiction.net is a suitable community to provide lessons about the role of encouragement in informal learning. Maintaining mass participation for over a decade, and accumulating millions of stories, the community has motivated young people to write and continue writing without money or school credit. One major factor in this phenomenon is *affinity*: shared interests and identities that motivate connection and build a foundation for supportive relationships [143]. In addition to shared interest in fandom, many writers come from marginalized identities – FanFiction.net writers are majority female and queer. Because of this, they often challenge mainstream narratives by rewriting them to include alternative perspectives [86,99,145]. As a result, they attract audiences who connect with both the content and the writers. The experience of connecting with audiences who resonate with the stories can potentially be very powerful for authors.

Do reviews make a big difference in author participation outcomes? How much audience connection is needed to motivate continued writing? In this paper, our intention is to understand the effect of reviews on participation across the greater Fanfiction.net community. Conducting survival analysis can reveal how different amounts of incoming reviews might impact writing behavior. Thus, our research question is:

## **RQ: How do reviews predict author participation on Fanfiction.net?**

To answer this, we developed a model to predict authors' probability over time of publishing a new fanfiction chapter based on their rate of incoming reviews since their most recent publication. *Survival modeling* is a form of statistical analysis, popularized for predicting patient survival in medical contexts, that is particularly useful for predicting the time until some event occurs [230]. The term *hazard*, so termed because survival modeling often predicts negative events, refers to the probability of the event of interest occurring at a given point in time. The model can be used to determine how an independent variable influences that probability [164]. We will use survival analysis to estimate the "hazard" of an author publishing a new chapter to FanFiction.net. We can also use this to test the difference in hazard across groups of authors, such as authors with different numbers of incoming reviews.

This chapter contributes a model of Fanfiction.net participation that predicts an author's variable probability over time of publishing a new chapter based on the rate of reviews received for that author's most recent chapter publication. For instance, our model predicts that authors receiving less than 0.09 reviews per day (or roughly less than three reviews per month) have a 19.8% probability of posting another chapter within 90 days, while authors who receive 0.09 to 1.02 reviews per day have a 90.1% probability of posting again within that time. This new empirical evidence demonstrates the connection between distributed mentoring on FanFiction.net and continued participation in the community. Our findings build quantitative support for the theory of distributed mentoring by measuring the effect of affective support, a key component of mentoring, provided through reviews. In addition to the findings of this chapter,

### 6.1.2 Methodological Contribution of this Chapter

Characterizing the behavioral factors impacting retention in informal learning communities is critical for understanding and supporting overall community health and longevity. Prior work has begun to analyze the relationship between feedback and participation across other communities. For instance, positive feedback in the form of “love its” predicted increased participation and sharing among inexperienced programmers in the Scratch programming community, a site that struggles with early user attrition [85]. On Wikipedia, positive sentiment in feedback exchanged between editors was associated with increased knowledge reuse [91].

By adapting survival modeling analysis to the problem, we are making novel methodological contributions to the study of online communities. There are only a handful of survival analysis papers in the space [225,273], and to the best of our knowledge, our analysis is the first in this field to use the weighted-residual score test or the Peto-Peto-Prentice test.\* For this reason we will describe our method and test implementation in detail, with the intention of increasing access to this method among other social computing researchers. To check the weighted-residual score test we ran a search of the ACM database with key terms “survival”, “residual”, and “score”, and we ran a search of Google Scholar with key terms “social computing”, “residual”, “score”, and “survival”. To check the Peto-Peto-Prentice test we ran a search of the ACM database with key terms “Peto” and “Prentice”, and we ran a search of Google Scholar with key terms “social computing,” “Peto,” and “Prentice”. We reviewed all pages of the ACM searches and the first five pages of Google Scholar results.

## 6.2 Methodology

This section describes our methodology of survival analysis modeling. First, we present a high-level overview of the process of choosing an appropriate model as well as our model choice. Next, we describe our dataset and analysis sample. Finally, we walk through the details of the analysis variables, tests, and R packages used in our analysis.

### 6.2.1 Survival Modeling in Social Computing

Survival modeling is a form of regression modeling common in medical research for estimating the probability of a patient's survival over time across different treatment groups. While this type of analysis is more commonly used in the area of healthcare, it has also been employed in social computing research. For instance, Yang et al. used parametric survival modeling to estimate the student dropout rates in massive open online courses [274]. The advantage of performing a survival analysis is to give less biased estimates than other regression techniques for time-to-event modeling. Another way that survival modeling has been used in social computing is to understand the connection between user engagement and the lifespan of the greater online community [225]. Raban et al. [2010] used semi-parametric Cox regression to demonstrate a connection between user engagement and the sustained membership [225]. Although we similarly are modeling the time until an event of interest, in our case the event of an author publishing fanfiction, our model differs from this prior work because we found that the semi-parametric Cox regression model would not apply (see Section 2.1). We elaborate in the methods section on how a social computing researcher may check the appropriate assumptions and choose the correct survival analysis model.

## 6.2.2 Determining the Appropriate Model

Creating a survival model starts with determining which type of model is most appropriate for the analysis data. The researcher must decide whether to use the semi-parametric Cox Proportional Hazards approach or a parametric approach, which requires an assumption that the data matches a specific distribution. One aspect to making this determination is to test if the data meet the proportional hazards assumption, which is a requirement for using the Cox Proportional Hazards model but not necessary for parametric modeling [164]. After a thorough review of methods used across multiple fields, including medical research of human-generated data, we decided to use a weighted-residuals score test to determine if our data meets the proportional hazards test. It has become a standard test for this purpose because of the ease of implementation and high statistical power associated with the test [208].

We emphasize use of the weighted-residuals score test to establish if data meet the proportional hazards assumption in order to underscore the need for this as a standard practice in social computing survival analyses. The need to test for proportionality of hazard rates before running tests to compare differences between survival curves is a documented issue; researchers have called into question previously published results that failed to test this assumption. If the proportional hazards assumption is violated, this will affect the validity of significance testing on the semi-parametric Cox Proportional Hazards approach [31]. Running the weighted-residuals score test on our data, the results showed that our data do not meet the proportional hazards assumption. This outcome had consequences – which we will describe more fully in the following sections – for statistical testing and modeling decisions in our analysis.

### 6.2.3 Visualizing Kaplan-Meier Curves

Kaplan-Meier curves are estimates of survival curves (i.e. the probability of an event occurring over time) based on observed data [129]. Due to the properties of our data, we visualized our dataset using these curves (see Section 3.2.2), as they are particularly useful for analyzing data like ours with right-censored observations [92]. We use these Kaplan-Meier curves to observe any differences between review rate levels and the likelihood of publishing a chapter over time.

### 6.3.4 Significance Testing with the Peto-Peto-Prentice Test

Another consequence of our data not meeting the proportional hazards assumption is that the Mantel-Haenszel log-rank test, a common test for these purposes, would no longer be appropriate and instead we needed to use the Peto-Peto-Prentice test to determine the statistical significance of the observed differences between three curves [92,132]. The Peto-Peto-Prentice test is a modification of the Gehan-Wilcoxon test, which places more importance on information at the beginning of the survival curve and therefore allows events that occur earlier to receive more weight than those that occur later [159]. This makes sense in our case, as an author publishing a new chapter days after publication of a previous chapter should be seen as a greater level of engagement in the community than delaying publication of a new chapter until months later. In relation to the shape of our data, the Peto-Peto-Prentice test is particularly applicable to our situation because the proportional hazards assumption is violated, the rate of right-censoring is relatively low at only 12.4%, and the groups of the stratified variable are equal in size [92]. In other words, the Peto-Peto-Prentice test is the most appropriate for our analysis because the relative likelihood that authors from the three review rate groups will publish a new chapter changes depending on how many days it has been since that author last published a chapter, a

large majority of the chapters in the dataset are published as opposed to unpublished, and we split the authors into three evenly sized groups.

### 6.3.5 Building a Parametric Model

Next we move on to building our parametric model. A model is parametric if it is based on an assumed underlying distribution in which all information the model uses for prediction purposes is captured in one or more parameters. The Akaike Information Criterion (AIC) is an estimator of prediction error that can be used to determine the relative quality of predictions across multiple statistical models for a given dataset. The Bayesian Information Criterion (BIC) is a related method used to select a model from a finite set of options[174]. To land on the distribution most appropriate for our data, we ran both AIC and BIC comparisons of nine distributions. Using AIC for model selection has a risk of overfitting the data while using BIC has a risk of underfitting so if both tests select the same model – as in our case – this suggests a higher degree of confidence that the chosen distribution is appropriate for the data [174]. There are examples of distribution selection using this method in social computing literature [166]. After running the comparisons for our dataset, we determined that the Weibull distribution (described below) had the lowest AIC and BIC scores and therefore would be best for our situation [221]. From here we constructed our parametric survival model assuming the Weibull distribution and used it for prediction purposes to compute estimated survival probabilities for a handful of points in time for each level of our stratified variable. Others in social computing have used survival models assuming the Weibull distribution for prediction purposes as well, such as a study that used the Weibull distribution to predict the likelihood of online content becoming popular [181]. To validate the quality of the model predictions, we report the  $R^2$ , Dxy, g, and gr performance

metrics as calculated through a bootstrap resampling technique. This is a common way to validate and report on the performance of a predictive model like this[52].

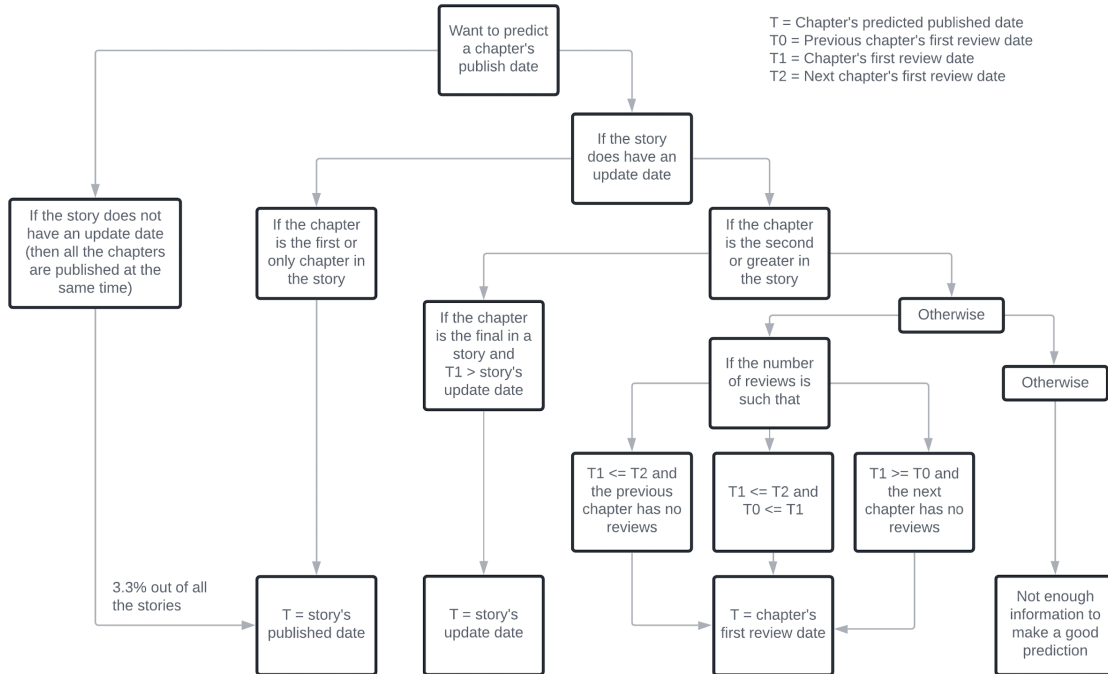
### 6.3.6 The Weibull Distribution

In our analysis, the survival times of individual authors are being estimated parametrically with the model assuming a Weibull distribution. A Weibull distribution is a continuous probability distribution often used to model survivorship due to its flexibility in producing a curve that takes on a wide variety of shapes [221]. A similar paper analyzing the effect of informational support on member retention in an online community via a parametric survival model assuming a Weibull distribution was published by Xing et al. in 2018 [269]. Like Yang et al. [2013], the authors cited use of this method to produce less biased estimates than traditional regression techniques due to the nature of the truncated time series data [269]. Additionally, it has been shown that if the distribution of survival times can be well-approximated by a Weibull distribution, doing so can provide practical benefits by affording the researcher the ability to make a wider range of inferences [44]. Of particular interest to our analysis, use of the Weibull allows the researcher to quantify improvement in survival time between different groups of participants.

### 6.3.7 Building an Analysis Dataset

The analysis dataset for this study was built from the Fanfiction.net archive we gathered in Chapter 3. The archive contains 16 years of FanFiction.net publications, 28 million chapters of fanfiction, 176 million reviews and 8.5 million users. Our archive provided exact publication timestamps for each story but not for each chapter. Accurate timestamps for reviews were also available. Therefore, we estimated chapter publication times for use in this analysis. We created a

ruleset to estimate as many as possible based on other metadata. The flowchart below shows the process by which a chapter's publication date was estimated.



**Figure 6.3.7:** This is a flowchart depicting the process that was used to estimate chapter publication timestamps. The questions asked when navigating the flowchart are related to the story's update date, the number of chapters in the story, the dates of reviews on the current, previous, and next chapters. Based on answers to those questions, if enough information was present to make a prediction we ended up using one of three dates available in the dataset to make the chapter publication timestamp estimate: 1) the story's published date; 2) the story's update date; or 3) the chapter's first review date.

Next, we created a sample from the original dataset of 8.5 million users. To generate the sample, we chose 100,000 authors from the dataset using a random number generator. We then excluded

authors who did not have timestamp estimates for one or more of their chapters, leaving us with 63,268 authors. Lastly, we excluded authors who only published one chapter of fanfiction, leaving us with a final sample of 34,290 authors. We then aggregated chapter metadata for each of the authors in this final sample. In the final sample of 34,290 authors, each data point contains the amount of time that passed between authors' publications and the number of reviews they received during that time. Because these numbers were between chapters, the first chapter an author published was excluded, and chapters with zero time since the previous chapter publication were also excluded.

After this filtering, we were left with a sample of chapters that had received a higher quantity of reviews in relation to the population. For the sample, the mean quantity of new reviews received on each chapter published is 10.3 and the median is 5.0. For the 100,000 author population, the mean is 3.2 and the median is 1.0.

**Table 6.3.7:** This table provides a summary of some key statistics to illustrate similarities and differences between the randomly sampled 100,000 author dataset, the dataset that remained after timestamp predictions, and the final dataset that remained after excluding any author who did not have timestamp estimates for all of their chapters.

<b>Metric</b>	<b>Raw Data</b>	<b>Predictable Timestamps</b>	<b>Analysis Dataset</b>
Total Number of Authors	100,000	63,268	34,290
Total Number of Stories	442,091	169,156	118,147
Total Number of Chapters	1,849,998	431,607	380,598
Average Chapters per Author	18.5	6.8	8.3
Average Stories per Author	4.4	2.7	3.2
Average Chapters per Story	4.2	2.6	2.6
Average Words per Story	9,218.9	5,826.5	6,232.9
Average Reviews per Story	26.3	24.1	27.0
% Stories Marked Complete	50.1%	43.9%	45.7%

### 6.3.8 Description of Analysis Dataset

The analysis dataset comprises 380,598 published chapters from 118,147 stories published by 34,290 unique authors representing 2,979 different fandoms. All published chapters have timestamps between 4/27/1999 - 11/20/2016. We assume a set of unpublished chapters as well, one from each story that had at least one chapter published by 11/20/2016 but the story was not marked as finished by the author at that time. The dataset contains 47,383 of these “unpublished” chapters that we assume are still in the process of being written. These unpublished chapters are assigned a timestamp of 11/20/2016 because it represents the end of data collection. (See Section 2.10 for more details).

For each chapter in this analysis, we tracked a binary variable titled “Complete,” which represents whether the story had been marked completed by the author as of 11/20/2016. Note that this date is the final date of observation in our dataset so unpublished chapters are right-censored. Right-censoring happens when a participant leaves a study before the event of interest has occurred [92]. This means that the value of the data point is higher than what is recorded – although it is not known how much higher – and that the data does not tell us whether

or not the event has yet occurred. In our case, since the data collection was cut off on 11/20/2016, it is unclear if a story marked as incomplete remains so to this day or has been completed sometime since. In either case, our dataset and analysis treat these two instances in the same manner – as if the story has not been completed, with an indication that the data point is right-censored. In our data set, 12.4% of the chapter publication data points are right-censored. This is typically referred to as the censoring rate.

The intent of our model is to predict the event of chapter publication based on the rate of new reviews received. In this sense, the probability of chapter publication can be thought of as the dependent variable, and the rate of new reviews as an independent variable.

Our analysis dataset contains a time variable for each row of data. The time variable of this analysis is a continuous numerical variable titled “Days Since Last Publish” and represents the number of days in 24-hour time intervals from the publication timestamp of an author’s previous chapter until the publication timestamp (or 11/20/2016 for unpublished chapters) of the chapter in question. Note that this requirement to measure against the publication timestamp of the previous chapter is what requires the exclusion of all first chapters from the dataset, as well as all authors who only published one chapter.

We stratified the dataset categorical by a three-pronged categorical variable. The variable was titled “New Review Rate Categorical” and was divided into the three quantiles (bottom, middle, and top third of the observed data) of the quantity of new reviews received by an author from the publication timestamp of the previous chapter up until the publication timestamp (or 11/20/2016

for unpublished chapters) of the chapter in question divided by the number of 24-hour time intervals over that same period of time. The three categories delineated into three equal-sized quantiles of rate of new reviews received per day as follows:

Least =  $[0, 0.09]$

Mid =  $(0.09, 1.02]$

Most =  $(1.02, \text{inf}]$

We compared survival rates at 7, 30, and 90 days since publishing the previous chapter for the three “New Review Rate Categorical” categories of Least, Mid, and Most. We chose these three cutoffs as they align with one week, one month, and three months since publishing the previous chapter, and previous work had shown that authors often choose such boundaries when deciding when to publish [42].

**Table 6.3.8:** Variables used in the survival analysis and their definitions.

<b>Variable</b>	<b>Definition</b>
Days Since Last Publish	The number of days in 24-hour time intervals from the publication timestamp of an author's previous chapter until the publication timestamp (or 11/20/2016 for unpublished chapters) of the chapter in question.
New Review Rate	The quantity of new reviews received by an author from the publication timestamp of the previous chapter up until the publication timestamp (or 11/20/2016 for unpublished chapters) of the chapter in question divided by the number of 24-hour time intervals over that same period of time.
New Review Rate Categorical	The New Review Rate variable divided into three equal-sized quantiles of rate of new reviews received per day: Least, Mid, Most.

## 6.4 Conducting Survival Analysis

In this section we focus on the tools and packages we used to perform the process described above. Once the dataset and new variables were defined, we ran the analysis in R using the “rms” and “survminer” packages. First, we built a survival model using the function `Surv()` with “Days Since Last Publish” as the time variable and “Publish” as the event variable. We then followed the steps listed in the three subsections below:

### 6.4.1 Checking Assumptions

We checked the proportional hazards assumption using the `cox.zph()` function on the residuals of the continuous version of the “New Review Rate” variable to test the proportional hazards assumption. We also plotted a Schoenfeld chart to visualize the data and check if it looked randomly distributed. When the proportional hazards assumption failed, it meant that the relative likelihood of publishing a chapter based on the “New Review Rate” variable changes over time.

In order to handle this violation of the assumption, we fit a survival model with “New Review Rate Categorical” as a three-pronged categorical variable (as described above) for stratification.

#### 6.4.2 Kaplan-Meier Curves and Peto-Peto-Prentice Significance Testing.

We plotted Survival Curves, Cumulative Event Curves, and Cumulative Hazard Curves for this model using `ggsurvplot()` and checked the significance of any differences along the strata via a Peto-Peto-Prentice test using `survdiff()`. We then ran pairwise comparison to determine where the statistical differences occurred between the three groups. These tests check if there were significant differences between the observed survival curves (i.e. the likelihood of publishing another chapter over time) of the three groups of authors based on the quantity of reviews they received on previously published chapters.

#### 6.4.3 Parametric Weibull Modeling.

To determine which probability distribution we should assume for our parametric survival model, we compared both the AIC and BIC (see Section 3.2.3) results for the following distributions: log-logistic, Weibull, log-normal, log-Gaussian, Rayleigh, exponential, Gaussian, logistic, extreme. Both the AIC and BIC were lowest for the Weibull distribution so we assumed this distribution for our model, using the `psm()` function to build it. We validated the quality of the model’s predictions based on the  $R^2$ ,  $D_{xy}$ ,  $g$ , and  $gr$  test statistics that are output as a result of bootstrap resampling performed by the function. Finally, we compared survival rates at 7, 30, and 90 days since publishing the previous chapter for the three “New Review Rate Categorical” categories of Least, Mid, and Most.

## 6.5 Findings

In this section, we will discuss findings from our survival analysis on the Fanfiction.net dataset. We start by introducing a categorical independent variable, new review rate, and reporting the significance of differences in outcome under the Weibull model. Then, we report the findings of our weighted-residuals score test, showing that the proportional hazards assumption is not applicable to our dataset and demonstrating the need for a parametric model. We plot survival curves present in the data, and finally present a parametric weibull model that can be used to predict chapter publication behavior based on reviews.

### 6.5.1 Model Specification and Validation

The results and components of the parametric model using the Weibull distribution are found in the table below for each level of the New Review Rate Categorical variable and log(scale). All variables in the model are statistically significant with p-values  $< .0001$ .

**Table 6.5.1:** Table of model variables with regression coefficients, standard errors, Z-scores, and p-values.

<b>Variable</b>	<b>Coefficient</b>	<b>SE</b>	<b>Z</b>	<b>p</b>
Least	7.11	<0.01	1,169.1	<0.01
Mid	-4.06	<0.01	-521.8	<0.01
Most	-5.80	<0.01	-746.2	<0.01
Log(scale)	0.55	<0.01	389.4	<0.01

### 6.5.2 Checking Assumptions

We started by checking the proportionality of our data by using a weighted-residuals score test.

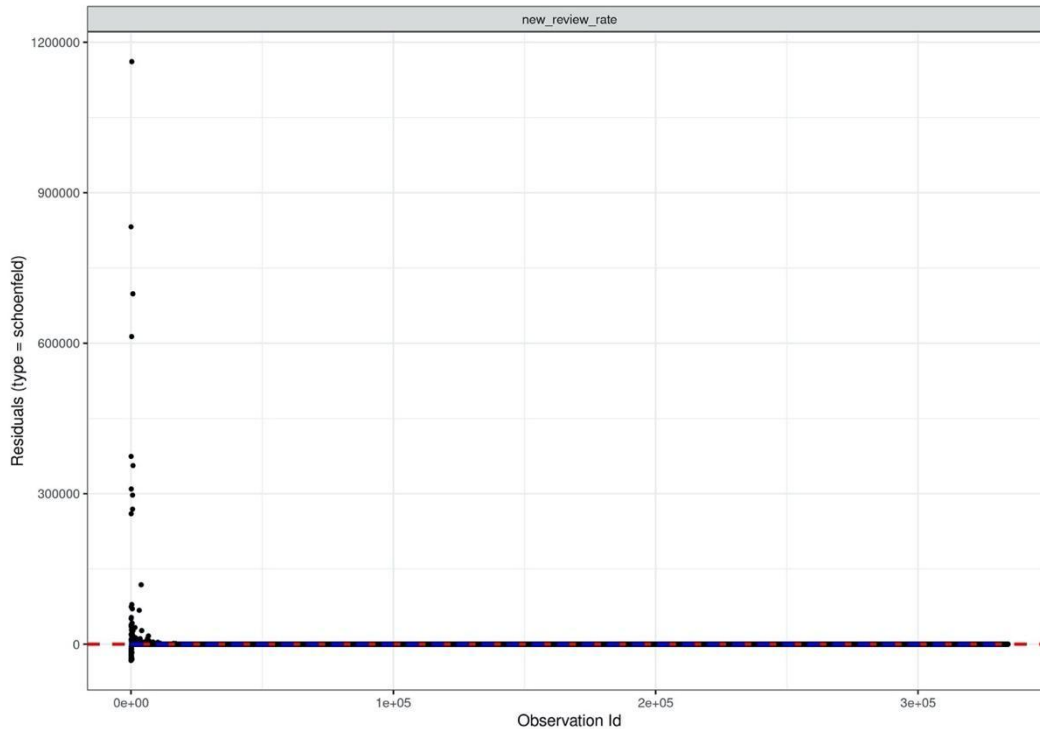
The results of testing the residuals of the continuous New Review Rate variable for the

proportional hazards assumption can be seen in the table below. The p-value  $<.01$  indicates that the data does not meet the assumption so we know that the Cox Proportional Hazard model and Mantel-Haenszel log-rank testing would not be appropriate for our analysis.

**Table 6.5.2:** This includes results from a weighted-residuals score test of the proportional hazards assumption. With a p-value  $< .05$ , the New Review Rate variable does not meet the assumption so we know that our data is not sufficiently proportional.

<b>Variable</b>	<b>Chi Squared</b>	<b>DF</b>	<b>p-value</b>
New Review Rate	26,690	1	$<0.01$

In addition to using a weighted-residuals score test, we can also visually confirm this finding. The output of the Schoenfeld chart for visualizing the appropriateness of the proportional hazards assumption can be seen below. The observations are not distributed as a random walk starting and ending at zero, providing further visual confirmation that the data does not satisfy the proportional hazards model [272].



**Figure 6.5.2:** This Schoenfeld chart visually demonstrates that the New Review Rate variable does not meet the proportional hazards assumption, as the observations are not distributed as a random walk starting and ending at zero. This provides visual confirmation of the need to use parametric survival modeling and significance testing alternatives beyond the Mantel-Haenszel log-rank test for our analysis.

### 6.5.3 Kaplan-Meier Curves and Peto-Peto-Prentice Significance Testing

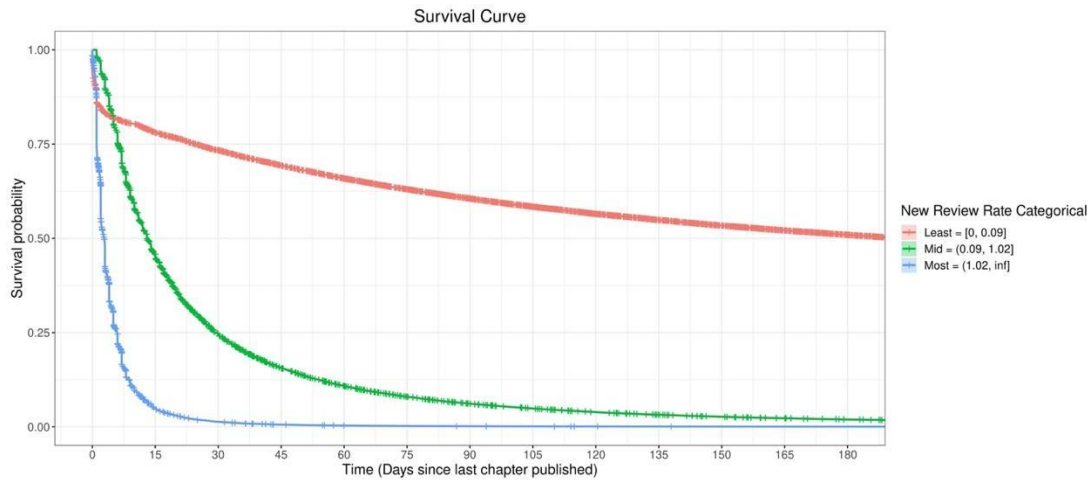
In order to visualize the survival, event, and hazard curves we then performed a Kaplan-Meier analysis. The results of this non-parametric analysis are below. Table 6.5.3A shows the median and 95% upper and lower confidence levels of the number of days before publishing a new chapter for each level of the New Review Rate Categorical variable. In other words, we estimate the true median would lie between these values in 95% of instances. Note that as we move from Least to Most in terms of the New Review Rate Categorical variable, the number of observations in which an event (i.e. publication of a new chapter) occurs increased and the median number of

days between the occurrence of events decreased. This tells us that higher rates of reviews received were associated with more authors continuing to publish, and those that continued to publish tended to publish at faster rates.

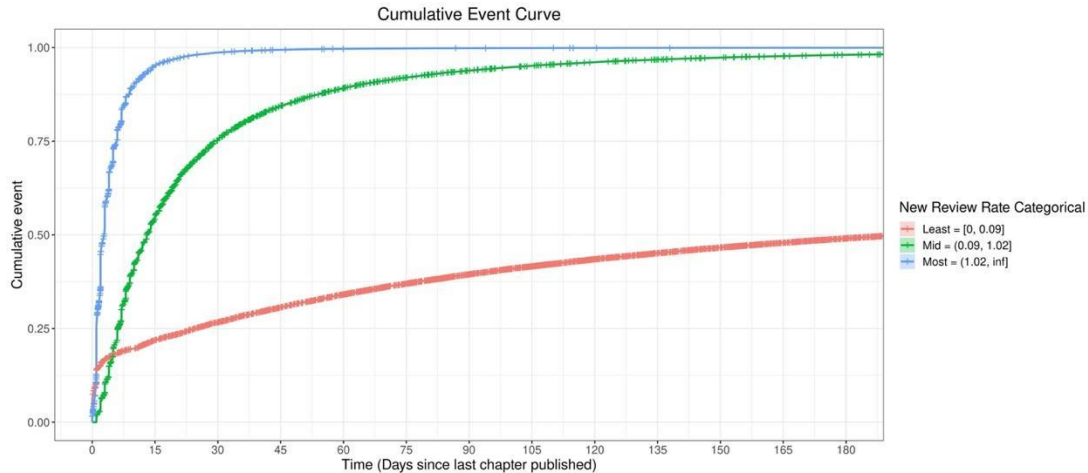
**Table 6.5.3A:** This table contains the number of observations, the number of those observations that resulted in an event occurring (i.e. chapter being published), the median time between events occurring (i.e. the number of days between chapters being published), and 95% lower and upper confidence levels for the median. This tells us that higher rates of reviews received were correlated with greater quantities and frequencies of continued publication of chapters.

<b>New Review Rate</b>	<b>Observations</b>	<b>Events</b>	<b>Median</b>	<b>95% Lower</b>	<b>95% Upper</b>
Least	127,229	80,832	193.4	189.1	197.5
Mid	127,229	126,459	13.0	13.0	13.1
Most	127,229	127,014	2.8	2.8	2.9

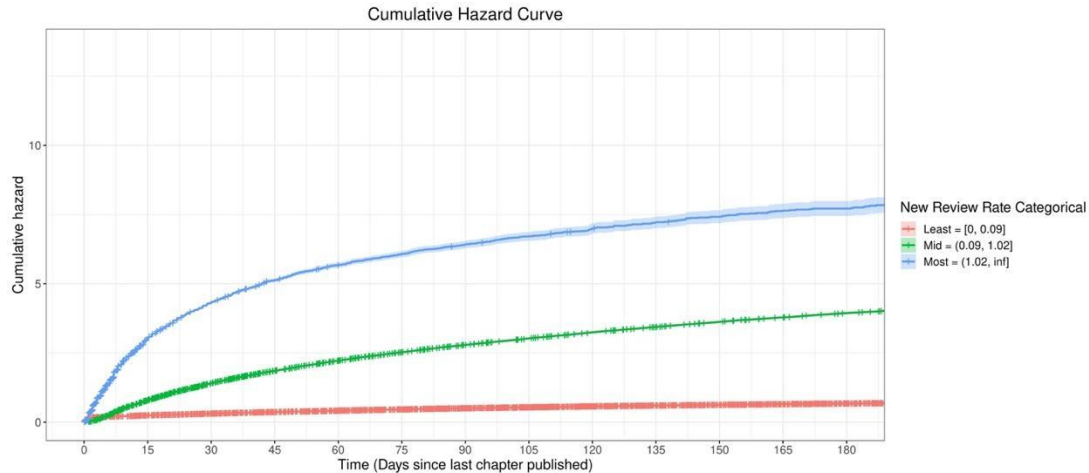
After reviewing the summary statistics, we moved to the creation of charts to visualize author behavior over time. The charts below show the survival curves, cumulative event curves, and cumulative hazard curves across the New Review Rate Categorical strata with the p-value relating to the Peto-Peto-Prentice test to determine significance of any differences between the survival in one or more of the levels of the stratified variable. In each chart, the p-value is statistically significant, indicating that authors within different levels of the New Review Rate Categorical variable differed significantly in terms of their probability of publishing another chapter over time. This means that the rate of reviews an author received on previous chapters was positively related to their likelihood of publishing another chapter.



**Figure 6.5.3A:** This chart shows the survival probability of the Least, Mid, and Most levels of the New Review Rate Categorical variable over the first 180 days since a chapter is published. From roughly one week on, the chart shows those receiving the least reviews with the highest survival probability (i.e. lowest probability of publishing another chapter) and those receiving the most reviews with the lowest survival probability (i.e. highest probability of publishing another chapter). Essentially, receiving a higher rate of reviews on previous chapters was correlated with a higher probability of publishing a new chapter at any point in time after roughly one week since the previous chapter was published.



**Figure 6.5.3B:** This chart shows the cumulative probability of an event occurring (i.e. a new chapter being published) for the Least, Mid, and Most levels of the New Review Rate Categorical variable over the first 180 days since a chapter is published. From roughly one week on, the chart shows those receiving the least reviews with the lowest cumulative event probability (i.e. lowest probability of having published another chapter at that point in time) and those receiving the most reviews with the highest cumulative event probability (i.e. highest probability of having published another chapter at that point in time). Essentially, receiving a higher rate of reviews on previous chapters was correlated with a higher probability of having published a new chapter at any point in time after roughly one week since the previous chapter was published.



**Figure 6.5.3C:** This chart shows the cumulative hazard of an event occurring (i.e. the expected number of new chapters that would have been published to that point in time, assuming it was a repeatable event) for the Least, Mid, and Most levels of the New Review Rate Categorical variable over the first 180 days since a chapter is published. From roughly one week on, the chart shows those receiving the least reviews with the lowest cumulative hazard (i.e. fewest expected number of chapters published to that point in time) and those receiving the most reviews with the highest cumulative hazard (i.e. highest expected number of chapters published to that point in time). Essentially, receiving a higher rate of reviews on previous chapters was correlated with a higher expectation of the quantity of new chapters published at any point in time after roughly one week since the previous chapter was published. By 180 days, the expected number of chapters to have been published is less than one for those least reviewed, roughly three for the mid-range of reviews, and roughly eight for the most highly reviewed authors.

After visualizing these differences, we turned to the Peto-Peto-Prentice test to fully check the statistical significance of what we observed. Without validating through the use of this test, we would not know if the results observed in the Kaplan-Meier curves were due to chance alone. As

mentioned earlier, the results of the Peto-Peto-Prentice test were statistically significant. In other words, observing results like these due solely to chance would be very unlikely. The results of the test were as follows:

$$\chi^2(2, n = 188, 983); p < 0.01$$

The results of the test above told us that at least two of the three groups differed in a statistically significant way. To determine which of the groups differed significantly, we did pairwise comparisons of the three levels of the New Review Rate Categorical variable using the Peto-Peto-Prentice test with Benjamini-Hochberg (BH) p-value adjustment, which is a technique used to adjust p-values to account for multiple testing [15]. All three levels were found to differ significantly from one another with p-values < .01. This tells us that these three groups of reviews received by authors were observed to continue publishing chapters at statistically significantly different rates.

**Table 6.5.3B:** This table shows the pairwise comparisons of the three levels of the New Review Rate Categorical variable based on a Peto-Peto-Prentice test with BH p-value adjustment to take multiple comparisons into account. All levels of the variable were found to differ in a statistically significant way with p-values < .01.

<b>New Review Rate</b>	<b>Least</b>	<b>Mid</b>
Mid	<0.01	-
Most	<0.01	<0.01

#### 6.5.4 Parametric Weibull Modeling

We made the determination of which distribution would best fit our data by running both AIC and BIC comparisons of nine potential distributions. The results of this comparison showed that the AIC and BIC scores for Weibull distribution were lowest and therefore most appropriate for our situation. The results for all nine distributions are ordered by lowest to highest AIC (and BIC) in table 6.5.3C below.

**Table 6.5.3C:** This table shows the nine distributions we compared to determine which would best fit our parametric survival analysis based on the data. The distributions are ordered by lowest to highest AIC (and BIC) score. The Weibull had the lowest AIC and BIC scores and therefore was the best fit for our analysis.

<b>Distribution</b>	<b>AIC</b>	<b>BIC</b>
Weibull	2,898,683	2,898,726
log-logistic	2,929,977	2,930,020
log-normal	3,013,775	3,013,819
log-gaussian	3,013,775	3,013,819
exponential	3,108,703	3,108,746
logistic	5,413,780	5,413,823
Gaussian	5,615,551	5,615,594
extreme	5,770,043	5,770,086
Rayleigh	28,565,301	28,565,345

After constructing the parametric survival model with an assumption of a Weibull distribution, we moved into using the model for prediction purposes. We made survival rate predictions based on the Weibull model for 7, 30, and 90 days since a chapter was published for the three levels of

the New Review Rate Categorical variable. Those results show a stark difference in predicted survival among the three groups and over time. Our model predicts that authors who have received a higher rate of reviews on their most recent chapter publication are more likely to have published another chapter after 7, 30, or 90 days since that most recent chapter was published.

**Table 6.5.3D:** This table shows expected survival rates predicted using our Weibull model for each level of the New Review Rate Categorical variable after 7, 30, and 90 days since the author’s last chapter was published. The results indicate that our model predicts higher rates of chapter publication based on higher rates of reviews received on an author’s most recent chapter publication.

<b>Days Since Publish</b>	<b>Least</b>	<b>Mid</b>	<b>Most</b>
7	95.1%	58.9%	23.5%
30	89.0%	23.9%	3.5%
90	80.2%	9.9%	0.2%

In summary, we find a significant link between the new review rate category and likelihood of publishing a chapter of fanfiction. After 7, 30, and 90 days, authors who are in the “Least” new review rate category, receiving up to 0.09 reviews per day, have a 95.1%, 89% and 80.2% probability respectively of “survival” (i.e. they will not have published another chapter of fanfiction at those times). In the “Mid” new review rate category, 0.09 to 1.02 reviews per day, this probability is significantly lower: 58.9%, 29.3% and 9.9% for 7, 30 and 90 days respectively.

Authors in the “Most” new review rate category, receiving 1.02 or more reviews per day, have a survival probability of 23.5%, 3.5% and 0.2% after 7, 30 and 90 days.

## 6.6 Discussion

In this section, we will interpret the main findings of this chapter, in particular, drawing conclusions from the predictions made in our model in terms of how feedback affects continued writing behavior. We will then discuss the implications of this work for distributed mentoring theory, as well as limitations to consider in interpreting the results.

### 6.6.1 Interpretation of Findings

Our results show that higher rates of reviews received by an author are significantly correlated with how much that author is likely to publish on the site over time. Note that causation and directionality of this relationship is not statistically tested. The Peto-Peto-Prentice testing and subsequent pairwise comparisons lead to the conclusion that the Least, Mid, and Most levels of the New Review Rate Categorical variable all had statistically significant differing survival rates. The cumulative hazards chart – which tells us the number of times that an event is likely to occur over a given time period assuming that the event is repeatable – showed the Most group with roughly six chapters published over a 180 day period, the Mid group with roughly four chapters, and the Least group with less than one chapter published over the same time period.

The predictions from our Weibull model also lead us to a similar conclusion. For example, 30 days after publishing their most recent chapter, an author who has received a quantity of reviews over that time period to place them in the Least category for the New Review Rate Categorical variable is predicted to have a survival rate of 89.0% (or a 11.0% chance of publishing a chapter

by that day). In comparison, authors in the Mid and Most categories after 30 days since the publishing of a previous chapter would have survival rates of 29.3% and 3.5% respectively (or 70.7% and 96.5% chances of publishing a chapter by that day). These are wide differences in the likelihood of publishing a chapter based on reviews received, and indicate that an increased rate of reviews received by an author predicts greater participation by that author on FanFiction.net in the form of publishing more chapters. These methods and results may provide guidance for future research into the integration of qualitative and quantitative data to come up with a meaningful model of how to encourage engagement in any online community.

#### 6.6.2 Implications for Distributed Mentoring Theory

The main findings of the present study support prior ethnographic investigation of fanfiction communities by a quantitative examination of FanFiction.net over a long time period. In a 2017 ethnographic study, Evans et al. described a situation in which fanfiction authors experience mentoring beyond traditional dyadic mentor/mentee relationships by receiving assistance through one-to-many channels, where individually small interactions aggregate to form a richer, more complete form of distributed mentoring [93]. They coined the term abundance to describe the cumulative encouragement present in large numbers of fanfiction reviews, which were found to be a crucial source of motivation for authors to continue writing, and may also help authors understand if they are on the right track in terms of plot, pacing and writing. Prior work has quantified the abundance effect by correlating reviews with increased measures of textual lexical diversity, demonstrating that an author who has accumulated about 700 reviews writes like they are a year older (after controlling for maturation) [109]. The present study complements this finding by demonstrating the predictive relationship between reviews and continued participation. An ego network clustering analysis by Davis et al. [2021] shows that among active

authors, this support in the form of reviews comes from a combination of close, distant and one-off relationships [72]. The present work augments these previous descriptions of the structure of distributed mentoring and its effects on FanFiction.net authors.

These findings can also be framed as a case study of how distributed mentoring is a mechanism for promoting participation and learning in an online affinity space. We hypothesize that the relationship between the abundance of feedback and continued participation extends not only to fanfiction and other fandom communities, but to online affinity spaces, described by Gee as any place where people of diverse skills gather over shared interests and identities [119], and affinity networks as described by Ito [143]. Fanfiction has served as a key example community in this legacy of literature describing online informal learning, and in fanfiction and across other communities, Ito describes affinity as the glue that holds together relationships. As we've discussed, on FanFiction.net, relationships are composed partly of the exchange of fanfiction reviews, and in the present study we've measured the impact of fanfiction reviews on participation. Although the scope of the present study is limited only to a single fanfiction community of over 1 million authors over decades, we speculate that the relationship could hold among other creative online communities where affinity is central in new forms of literacy, such as illustration, streaming, podcasting, role playing and so on.

This work demonstrates novel usage of survival analysis for predicting participation in an online community, and we believe this method holds potential for further study of behavior online. Although the dependent variable in this case was the event of posting another chapter of fanfiction, any event could be substituted. Moreover, this class of models is highly flexible in its

applicability for studying changes in state. For instance, a survival analysis could be used to predict transitions between modes of participation described by Jenkins, from passive consumer to active producer. Or, for another example, transitions people make in Preece's reader-to-leader framework. However, researchers interested in this class of models should be cautioned to check model assumptions such as the proportional hazards assumption, as we've done in the present work. A prior analysis of survival usage in research invalidated numerous studies after it was found that assumptions were not appropriately checked [31]. In any case, survival analysis promises many interesting avenues for future work at CSCW.

#### 6.6.4 Limitations & Looking Ahead

One of the main limitations of this study is that our data were not collected experimentally. This means that we cannot make definitive causal statements regarding the correlations we observe between variables. Another limitation is that our dataset skews toward more highly reviewed authors. Our final dataset had a mean quantity of reviews per chapter of 10.3 and a median quantity of reviews of 5.0, while the mean quantity of reviews per chapter is 3.2 and the median quantity of reviews is 1.0 for the 100,000 authors dataset. We had to use this set of authors due to a lack of chapter publication time stamps available for chapters that received zero reviews.

This chapter capstones our analysis of the fanfiction.net dataset by examining the motivational impact of distributed mentoring. Next, in Chapter 7, we will interview writers in order to elaborate on our quantitative findings, contextualize our results, and uncover design implications for building online communities that support learning. We will build new theory around how authors find feedback providers and build supportive relationships, as well as look at how motivational support extends beyond reviews into writing sprints, fandom events, and

overcoming creative blocks. This quantitative-to-qualitative elaboration study will create a richer picture of the whole of feedback seeking, relationship development and cross-platform connection.

## 6.7 Chapter Summary

In this chapter, we set out to explore the question of how reviews received by authors on FanFiction.net affect their continuing participation on the site. Prior qualitative analysis has shown that reviews had an important motivational impact on fanfiction writers, providing affective support that is definitive of mentoring [129]. To generalize these findings from ethnographic study to the scale of all fanfiction.net authors, we performed this analysis to measure the extent of the effect of reviews on participation on our dataset. Our quantitative analysis took the form of a survival analysis, which included the creation of non-parametric Kaplan-Meier curves to visualize the situation, hypothesis testing to determine if the observed results were statistically significant, and parametric modeling to build a predictive model based on the rate of reviews an author receives over variable periods of time. We applied methods novel to informal learning science – the weighted-residuals score test and the Peto-Peto-Prentice significance test – and demonstrated their applicability to this type of social data. Our results confirmed our hypothesis that receiving a higher rate of reviews would be predictive of continued author participation, as measured by higher rates of publishing chapters in relation to higher rates of reviews received. We hope this work will be helpful for future research involving integration of qualitative and quantitative data to develop models of engagement in online communities.

# Chapter 7: Fanfiction Writer Interviews: A Case Study of Online

## Fanfiction Writers

Co-authors: Regina Cheng\*

\*Co-first-author

### 7.1 Chapter Introduction

In this chapter, we move from establishing the effects of feedback networks in statistical analyses to a qualitative expansion, exploring fanfiction writers' feedback practices through interviews with writers. We unpack social and psychological challenges that writers face when engaging in online critique exchange, with special attention to the strategies writers have used to overcome them, as well as the community practices among writers that help to facilitate connection. This chapter presents the findings of 29 interviews that investigated how writers seek feedback, identify feedback providers and build lasting connections. In particular, we identify four distinct practices throughout the creative process that writers use to get feedback corresponding to their needs. Our findings surface the importance of affinity and trust in online feedback exchange, holding key implications for feedback exchange systems across creative domains. In our discussion, we illustrate how writers built relationships in public and private online spaces, and pass on advice from our interviewees to other writers. The contributions of this chapter include design considerations that address a range of social needs in feedback, including helping feedback seekers signal interests and identities, supporting authentic relationship-building during feedback exchange, and building inclusive, safe community spaces for feedback.

### 7.1.1 Seeking Feedback: How Writers Build Connections

Audience interaction is a crucial part of the experience of fanfiction writers in online fanfiction communities. We have established the importance of feedback through quantitative analyses of lexical development and participation in the prior chapters of this dissertation. Additionally, there is a rich set of literature that describes the importance of feedback. Prior research has raised how authors establish themselves in relation to their audiences in author notes [20,23,219], and how they must learn to parse through reviews in order to gather insights [93,219]. One important practice writers may engage in is *beta reading*, where writers seek out a round of in-depth feedback over their draft fic before it is posted [22,162]. Other than reviews and beta reading exchanges, prior research has shown, though not explored in depth, that feedback relationships also extend across many public and private online channels [6,186].

This chapter aims to further unpack fanfiction writers' feedback practices. First, we elaborate on the different times that writers seek and receive feedback, what kind of feedback they request, and whom they seek feedback from at different times. Second, we investigate how writers establish the connections that they use for feedback, what strategies they use to find the right feedback providers, and how they overcome any barriers to building feedback relationships. Ultimately, the goal of this study is to understand how online affinity supports feedback exchange, and identify design implications for future feedback systems as well as recommendations for creators. We thus ask the following research questions:

RQ1: How do fanfiction writers seek feedback from their online affinity networks?

RQ2: How do fanfiction writers identify and build connections for feedback?

This work contributes a qualitative analysis in order to deepen our understanding of how social needs are met during feedback exchange in different stages in the creative process, how feedback relationships develop and move across spaces, and how the ecology of online platforms supports feedback exchange. This complements our quantitative analyses from the prior chapters in this dissertation by expanding the scope under study from reviews to all stages of feedback, from reviewers to all feedback providers, and from Fanfiction.net to all platforms used by fanfiction writers. The method gives us a rich view that is connected grounded in the experiences of writers, and as a result, we are able to provide design implications for cultivating connection and relationship-building in feedback systems.

#### 7.1.2 Online Feedback Exchange

HCI and CSCW researchers have studied online feedback exchange in both educational [59,60,176] and informal settings [57,168,171,275]. Several works in this area present new systems where non-expert peers or crowdworkers compose feedback for creative work [41,175,190,209,271]. However, creators run into socio-psychological challenges while they engage feedback exchanges facilitated by these systems [105]. For example, they may feel uncomfortable and vulnerable in sharing early-stage work to strangers in the first place [170]. They may also face challenges with summarizing their context and needs in a short text blurb to someone unfamiliar with their work [57]. Additionally, creators are often uncertain about the extent to which they can trust feedback from strangers without knowing their expertise and background [79].

A careful examination of how people resolve these socio-psychological challenges in naturalistic settings may help to illuminate what is missing from researcher-designed feedback exchanges. Fanfiction writers, among other creators who participate informally in online public spaces, engage in feedback exchange as a part of socially-situated learning fueled by shared affinity [143]. In contrast with crowd-based and peer-based feedback systems where feedback is routed between users in exchange for currency or class credit, online affinity networks support spontaneous feedback exchange as part of the participatory culture [154]. The implications from these settings may translate more widely. Feedback exchange undoubtedly plays an important role in the process of producing creative work across fields ranging from interaction design [171] to creative writing [42]. Thus, there is potential to contribute to the body of literature studying how creators seek feedback from instructors and peers to improve their work, extend their knowledge and creative skills [40,224], and test their work with target audiences [26,68,94,227].

To address growing needs for more, better, and faster feedback, the HCI community has continuously advanced the design of peer-based and crowd-based feedback systems. For example, researchers have designed systems for in-person or online classes, scaffolding students to provide feedback to each other with rubrics [175], expert's knowledge [209,246], and structured micro tasks [41]. Researchers have also developed scalable crowd-based systems that prompt crowdworkers with domain-knowledge support [190], leverage machine learning methods to control feedback quality [172], and structure feedback with rubrics made by experts [279]. But despite the growing abundance of research on online feedback systems, socio-psychological dynamics between feedback seekers and providers have not been fully understood and addressed [105]. For example, there are mixed signals regarding the effect of

anonymity and criticism on feedback exchange. On the one hand, anonymity can encourage more specific, critical feedback [138]; on the other hand, anonymous criticism can result in annoyance and frustration for recipients [210]. There are also challenges of motivating feedback providers to put authentic effort into a stranger's creation [175].

In recent years, because of the expansion of the creative industry and the resulting demand for feedback, exchanging feedback over the internet has become an increasingly common practice for creators, especially those who do not have access to high-quality feedback resources IRL [105,138]. Additionally, open questions remain regarding naturalistic online feedback exchange. Creators engaging in informal, interest-driven content creation face challenges with identifying high-quality and stable sources of feedback [63,270]. Feedback from online providers can often be underwhelming in quantity, quality, and concreteness [270]. Novice creators often feel self-conscious about their abilities and hesitate to put their creative work out for critique [63,170,195]. How do creators overcome these challenges? How do they find a community where they are comfortable asking for feedback? How do they solicit feedback that is best suited to their needs? Facing a network of strangers with diverse backgrounds and expertise, how do creators choose whose input to trust [139,275]?

With these questions in mind, we conducted this study to unpack how fanfiction writers leverage their online, interest-driven communities for feedback—how they interact with other community members, what challenges they face, and whether and how they manage to overcome these challenges—with the goal of learning from fanfiction communities and identifying research and design opportunities for online feedback more broadly.

### 7.1.3 Online Affinity and Fanfiction Writers

The internet enables people with niche media interests to communicate and connect with others who share their passion, accelerating a transformation of media fandom that blurs the lines between consumption and production [149]. People creatively expand media, learning how to do so as they engage with *online participatory cultures*—internet cultures where barriers to creative production are low, support for creators is strong, and informal mentoring is commonplace [154]. In addition to transforming media itself, this phenomenon has changed the way researchers define media literacy, as well as media literacy learning [242].

Core to the online participatory culture is *affinity*, which describes the interests, identities and culture that individuals share. The term "affinity" was popularized in the study of informal online learning by James Gee [2005], who coined *affinity space* in reference to places, often online, that draw people of diverse ages and backgrounds to create content, interact with each other, and share knowledge. Later ethnographic investigation by Ito et al. [2018] has described *online affinity networks* in reference to interest-driven networks of people who self-affiliate and interact across the open internet. In online affinity networks, the activities of content creation, learning, and social support are often intertwined. For example, online health communities not only afford members to seek support and exchange information, but also allow them to share and practice expressive writing as they journal their experience and emotion [191]. Similarly, fanfiction writers provide each other with social support as they express queer identities and share narratives through writing [88].

The lens of affinity helps to inform our understanding of feedback exchange in online fanfiction communities. Expertise in fanfiction spaces is distributed so that each individual member brings a different set of skills and knowledge. As a result, mentoring is a fluid exchange with shifting roles of mentor and mentee [25,72]. Learners may find the support they need distributed among many people, and they actively process and correlate knowledge from artifacts of work, social interactions, and feedback [42]. As we have described in our discussion of distributed mentoring in Chapter 2, the reviews exchanged in online fanfiction websites accumulate to a whole of mentorship that helps fulfill writers' needs for affirmation and constructive critiques. This correlates with improvements in writing [93,109]. Furthermore, the ability to continuously develop writing based on public feedback is transferable to other areas of life such as academic writing [75]. However, Fanfiction.net reviews are just the tip of the iceberg in overall collaboration among fanfiction writers.

Feedback exchange in fandom was commonplace pre-internet, as was collaboration among social circles of fans in their homes, in mini-conventions (i.e., 50 or so people), and in large conventions where people traveled long distances to be physically colocated [11]. During the development of the early internet, women fans began creating private channels online where they could socialize and discuss fandom [36]. The semi-public and private fan spaces observed in earlier research have contemporary parallels. Writers participate in close-knit online groups to critique each other's works [186], engage in the practice of beta reading [162], and often collaborate to create fics and mixed-media content [160]. A behind-the-scenes look at these types of interactions can expand our model of mentoring and feedback beyond reviews, help us understand fan communities and inform the design of future feedback spaces and systems.

## 7.2 Method: Interviewing Writers

### 7.2.1 Participants and Recruitment

We conducted 29 semi-structured interviews with fanfiction writers, sourced from a recruitment survey we distributed on Tumblr in November 2017. In the survey, we asked participants to report demographic information, years of experience in writing fic, and platforms that they used for fanfiction-related activities. Among the 1,888 respondents, we stratified active writers into groups based on their self-reported experience levels, which spanned from 18 months to over 20 years. We then sent interview invitations within each experience level to ensure that we would hear from newer community members as well as those who have been writing fanfiction for decades, which contributes different perspectives of feedback exchange. We also ensured our participant group contained users of a range of different fanfiction platforms so that our findings could be established on user experience across a diverse set of platforms and communities. We contacted interview participants by email or by Tumblr direct message. As this was unfunded research, we were unable to offer any compensation to participants; this was entirely a volunteer effort.

We collected self-reported demographic information (age, race, nationality, and gender) in the recruitment survey. Since some participants were well known in the community, a combination of their quotes in our study and demographic information might deanonymize them. Therefore, to protect the anonymity of our participants, instead of mapping individual participants to their demographic information in a table, we summarize the profile of our participants as follows.

Out of the 29 participants, we were able to successfully record demographic information from 26 of them. At the time of the survey (about one year prior to the interviews), 4 participants self-reported their age as 16-18, 4 were age 19-23, 7 were age 24-29, 6 participants were 30-40 years old, 3 participants were 40-50 years old, and 2 participants were 50 or older. In self-reported race, 21 were white, one was Hispanic and white, one was Latinx and white, one was Filipino, one was black/African American, and one declined to provide information about their race. In nationality, 17 were from the United States, 4 were from the United Kingdom, 2 were from Canada, one were from France, one were from Italy, and one were from Australia. In gender, 14 were women and 11 were nonbinary, transgender men, genderqueer, bigender, or agender. Zero participants self-reported as cisgender men. One participant preferred not to disclose their gender.

Instead of a single fanfiction archival website or a single fandom, we chose Tumblr, a popular social media platform among fan creators, as a suitable recruitment channel for learning about a cross-section of experiences across fandoms and sites. While we recruited our participants from Tumblr alone, during the interviews we encouraged participants to share experiences about any platforms or channels that they used for feedback. Tumblr is not an all-encompassing fan platform, and fanfiction communities have historically needed to migrate platforms due to policy and other factors. Our interviews occurred in January to February 2019, during a time when migration away from Tumblr was ongoing after the infamous December 2018 NSFW content purge (See: Fanlore [286]). As a result, our participants had experienced multiple platforms in the past, or were actively exploring new ones. Therefore, our analysis develops themes from diverse experiences across many fandoms and fanfiction-related communities.

### 7.2.2 Semi-Structured Interviews

Each semi-structured interview was 60 minutes long and was conducted over Google Hangouts by one of the co-first-authors, while the other observed. The interviews focused on three broad areas: participants' practices of seeking feedback on their fanfiction, their connections with feedback providers, and their use of technology in the process of getting feedback. In the optional second part of the interview, participants shared and talked through an experience in which they received feedback they considered valuable. Interviews were audio or video recorded according to participants' consent.

### 7.2.3 Qualitative Data analysis

The authors of this paper manually transcribed all of the approximately 30 hours interview data. Then, they coded the interview data using a grounded theory methodology as outlined by Charmaz [2006] [51]. There was an iterative open coding phase followed by a closed coding phase. During the open coding phase, the authors built a qualitative coding set over four iterations of open coding. During each open coding iteration, the authors separately performed generative open coding on the same two transcripts, and then discussed the transcripts line-by-line to come to agreement. After each open coding iteration, they thematically categorized codes, building a hierarchy by using an affinity diagram. After agreeing on completion of the open coding phase, the authors divided the remaining transcripts for a closed coding phase. They separately coded the remaining transcripts and met to discuss any concerns and needed modifications to the coding set. The resulting final codebook contained 131 codes categorized into 9 major themes and 22 sub-themes.

Over the course of the interviews and coding phases, the authors wrote 23 memos to synthesize ideas from the interviews and coding set. Each memo described an emergent theme (i.e., combination of codes) from the study. The authors furthermore performed a thematic pass of each transcript, highlighting and commenting on excerpts that related to the major themes of the study. Over the course of interviewing, transcribing, highlighting, coding, and writing memos, the authors transformed the raw qualitative dataset into a series of themes on social feedback exchange practices in online affinity networks.

#### 7.2.4 Researcher Positionality

Our positionalities as researchers place us adjacent to the community of fanfiction writers. Jenna self-identifies as queer, transgender, autistic, and an avid roleplayer, gamer, and consumer of fan works, as well as a mixed-method researcher of online communities. Ruijia is also a mixed-method researcher of online communities, as well as an active creator and consumer of online fan works. Sharing identities with our participants and familiarity with fandom helped us establish common ground and build trust during the interviews.

### 7.3 Findings

#### 7.3.1 How do fanfiction writers seek feedback in online affinity networks?

In this section, we'll discuss the different social needs in feedback exchange at different stages in the creative process, and how a variety of public or private online channels support these needs. We identify four distinct practices of feedback exchange and name them using direct quotes from participants: "throw ideas at each other," "give my friends a little snippet," "beta reading," and "all I want for Christmas are reviews."

#### 7.3.1.1 “Throw Ideas at Each Other”

The earliest point in fanfiction writing where writers seek feedback is while brainstorming story ideas. It is a common practice for writers to describe half-baked ideas to one feedback provider, or a small group, and bounce ideas. For example, P1 described a typical situation where members of a fanfiction-specific group chat showcased and discussed story ideas with each other:

*“Somebody says 'I'm really stuck with this idea,' and they're talking about their idea. So then it's a case of getting them to open up about what the idea is, and what they want to achieve with the story, and how they feel about writing it, and then it becomes a discussion sort of about the mechanics of writing it, and how they're going to do it, and getting them into a position where they feel that they do want to write it, and they feel confident about starting or continuing, or the direction that they want to go in.” (P1)*

As illustrated in the above example, writers talked through ideas with other writers to identify problems before they became deeply involved in the writing. They discussed strategies, planned for the plot, and got affirmation to continue writing. Our participants reported that even in cases where they themselves had no direct need for feedback, it was valuable to get inspiration from others' ideas: “it can be inspiring to hear people's ideas, even if you don't want to use them, because it just helps spur your own creativity.” (P18)

We found that group chats (e.g., Discord servers) were particularly felicitous spaces for feedback during writers' ideation stage. Since getting feedback in the ideation stage was a dynamic process

that often involved back-and-forth discussion and debate, participants shared that they would prefer informal and immediate exchanges with others. Group chats afforded this type of interaction:

*"When we were talking about the actual content of the fics we were writing, we would just throw ideas at each other, oh this character did that? It would be really cool if this person reacted in that way. Or I think that's kind of out of character, maybe this should happen instead, kind of thing. Because it was an online group chat, it was just like immediate responses." (P20)*

Besides getting dynamic and conversational feedback, participants also reported their preference to engage with multiple people in the ideation process so that they could get comprehensive feedback from different angles:

*"[On Discord:] that's a good way to get ideas, good place to discuss ideas and kind of figure out how you want to make something work in a story. And just exploring different aspects and discussing that with people." (P25)*

Although getting feedback from lots of people early on was beneficial, many participants considered getting feedback on half-baked ideas to be a very private endeavor. Showing ideas for stories that they themselves are not sure about requires trusting and intimate relationships. For that reason, participants turned to group chat services, which afford non-public conversations with a small group of close friends. With the commonly mentioned group chat service Discord, writers leveraged the "subchannel" feature to create different layers of privacy for conversation

than in a bigger group. With only a small group of close friends, writers were more willing to open up about their ideas and discuss their thoughts:

*"If it's to my friend, it's before I'm done or before I've even been drafting it... Because my friends, they are part of the writing process. I bounce ideas off of them, I plot with them, and I help them plot their things. They're part of the feedback cycle from the beginning." (P29)*

Group chats also supported social activities that were not necessarily limited only to serious feedback exchange. Social activities, such as joking around about ideas, or even roleplaying characters to flush out thoughts, were also an important part of the brainstorming process:

*"A lot of what brainstorming together sounds like is us joking around about the characters, or joking around about fanfiction tropes that we really enjoy. We'll be like, and what if this dramatic thing happens. And we'll do a quick little joke roleplay with the characters, that's like, we're joking, the dialogue that we're saying is not going to be involved but a lot of times it gets us thinking about the different possibilities." (P17)*

Writers blurred the boundary between socialization and feedback in ideation conversations, as shown in the above example. They brainstormed together with their friends, getting feedback in a casual, interactive, and converging manner.

### 7.3.1.2 “Give My Friends a Little Snippet”

After deciding on the story idea, the next stage where writers needed feedback was after they jotted down their ideas into short little snippets of a few sentences to a few paragraphs. Similarly to the ideation stage, writers posted in-progress snippets of their writing to small group chats with close friends who shared the same interest in the fandom. For example, P12 talked about sharing a snippet of their work with a group of friends when they were not sure what to write next: "Sometimes I will give my friends a little snippet and be like, I'm stuck here what do you think I should do." In another example, P9 posted an initial outline of their story to a group of friends and asked for their opinion on the plot line:

*"A lot of times I have issues just flushing out the plot, sort of my biggest issue, so I will just show people my outline and stuff, and I'll talk it through with them and they will help me to flesh out my plot a little bit more." (P9)*

When writers felt unsure about some aspects of their writing, they preferred to quickly troubleshoot or get reactions on the in-progress work, rather than to wait until they completed the entire draft. Additionally, sending in-progress work to a group of fandom friends increased the chance of getting quick help and different perspectives:

*"I'll post a snippet of a scene and be 'hey, how do you guys think about this part? I am working on it right now'. With the discord group they are very immediate. They're really good for in-the-moment help." (P15)*

*"If it's a minor problem, I might just sort of say, 'can someone look at this paragraph and tell me what's wrong with it?' So you might throw just that paragraph into the group chat and then everyone can kind of chip in and see what they think." (P1)*

Having close relationships with feedback providers eased feelings of vulnerability while sharing and asking for help with in-progress work. Participants described instances where being in a small private group chat dedicated to feedback exchange gave them a sense of safety and closeness, lowering the social anxiety associated with revealing their confusion and weakness. They felt comfortable sharing their uncompleted and unedited work without worrying about being looked down at:

*"Because I know them so well I don't need to pretend like I am a upper level author that I know what I am doing all the time... I will just say to them like, 'hey guys I really can't solve this characterization right now.' It makes me feel more open to talk about it." (P9)*

Participants also explained that, oftentimes, they posted small pieces of their work in the hope of getting encouragement and affirmation. Their friends were likely to respond with praise and encouragement, which would be a great motivation booster to the writer. The social, friendly and playful atmosphere in group chats fed back to the effectiveness of the feedback exchange process. For example, P10 talked through an experience when they faced difficulties in writing and members in the group chat assisted in a relaxing way, helping them regain confidence in writing:

*"They came in and kind of broke that tension in a really nice and organic way. And sometimes just, even though I'm very introverted, turning to to my trusted group of friends and having them help me troubleshoot is very, um, it turns a problem into something that's really fun and silly."*  
(P10)

### 7.3.1.3 "Beta Reading"

When writers finished a first draft or a large portion of the story, they commonly asked for feedback in the form of *beta reading*, a widely used concept in the community that refers to feedback activities for a written but unpublished draft. Feedback providers, who were often called "beta readers," would read through the entire draft, provide editing suggestions, and engage in discussion with the writer about the story content such as plot holes, characterization, and writing style:

*"If I'm having problems after the writing process, like after I have the first draft and get something done, I sent it to what I call my 'beta,' my editor, and I go: 'read it over and make sure I haven't really screwed something somewhere. Make sure it looks okay and make sense.' I don't want myself to be like 'oh wait somebody's arm was over here and now it's not.' "* (P3)

Beta reading feedback activities often happen non-publicly between the writer and beta readers. Beta readers are often provided with unpublished drafts of the story, and have the permission to directly comment on or even edit the drafts. Many of our participants also combined private communication channels. In one common example, the beta reader would read and comment on a shared document, while simultaneously chatting with the writer in a separate chat tool, such as

Tumblr or Discord direct message. With this combination, the beta reader can leave major comments in the doc, while raising questions on small points, discussion and clarification in real time back-and-forth in the chat. Similar to what we discovered in semi-public group chats, sometimes the conversation could digress from feedback exchange to general socialization and discussion on the context of the story. This type of socialization can strengthen the bond between the feedback provider and the writer, cultivating trust and consistent beta reading relationships.

Beta readers were provided with unpublished fanfiction drafts and given permission to directly comment or (in rare, high-trust cases) even edit the drafts. These interactions usually happened in private channels, such as privately shared text documents (e.g., Google Docs), one-to-one direct messaging chats, or emails. Coupled with the usage of private communication channels was commonly a close relationship between the writer and their beta readers. Participants described their beta readers as people with whom they have an established trusting relationship. For instance, P3 reported that "most of my beta readers are also my friends," and P1 summarized that their choice of beta readers were always "someone whose opinions you trust, who you know."

Close, one-to-one relationship was important to beta reading because it lowered social barriers associated with criticism. Participants indicated that established relationships made giving and receiving criticism easier, because it was considered more socially acceptable to "be quite honest and say it's not working" with a friend (P1). When the writer trusted the feedback provider, it was easier for the feedback provider to be completely honest and straightforward, because they would have had the expectation that the writer would receive their critique gracefully without worrying about harming the relationship:

*"If I have trust with someone already..., they can trust me not to take any feedback personally. I think a lot of people are reluctant to be overly critical of stories, [but] if you have that relationship, I know where they're coming from and they know where I'm coming from so they can say: 'oh, I think you mean this or I think this might sound a little bit better.' " (P10)*

Established beta reading relationships also resulted in more substantial feedback exchange. Compared to in-progress feedback on snippets, where often writers are looking to share their excitement and get encouragement, writers more frequently desired serious, constructive feedback for their drafts before posting to public online spaces. For example, P12 mentioned that their beta reading was not "just a simple exchange of a compliment and thank you." Instead, the feedback exchange involved "more information shared" and "more communication going on." Writers trusted beta readers to provide informative and substantial feedback that would actually help them improve their work:

*"You also can trust that they're going to give you honest feedback. They're not just going to say, 'oh yeah it's great,' and not actually point out all the gaping plot holes in it." (P26)*

*"It's building something with my friends. I know these people will do better than some of the people who leave a 'wow, I like that' sort of comment on a story, because there's just more information shared, there's more communication going on. It's not just a simple exchange of a compliment and thank you. It's not shallow." (P12)*

Beyond being honest and pointing out areas of improvement, a beta reader as a friend would also be more thoughtful when providing feedback. Because the beta reader and the writer commonly socialized about life beyond fanfiction feedback, the beta reader had personal knowledge about the writer and the context of their writing. The beta reader would therefore tailor the delivery of the feedback to the writers' emotional status. For instance, P20 shared a story where they tried to help a friend's story with a critique, while and at the same time, communicated the critique in a considerate and encouraging manner given the writer's personal circumstance:

*"I also know that for that particular person if I knew they were having trouble, they were going through something in their personal lives, I would kind of feel out if they weren't looking for that kind of feedback. I would make sure that whatever I said wouldn't add to their emotional distress." (P20)*

Relationships with beta readers also mean mutual knowledge about expertise and preferences. Asking for feedback from a stranger could be risky because, in P12's words, the writer might "have no idea if this is something they actually want to read," and they "don't want to throw it at someone if they're not going to like it in some way." (P12) On the contrary, when working with beta readers that they were familiar with, the writer could selectively ask for feedback that aligned with their strengths and interests:

*"My beta varies in different fandoms depending on which one I was writing in... I tend to reach out to them based on who betas what type of fic for me. When I write for Yuri! On Ice is that I have a certain person that I go to and she reads all of those fics. When I work in the Hockey*

*fandom, I have a friend who reads all of that stuff I've got to try to work at. I got a friend, when I wrote my K-pop stuff, she's the only person who touches all of that... [It depends on] how much can they contribute, how much they already institutionally know about this thing." (P3)*

*"If it's a certain type of story, I'll contact someone who I think might be more interested, you know, certain fandoms, obviously, certain ships, I'll ask different people to take a look at." (P10)*

On the other hand, feedback providers who knew the writer well often gave feedback that was tailored to the writer's strengths and weaknesses, writing style, and usual feedback needs. In many cases, they would have a shared context about the story, which made the feedback exchange process more efficient. In the words of the participants, a beta reader is someone who "understands what I'm going for usually," (P10) who they "have been writing for a long time with" so they "trust their judgment" (P29), and who "will be looking for sorts of things that I'm looking for them to look for." (P26)

Lastly, a close relationship with a beta reader lowered the barrier to asking for feedback that required extensive effort. Beta reading usually takes a lot of time and effort, especially for long and multi-chapter fics. Writers preferred a beta reader that stuck through the whole story in comparison with someone who jumped in once in a while, because of the substantial investment needed to get familiar with the deep content:

*"It's easier because if they've already read the first five chapters they can just read six, seven, and eight. Whereas for a new beta reader, all of a sudden they have to read not just the three new*

*ones but also all the past ones. It's easier to say 'hey I'm going to write this 45 chapter fanfiction,' than 'hey can you read this 45 chapter fanfiction...' " (P24)*

With an established relationship, it was also more acceptable to follow up with a question and further discussion on the feedback:

*"[Because of] the fact that we're good friends and we have that relationship, I felt okay going back to her and asking for clarification about that scene." (P10)*

#### 7.3.1.4 "All I Want for Christmas are Reviews"

After publicly posting their stories online, writers got feedback in the form of public reviews, a common affordance of fanfiction websites and social media. Although this type of feedback has been studied the most in research literature, it is in fact the last stage of feedback exchange in the creative process. In contrast to the earlier stages, the most common type of public review, as observed by our participants, was simple and surface level words of encouragement from online strangers. Although not directly helpful to their story and writing skills, encouraging words and positive reactions provided writers with indicators that their genre and plot worked for their audiences, which boosted their confidence and incentivized them to write more in the future.

In order to get more reviews, writers strived to ensure that their fics would be broadly visible to an interested audience. Participants reported a strategy of "cross-posting," meaning they would post their fanfiction on multiple platforms, ranging from sites specialized for fanfiction archival such as FFN (Fanfiction.net) and AO3 (Archive of Our Own) to general social media platforms such as Twitter and Tumblr. As P10 pointed out, "If I'm posting something on Archive of Our

Own, there's always a post on Tumblr about it." Cross-posting helped ensure the fanfiction reached a wider audience than posting on a single platform.

Participants shared that they would tailor their posting style to the different user preferences and behaviors on different platforms. On the one hand, fanfiction sites had an audience that was genuinely enthusiastic about the story itself. For this reason, readers on these platforms were considered to be more "serious"—as P13 described using imagery, readers on fanfiction sites would read fanfiction like they were "reading a book by fire in the evening." As a result, writers would post well-polished, sometimes long and multi-chapter fics on those platforms. On the other hand, posting on social media would ensure more serendipitous exposure of the fanfiction, reaching a larger body of readers who were not yet aware of the particular story. Therefore, writers posted their fics on social media as an advertisement. Sometimes writers would ask their followers to share their social media previews, broadcasting the fiction to an audience outside of their followers. Besides increasing general visibility, writers also considered it important to make their stories seen by readers who would truly appreciate their stories.

Posting on a platform which afforded tagging and categorizing stories was considered an important factor for this purpose. On both social media and fanfiction archival sites, writers would spend a lot of time and effort on tagging, with the hope that the fiction would be discovered easily by the target audience. They would also leverage the tagging system to mark out potential triggers, content that might disturb some readers or reraise trauma. Trigger warnings reduced the risk of receiving comments attacking the story and writer from someone upset by parts of the content.

Another practice for soliciting public feedback was to communicate appreciation for reviews with readers. Participants reported that in "author's notes"—a common fanfiction practice where writers attach a short block of text to the beginning or the end of their fiction—they would explicitly ask for reviews, for example: "All I want for Christmas are reviews" (P2), "positive reviews are welcomed" (P4).

Although participants generally appreciated any encouraging reviews, they preferred reviews that were both positive and constructive, providing advice for improvement and ideas for new stories. In order to get more positive and meaningfully constructive reviews, writers made sure that their fanfiction reached the right audience who would appreciate the story. Writers chose platforms based on where they believed their audience would prefer to see the content. For example, a story about a certain pairing had more supporters on FFN compared to AO3, so writers would post the story on FFN in order to get more praise and avoid conflict. Another participant described AO3 as a site with a more inclusive culture, so they would be more likely to post queer-related stories on AO3 than on FFN. Writers learned the culture of different platforms by observing the amount of fanfiction about a specific topic/pairing and the amount of positive reviews.

### 7.3.2 How do fanfiction writers identify affinity and build online connections for feedback?

For writers who do not already have established feedback connections, it is important to build new connections, especially with those in the fandom who have the interest and expertise to be feedback providers. However, finding new connections in the community is never easy or guaranteed. In this section, we report our findings on five practices that fanfiction writers used

across public and private channels to find and build feedback relationships: connecting through public comments, participating in social events, "just-reaching-out," engaging in small private communities, and disclosing identities.

#### 7.3.2.1 Connecting Through Public Comments

Connections with feedback providers often started in public spaces. The public comment sections under published stories in fanfiction archival websites such as FFN and AO3 were a salient place for writers to identify feedback providers. One important strategy was connecting through public comments. Although comments were often a valuable source of feedback in-and-of themselves, each new comment could also function as a digital introduction to someone in the community. Several participants talked about relationships that initiated through comments:

*"I've made friends with a lot of people who started out just commenting on my fics a lot. You end up commenting back, and start talking... It's like hand picking your friends, this person already writes all these things." (P13)*

Writers noticed people who were repeatedly commenting on their work. "You start recognizing the tag sign and the pictures" (P28). That name recognition from repeat commenting was sometimes a starting point for building relationships across platforms:

*"I might go and read their work and leave a comment, or they might end up being part of the same discord, or if I do come across their Tumblr I might look at it. I usually respond to the comment and say 'thank you,' and if they left analysis, I (will) talk back and forth." (P29)*

One strategy writers used to make new connections was to comment on the fics they were reading, making sure to comment after each new chapter was posted. By repeatedly commenting on the fics they were reading, writers started building name recognition with others in the community. This was also part of building a community-based norm of reciprocal commenting.

*"I try to treat people how I would want. If I read a fic that is good, I leave a message, saying 'hey, here's what I liked, keep up the good work.' If someone takes the time to actually communicate [back], I'll leave one on every chapter. As an author, I always reply to comments."*  
(P7)

Additionally, writers would reply to every single comment they received, which was often considered as a reciprocal norm in the community:

*"You have regular commenters who read all your stuff or subscribe so they get alerts when you post something new. I try to reply to every comment that I get and I think it encourages people to respond more... I think I get more comments if I comment back."* (P13)

As P13 stated, replying to comments was considered to be a useful strategy to solicit future public feedback. This widespread norm helped build connections and establish a sense of community. However, P13 also pointed out that in the case of larger fandoms, they would get "a ton of comments" and they were "not really expected to reply since it's such a huge volume." This implies that it is relatively more difficult to make one's comment stand out or spot salient

commenters in large fandoms. Initiating a feedback connection through public comments was considered more challenging in this situation.

#### 7.3.2.2 Participating in Social Events

Participating in online fandom events was another way of initiating and building connections for feedback. These events were organized by fans in a variety of forms and scales, combining fanfiction with fanart, role play, discussion forums, video games, etc. Events encouraged writers to write and share stories based on certain topics, creating spaces where they found new connections with people who had similar interests in the topic, story, or even specific relationships between characters. During the events, writers often had opportunities to interact with each other and engage in each others' stories. In many cases, the connections they made in these spaces turned into online friendships and feedback providers. For example, P29 shared the story of meeting both of her closest beta readers in fandom events:

*"[In the case of her first beta reader], we joined the same forum for girls into star wars. We shared stories with each other and helped each other on stories. [That was] November 2011 [when] we were doing Nanowrimo (National Novel Writing Month). And the other friend, I met her in the youth forums in the roleplay section. There was this roleplay, everyone made their own character, we got to know each other through writing together on that roleplay." (P29)*

For instance, one participant told us about a long-term relationship that began within a fandom subreddit. Another participant talked about how friends they made in world of warcraft became feedback providers. And another participant talked about meeting new audiences while posting

fanart to tumblr. Although these spaces are not fanfiction specific, writers are able to find people with a shared affinity for fandom, and leverage this affinity to make connections.

Such community writing events were usually organized with the goal of facilitating opportunities for people to connect. P2 talked about how they organized a Secret Santa, a holiday exchange where members of the fandom submitted prompts for a story they would desire to read. Event attendees swapped prompts and wrote each other fanfiction. This provided attendees with an opportunity to connect with someone who shared interests. In addition, the organizers of these events often required attendees to have their work go through beta reading, and volunteers would be there to beta read the works. Our participants shared their appreciation of these events in that they offered chances to connect with and test out a new beta reader, getting feedback and making a new connection simultaneously. For instance, P20 shared that normally, they often had difficulty finding beta readers online because they were unsure about whether strangers would be interested in and committed to their stories:

*"Finding betas for my fics is always super hard,... I know for longer fics or works in progress especially, it's hard to find someone who's committed to, not only taking on a longer project, but also just kind of committing to whatever content I was writing about..."*

For P20, participating in fandom events was an effective way to not only get exposure to a group of writers in the community who were interested in beta reading for others, but also to learn about their strengths and interests so that they could identify suitable feedback providers for their work:

*"The times I did find beta readers and they were committed to what I was doing would be like for a challenge, like a 'big bang,' or a 'reverse bang,' where it was required that every fic was beta read by someone. So if I was writing for a 'big bang,' either the moderators would assign a beta reader to me, or they would have a list of beta readers who were interested in beta reading, and I would literally just go down the list and find someone. From my experience, the way those lists were formed [is that] the beta reader would list their strengths." (P20)*

Big Bangs are a kind of fan community event where writers write and share stories with assigned artists in the fandom, then the artists create fan art work based on the stories. The "reverse bang" mentioned next is a similar community event, where writers write fanfictions based on fan art works (See: Fanlore [287]). As part of the event, volunteers would self-organize to list themselves as available for beta reading.

*"They would also list their weakness and all that stuff... I would kind of cross out the ones that couldn't beta my content because they either, their strengths were for something I was not looking for, or they listed a trigger that was inside my content and that just cut down my list significantly. When I went through that list, and I had a few people in mind to contact, I would actually try to find either like their writing profile to see if they'd written things before, or if they had a blog, literally I would just read their about and see if they used correct grammar and English. So that would help out a lot." (P20)*

Events also helped lower the barrier to making contact. As we mentioned previously, writers found it challenging socially to reach out to an online stranger, even in cases where they have identified the stranger as a potential good feedback provider. Community events offered both the communication channel and "excuses" for writers who would like to reach out. For instance, P9 shared their experience serving as a beta reader in an event:

*"I have two Discord servers and one of them was just for this one ship in [my fandom]. And its just for writers, fan artists, and 'scholars' as the title of the role, which are the beta readers... You can pin the scholars on Discord or add all the scholars. So they will be like 'hey, I need a beta reader, can someone look at this?' Then I will get the notification so I can look at it if they want me to." (P9)*

In the community event group chat, because of the same interest and the sense of community created by events, writers often feel the easiness to externalize their their need for feedback and reach out:

*"We did a 'big bang' in the fandom and in the side bar within a channel, there was a person saying 'who can help me decide a major plot point?' And I was there, I said that I can help you. Then we started to chat that. " (P11)*

### 7.3.2.3 Just Reaching Out

When we asked fanfiction writers for their advice to newer writers in seeking feedback, the almost unanimous recommendation was to "just reach out." This advice reflects the most common barrier fanfiction writers face in making connections: a feeling of social anxiety.

Writers described the fear that the person they were reaching out to could be too busy, or unfriendly to cold reach-outs. But participants who provided this advice said they had experienced relief to find that the other writers they reached out to were responsive and positive.

Writers recommended asking for feedback in cold reach-outs via social media posts, comments, group chat messages and private direct messages. In a social media post, a writer might describe their work and state what they're looking for in a feedback provider. Then they would reach out to people who comment on the post volunteering to give feedback (P26). Another participant shared an experience of asking for help by commenting on a favorite author's post:

*"That's how I got started. I made a comment on a story on Fanfiction.net that day: 'I've got this story I want to write, what should I do?' And they PMed (private messaged) me and told me exactly what to do. And they encouraged me to write it, they encouraged me to put it up and I did. And there was just no stopping me after that." (P6).*

In addition to public outreach, writers recommended reaching out to people in direct messages. One strategy was to find a group of people and reach out in a group chat:

*"I would say the most reliable in terms of the people who keep coming back over and over, even as I switched fandoms, it's been finding friendship group first. Find a group of people who tend to agree on your weird fandoms and your divisive opinions and create that community, and then show them your precious little child and say, what do you think?" (P23)*

An out-of-the-blue direct message was a tried-and-true strategy among several participants. Several writers expressed the sentiment that social anxiety is a widespread problem holding them back, but after having reached out, they've been relieved to find that the community is overwhelmingly kind and helpful:

*"I know 90 percent of the reason most of us are on this site is we're introverts who have anxiety. We're really scared of putting ourselves out there, but if you just ask someone, if you just talk to someone, you know, make a post and share it around, I told someone the other day that most writers would rather die than discourage another person writing. So even if they don't have time or they don't think they're the right person to read this thing, so few people will be outright rude or cruel, and so everything that all of us are afraid of is kind of silly [laughs]. I've just found every single time I've reached out to someone in fandom they've reached right back in their own way. So I'd definitely say, that is the advice is just go for it." (P15)*

*"Fandom is very welcoming and it's very like 'take care of our own.' We can sort of come in, sit down and have a drink, we'll take care of you and we'll help you however we can. And I've found that to be true across multiple fandoms and over the years." (P14).*

Whatever the channel was, fanfiction writers found a lot of success in making feedback connections by just reaching out to others in the community.

#### 7.3.2.4 Engaging in Small Private Communities

Beyond close one-to-one interpersonal connections, fanfiction writers found connections with small, close communities, friend groups where they felt comfortable getting ideation and

in-progress feedback. A small, close community could take the form of a Discord server, a chat group on Facebook or Skype, a board on a less-traveled forum, or the right intersection of tags on AO3. These channels were characterized by being highly niche, comfortable, and small enough in scale that everyone participating could get to know each other. Earlier, we discussed the role of these highly trusted groups in feedback, but these small, close communities also provided supportive connections writers needed to thrive. For participants, this meant connecting with relatable people who made them feel comfortable, encouraged them, and gave them feedback on ideas and writing. For example, one author spoke with us about a set of Discord servers that brought together queer women who shared interest in a certain pair of characters from a certain animated series:

*"I particularly like that there's sort of these little communities of queer women or mostly queer women or queer aligned groups... It's just nice to talk to people who get it, who get why you're so excited." (P4)*

The people in this group had a common ground because they shared an underrepresented identity and they were into the same fandom. We define the term *affinity intersections* to describe the small, close communities occurring at niche intersections of interests and identities. In P4's experience, affinity intersections created a safe environment to talk about writing queer sexuality into fanfiction:

*"I've seen how friendly and nonjudgmental everyone is in responding [to others]. That makes me feel quite safe to go and ask them, 'how do I write this thing?' And it's something that's quite sort of deeply personal and intimate." (P4)*

A shared Discord server provided writers with a safe place where they could connect with each other in a carefully moderated and curated group. Chat groups also became spaces to commiserate, give each other encouragement, and hold each other accountable for writing. This did a great deal to help writers break through and make progress when they were feeling frustrated or stuck. Writers organized little 'sprint' events, where they each agreed to write as much as they could for a short period of time:

*"We will set time and be like 'in the next 30 minutes, we are going to write as much as you can and when we come back, share the sentences...' Some people come back be like 'I wrote a thousand words' and I will be like 'I got 10'. I will be like I didn't come up with anything but they will be like 'well those 10 words you didn't have them before.' So overall it's a positive thing." (P3)*

Connecting with a small group at an affinity intersection was also a great way to meet feedback providers. Since these small communities were places where people shared the same niche interests, writers felt that there was a high likelihood that others would respond to requests for feedback. Having an ongoing relationship with feedback providers helped writers get deeper, more thoughtful feedback. They felt understood by their in-group because of their shared context.

*"They've all read my fic pretty in depth. So I can be like remember when this happened, or where should I go for this part of, you know, my next venture into this universe or whatever. They know what's up there so I don't have to re-explain everything or force them to watch the show or something, so they can understand what I'm thinking all the time." (P17)*

The benefit of affinity intersections boils down to being understood by others. Writers in these tight-knit communities mutually understand each others' interests, their writing contexts, and the experience of writing fanfiction. As a result, writers in the same close community would offer encouragement and comments to each other in public spaces like Tumblr and AO3.

*"When I get the same people commenting on things that I've written, that makes me feel like I'm part of a little group... I'm part of the gang that does this. And privately talking to people who's stuff I read who are other fans, it's a quite nice feeling of belonging... there's a sort of comment exchanging between writers in fanfic, you know, I'll comment on yours and you'll comment on mine, cause we all know how much we love it." (P4)*

To summarize, small, close communities formed around shared interests, creating spaces where people felt comfortable, found connections and received support. People maintained the small community connection in public internet spaces, helping promote a sense of support even while participating in larger fandom contexts. This was particularly important for fanfiction writers that tackled topics that were underrepresented, taboo, or centered on marginalized identities.

### 7.3.2.5 Disclosing Identities

Finally, disclosure of IRL identity was a step that some fanfiction writers took to different degrees in their online relationships. With only one exception, all participants posted their fictions pseudonymously, and therefore, fanfiction community members knew each other primarily by their internet handles. IRL identity disclosure could be an incidental or intentional step as writers exchanged feedback and built relationships with each other. Some participants discussed occasions where they disclosed their IRL identity to people whom they had initially met through fandom:

*"Once you get past that little bit of a hump of being almost like unsure if you should identify yourself or not, you can make some really good friends. And it's been, it's an honor when somebody says: 'oh, by the way, my name is.' And then of course you say: 'well, that's great. My name is,' and hopefully you can build friendship." (P6)*

Several writers connected IRL identity disclosure with building friendship and trust. A norm in place was that writers did not ask people to disclose their identities, so much as take the step themselves. If the other person reciprocated, this would change the dynamic of the relationship to be closer:

*"I'm not calling them by their username in my head anymore. And a person we've been messaging for 5 years, we learned each other's name 3 weeks ago. It's a warm fuzzy feeling, and we message now more than we used to. I think it definitely is part of [becoming closer]." (P15)*

However, writers noted a barrier to IRL identity disclosure: a culturally widespread fear that internet strangers are dangerous. When talking about disclosure, writers named themselves, their siblings, children, and close family members as people they wanted to protect by remaining pseudonymous:

*"I think like a lot of people in who are now in their twenties, I grew up on, you don't give out your real name, you don't say what city you're in. There are mad axe-murderers on the internet and they will track you down." (P23)*

In their experiences with actually disclosing their identities to other individuals, our participants dispelled this belief, noting that most fandom people were actually nice. This fear of real-world violence created a barrier to connection with others online, and in overcoming this, they found rewarding relationships. However, participants shared that basic precautions and common sense were still important for deciding when and to whom someone should disclose:

*"There's not any set guidelines. I think it really depends on who you talk to... how long have you been with the person? What type of things do you talk about? Do you feel like it's safe to give that information? ...You kind of have to sometimes make a snap judgment and ultimately it worked out fine in this one case... it really does have to come down to instinct, gut, sometimes, there's no kind of set formula to be sure." (P21)*

In the cases where a trusting relationship fostered by identity disclosure was established, such a relationship is in fact intertwined with feedback relationships. Participants shared that close

relationships with beta readers were at times the same relationship with IRL identity disclosure. For example, P11 shared that:

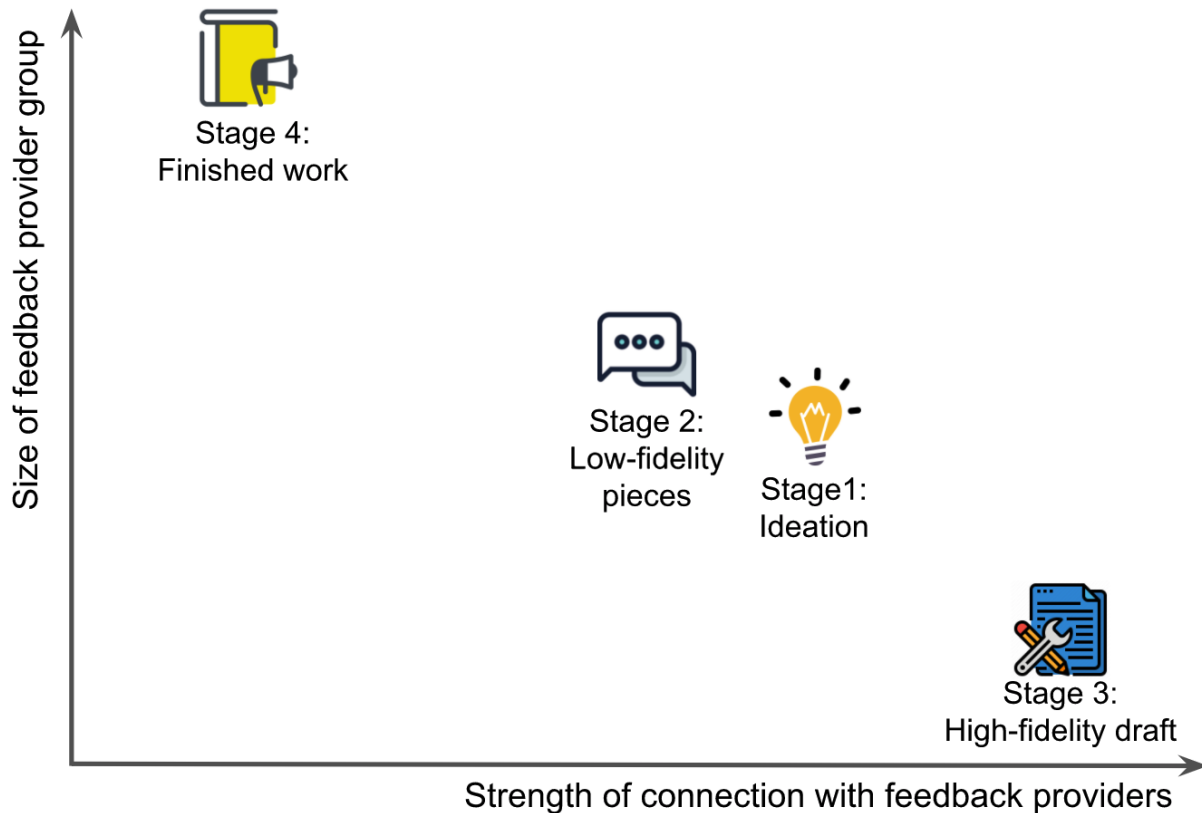
*"And also since me and my betas work on [Google] drive, and the drive documents are linked to my personal email, they can see my name, but it's a rare occasion. Few people know my name and surname in the fandom community." (P11)*

Although real life identity disclosure was not strictly necessary for critique, the type of trust needed for identity disclosure was transferred to trust in the sense of believing someone will give well-intentioned, constructive, and accurate feedback.

## 7.4 Discussion

It is no secret to the CSCW community that creative work benefits from collaborative effort. Taking a different approach from the rich literature on creativity support via crowdsourcing, our study further unpacks how creativity and feedback exchange can thrive in a socially situated and personally interconnected manner. In this paper, we presented findings from our interview study with 29 online fanfiction writers, surfacing their feedback practices along with how they identified and built feedback connections in online affinity networks. Next, using the example of fanfiction writers, we synthesize our findings into theories of creative feedback exchange: how creators' social needs in feedback vary during different stages of the creative process, how feedback and personal relationship development are intertwined, and how feedback exchange crosses an ecology of online platforms. Finally, we discuss the implications to the design of future online feedback systems.

#### 7.4.1 Social needs in feedback exchange throughout the creative process



**Figure 7.4.1: Needs in the size of feedback provider group and the strength of connection with feedback providers in different stages of creative process.**

The need for feedback is present in all stages of creative work: brainstorming, implementation, iteration, and presentation. Furthermore, as Foong et al. [2017] pointed out, online feedback exchange is a complex multi-step process. Deriving from our specific example of fanfiction writing, our results add a new dimension to Foong et al.'s [2017] framework of online feedback exchange—the different *types* of feedback sought out and exchanged at corresponding stages of the creative process.

In our findings, we described four distinct types of feedback practices in the words of our participants: "*throw ideas at each other*", "*give my friends a snippet*", "*beta reading*", and "*All I want for Christmas are reviews*". Adapting Amabile's [1998] [5] model on stages of the individual creative process—preparation, generation, validation and assessment—we map each feedback practice to a creative stage. In the *ideation* stage, creators brainstorm together and exchange inputs on each others' ideas; In the next stage, creators have done some initial generation and collected some *low-fidelity pieces*. In our example of fanfiction writers, writers show each other snippets of work and hope for reactions. After having a *high-fidelity draft*, creators look for feedback for the entire draft and details. In the case of fanfiction writers, that means intense, top-to-bottom "beta reading." In the final stage, when the creators have finished their work, they present it to the public for feedback.

Our study uncovers distinct social needs in feedback exchange for these four stages. While studies of online feedback exchange laud the quantity of feedback and providers, resulting in systems that aim for collecting feedback at scale (e.g. Xu et al. [2014], Luther et al. [2015]), we discovered a much more intricate story from fanfiction writers—a multi-layer social network that includes many shallow, infrequent reviewers and a few close, substantive feedback providers [72]. As depicted in Figure 7.4.1 above, we mapped out the social needs in terms of the need of the strength of social connection with feedback providers and the need of the size of the feedback provider group across different spaces. We'll further explain the needs as follows using the example of fanfiction writers.

In Stage 1, creators often need feedback providers to spend time with them to "throw ideas at each other." While most research focuses on public online spaces, where feedback often happens unidirectionally and asynchronously between online strangers [93,171], we surfaced feedback practices as early as when creators are still forming their ideas. In the case of fanfiction writers, this type of feedback exchange is interactive, playful, and socially embedded. Therefore, instead of posting their ideas in public, creators engage in this kind of feedback interaction with a small group of people who are already friends with them and in relatively private spaces, where they can chat in real time and have a dynamic conversation.

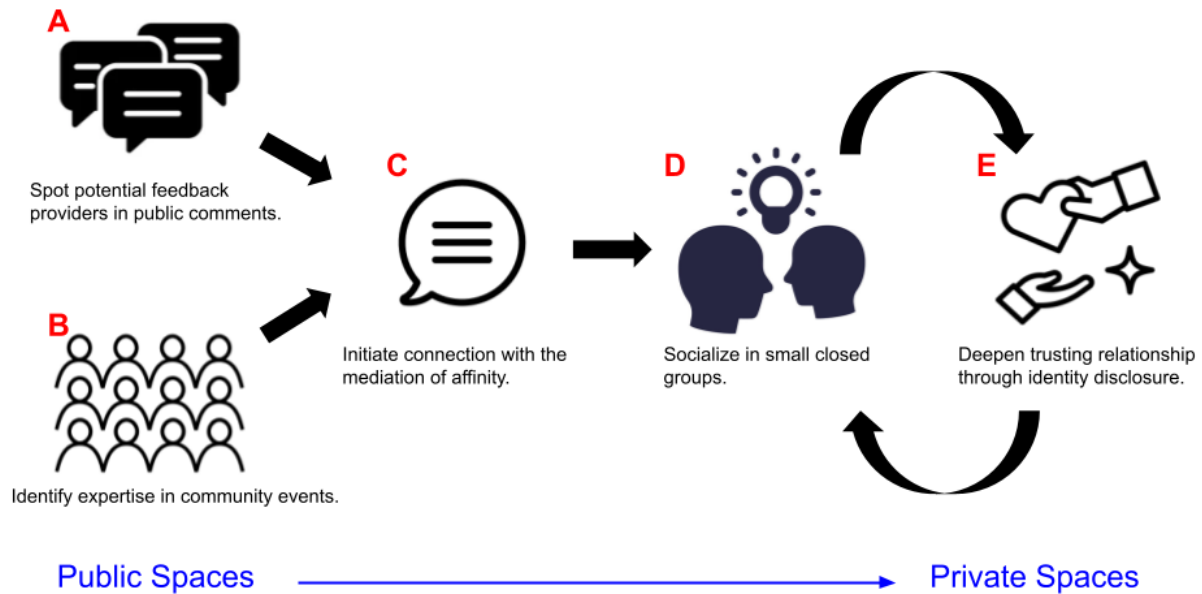
Similarly, in Stage 2, writers write small, experimental snippets of their story and gradually build up a bigger plot. Echoing prior literature [63,170], our findings show that creators in general consider such low-fidelity works-in-progress as informal and private. They refrain from presenting low-fidelity work for feedback in completely public spaces. However, contrary to assumptions in previous literature that creators generally do not spontaneously seek feedback online for early in-progress work [163,170], we found that they indeed do, but instead in relatively private channels among people with whom they have an ongoing connection. Despite the needs of privacy and close connection with providers, feedback from multiple perspectives is welcome, as creators would like to test out pieces of work, collect reactions, and avoid any potential problems at an early stage. In our case study of fanfiction writers, they also encountered creative blocks in the process of writing the story and sought encouragement from friends.

In Stage 3, where creators have put together a high-fidelity draft of their work, such as a completed first draft of a fiction, creators need one or just a few consistent feedback providers

with whom they have a close relationship. Previous literature has shown that after receiving feedback, creators need to sort out useful pieces of information from feedback that involves multiple or even contradictory suggestions [79]. This can be challenging when they are unfamiliar with the feedback providers' expertise and perspectives [58,79]. Fanfiction writers avoid this issue by seeking feedback from a single provider who has worked with them previously, so that they are familiar with their style, strengths, and needs. A close relationship with their feedback providers also means that providers are more likely to invest the effort needed to generate thoughtful and constructive feedback.

Finally, in Stage 4, creators post finished work on social media and online archives. At this stage, creators are showcasing their work, and they appreciate or even adore comments coming in from a large number of online acquaintances and strangers. Prior studies of online mentoring have identified types of feedback in public online spaces, including encouragement, constructive critique, and discussion-style sense-making interactions [93,171]. Our findings add that, at this final stage of creation, creators want to seek affirmation for their work and develop the confidence to continue future creation. Criticisms, although in some cases may be constructive, are frequently deemed as inappropriate and in fact relatively rare [93]. We also uncovered that creators use public feedback as a channel to identify potential new feedback providers who hint their expertise in public comments by complimenting specific aspects and excerpts in the writing.

## 7.4.2 Feedback and Relationships From Public to Private Spaces



**Figure 7.4.2: A hypothetical user journey of finding and forming relationships with feedback providers in online affinity networks.**

Our study points to the conclusion that personal, authentic connection with feedback providers is crucial to effective feedback exchange. Moreover, prior research observes that it is challenging for creators to find high quality, stable sources of feedback online[139,270], especially for newcomers [195]. Our case study illustrates that the feedback exchange in public fanfiction archives is not just "feedback exchange" per se, but also an integral part of finding new connections with people who share affinities. In our second findings section, we report our findings about how fanfiction writers identify and build relationships with feedback providers. We summarize this process into a hypothetical user journey presented in the Figure 7.4.2 above.

We explain the development of feedback relationships using the example of fanfiction writers. For a new writer who has just started sharing their stories online, identifying potential feedback providers in public feedback exchange spaces (i.e., comment sections on fanfiction websites) is a good first step towards building relationships for feedback, as indicated as Step A in Figure 7.4.2. Strategies include commenting on every fic they read, as well as replying to every comment they received. Writers who comment on everything they read do so in order to respect the culture of the space by reciprocating others' efforts. This finding complements a prior study of a photography critique community, where reciprocal feedback exchange was desired but not often observed [270]. We add that exchanging public comments in a reciprocal manner also means exchanging information about interest, strength, and expertise, offering a pathway for creators to forge new connections with their audiences.

An alternative approach to initiating a relationship for feedback is through participating in community social events, as shown as Step B in Figure 7.4.2. In contrast to peer- or crowd-based feedback systems where the exchange is completely separated from socialization, our finding suggests that feedback exchange can be enhanced by the opportunity to socialize with feedback providers. As described by our participants, certain features of fandom events (e.g., a list of beta readers) helped them identify who would have the interest and expertise needed to meet their feedback needs. Echoing prior literature on how online participatory culture fuels learning [25,149], our finding indicates that a social atmosphere created by shared interests and passion can support effective feedback exchange.

Practices of reciprocal public feedback exchange and participation in social events helped lower the social barrier to initiating feedback requests (Step C in Figure 7.4.2), as it is mediated by the affinity and rapport built in the previous steps. Our participants advised newer writers to "just-reach-out" to established members in fandom for feedback, which seems contradictory to previous research that indicates novices tend to reserve to themselves in terms of feedback because they do not want to expose their vulnerable status [57,195]. Our explanation is that shared interests and identities in online affinity networks help mitigate such socio-emotional challenges for novices. Consistent with design frameworks on how to engage novices in contributing to peer productions [173], our findings show that bond-based connection can also foster novices' confidence in presenting themselves for feedback.

Step D in Figure 7.4.2 marks the stage where the writer finds small, close communities, where they often solicit feedback for in-progress work. Interestingly, these groups are usually not established for the purpose of feedback *per se*, but for socializing writers with similar interests, opinions and, many times, marginalized identities. Prior research has drawn attention to such private fandom spaces, where users feel more comfortable with disclosing a marginalized identity [90] as well as gathering together to overcome discrimination and hate [99,100,101]. Our findings suggest that the welcoming and safe environment that supports vulnerable identities may also help alleviate the vulnerability associated with presenting early-stage work for feedback. Writers built trust through a reciprocal process of socialization over time and personal disclosure (Step E in Figure 7.4.2). They turned to their trusted connections for in-progress feedback, support when they were stuck, and critique on high-fidelity work, because this trust helped them overcome emotional vulnerability in the creative process. While previous research

has explored the possibility to generate scalable, specifically critical feedback from anonymized feedback providers [138], our study raises the question of whether such critiques can meet the emotional needs of creators.

#### 7.4.3 Feedback and the ecology of online spaces

Our study finds an interrelationship between feedback and online space. Individual relationships between writers and feedback providers can move from public to private online spaces, and multiple social channels are involved in the creative process, often simultaneously. This is different from the migration of fandoms from one platform to the next, a long lasting phenomenon in fanfiction communities identified by [99], which occurs due to evolving opinions, norms, and discrimination toward certain groups at a community level. We also observed platform migration as public, structural hostility towards queer creators persisted during our interviews in the form of the Tumblr NSFW ban. Our participants discussed how bans and purging of queer content had uprooted their online communities:

*"When Tumblr banned not safe for work, it was really distressing for a bunch of us who don't really fit on the very heteronormative sexual scale. So there was a lot of trying to figure out where we were going to go now, where we were, how would we stay connected, how would we continue to figure out and find stuff that we enjoyed." (P25)*

As a result, many writers moved to small, private online spaces to continue sharing and exchanging feedback on their creation.

While platform migration is disruptive to feedback exchange, the everyday use of multiple platforms together can be beneficial, our finding suggests that feedback exchange, and the social activities that nourish effective feedback exchange, happen across multiple public and private platforms, echoing social computing literature that indicates that individuals tend to use an ecology of social media platforms at the same time [124,280]. While prior research has begun to explore how different types of feedback can be solicited from different platforms [275], we elaborate that creators intentionally choose platforms and adjust their behaviors accordingly to seek feedback and connect with feedback providers.

Specifically, we learned from our participants that large, public fanfiction archives and event servers afforded writers with one-to-many social messaging such as reviews, access to fics written by others who share interests, opportunities to meet new people, and potential for discovering feedback providers. Open social media platforms such as Tumblr were used for advertising and reaching out to different populations. Private messaging channels like Discord, on the other hand, provided writers with smaller and more intimate spaces for discussing half-baked ideas and developing authentic relationships with feedback providers. Collaborative writing services like Google Docs supported writers in intensive editing and back-and-forth discussion with beta readers.

In particular, our findings point to the importance of close-knit communities and private spaces in online feedback exchange. Writers gravitated towards small community spaces, where they found the safety both to express themselves and receive critique in feedback that they could be sure was well-intentioned and kind. This was especially important for writers taking on topics

that were marginalized in mainstream media. In other words, we observed that small, close communities are the spaces where transformative work happens. This need for closed groups in online fandom, especially for those who create media that challenges cisheteronormative narratives, traces back to pre-internet and early-internet ethnographic research. Hostility towards women in general and homoerotic works specifically, both before the internet and in its early days, spurred the creation of small, private counter-spaces where women would create slash fiction [11,36].

Other than providing necessary safety conditions for challenging norms surrounding gender and sexuality, we found that private group chats were a crucial part of creative support for fanfiction writers. The safety they felt promoted relationship-building by making it possible for people to disclose more about their interests, identities and personal stories. This created common ground that lowered social barriers, motivated feedback providers, and established trust while giving and receiving critique, generating ideas, and seeking encouragement and support.

While many studies on online feedback focus primarily on large, open online communities [56,171,270], we argue that future researchers should pay more scholarly attention to small close spaces, such as group chats, email threads, shared documents, and so on. Researchers could investigate these niche spaces to understand marginalized creators and their feedback and creative practices that are otherwise invisible to the public and support their needs. Additionally, existing studies of online feedback largely focus on a single platform, which dismisses the fact that feedback exchange naturally happens across an ecology of social channels. As our findings shed light on creators' feedback practices and choices across a range of different platforms, we

hope to call for future research and design to engage diverse technical and social affordances, as well as the distinct types of social relationships fostered by different platforms in the feedback exchange process.

#### 7.4.4 Design Considerations For Supporting Online Feedback

Drawing from our insights presented above, we delineate the design opportunities for designers and researchers of online feedback systems to consider, especially regarding socio-emotional factors in feedback exchange. Albeit the limitation that not all findings from fanfiction communities may extend to every creative community, we urge designers and researchers to consider the following implications of our study as areas for future exploration in their respective feedback-exchange communities and platforms.

##### 7.4.4.1 Address a range of social needs in feedback

Our study identified different social needs in feedback at different stages of the creative process. This finding indicates that designers of future systems should not build a one-size-fits-all solution for feedback exchange. Instead, systems should account for differing needs with flexible options in terms of selecting the right audience and communication channel. For example, users should be able to adjust the number of feedback providers that they want, choose between communication channels that are private or visible in public, and decide whether they want feedback from online strangers or people they know. Another possible design direction is that systems should be able to guide users towards strategies that meet their feedback needs, perhaps based on their activity histories and which stage they are at. For instance, the system could suggest feedback providers that have worked effectively with the user in the past when they need

feedback on high-fidelity drafts, or recommend that the user broadcast their creation to a broader audience when they finish the work.

#### 7.4.4.2 Help feedback seekers signal interests and identity

Affinity in interests and identities motivated fanfiction writers to effectively exchange feedback. Future systems should support users to express their interests and identity in their feedback requests and connect them with compatible feedback providers. In particular, lessons can be taken from the design of Archive of Our Own, which prompts authors to attach signals of their interest and identity to their creations, in the form of free form authors' notes and checklist of user-created tags, so that their work could be seen by people who are interested in similar topics and hold similar views [100]. Fanfiction writers carefully select tags in order to make their work visible in public to the right audience of potential feedback providers. Future systems could consider similar approaches and integrate mechanisms such as reflective practices [240] and visual categories [270] to help creators communicate interests and identity.

#### 7.4.4.3 Support authentic relationships in feedback exchanges

Fanfiction writers preferred feedback providers with whom they had persistent, authentic and supportive relationships, as they knew the writers' previous work and goals, could balance emotional support with critical feedback, and had consistently provided quality feedback along a known domain of expertise. Designers of future systems should take this need into account and support formation and growth of authentic relationships between feedback seekers and providers. Fanfiction writers cultivated network-building practices such as commenting on every work they read, replying to every comment they received, and normalizing cold reach-outs over direct

message. Designers of feedback systems should consider how they might promote similar norms and afford access for people to reach out and connect in both public and private channels.

Further, fanfiction writers were able to deepen these relationships online through mutual social interaction, self-disclosure, and feedback exchange over time and across multiple communication channels. Future feedback systems should strive to scaffold these activities to support authentic relationships. To do so, systems could encourage repeated feedback interactions, perhaps through offering the option for users to work with feedback providers repeatedly, supporting long-term relationship development. Systems could also create channels for synchronous socialization or off-topic discussions alongside feedback exchange so that users can feel they are interacting with "real people" [106]. In addition, instead of forcing users to stay anonymous, systems could offer options for users to use consistent pseudonyms and express their personality, helping users recognize each other and feel authentic.

#### 7.4.4.4 Build inclusive, safe spaces for feedback

All of the above require a comfortable and safe environment. Future feedback systems should provide creators with a comfortable space so that they can safely be vulnerable, such as sharing early-stage work and reacting to criticism. The private help room presented in [106] is a great example of such design. Furthermore, social computing designers and researchers should consider historical exclusivity towards marginalized identities in the design of online spaces, and build spaces that include creators of all identities. Modeling after communities of fanfiction writers, designers may consider the role of semi-public and private spaces in creating safety. Crucially, access to these spaces must be controlled by community members. In addition,

designers of public feedback spaces may embrace inclusivity as a design value and instantiate it in the design of the platform [100].

#### 7.4.4.5 Implications for Fanfiction Writers

We are well-aware that there is an overlap between social computing researchers, fanfiction writers, and fanfiction community practitioners. We hope the insights from our study could pay back to the fanfiction writing community, especially for those who seek feedback on their work and those who offer feedback to others. We offer the following advice for fanfiction writers and other creatives.

- Think about how you might gather feedback throughout your creative process. As we have discussed above, feedback is helpful in the ideation stage, in early production, during creative blocks, at finishing stages and on the final work. The best audiences channels for receiving differ throughout, therefore, it will be important to cultivate a presence in smaller, private spaces where it is safer to be vulnerable during early creative phases. Additionally, consider strategies for reaching a wider audience with work you want to share more broadly, such as cross-posting to multiple sites and using the right tags.
- Participate in community events, public discussions and semi-public chat groups. These strategies helped fanfiction writers make some of the most impactful connections they reported during the interviews. When people are participating in the same writing events, the same role-play forums, the same Reddit threads, Discord servers and so on, they are more likely to share interests and affinity. Participation is the key to seizing these opportunities to make connections with people who are more likely to be interested in your work, and therefore more invested in giving helpful feedback.

- Seek out small, close communities that share your most niche interests. These spaces are where people socialize, grow relationships, build trust, and find encouragement. When people share the same deep, intersecting interests, the feedback they give is more likely to be high-quality in terms of referencing relevant domain expertise and fandom knowledge, and in levels of effort.
- “Just reach out” to writers you admire. This is a tried-and-true strategy, where the worst case consequence is to be ignored or feel modestly embarrassed, and the best case outcome is to make a promising new connection. Although cold reach-outs often raise feelings of vulnerability, our participants agreed that other writers are welcoming and considerate, which is why this was the most frequent advice our interviewees offered.
- For those who are more central in the community, consider how you might help less-established community members get connected. Help other members, especially newcomers, identify feedback resources and establish feedback relationships by making introductions. Other strategies to consider include warmly responding to reach-outs, organizing events, encouraging norms such as reciprocity in comments, and cultivating safe spaces for writers to engage in transformative work.

Writers and other creatives looking to make connections with feedback providers may consider the strategies described above. As researchers, we’ve also applied many of these lessons in our own lives. These experiences along with the powerful stories we heard from writers stand as evidence that these practices make a difference.

## 7.5 Chapter Summary

Fanfiction writers were some of the earliest adopters of the internet [62]. This ever-evolving community of communities has transformed media consumption and production [150], inspired new understandings about how shared interests drive learning [143], and innovated in the design of internet spaces to incorporate values and norms around accessibility, inclusivity and identity [100]. Social computing researchers interested in these topics can learn quite a bit from fanfiction communities, and indeed, conducting this set of interviews has changed the authors' approach to their research. The stories we heard from fanfiction writers helped us believe that the internet can be designed to be better than it is now, a place for creators of all types of media from all backgrounds to learn from each other. Our grounded theory of feedback-seeking in fanfiction communities expanded knowledge about the role of feedback throughout the creative process and established an interrelationship between online connection and feedback. We discussed strategies writers used and provided future directions for research and design around online feedback exchange systems. We recommend that designers and researchers of online creative spaces consider how they will afford connections between people of like interests, support the growth of authentic connections and instill values of reciprocity and inclusivity. We also encourage readers who are passionate about the topic of designing inclusive, authentically connected communities for learning to "just reach out" to us and continue the conversation.

## Chapter 8: Dissertation Conclusion

### 8.1 Chapter Introduction

I will conclude this dissertation with a discussion of the implications and contributions of research presented throughout the previous chapters. To contextualize this discussion, in the first section of this chapter I will overview the motivations and research questions pursued in this line of research. Then, I will review the primary findings of each chapter, and how they contribute to distributed mentoring theory. Then, I will discuss this work's contributions to the methodology of human-centered data science, as well as implications for designing human-centered systems that support creative growth and feedback exchange.

### 8.2 The Importance of Distributed Mentoring Fanfiction Communities

Fanfiction is a massive phenomenon of cultural transformation, from literal transformation of mainstream stories to the establishment of online counterspaces. The deep impact that fanfiction has for millions of people warrants scholarly investigation, which is why, for decades, researchers have been participating in and documenting fan spaces [11,23,38,62,144,145]. A particular transformation of interest to us is that of learning – we are interested in understanding the impact that fanfiction communities have on human development, and the mechanisms underlying this new form of learning, that only began to emerge 30 years ago. Understanding how people informally learn online today, and how to support them can inform design and practice in the future, as online communities become increasingly relevant and present in the daily lives of everyone who uses the internet. Fanfiction communities have been at the center of theories about media, literacy, learning and identity because they have been around since the

beginning of the internet, they are influential and impactful on their own and they are prototypical online creative communities with translatable implications for other creative online spaces. This makes fanfiction a suitable setting to study feedback exchange and network development.

In addition to contributing insights about network-building and feedback to the fanfiction community, we believe that researchers across disciplines have much to take away from this body of work. Our findings about how writers learn and build connections may be translated across other online feedback exchange networks and creative online communities. We also delivered new methods in our investigation of distributed mentoring in the fanfiction community that may be applied in other informal learning spaces to quantify the impact of networked interactions between people on developmental and behavioral outcomes. These included novel uses of machine learning and statistical analysis methods: training a neural network to classify fanfiction reviews, quantifying the effects of reviews with an autoregressive mixed effect model, describing mentoring networks using k-means clustering, and conducting survival modeling analysis to understand community participation.

I advocate not just for more use of data science, but for a human-centered data science methodology [9] that is both scalable to phenomena involving millions of people and committed to remaining grounded in the context of ethnographic investigation. This is particularly important for advancing science in informal learning because researchers do not own networked publics or the data produced by them, and therefore these settings must be studied with consideration for community norms and values [90]. In addition to ethical considerations, a mixed method

approach in this space is important for triangulating data science findings with learning theories and for translating quantitative findings to practical implications for the design of online spaces that support learning and creativity.

### 8.3 Review of Findings

In this section, I will briefly summarize the findings of chapters 3, 4, 5, 6, and 7:

In chapter 3, we longitudinally measured the effect of distributed mentoring on lexical development in fanfiction writers. We described in detail how we gathered a relevant dataset from Fanfiction.net, which laid the foundation for our initial analyses as well as research throughout the dissertation. We found that the mean measure of textual lexical diversity (MTLD) of a fanfiction chapter was 97.35. We also parsed user profiles to find that the mean self-reported age on Fanfiction.net was 16.8 years old. MTLD increases generally during late adolescence in this population, from an average MTLD of 93.6 for fanfiction chapters written by 15-year-olds to 97.1 for writers self-reported to be age 19. Using a mixed linear model, we measured a significant and positive MTLD increase of 1.66 for each year that writers participated in Fanfiction.net. Our next model contradicted our hypothesis that highly reviewed chapters would be followed by larger increases in MTLD from one chapter to the next – a finding that warranted more examination in Chapter 4. Finally, we modeled the cumulative effect of maturation and reviews, finding a coefficient of 0.0032 for maturation in days and 0.0018 for reviews. These results indicate that feedback and maturation have differentiable effects on lexical development, with about 700 reviews predicting the same change in MTLD as one year of maturation.

Chapter 4 significantly expanded our analysis of the effect of distributed mentoring on lexical development. In order to unpack the role of different types of reviews, we trained a neural network to classify millions of reviews, based on our manually classified sample, into three groups: shallow positive, targeted, and update encouragement. We also advanced our previous model by using an autoregressive term to control for reverse-causation in our analysis. Our Model 1 coefficients for shallow positive ( $\beta=0.027$ ), targeted ( $\beta=0.014$ ) and update encouragement ( $\beta=-0.029$ ) imply that only shallow positive and targeted reviews contribute to lexical development, whereas update encouragement reviews predict a decrease in the next chapter's MTLN. Additionally, we examined the effect of sending reviews, finding a positive coefficient ( $\beta=0.018$ ) for sending targeted reviews and negative coefficients for sending shallow positive ( $\beta=-0.0087$ ) and update encouragement ( $\beta=-0.013$ ) reviews. The results make visible the importance of reciprocal feedback exchange for lexical development by showing how sending reviews can be as impactful as receiving them.

In Chapter 5, we turned our attention to understanding the structure of distributed mentoring networks, as well as writer perceptions of different types of relationships within their networks. We transformed the Fanfiction.net dataset into a network graph, partitioned the relationship graph into author ego networks, and divided relationships within each author's network into layers using k-means clustering. Our main finding from this analysis was that the mean optimal number of clusters  $k^*$  was 2.36, indicating that relationships on Fanfiction.net are characterized by a 2-to-3 layer social structure. In the 2-layer solution, which applies to two thirds of highly active authors, the inner layer of 11 reviewers send feedback on a weekly basis, while their outer layer of 59 reviewers on average sends 1 review each per month. Inner layer reviewers were also

more likely to send targeted feedback and less likely to send update encouragement. Our interviews uncovered the motivational and socio-emotional support that close and distant relationships can provide, emphasizing the support, kinship and catharsis that close relationships can provide, and the motivational boost of seemingly small, infrequent positive remarks.

In Chapter 6, we modeled the motivational effect of distributed mentoring. We adapted survival modeling analysis to make predictions about how receiving different amounts of feedback impact the likelihood that a person would continue writing fanfiction, the amount of time between fanfiction chapters and total number of predicted chapter publications within a set time period. Stratifying authors into three categories, Least, Mid and Most, based on how much feedback they receive, we find that only 11% of writers in the Least category will post another chapter within 30 days, while 70.7% and 96.5% in the Mid and Most category will add to their stories in that amount of time. We were also able to make pairwise comparisons that demonstrate that these dramatic categorical differences predicted by our model are also statistically significant on our longitudinal sample of 34 thousand authors. These findings measure the affective component of distributed mentoring by demonstrating how community support motivated years of large-scale participation on Fanfiction.net.

Finally, in Chapter 7, we conducted interviews to explore how fanfiction writers connect with feedback providers, build relationships, and seek feedback throughout creative stages and across the ecosystem of online platforms. This greatly expanded the context under study to include interactions outside of reviews on Fanfiction.net and situate our prior analyses within a more holistic depiction of networked interaction in fandom. We constructed a grounded theory that

reflects our understanding of fanfiction writers' feedback strategies throughout creative stages, from ideation, to sharing in-progress snippets, to beta reading and finally asking for reviews. Additionally, we outlined strategies that fanfiction authors use to identify feedback providers and build connections, including connecting through comments, participating in fandom events, just reaching out to strangers, engaging in small, private community spaces and building trust through identity disclosure. These findings imply that designers of online creative spaces need to consider how they will promote connections between people of like interests, support the growth of authentic connections and instill values of reciprocity and inclusivity.

#### 8.4 Contributions to Theory and Practice

This dissertation contributes new knowledge that significantly expands on prior understanding of distributed mentoring in fanfiction communities (Campbell et al 2016, Davis et al 2017, Aragon & Davis), adding substantial evidence and detail to the theory overall and expanding the theory by answering key questions. We asked and answered questions to tell us how much impact the abundance of interactions between writers and their reviewers have on their development. In particular, we operationalized the developmental outcome with the measure of lexical diversity (McCarthy & Jarvis), which is associated with writing quality, vocabulary development and linguistic skill. In addition to modeling the effects of distributed mentoring on lexical development, we asked about the impact of affective support provided by reviewers on continued participation in writing. These novel analyses complement prior ethnographic research (Campbell et al 2016, Davis et al 2017, Aragon & Davis), in distributed mentoring by quantifying two key attributes underpinning the theory, and generalizing prior knowledge from a small sample of writers in three Fanfiction.net fandoms to millions of writers across all Fanfiction.net fandoms.

Beyond validating key aspects of distributed mentoring, we elaborated on the theory by contributing novel qualitative and quantitative research examining questions about how distributed mentoring networks are structured, and how writers build their networks and seek feedback from them. We contributed a network structure analysis of distributed mentoring networks showing how connections between writers and reviewers are organized into layers, and we described the frequency and types of reviews exchanged in each layer. Then, from a series of interviews with fanfiction writers, we constructed a new grounded theory that elaborates on prior knowledge about distributed mentoring and creative feedback with a deep examination of writers' feedback practices. Our theory revealed differences throughout the creative process in who writers seek feedback from, what communication channels they use and how they solicit feedback. We also identified key social barriers to building effective feedback networks and outlined strategies that fanfiction authors use to build their networks. These findings contributed implications for design researchers to facilitate better feedback.

In addition to theoretical contributions, this dissertation contributed groundbreaking applications of machine learning, data analysis and mixed-method research (MacQueen, Pinder III, Bates, Devlin, Ng'andu) to research lineages at the interdisciplinary intersection of online informal learning, media literacy and fan studies (Ito 2018, Black 2008, Jenkins 2019). We trained a machine learning classifier to categorize fanfiction reviews by qualitative types so that they could be used to model the effects of feedback. This is a novel technique built on the qualitative-to-quantitative transformation method proposed by Scott et al. [2012], but improved by the use of a neural network algorithm (Devlin) to achieve near-human accuracy. We

introduced a novel use of autoregressive linear mixed modeling [12,112] to study online informal learning, contributing an approach to understanding the effects of feedback in informal settings that can be compared to experimental designs used more frequently in learning sciences. We adapted Dunbar et al.'s [2015] social network structure analysis method to uncover the layered structure of distributed mentoring on Fanfiction.net. In addition to being the first such application of k-means clustering method [192] to understand relationship networks in a learning context, we incorporated the method into a quantitative-to-qualitative explanatory mixed methods design, demonstrating how rich contextual insight can complement this data science technique. We conducted survival model analysis [181] on the Fanfiction.net dataset, which was a novel application of this class of models in the space of studying online informal learning. In particular, we demonstrated the first use of the weighted-residuals score test and the Peto-Peto-Prentice significance in this field [92,132]. The weighted-residuals score test is crucial to determining the type of survival model to use, and Peto-Peto-Prentice significance testing enables hypothesis testing across categorical groups. And throughout the dissertation, we contribute in-depth explanations of our methods with the hope that the high detail enables the techniques we used to be replicated in future research.

## 8.5 Conclusion

This dissertation envisioned how we can uncover the powerful, positive effects of networked interactions using innovative human-centered data science methods. The research presented throughout was a result of interdisciplinary collaboration among researchers who shared the view that fanfiction communities have lessons to teach us about how to amplify creativity and literacy development, especially among adolescents and young adults. Using machine learning and statistical analysis in mixed-method designs, we were able to quantify and expand important

theoretical principles of distributed mentoring, showing how fanfiction writers can find the support to continue developing transformative stories from networks of their peers. I hope this dissertation will be useful to other researchers in the field interested in this methodology as well as those inspired by fandom to instill positive values in online communities. I also welcome readers to take the advice of fanfiction writers and just reach out!

## Contribution Statement for Coauthored Chapters

In this section, I wish to briefly explain my contributions in Chapters 4, 5, 6, and 7, which were each co-first-authored collaboratively by myself and another student (a different student for each of these four chapters), and published in this dissertation with consent.

- In Chapter 4, I was a co-first-author with Linda Wu. Throughout the research, I led a group of team leads as multiple teams worked in coordinated efforts to sample, classify and analyze the Fanfiction.net data archive. I personally curated the final analysis sample, made intellectual contributions to each hypothesis, and met 1:1 regularly with Linda as we developed the model. I contributed much of the writing and editing in the first submission version of the paper, and I re-edited the work for publication as a dissertation chapter with additions to the methods and discussion.
- In Chapter 5, I was a co-first-author with Ruby Davis. I was a leader in the quantitative efforts and a contributor to the qualitative effort in this mixed-method project. Throughout our project meetings, I made intellectual contributions to the effort of replicating Dunbar's method on the FFN dataset (Niharika Sharma contributed heavily here too). I personally curated the analysis data sample by translating our data to a relationship graph, computed reviewing frequencies, and merged clustering results with

review classification data. I made significant contributions to the writing and editing efforts for our publication of this work in Connected Learning Summit. In re-editing the original work into a dissertation chapter, I contributed more methodological description and discussion. Additionally, because the qualitative section was not published in the original paper, and Ruby and I both felt that it was an important complement to the work, I added in the qualitative findings with additional editing and discussion for the chapter.

- In Chapter 6, I was co-first-author with John Fowler. I contributed to the intellectual idea of conducting survival analysis to understand drop-off in fanfiction writing, and collaborated with Matt Davidson on writing the first version of the paper, which was a class project. I curated the dataset used in the original analysis as well as the final version published in this chapter. As we moved the project into our research group, I worked with John on refining the analysis into a publishable paper, and contributed a significant portion of the writing and editing in the first submission version of the paper. For this dissertation, I re-edited the paper into a chapter, adding a new introduction, new discussion, and additional description of the methods.
- In Chapter 7, I was co-first-author with Regina Cheng. Regina and I collaborated throughout this work as equal first-author contributors from the start. I contributed to the intellectual ideas in the research questions, as well as the idea of using grounded qualitative analysis to build a theory of feedback. We co-wrote the interview protocol, and took turns moderating the interviews. Regina and I were both present for every interview. We collaborated directly on coding the interview data and conducting the analysis. I contributed about half of the writing in the first version of this paper, and did lots of editing to turn this work into a dissertation chapter.

The above disclosure is meant to clarify my role within the co-first-authored chapters. I am honored to have worked with great researchers in my time at UW!

## References

1. Sandra Schamroth Abrams and Jayne C. Lammers. 2017. Belonging in a Videogame Space: Bridging Affinity Spaces and Communities of Practice. *Teachers College Record* 119, 12.
2. Mona Humaid Aljanahi. 2019. “You Could Say I’m a Hardcore Fan of *Dragon Ball Z*”: Affinity Spaces, Multiliteracies, and the Negotiation of Identity. *Literacy Research and Instruction* 58, 1: 31–48.
3. Alyse Marie Allred and Colin M. Gray. 2021. “Be Gay, Do Crimes”: The Co-Production and Activist Potential of Contemporary Fanzines. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2: 1–35.
4. Donna E. Alvermann. 2008. Why Bother Theorizing Adolescents’ Online Literacies for Classroom Practice and Research? *Journal of Adolescent & Adult Literacy* 52, 1: 8–19.
5. Teresa M. Amabile. 1988. A Model of Creativity and Innovation in Organizations. In B. Staw and L.L. Cummings, eds., *Research in Organizational Behavior*. JAI Press, Greenwich, CT, 123–167.
6. Cecilia Aragon and Katie Davis. 2019. *Writers in the secret garden: fanfiction, youth, and new forms of mentoring*. The MIT Press, Cambridge, Massachusetts.
7. Cecilia Aragon, Clayton Hutto, Andy Echenique, et al. 2016. Developing a Research Agenda for Human-Centered Data Science. *Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion*, ACM, 529–535.
8. Cecilia R. Aragon, Sarah S. Poon, Andrés Monroy-Hernández, and Diana Aragon. 2009. A tale of two online communities: fostering collaboration and creativity in scientists and children. *Proceedings of the seventh ACM conference on Creativity and cognition*, ACM, 9–18.
9. Cecilia Rodriguez Aragon, Shion Guha, Marina Kogan, Michael Muller, and Gina Neff. 2022. *Human-centered data science: an introduction*. The MIT Press, Cambridge, Massachusetts.
10. Paula M. Bach, Robert DeLine, and John M. Carroll. 2009. Designers wanted: participation and the user experience in open source software development. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, 985–994.
11. Camille Bacon-Smith. 1992. *Enterprising women: television fandom and the creation of popular myth*. University of Pennsylvania Press, Philadelphia.
12. Douglas Bates, Martin Mächler, Ben Bolker, and Steve Walker. 2015. Fitting Linear Mixed-Effects Models using lme4. *Statistical Software* 67, 1: 1–48.
13. Mahir Bathija and Kush Tekriwal. 2019. Do Substantive Reviews Improve Authors’ Writing? *Fanfiction Data Science*. Retrieved from <https://fanfictiondatascience.tumblr.com/post/185799483415/do-substantive-reviews-improve-authors-writing>.
14. Jane M. Becker. 2014. Stories around the Digital Campfire: Fan Fiction and Copyright Law in the Age of the Internet. *Connecticut Public Interest Law Journal* 14: 133.
15. Yoav Benjamini, Ruth Heller, and Daniel Yekutieli. 2009. Selective inference in complex

- research. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 367, 1906: 4255–4271.
16. Sue Bennett and Martin Oliver. 2011. Talking back to theory: the missed opportunities in learning technology research. *Research in Learning Technology* 19, 3.
  17. Drew Berkowitz. 2013. Framing the Future of Fanfiction: How The New York Times' Portrayal of a Youth Media Subculture Influences Beliefs about Media Literacy Education. *Journal of Media Literacy Education*.
  18. Lisa Beutelspacher and Maria Henkel. 2022. Information Literacy in Video Games' Affinity Spaces—A Case Study on Dota 2. In S. Kurbanoglu, S. Špiranec, Y. Ünal, J. Boustany, and D. Kos, eds., *Information Literacy in a Post-Truth Era*. Springer International Publishing, Cham, 302–313.
  19. Rebecca Black, Jonathan Alexander, Vicky Chen, and Jonathan Duarte. 2019. Representations of Autism in Online *Harry Potter* Fanfiction. *Journal of Literacy Research* 51, 1: 30–51.
  20. Rebecca W. Black. 2005. Access and Affiliation: The Literacy and Composition Practices of English-Language Learners in an Online Fanfiction Community. *Journal of Adolescent & Adult Literacy* 49, 2: 118–128.
  21. Rebecca W Black. 2006. Language, Culture, and Identity in Online Fanfiction. *E-Learning and Digital Media* 3, 2: 170–184.
  22. Rebecca W Black. 2007. Fanfiction Writing and the Construction of Space. *E-Learning and Digital Media* 4, 4: 384–397.
  23. Rebecca W. Black. 2008. *Adolescents and online fan fiction*. Peter Lang, New York.
  24. Rebecca W Black. 2009. Online Fan Fiction and Critical Media Literacy. *Journal of Computing in Teacher Education* 26, 2: 75–80.
  25. Rebecca W. Black. 2009. English-Language Learners, Fan Communities, and 21st-Century Skills. *Journal of Adolescent & Adult Literacy* 52, 8: 688–697.
  26. Bernadette Blair. 2006. Perception interpretation impact ;an examination of the learning value of formative feedback to students through the design studio critique. *Doctoral thesis, Institute of Education, University of London*. Retrieved March 2, 2023 from <https://discovery.ucl.ac.uk/id/eprint/10019831/>.
  27. Paul D. Bliese and Robert E. Ployhart. 2002. Growth Modeling Using Random Coefficient Models: Model Building, Testing, and Illustrations. *Organizational Research Methods* 5, 4: 362–387.
  28. booksandgalore. The Importance of Feedback on Fanfiction. Retrieved from <https://booksandgalore.tumblr.com/post/186575328788/the-importance-of-feedback-on-fanfiction/amp>.
  29. David Boud and Heather Middleton. 2003. Learning from others at work: communities of practice and informal learning. *Journal of Workplace Learning* 15, 5: 194–202.
  30. David Boud and Elizabeth Molloy. 2013. Rethinking models of feedback for learning: the challenge of design. *Assessment & Evaluation in Higher Education* 38, 6: 698–712.
  31. George Bouliotis and Lucinda Billingham. 2011. Crossing survival curves: alternatives to the log-rank test. *Trials* 12, S1: A137.
  32. Bozkurt, Aras, Jung, Insung, Xiao, Junhong, et al. 2020. A global outlook to the interruption of education due to COVID-19 pandemic: Navigating in a time of uncertainty and crisis. .
  33. Bronwen Thomas. 2011. What Is Fanfiction and Why Are People Saying Such Nice

- Things about It?? *Storyworlds: A Journal of Narrative Studies* 3: 1.
34. Michael Brooks. 2013. Affect Labeller of Expressions. Retrieved from <https://github.com/etcgroup/alo>.
  35. Michael Brooks, Katie Kuksenok, Megan K. Torkildson, et al. 2013. Statistical affect detection in collaborative chat. *Proceedings of the 2013 conference on Computer supported cooperative work*, ACM, 317–328.
  36. Rhiannon Bury. 2005. *Cyberspaces of their own: female fandoms online*. Peter Lang, New York.
  37. Kristina Busse. 2006. Fandom-is-a-Way-of-Life versus Watercooler Discussion; or, The Geek Hierarchy as Fannish Identity Politics. *Flow: A Critical Forum on Television and Media Culture*. Retrieved February 17, 2023 from <https://www.flowjournal.org/2006/11/taste-and-fandom/>.
  38. Kristina Busse. 2017. *Framing Fan Fiction: Literary and Social Practices in Fan Fiction Communities*. University of Iowa Press.
  39. Kristina Busse and Alexis Lothian. 2009. Bending gender: Feminist and (trans) gender discourses in the changing bodies of slash fan fiction. In *Internet Fictions*. Cambridge Scholars Publishing, 105–127.
  40. Deborah L. Butler and Philip H. Winne. 1995. Feedback and Self-Regulated Learning: A Theoretical Synthesis. *Review of Educational Research* 65, 3: 245–281.
  41. Julia Cambre, Scott Klemmer, and Chinmay Kulkarni. 2018. Juxtapeer: Comparative Peer Review Yields Higher Quality Feedback and Promotes Deeper Reflection. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, ACM, 1–13.
  42. Julie Campbell, Cecilia Aragon, Katie Davis, Sarah Evans, Abigail Evans, and David Randall. 2016. Thousands of Positive Reviews: Distributed Mentoring in Online Fan Communities. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, ACM, 691–704.
  43. David Carless, Diane Salter, Min Yang, and Joy Lam. 2011. Developing sustainable feedback practices. *Studies in Higher Education* 36, 4: 395–407.
  44. Kevin J. Carroll. 2003. On the use and utility of the Weibull model in the analysis of survival data. *Controlled Clinical Trials* 24, 6: 682–701.
  45. Simon M. Ceh and Mathias Benedek. 2021. Where to Share? A Systematic Investigation of Creative Behavior on Online Platforms. *Creativity. Theories – Research - Applications* 8, 1: 108–123.
  46. Ling Cen, Dymitr Ruta, Leigh Powell, Benjamin Hirsch, and Jason Ng. 2016. Quantitative approach to collaborative learning: performance prediction, individual assessment, and group composition. *International Journal of Computer-Supported Collaborative Learning* 11, 2: 187–225.
  47. Kelly Chandler-Olcott. 2015. Anime and Manga Fandom: Young People’s Multiliteracies Made Visible. In J. Flood, S.B. Heath, and D. Lapp, eds., *Handbook of research on teaching literacy through the communicative and visual arts*. Routledge, New York, 275–286.
  48. Kelly Chandler-Olcott and Elizabeth Lewis. 2010. I think they’re being wired differently. Secondary teachers’ cultural models of adolescents and their online literacies. In D.E. Alvermann, ed., *Adolescents’ online literacies : connecting classrooms, digital media, and popular culture*. Peter Lang, 163–182.
  49. Kelly Chandler-Olcott and Donna Mahar. 2003. Adolescents’ anime-Inspired “Fanfictions”: An Exploration of Multiliteracies. *Journal of Adolescent & Adult Literacy* 46,

7: 556–566.

50. Keidra Chaney and Raizel Liebler. 2007. Canon vs. fanon: folksonomies of fan culture. *Media in Transition 5: Creativity, Ownership and Collaboration in the Digital Age*: 1–16.
51. Kathy Charmaz. 2006. *Constructing grounded theory*. Sage Publications, London ; Thousand Oaks, Calif.
52. Hung-Chia Chen, Ralph L Kodell, Kuang Fu Cheng, and James J Chen. 2012. Assessment of performance of survival prediction models for cancer prognosis. *BMC Medical Research Methodology* 12, 1: 102.
53. Juanjuan Chen, Minhong Wang, Paul A. Kirschner, and Chin-Chung Tsai. 2018. The Role of Collaboration, Computer Use, Learning Environments, and Supporting Strategies in CSCL: A Meta-Analysis. *Review of Educational Research* 88, 6: 799–843.
54. Ruijia Cheng, Sayamindu Dasgupta, and Benjamin Mako Hill. 2022. How Interest-Driven Content Creation Shapes Opportunities for Informal Learning in Scratch: A Case Study on Novices’ Use of Data Structures. *CHI Conference on Human Factors in Computing Systems*, ACM, 1–16.
55. Ruijia Cheng and Jenna Frens. 2022. Feedback Exchange and Online Affinity: A Case Study of Online Fanfiction Writers. Retrieved March 16, 2023 from <http://arxiv.org/abs/2209.12810>.
56. Ruijia Cheng and Mark Zachry. 2020. Building Community Knowledge In Online Competitions: Motivation, Practices and Challenges. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2: 1–22.
57. Ruijia Cheng, Ziwen Zeng, Maysnow Liu, and Steven Dow. 2020. Critique Me: Exploring How Creators Publicly Request Feedback in an Online Critique Community. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2: 1–24.
58. Adam Connor and Aaron Irizarry. 2015. *Discussing design: improving communication and collaboration through critique*. O’Reilly, Beijing ; Cambridge.
59. Amy Cook. 2019. Using Interactive Learning Activities to Address Challenges of Peer Feedback Systems. Retrieved February 26, 2023 from [https://kiltub.cmu.edu/articles/thesis/Using\\_Interactive\\_Learning\\_Activities\\_to\\_Address\\_Challenges\\_of\\_Peer\\_Feedback\\_Systems/8153042/1](https://kiltub.cmu.edu/articles/thesis/Using_Interactive_Learning_Activities_to_Address_Challenges_of_Peer_Feedback_Systems/8153042/1).
60. Amy Cook, Jessica Hammer, Salma Elsayed-Ali, and Steven Dow. 2019. How Guiding Questions Facilitate Feedback Exchange in Project-Based Learning. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, ACM, 1–12.
61. Bill Cope, Mary Kalantzis, and New London Group, eds. 2000. *Multiliteracies: literacy learning and the design of social futures*. Routledge, London ; New York.
62. Francesca Coppa. 2006. *Fan fiction and fan communities in the age of the Internet: new essays*. McFarland & Co, Jefferson, N.C.
63. Patrick A. Crain and Brian P. Bailey. 2017. Share Once or Share Often?: Exploring How Designers Approach Iteration in a Large Online Community. *Proceedings of the 2017 ACM SIGCHI Conference on Creativity and Cognition*, ACM, 80–92.
64. John W. Creswell. 2022. *A concise introduction to mixed methods research*. SAGE, Los Angeles.
65. John W. Creswell and Vicki L. Plano Clark. 2017. *Designing and conducting mixed methods research*. SAGE Publications, Los Angeles.
66. Kevin Crowston, Xiaozhong Liu, and Eileen E. Allen. 2010. Machine learning and rule-based automated coding of qualitative data: Machine Learning and Rule-Based

Automated Coding of Qualitative Data. *Proceedings of the American Society for Information Science and Technology* 47, 1: 1–2.

67. Jen Scott Curwood, Alecia Marie Magnifico, and Jayne C. Lammers. 2013. Writing in the Wild: Writers' Motivation in Fan-Based Affinity Spaces. *Journal of Adolescent & Adult Literacy* 56, 8: 677–685.
68. Deanna Dannels, Amy Housley Gaffney, and Kelly Norris Martin. 2008. Beyond Content, Deeper than Delivery: What Critique Feedback Reveals about Communication Expectations in Design Education. *International Journal for the Scholarship of Teaching and Learning* 2, 2.
69. Sayamindu Dasgupta, William Hale, Andrés Monroy-Hernández, and Benjamin Mako Hill. 2016. Remixing as a Pathway to Computational Thinking. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, ACM, 1438–1449.
70. Sayamindu Dasgupta and Benjamin Mako Hill. 2017. Scratch Community Blocks: Supporting Children as Data Scientists. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM, 3620–3631.
71. Katie Davis and Simrat Singh. 2015. Digital badges in afterschool learning: Documenting the perspectives and experiences of students and educators. *Computers & Education* 88: 72–83.
72. Ruby Davis, Jenna Frens, Niharika Sharma, Meena Devii Muralikumar, Cecilia Aragon, and Sarah Evans. 2021. How Relationships Emerge Online and What They Mean for Amateur Creators. In *Mentorship Network Structure*. 36–45.
73. Phillip Dawson. 2014. Beyond a Definition: Toward a Framework for Designing and Specifying Mentoring Models. *Educational Researcher* 43, 3: 137–145.
74. Abigail De Kosnik. 2016. *Rogue archives: digital cultural memory and media fandom*. The MIT Press, Cambridge, Massachusetts.
75. Katherine DeLuca. 2018. Shared Passions, Shared Compositions: Online Fandom Communities and Affinity Groups as Sites for Public Writing Pedagogy. *Computers and Composition* 47: 75–92.
76. Aaron Alan Delwiche and Jennifer Jacobs Henderson, eds. 2013. *The participatory cultures handbook*. Routledge, New York.
77. Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Retrieved February 27, 2023 from <http://arxiv.org/abs/1810.04805>.
78. Catherine D'Ignazio and Lauren F. Klein. 2020. *Data feminism*. The MIT Press, Cambridge, Massachusetts.
79. Steven Dow, Elizabeth Gerber, and Audris Wong. 2013. A pilot study of using crowds in the classroom. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM, 227–236.
80. Steven Dow, Anand Kulkarni, Brie Bunge, Truc Nguyen, Scott Klemmer, and Björn Hartmann. 2011. Shepherding the crowd: managing and providing feedback to crowd workers. *CHI '11 Extended Abstracts on Human Factors in Computing Systems*, ACM, 1669–1674.
81. Mark Duffett. 2013. *Understanding fandom: an introduction to the study of media fan culture*. Bloomsbury, New York.
82. Jennifer Duggan. 2022. Transformative Readings: Harry Potter Fan Fiction, Trans/Queer

- Reader Response, and J. K. Rowling. *Children's Literature in Education* 53, 2: 147–168.
83. Jennifer Duggan. 2022. “Worlds. . .[of] Contingent Possibilities”: Genderqueer and Trans Adolescents Reading Fan Fiction. *Television & New Media* 23, 7: 703–720.
  84. R. I. M. Dunbar. 2020. Structure and function in human and primate social networks: implications for diffusion, network stability and health. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 476, 2240: 20200446.
  85. R. I. M. Dunbar, Valerio Arnaboldi, Marco Conti, and Andrea Passarella. 2015. The Structure of Online Social Networks Mirror Those in the Offline World. *Social Networks* 43: 39–47.
  86. Brianna Dym, Cecilia Aragon, Julia Bullard, Ruby Davis, and Casey Fiesler. 2018. Online Fandom: Boldly Going Where Few CSCW Researchers Have Gone Before. *Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 121–124.
  87. Brianna Dym, Jed Brubaker, and Casey Fiesler. “theyre all trans sharon”: Authoring Gender in Video Game Fan Fiction. *Game Studies*: 18.
  88. Brianna Dym, Jed R. Brubaker, Casey Fiesler, and Bryan Semaan. 2019. “Coming Out Okay”: Community Narratives for LGBTQ Identity Recovery Work. *Proceedings of the ACM on Human-Computer Interaction* 3, CSCW: 1–28.
  89. Brianna Dym and Casey Fiesler. 2020. Ethical and privacy considerations for research using online fandom data. *Transformative Works and Cultures* 33.
  90. Brianna Dym and Casey Fiesler. 2020. Social Norm Vulnerability and its Consequences for Privacy and Safety in an Online Community. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW2: 1–24.
  91. ETH Zurich, Mihai Grigore, Christoph Rosenkranz, University of Cologne, Cologne, Germany, Juliana Sutanto, and Lancaster University. 2015. The Impact of Sentiment-driven Feedback on Knowledge Reuse in Online Communities. *AIS Transactions on Human-Computer Interaction* 7, 4: 212–232.
  92. İlker Etikan. 2018. Choosing statistical tests for survival analysis. *Biometrics & Biostatistics International Journal* 7, 5.
  93. Sarah Evans, Katie Davis, Abigail Evans, et al. 2017. More Than Peer Production: Fanfiction Communities as Sites of Distributed Mentoring. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 259–272.
  94. Mukaddes Fasli and Badiossadat Hassanpour. 2017. Rotational Critique System as a Method of Culture Change in an Architecture Design Studio: Urban Design Studio as Case Study. *Innovations in Education and Teaching International* 54, 3: 194–205.
  95. Gerasimos Fergadiotis, Heather Harris Wright, and Samuel B. Green. 2015. Psychometric Evaluation of Lexical Diversity Indices: Assessing Length Effects. *Journal of Speech, Language, and Hearing Research* 58, 3: 840–852.
  96. fffinnagain. Sound interest — Fandom Stats posts. *Fandom Stats posts*. Retrieved March 16, 2023 from <https://fffinnagain.tumblr.com/fandomstats>.
  97. Deborah A. Fields, Michael Giang, and Yasmin Kafai. 2014. Programming in the wild: trends in youth computational participation in the online scratch community. *Proceedings of the 9th Workshop in Primary and Secondary Computing Education*, ACM, 2–11.
  98. Deborah A. Fields, Yasmin B. Kafai, and Michael T. Giang. 2017. Youth Computational Participation in the Wild: Understanding Experience and Equity in Participating and

- Programming in the Online Scratch Community. *ACM Transactions on Computing Education* 17, 3: 1–22.
99. Casey Fiesler and Brianna Dym. 2020. Moving Across Lands: Online Platform Migration in Fandom Communities. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW1: 1–25.
  100. Casey Fiesler, Shannon Morrison, and Amy S. Bruckman. 2016. An Archive of Their Own: A Case Study of Feminist HCI and Values in Design. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, ACM, 2574–2585.
  101. Casey Fiesler, Shannon Morrison, R. Benjamin Shapiro, and Amy S. Bruckman. 2017. Growing Their Own: Legitimate Peripheral Participation for Computational Learning in an Online Fandom Community. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 1375–1386.
  102. Frank Fischer, Cindy E. Hmelo-Silver, Susan R. Goldman, and Peter Reimann, eds. 2018. *International handbook of the learning sciences*. Routledge, New York, NY.
  103. Monica Flegel and Jenny Roth. 2016. Writing a New Text: The Role of Cyberculture in Fanfiction Writers’ Transition to “Legitimate” Publishing. *Contemporary Women’s Writing* 10, 2: 253–272.
  104. Joseph L. Fleiss, Bruce Levin, and Myunghee Cho Paik. 2003. *Statistical Methods for Rates and Proportions*. Wiley.
  105. Eureka Foong, Steven P. Dow, Brian P. Bailey, and Elizabeth M. Gerber. 2017. Online Feedback Exchange: A Framework for Understanding the Socio-Psychological Factors. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM, 4454–4467.
  106. Denae Ford, Kristina Lustig, Jeremy Banks, and Chris Parnin. 2018. “We Don’t Do That Here”: How Collaborative Editing with Mentors Improves Engagement in Social Q&A Communities. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, ACM, 1–12.
  107. Megan Justine Fowler. 2019. Rewriting the school story through racebending in the Harry Potter and Raven Cycle fandoms. *Transformative Works and Cultures* 29.
  108. Jenna Frens. 2017. lexical\_diversity. Retrieved from [https://github.com/jennafrens/lexical\\_diversity](https://github.com/jennafrens/lexical_diversity).
  109. Jenna Frens, Ruby Davis, Jihyun Lee, Diana Zhang, and Cecilia Aragon. 2018. Reviews Matter: How Distributed Mentoring Predicts Lexical Diversity on Fanfiction.net. *CoRR* abs/1809.10268.
  110. Katharina Freund. 2016. “Fair use is legal use”: Copyright negotiations and strategies in the fan-vidding community. *New Media & Society* 18, 7: 1347–1363.
  111. Niamh Froelich, Arthur Liu, Ruoxi Shang, et al. 2021. Reciprocity in Reviewing on Fanfiction.Net. In C. Stephanidis, M. Antona, and S. Ntoa, eds., *HCI International 2021 - Posters*. Springer International Publishing, Cham, 39–44.
  112. Ikuko Funatogawa and Takashi Funatogawa. 2018. *Longitudinal Data Analysis: Autoregressive Linear Mixed Effects Models*. Springer Singapore, Singapore.
  113. Dilrukshi Gamage, Thomas Staubitz, and Mark Whiting. 2021. Peer assessment in MOOCs: Systematic literature review. *Distance Education* 42, 2: 268–289.
  114. Emilia F. Gan, Benjamin Mako Hill, and Sayamindu Dasgupta. 2018. Gender, Feedback, and Learners’ Decisions to Share Their Creative Computing Projects. *Proceedings of the ACM on Human-Computer Interaction* 2, CSCW: 1–23.

115. James Paul Gee. 2004. *Situated language and learning: a critique of traditional schooling*. Routledge, New York.
116. James Paul Gee. 2008. 7. Learning in semiotic domains: A social and situated account. In M. Prinsloo and M. Baynham, eds., *AILA Applied Linguistics Series*. John Benjamins Publishing Company, Amsterdam, 137–149.
117. James Paul Gee. 2012. *Situated Language and Learning: A Critique of Traditional Schooling*. Routledge.
118. James Paul Gee. 2017. *Teaching, learning, literacy in our high-risk high-tech world: a framework for becoming human*. Teachers College Press, New York, NY.
119. James Paul Gee. 2018. Affinity spaces: How young people live and learn on line and out of school. *Phi Delta Kappan* 99, 6: 8–13.
120. James Paul Gee and Elisabeth Hayes. 2010. *Women and gaming: the Sims and 21st century learning*. Palgrave Macmillan, New York.
121. Elizabeth M. Gerber and Julie Hui. 2013. Crowdfunding: Motivations and deterrents for participation. *ACM Transactions on Computer-Human Interaction* 20, 6: 1–32.
122. Elizabeth Gilliland. 2016. Racebending fandoms and digital futurism. *Transformative Works and Cultures* 22.
123. Vlad Glaveanu, Todd Lubart, Nathalie Bonnardel, et al. 2013. Creativity as action: findings from five creative domains. *Frontiers in Psychology* 4.
124. Joseph A. Gonzales, Casey Fiesler, and Amy Bruckman. 2015. Towards an Appropriate CSCW Tool Ecology: Lessons from the Greatest International Scavenger Hunt the World Has Ever Seen. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ACM, 946–957.
125. Enrico Grazzi. 2012. The sociocultural dimension of ELF in the English classroom: the case of fanfiction through social networking. *A Journal of TESOL Italy* 38, 1: 7.
126. Christine Greenhow and Cathy Lewin. 2016. Social media and education: reconceptualizing the boundaries of formal and informal learning. *Learning, Media and Technology* 41, 1: 6–30.
127. Carmen L.Z. Gress, Meghann Fior, Allyson F. Hadwin, and Philip H. Winne. 2010. Measurement and assessment in computer-supported collaborative learning. *Computers in Human Behavior* 26, 5: 806–814.
128. Allyson Hadwin and Mika Oshige. 2011. Self-Regulation, Coregulation, and Socially Shared Regulation: Exploring Perspectives of Social in Self-Regulated Learning Theory. *Teachers College Record* 113, 2: 240–264.
129. Jr Harrell. 2015. *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*. Springer International Publishing : Imprint: Springer, Cham.
130. John Hattie and Helen Timperley. 2007. The Power of Feedback. *Review of Educational Research* 77, 1: 81–112.
131. Samantha Hautea, Sayamindu Dasgupta, and Benjamin Mako Hill. 2017. Youth Perspectives on Critical Data Literacies. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM, 919–930.
132. Avijit Hazra and Nithya Gogtay. 2017. Biostatistics Series Module 9: Survival Analysis. *Indian Journal of Dermatology* 62, 3: 251–257.
133. Khe Foon Hew. 2018. Unpacking the Strategies of Ten Highly Rated MOOCs: Implications for Engaging Students in Large Online Courses. *Teachers College Record: The*

- Voice of Scholarship in Education* 120, 1: 1–40.
134. James Hollan, Edwin Hutchins, and David Kirsh. 2000. Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Transactions on Computer-Human Interaction* 7, 2: 174–196.
  135. Lars Hornuf and Daniel Vrankar. 2022. Hourly Wages in Crowdfunding: A Meta-Analysis. *Business & Information Systems Engineering* 64, 5: 553–573.
  136. Katherine Anderson Howell, ed. 2018. *Fandom as Classroom Practice: A Teaching Guide*. University of Iowa Press.
  137. Iris Howley. 2015. Leveraging Educational Technology to Overcome Social Obstacles to Help Seeking. Retrieved February 26, 2023 from [https://kilthub.cmu.edu/articles/thesis/Leveraging\\_Educational\\_Technology\\_to\\_Overcome\\_Social\\_Obstacles\\_to\\_Help\\_Seeking/6720425/1](https://kilthub.cmu.edu/articles/thesis/Leveraging_Educational_Technology_to_Overcome_Social_Obstacles_to_Help_Seeking/6720425/1).
  138. Julie Hui, Amos Glenn, Rachel Jue, Elizabeth Gerber, and Steven Dow. 2015. Using Anonymity and Communal Efforts to Improve Quality of Crowdsourced Feedback. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing* 3: 72–82.
  139. Julie S. Hui, Matthew W. Easterday, and Elizabeth M. Gerber. 2019. Distributed Apprenticeship in Online Communities. *Human-Computer Interaction* 34, 4: 328–378.
  140. Edwin Hutchins. 2006. *Cognition in the wild*. MIT Press, Cambridge, Mass.
  141. Mizuko Itō, Sonja Baumer, Matteo Bittanti, and Judd Antin, eds. 2013. *Hanging out, messing around, and geeking out: kids living and learning with new media*. MIT Press, Cambridge, Mass. London.
  142. Mizuko Itō, Heather Horst, Matteo Bittanti, et al. 2009. *Living and Learning with New Media: Summary of Findings from the Digital Youth Project*. The MIT Press.
  143. Mizuko Itō, Crystle Martin, Rachel Cody Pfister, Matthew H. Rafalow, Katie Salen, and Amanda Wortman. 2018. *Affinity online: how connection and shared interest fuel learning*. New York University Press, New York.
  144. Mizuko Itō, Daisuke Okabe, and Izumi Tsuji, eds. 2012. *Fandom unbound: otaku culture in a connected world*. Yale University Press, New Haven.
  145. Anne Elizabeth Jamison. 2013. *Fic: why fanfiction is taking over the world*. Smart Pop, an imprint of BenBella Books, Inc, Dallas, Texas.
  146. Nina Janasik, Timo Honkela, and Henrik Bruun. 2009. Text Mining in Qualitative Research: Application of an Unsupervised Learning Method. *Organizational Research Methods* 12, 3: 436–460.
  147. Jeroen Janssen and Ingo Kollar. 2021. Experimental and Quasi-Experimental Research in CSCL. In U. Cress, C. Rosé, A.F. Wise, and J. Oshima, eds., *International Handbook of Computer-Supported Collaborative Learning*. Springer International Publishing, Cham, 497–515.
  148. Scott Jarvis. 2013. Chapter 1. Defining and measuring lexical diversity. In S. Jarvis and M. Daller, eds., *Studies in Bilingualism*. John Benjamins Publishing Company, Amsterdam, 13–44.
  149. Henry Jenkins. 2006. *Fans, bloggers, and gamers: exploring participatory culture*. New York University Press, New York.
  150. Henry Jenkins. 2006. *Convergence culture: where old and new media collide*. New York University Press, New York.
  151. Henry Jenkins. 2009. *Confronting the challenges of participatory culture: media education for the 21st century*. The MIT Press, Cambridge, MA.

152. Henry Jenkins. 2013. *Textual poachers: television fans and participatory culture*. Routledge, New York.
153. Henry Jenkins. 2019. 'Art Happens not in Isolation, But in Community': The Collective Literacies of Media Fandom. *Cultural Science Journal* 11, 1: 78–88.
154. Henry Jenkins, Mizuko Itō, and danah boyd. 2015. *Participatory culture in a networked era: a conversation on youth, learning, commerce, and politics*. Polity Press, Cambridge, UK ; Malden, MA.
155. Petr Johanes. 2019. Start of a Science: An Epistemological Analysis of Learning at Scale. *Proceedings of the Sixth (2019) ACM Conference on Learning @ Scale*, ACM, 1–10.
156. Bethan Jones. 2014. Fifty shades of exploitation: Fan labor and “Fifty Shades of Grey.” *Transformative Works and Cultures* 15.
157. Tali Kahan, Tal Soffer, and Rafi Nachmias. 2017. Types of Participant Behavior in a Massive Open Online Course. *The International Review of Research in Open and Distributed Learning* 18, 6.
158. Andreas M. Kaplan and Michael Haenlein. 2010. Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons* 53, 1: 59–68.
159. Pinar Gunel Karadeniz and Ilker Ercan. 2017. Examining Tests for Comparing Survival Curves with Right Censored Data. *Statistics in Transition New Series* 18, 2: 311–328.
160. Karen Hellekson. 2009. A Fannish Field of Value: Online Fan Gift Culture. *Cinema Journal* 48, 4: 113–118.
161. Julia Kasch, Peter van Rosmalen, Ansje Löhr, Roland Klemke, Alessandra Antonaci, and Marco Kalz. 2021. Students' perceptions of the peer-feedback experience in MOOCs. *Distance Education* 42, 1: 145–163.
162. Brittany Kelley. 2016. Chocolate Frogs for My Betas!: Practicing Literacy at One Online Fanfiction Website. *Computers and Composition* 40: 48–59.
163. Joy Kim, Sarah Serman, Allegra Argent Beal Cohen, and Michael S. Bernstein. 2017. Mechanical Novel: Crowdsourcing Complex Work through Reflection and Revision. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 233–245.
164. John P. Klein and Melvin L. Moeschberger. 2010. *Survival analysis: techniques for censored and truncated data*. Springer, New York, NY.
165. Avraham N. Kluger and Angelo DeNisi. 1996. The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin* 119, 2: 254–284.
166. Marios Kokkodis and Theodoros Lappas. 2016. Realizing the Activation Potential of Online Communities. *ICIS 2016 Proceedings Data Science and Business Analytics* 12.
167. Ksenia A. Korobkova and Rebecca W. Black. 2014. Contrasting Visions: Identity, Literacy, and Boundary Work in a Fan Community. *E-Learning and Digital Media* 11, 6: 619–632.
168. Yasmine Kotturi. 2022. Community-Based Approaches to Building Peer Support Systems for Work. .
169. Yasmine Kotturi, Andrew Du, Scott Klemmer, and Chinmay Kulkarni. 2017. Long-Term Peer Reviewing Effort is Anti-Reciprocal. *Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale*, ACM, 279–282.
170. Yasmine Kotturi and McKayla Kingston. 2019. Why do Designers in the “Wild” Wait to Seek Feedback until Later in their Design Process? *Proceedings of the 2019 on Creativity and*

- Cognition*, ACM, 541–546.
171. Yubo Kou and Colin M. Gray. 2017. Supporting Distributed Critique through Interpretation and Sense-Making in an Online Creative Community. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW: 1–18.
  172. Markus Krause, Tom Garnarcz, JiaoJiao Song, Elizabeth M. Gerber, Brian P. Bailey, and Steven P. Dow. 2017. Critique Style Guide: Improving Crowdsourced Design Feedback with a Natural Language Model. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM, 4627–4639.
  173. Robert E. Kraut and Paul Resnick. 2012. *Building Successful Online Communities: Evidence-Based Social Design*. The MIT Press.
  174. Jouni Kuha. 2004. AIC and BIC: Comparisons of Assumptions and Performance. *Sociological Methods & Research* 33, 2: 188–229.
  175. Chinmay E. Kulkarni, Michael S. Bernstein, and Scott R. Klemmer. 2015. PeerStudio: Rapid Peer Feedback Emphasizes Revision and Improves Performance. *Proceedings of the Second (2015) ACM Conference on Learning @ Scale*, ACM, 75–84.
  176. Chinmay Kulkarni, Koh Pang Wei, Huy Le, et al. 2013. Peer and self assessment in massive online classes. *ACM Transactions on Computer-Human Interaction* 20, 6: 1–31.
  177. Jayne C. Lammers, Alecia M. Magnifico, and Anlun Wang. 2022. Playful Multiliteracies: Fan-Based Literacies’ Role in English Language Arts Pedagogy. *Journal of Adolescent & Adult Literacy* 66, 2: 80–90.
  178. Jayne C. Lammers and Valerie L. Marsh. 2015. Going Public: An Adolescent’s Networked Writing on Fanfiction.net. *Journal of Adolescent & Adult Literacy* 59, 3: 277–285.
  179. Colin Lankshear and Michele Knobel. 2003. *New literacies: changing knowledge and classroom learning*. Open Univ. Press, Buckingham.
  180. Jean Lave and Etienne Wenger. 1991. *Situated learning: legitimate peripheral participation*. Cambridge University Press, Cambridge [England] ; New York.
  181. Jong Gun Lee, Sue Moon, and Kavé Salamatian. 2012. Modeling and predicting the popularity of online contents with Cox proportional hazard regression model. *Neurocomputing* 76, 1: 134–145.
  182. Lauren Lewis, Rebecca W Black, and Bill Tomlinson. 2009. Let Everyone Play: An Educational Perspective on Why Fan Fiction Is, or Should Be, Legal. *International Journal of Learning and Media* 1, 1: 67–81.
  183. Guofang Li. 2012. Literacy Engagement through Online and Offline Communities outside School: English Language Learners’ Development as Readers and Writers. *Theory Into Practice* 51, 4: 312–318.
  184. Hongli Li, Yao Xiong, Xiaojiao Zang, et al. 2016. Peer assessment in the digital age: a meta-analysis comparing peer and teacher ratings. *Assessment & Evaluation in Higher Education* 41, 2: 245–264.
  185. Xing Li. 1998. *FanFiction.Net*. Retrieved from <https://fanfiction.net>.
  186. Chad Eric Littleton. 2011. The Role of Feedback in Two Fanfiction Writing Groups. .
  187. Heather Lotherington and Jennifer Jenson. 2011. Teaching Multimodal and Digital Literacy in L2 Settings: New Literacies, New Basics, New Pedagogies. *Annual Review of Applied Linguistics* 31: 226–246.
  188. Alexis Lothian, Kristina Busse, and Robin Anne Reid. 2007. “Yearning Void and Infinite Potential”: Online Slash Fandom as Queer Female Space. *English Language Notes* 45, 2: 103–111.

189. Sofie M. M. Loyens, Joshua Magda, and Remy M. J. P. Rikers. 2008. Self-Directed Learning in Problem-Based Learning and its Relationships with Self-Regulated Learning. *Educational Psychology Review* 20, 4: 411–427.
190. Kurt Luther, Jari-Lee Tolentino, Wei Wu, et al. 2015. Structuring, Aggregating, and Evaluating Crowdsourced Design Critique. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ACM, 473–485.
191. Haiwei Ma, C. Estelle Smith, Lu He, et al. 2017. Write for Life: Persisting in Online Health Communities through Expressive Writing and Social Support. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW: 1–24.
192. James MacQueen. 1967. Some methods for classification and analysis of multivariate observations. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*.
193. Alecia Marie Magnifico, Jen Scott Curwood, and Jayne C. Lammers. 2015. Words on the screen: broadening analyses of interactions among fanfiction writers and reviewers: Words on the screen. *Literacy* 49, 3: 158–166.
194. Leslie Manning. 2015. Negotiating Doctor Who: Neurodiversity and Fandom. In E. Thorsen, H. Savigny, J. Alexander, and D. Jackson, eds., *Media, Margins and Popular Culture*. Palgrave Macmillan UK, London, 153–165.
195. Jennifer Marlow and Laura Dabbish. 2014. From rookie to all-star: professional development in a graphic design social networking site. *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, ACM, 922–933.
196. Elena Martín-Monje, María Dolores Castrillo, and Jorge Mañana-Rodríguez. 2018. Understanding online interaction in language MOOCs through learning analytics. *Computer Assisted Language Learning* 31, 3: 251–272.
197. Lance Mason, Dan Krutka, and Jeremy Stoddard. 2018. Media Literacy, Democracy, and the Challenge of Fake News. *Journal of Media Literacy Education* 10, 2: 1–10.
198. J. Nathan Matias, Sayamindu Dasgupta, and Benjamin Mako Hill. 2016. Skill Progression in Scratch Revisited. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, ACM, 1486–1490.
199. Diana Mazgutova and Judit Kormos. 2015. Syntactic and lexical development in an intensive English for Academic Purposes programme. *Journal of Second Language Writing* 29: 3–15.
200. Alexander McAuley, Bonnie Stewart, George Siemens, and Dave Cormier. 2010. The MOOC Model for Digital Practice. .
201. Philip M. McCarthy and Scott Jarvis. 2010. MTLT, vocd-D, and HD-D: A validation study of sophisticated approaches to lexical diversity assessment. *Behavior Research Methods* 42, 2: 381–392.
202. Brian McInnis, Dan Cosley, Chaebong Nam, and Gilly Leshed. 2016. Taking a HIT: Designing around Rejection, Mistrust, Risk, and Workers’ Experiences in Amazon Mechanical Turk. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, ACM, 2271–2282.
203. Sharan B. Merriam and Elizabeth J. Tisdell. 2015. *Qualitative research: a guide to design and implementation*. John Wiley & Sons, San Francisco, CA.
204. James Milton and Jeanine Treffers-Daller. 2013. Vocabulary size revisited: the link between vocabulary size and academic achievement. *Applied Linguistics Review* 4, 1: 151–172.

205. Sunny Moraine. 2012. Fifty Shades of Grey and the Ethics of Fannish Prosumption - Cyborgology. *Cyborgology*. Retrieved February 23, 2023 from <https://thesocietypages.org/cyborgology/2012/06/06/fifty-shades-of-grey-and-the-ethics-of-fannish-prosumption/>.
206. Martin Mulder. 2014. Conceptions of Professional Competence. In S. Billett, C. Harteis, and H. Gruber, eds., *International Handbook of Research in Professional and Practice-based Learning*. Springer Netherlands, Dordrecht, 107–137.
207. Christa Mullis. 2019. Reflection: Autistic-Coded Characters and Fans in Fandom. *Canadian Journal of Disability Studies* 8, 2: 147–156.
208. Nicholas H. Ng'Andu. 1997. AN EMPIRICAL COMPARISON OF STATISTICAL TESTS FOR ASSESSING THE PROPORTIONAL HAZARDS ASSUMPTION OF COX'S MODEL. *Statistics in Medicine* 16, 6: 611–626.
209. Tricia J. Ngoon, C. Ailie Fraser, Ariel S. Weingarten, Mira Dontcheva, and Scott Klemmer. 2018. Interactive Guidance Techniques for Improving Creative Feedback. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, ACM, 1–11.
210. Thi Thao Duyen T. Nguyen, Thomas Garncarz, Felicia Ng, Laura A. Dabbish, and Steven P. Dow. 2017. Fruitful Feedback: Positive Affective Language and Source Anonymity Improve Critique Reception and Work Outcomes. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 1024–1034.
211. David J. Nicol and Debra Macfarlane-Dick. 2006. Formative assessment and self-regulated learning: a model and seven principles of good feedback practice. *Studies in Higher Education* 31, 2: 199–218.
212. Natalie G. Olinghouse and Joshua Wilson. 2013. The relationship between vocabulary and writing quality in three genres. *Reading and Writing* 26, 1: 45–65.
213. Jonas Oppenlaender, Thanassis Tiropanis, and Simo Hosio. 2020. CrowdUI: Supporting Web Design with the Crowd. *Proceedings of the ACM on Human-Computer Interaction* 4, EICS: 1–28.
214. Tim O'Reilly. 2005. What Is Web 2.0. *O'Reilly*. Retrieved February 25, 2023 from <https://www.oreilly.com/pub/a/web2/archive/what-is-web-20.html>.
215. Dionne Soares Palmer. 2010. Second Language Pragmatic Socialization in World of Warcraft. *ProQuest LLC*.
216. Rukmini Pande. 2020. How (not) to talk about race: A critique of methodological practices in fan studies. *Transformative Works and Cultures* 33.
217. Seymour Papert. 1993. *Mindstorms: children, computers, and powerful ideas*. Basic Books, New York.
218. Abelardo Pardo, Jelena Jovanovic, Shane Dawson, Dragan Gašević, and Negin Mirriahi. 2019. Using learning analytics to scale the provision of personalised feedback: Learning analytics to scale personalised feedback. *British Journal of Educational Technology* 50, 1: 128–138.
219. Juli J. Parrish. 2007. Inventing a Universe: Reading and Writing Internet Fan Fiction. Retrieved March 2, 2023 from <http://d-scholarship.pitt.edu/8963/>.
220. Khaliah Petersen-Reed. 2019. Fanfiction as Performative Criticism: Harry Potter Racebending. *Journal of Creative Writing Studies* 4, 1.
221. John E. Pinder, James G. Wiener, and Michael H. Smith. 1978. The Weibull Distribution: A New Method of Summarizing Survivorship Data. *Ecology* 59, 1: 175–179.

222. José C. Pinheiro and Douglas M. Bates. 2000. *Mixed-Effects Models in S and S-PLUS*. Springer International Publishing, Cham.
223. Jennifer Preece and Ben Shneiderman. 2009. The Reader-to-Leader Framework: Motivating Technology-Mediated Social Participation. *AIS Transactions on Human-Computer Interaction* 1, 1: 13–32.
224. Minna Puustinen and Jean-François Rouet. 2009. Learning with new technologies: Help seeking and information searching revisited. *Computers & Education* 53, 4: 1014–1019.
225. Daphne R. Raban, Mihai Moldovan, and Quentin Jones. 2010. An empirical study of critical mass and online community survival. *Proceedings of the 2010 ACM conference on Computer supported cooperative work*, ACM, 71–80.
226. Tabassum Rashid and Hanan Muhammad Asghar. 2016. Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior* 63: 604–612.
227. Ken Reily, Pam Ludford Finnerty, and Loren Terveen. 2009. Two peers are better than one: aggregating peer reviews for computing assignments is surprisingly accurate. *Proceedings of the 2009 ACM International Conference on Supporting Group Work*, ACM, 115–124.
228. Mitchel Resnick, John Maloney, Andrés Monroy-Hernández, et al. 2009. Scratch: programming for all. *Communications of the ACM* 52, 11: 60–67.
229. Ryan M. Rish and Joshua Caton. 2011. Building Fantasy Worlds Together with Collaborative Writing: Creative, Social, and Pedagogic Challenges. *The English Journal* 100, 5: 21–28.
230. Jahmeilah Roberson and Bonnie Nardi. Survival Needs and Social Inclusion: Technology Use Among the Homeless. 4.
231. Cristobal Romero and Sebastian Ventura. 2020. Educational data mining and learning analytics: An updated survey. *WIRES Data Mining and Knowledge Discovery* 10, 3.
232. Ricarose Roque, Sayamindu Dasgupta, and Sasha Costanza-Chock. 2016. Children’s Civic Engagement in the Scratch Online Community. *Social Sciences* 5, 4: 55.
233. Rod D. Roscoe and Michelene T. H. Chi. 2007. Understanding Tutor Learning: Knowledge-Building and Knowledge-Telling in Peer Tutors’ Explanations and Questions. *Review of Educational Research* 77, 4: 534–574.
234. Carolyn Rosé, Yi-Chia Wang, Yue Cui, et al. 2008. Analyzing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *International Journal of Computer-Supported Collaborative Learning* 3, 3: 237–271.
235. Jonathan A. Rose. 2020. “My Male Skin”: (self-)narratives of transmasculinities in fanfiction. *European Journal of English Studies* 24, 1: 25–36.
236. Lauren Rouse. 2021. Fan fiction comments and their relationship to classroom learning. *Transformative Works and Cultures* 35.
237. D. Royce Sadler. 1989. Formative assessment and the design of instructional systems. *Instructional Science* 18, 2: 119–144.
238. Shannon Sauro and Björn Sundmark. 2016. Report from Middle-Earth: fan fiction tasks in the EFL classroom. *ELT Journal* 70, 4: 414–423.
239. Shannon Sauro and Björn Sundmark. 2019. Critically examining the use of blog-based fanfiction in the advanced language classroom. *ReCALL* 31, 01: 40–55.
240. Donald A. Schön. 2017. *The Reflective Practitioner*. Routledge.

241. Dawn E. Schrader. 2015. Constructivism and Learning in the Age of Social Media: Changing Minds and Learning Communities: Constructivism and Learning in the Age of Social Media. *New Directions for Teaching and Learning* 2015, 144: 23–35.
242. Carlos A. Scolari, Maria-José Masanet, Mar Guerrero-Pico, and María-José Establés. 2018. Transmedia literacy in the new media ecology: Teens’ transmedia skills and informal learning strategies. *El Profesional de la Información* 27, 4: 801.
243. Taylor Jackson Scott, Katie Kuksenok, Daniel Perry, Michael Brooks, Ona Anicello, and Cecilia Aragon. 2012. Adapting grounded theory to construct a taxonomy of affect in collaborative online chat. *Proceedings of the 30th ACM international conference on Design of communication*, ACM, 197–204.
244. Julian Sefton-Green. 2004. Literature Review in Informal Learning with Technology Outside School. *Futurelab Report* 7.
245. Ruoxi Shang, Zile Xiao, Jenna Frens, and Cecilia Aragon. 2021. Giving and Receiving: Reciprocal Review Exchange in Online Fanfiction Communities. *Companion Publication of the 2021 Conference on Computer Supported Cooperative Work and Social Computing*, ACM, 171–174.
246. Amy Shannon, Jessica Hammer, Hassler Thurston, Natalie Diehl, and Steven Dow. 2016. PeerPresents: A Web-Based System for In-Class Peer Feedback during Student Presentations. *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, ACM, 447–458.
247. Bianca A. Simonsmeier, Henrike Peiffer, Maja Flaig, and Michael Schneider. 2020. Peer Feedback Improves Students’ Academic Self-Concept in Higher Education. *Research in Higher Education* 61, 6: 706–724.
248. Frans van der Sluis, Tim van der Zee, and Jasper Ginn. 2017. Learning about Learning at Scale: Methodological Challenges and Recommendations. *Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale*, ACM, 131–140.
249. Mel Stanfill. 2018. The Unbearable Whiteness of Fandom and Fan Studies. In P. Booth, ed., *A Companion to Media Fandom and Fan Studies*. John Wiley & Sons, Inc., Hoboken, NJ, USA, 305–317.
250. Ingo Steinwart and Andreas Christmann. 2008. *Support vector machines*. Springer, New York.
251. Katleen E. M. de Stobbeleir, Susan J. Ashford, and Dirk Buyens. 2011. Self-Regulation of Creativity at Work: The Role of Feedback-Seeking Behavior in Creative Performance. *Academy of Management Journal* 54, 4: 811–831.
252. Hoi K. Suen. 2014. Peer assessment for massive open online courses (MOOCs). *The International Review of Research in Open and Distributed Learning* 15, 3.
253. Ebony Elizabeth Thomas and Amy Stornaiuolo. 2016. Restorying the Self: Bending toward Textual Justice. *Harvard Educational Review* 86, 3: 313–338.
254. Keith Topping. 1998. Peer Assessment Between Students in Colleges and Universities. *Review of Educational Research* 68, 3: 249–276.
255. Catherine Tosenberger. 2014. Mature Poets Steal: Children’s Literature and the Unpublishability of Fanfiction. *Children’s Literature Association Quarterly* 39, 1: 4–27.
256. Carlos Toxtli, Siddharth Suri, and Saiph Savage. 2021. Quantifying the Invisible Labor in Crowd Work. .
257. Rebecca Tushnet. 2007. Copyright law, fan practices, and the rights of the author. 60–71.
258. Rebecca Tushnet. 2014. ‘I’m a Lawyer, Not an Ethnographer, Jim’: Textual Poachers and fair use. *The Journal of Fandom Studies* 2, 1: 21–30.

259. Lev Semenovič Vygotskij and Michael Cole. 1981. *Mind in society: the development of higher psychological processes*. Harvard Univ. Press, Cambridge, Mass.
260. wangmx928. 2019. BERT\_FF\_PyTorch\_shallow.ipynb. Retrieved from <https://gist.github.com/wangmx928/69fb5646de757d8f443b4cd87110190d>.
261. Thomas Wanner and Edward Palmer. 2018. Formative self-and peer assessment for improved student learning: the crucial factors of design, teacher participation and feedback. *Assessment & Evaluation in Higher Education* 43, 7: 1032–1047.
262. Tony J. Watson. 2008. Managing Identity: Identity Work, Personal Predicaments and Structural Circumstances. *Organization* 15, 1: 121–143.
263. Howard T. Welsler, Dan Cosley, Gueorgi Kossinets, et al. 2011. Finding social roles in Wikipedia. *Proceedings of the 2011 iConference*, ACM, 122–129.
264. Etienne Wenger-Trayner and Beverly Wenger-Trayner. 2015. Introduction to communities of practice. *Wenger-trayner*. Retrieved February 25, 2023 from <https://www.wenger-trayner.com/introduction-to-communities-of-practice/>.
265. Rebecca Hamilton White. 2014. Lexical richness in adolescent writing, insights from the classroom: An L1 vocabulary development study. .
266. Anna Wilson. 2021. Fan fiction and premodern literature: Methods and definitions. *Transformative Works and Cultures* 36.
267. Philip H. Winne. 2015. What is the state of the art in self-, co- and socially shared regulation in CSCL? *Computers in Human Behavior* 52: 628–631.
268. Billy Tak-ming Wong and Kam Cheong Li. 2020. A review of learning analytics intervention in higher education (2011–2018). *Journal of Computers in Education* 7, 1: 7–28.
269. Wanli Xing, Sean Goggins, and Josh Introne. 2018. Quantifying the Effect of Informational Support on Membership Retention in Online Communities through Large-Scale Data Analytics. *Computers in Human Behavior* 86: 227–234.
270. Anbang Xu and Brian Bailey. 2012. What do you think?: a case study of benefit, expectation, and interaction in a large online critique community. *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*, ACM, 295–304.
271. Anbang Xu, Shih-Wen Huang, and Brian Bailey. 2014. Voyant: generating structured feedback on visual designs using a crowd of non-experts. *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, ACM, 1433–1444.
272. Yishu Xue and Elizabeth D. Schifano. 2017. Diagnostics for the Cox model. *Communications for Statistical Applications and Methods* 24, 6: 583–604.
273. Diyi Yang, Tanmay Sinha, David Adamson, and Carolyn Penstein Rosé. 2013. “Turn on, Tune in, Drop out”: Anticipating Student Dropouts in Massive Open Online Courses. *Proceedings of the 2013 NIPS Data-Driven Education Workshop*: 1–8.
274. Qian Yang, Alex Scuito, John Zimmerman, Jodi Forlizzi, and Aaron Steinfeld. 2018. Investigating How Experienced UX Designers Effectively Work with Machine Learning. *Proceedings of the 2018 Designing Interactive Systems Conference*, ACM, 585–596.
275. Yu-Chun (Grace) Yen, Steven P. Dow, Elizabeth Gerber, and Brian P. Bailey. 2016. Social Network, Web Forum, or Task Market?: Comparing Different Crowd Genres for Design Feedback Exchange. *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, ACM, 773–784.
276. Kodlee Yin, Cecilia Aragon, Sarah Evans, and Katie Davis. 2017. Where No One Has Gone Before: A Meta-Dataset of the World’s Largest Fanfiction Repository. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, ACM, 6106–6110.

277. Kodlee Yin, Cecilia Aragon, Sarah Evans, and Katie Davis. CHI Note 2017 - Fanfiction Metadata Download. Retrieved from <http://research.fru1t.me>.
278. Ahmed Mohamed Fahmy Yousef and Tamara Sumner. 2021. Reflections on the last decade of MOOC research. *Computer Applications in Engineering Education* 29, 4: 648–665.
279. Alvin Yuan, Kurt Luther, Markus Krause, Sophie Isabel Vennix, Steven P Dow, and Bjorn Hartmann. 2016. Almost an Expert: The Effects of Rubrics and Expertise on Perceived Value of Crowdsourced Design Critiques. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, ACM, 1005–1017.
280. Peng Zhang, Haiyi Zhu, Tun Lu, Hansu Gu, Wenjian Huang, and Ning Gu. 2017. Understanding Relationship Overlapping on Social Network Sites: A Case Study of Weibo and Douban. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW: 1–18.
281. Jing Zhou. 1998. Feedback valence, feedback style, task autonomy, and achievement orientation: Interactive effects on creative performance. *Journal of Applied Psychology* 83, 2: 261–276.
282. Barry J. Zimmerman. 1990. Self-Regulated Learning and Academic Achievement: An Overview. *Educational Psychologist* 25, 1: 3–17.
283. 2023. Human-Centered Data Science Lab. *Human-Centered Data Science Lab*. Retrieved from <https://depts.washington.edu/hdsl/>.
284. Scratch - Imagine, Program, Share. Retrieved February 27, 2023 from <https://scratch.mit.edu/>.
285. AO3 Census: Masterpost. *Tumblr*. Retrieved March 16, 2023 from <https://centrumlumina.tumblr.com/post/63208278796/ao3-census-masterpost>.
286. Tumblr NSFW Content Purge - Fanlore. *Fanlore*. Retrieved March 15, 2023 from [https://fanlore.org/wiki/Tumblr\\_NSWF\\_Content\\_Purge](https://fanlore.org/wiki/Tumblr_NSWF_Content_Purge).
287. Big Bang - Fanlore. *Fanlore*. Retrieved March 15, 2023 from [https://fanlore.org/wiki/Big\\_Bang](https://fanlore.org/wiki/Big_Bang).