Title
Critical Algorithmic Literacy: Explorations of Algorithmic Bias in Elementary School

Author
Moss, Scott H

Publication Date
2023

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Critical Algorithmic Literacy: Explorations of Algorithmic Bias in Elementary School

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Education

by

Scott H. Moss

2023

ABSTRACT OF THE DISSERTATION

Critical Algorithmic Literacy: Explorations of Algorithmic Bias in Elementary School

by

Scott H. Moss

Doctor of Education

University of California, Los Angeles, 2023

Professor Nicole Anne Mancevice, Chair

This case study focuses on the implementation and analysis of critical algorithmic literacy (CAL) lessons in two grade 3/4 combination classes. The study involves one elementary school teacher and 36 students from a K-6 school in Southern California. By analyzing various data sources, I identified trends that could be helpful for future researchers and educators looking to introduce CAL in elementary education.

The data indicate that merging computer science and Kellner and Share's (2019) Critical Media Literacy Framework represents a promising method for teaching contextualized algorithmic literacy models, like CAL, to elementary students. The study examines the importance of clear instructional examples for helping students grasp the concept of algorithms and their societal effects. It also highlights that a student's understanding of bias and basic

computer science concepts can enhance their understanding of algorithmic bias and its societal impacts.

This study also illustrates how lessons designed for older students can be successfully modified for elementary students. It examines both the challenges and potential for the CAL framework's design. Furthermore, it uncovers various obstacles and effective practices for integrating CAL instruction with third and fourth graders. Future research aiming to foster CAL in classrooms should investigate how teachers evaluate student learning and the role of general computer science knowledge in enabling critical examination of algorithmically driven media.

The dissertation of Scott H. Moss is approved.

Douglas M. Kellner

Kristen Lee Rohanna

William A. Sandoval

Jeffrey Share

Nicole Anne Mancevice, Committee Chair

University of California, Los Angeles

2023

DEDICATION PAGE

Dedicated to the ones I love.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to extend my deepest gratitude to Dr. Nicole Mancevice, my esteemed dissertation chair. Through all phases of this dissertation, Dr. Mancevice provided unwavering guidance, offering meticulous feedback and invaluable insights that significantly contributed to the refinement of my writing. Her encouragement proved to be an invaluable source of motivation during the completion of this dissertation.

I am immensely grateful to Dr. Jeff Share, whose steadfast support from the beginning played a pivotal role in my academic journey. Dr. Share not only facilitated valuable connections by including me in meetings with esteemed scholars and practitioners but also afforded me the honor of co-presenting with him at a national educators' conference. Furthermore, it was through Dr. Share's recommendation that I had the privilege of having author and professor emeritus Dr. Douglas Kellner join my committee.

I also wish to express my heartfelt appreciation to Dr. Doug Kellner for his consistent support and encouragement as I endeavored to build upon his groundbreaking and important work. His extensive expertise and guidance have been invaluable, and I am truly honored to have had the opportunity to learn from such a distinguished scholar.

I extend my sincere acknowledgment to Dr. Kristen Rohanna for her significant contributions. In addition to serving on my committee, Dr. Rohanna's artful teaching and valuable advice served me well throughout this journey. My experiences in her qualitative research, continuous improvement, and equity-focused leadership courses will continue to shape my future endeavors toward making a positive impact within the field.

I must express my gratitude to Dr. William Sandoval for his invaluable participation on my dissertation committee and his thought-provoking feedback on my work. His profound insights and challenges expanded my understanding, fostering a deeper level of critical thinking in my research. Dr. Sandoval's contributions have left an indelible mark on this dissertation journey.

I'd also like to express my sincere thanks to Ms. Veronica Sage. As the teacher at the heart of the case study and the co-designer of the curriculum, her knowledge and passion for education were invaluable throughout this process. I am deeply grateful for her collaboration and exceptional teaching talents, which were central to this study.

Lastly, I would like to express my profound appreciation to my beloved wife, Laquita. Her unwavering support, patience, and steadfast belief in my abilities have been an immense source of strength throughout this doctoral journey. Her presence as a sounding board and thought partner has been invaluable, particularly during moments of stress and long writing sessions. I am also grateful for her impeccable proofreading and Microsoft Word formatting skills.

To all those mentioned above and to the countless others who have provided their support and encouragement, I extend my deepest gratitude. This dissertation would not have come to fruition without their invaluable contributions. It is with great appreciation that I acknowledge the role each of them has played in this academic endeavor.

CURRICULUM VITAE

March 23, 1961	Born, Portland, Oregon
1988	B.A., English San Diego State University San Diego, California
1990	Elementary School Teacher San Diego Unified Schools San Diego, California
1994	M.A., Educational Technology San Diego State University San Diego, California
1996	Adjunct Faculty, Educational Technology San Diego State University San Diego, California
1996	Online Instructor UCLA Extension Los Angeles, California
1998	Technology Coordinator Cajon Valley Union School District El Cajon, California
1999	Adjunct Faculty, Educational Technology National University San Diego, California
2008	Middle School Teacher Innovation Middle School San Diego, California
2017	Instructional Technology Outreach Coordinator Los Angeles County Office of Education Los Angeles, California

CHAPTER 1: INTRODUCTION

A.I. is probably the most important thing humanity has ever worked on. I think of it as something more profound than electricity or fire.

Sundar Pichai, Google CEO (2018)

Introduction to the Problem

Algorithmic-driven technologies are transforming our world. Every day, billions of people carry internet-connected computers that leverage the power of supercomputers, fast networks, cloud storage, and artificial intelligence. The major technology platforms use this algorithmic power, storage, and delivery to gain and maintain people's attention for financial gain (Wu, 2018; Zuboff, 2019). Although some public and private efforts exist to mitigate the harmful effects of these technologies, few measures exist to prepare students for the algorithm-driven world in which they live (UNICEF, 2020; Wang et al., 2022).

Digital algorithms comprise an invisible infrastructure that makes consequential decisions governing much of our lives (Trammell & Cullen, 2021). These algorithms influence media consumption, health care, finances, social interactions, and much more (Noble, 2018; O'Neil, 2017). The prevalence of the attention economy (Wu, 2018), artificial intelligence (AI), biased algorithms, surveillance capitalism (Zuboff, 2019), generative AI, and disinformation amplify the need for students to develop critical skills regarding how digital media influence their lives.

Young people spend significant parts of their lives viewing and interacting with algorithmically-driven media. A study by Common Sense Media, for example, found that children between the ages of 8-12 spend an average of five-and-a-half hours online each day (Rideout et al., 2022). YouTube consumes most of that screen time. Moreover, digital platforms such as Google, YouTube, and TikTok systematically monitor, analyze, and monetize children's online activities to serve profit-oriented objectives (Wang et al., 2022; Zuboff, 2019). Despite the impact of algorithmically-driven media on children's lives, most students have little knowledge of how these media are created, disseminated, and interpreted (Kellner & Share, 2017).

Study Description

This study examined the design, challenges, and promising practices for nine 45-minute lessons developed using the critical algorithmic literacy (CAL) framework. One teacher, Ms. Sage (a pseudonym), taught these lessons with two grade 3/4 combination classes from November 2022 to January 2023. I drew on multiple data sources to answer the research questions and determine the findings of this study. Data sources for my research included lesson planning materials, classroom observations, post-lesson debriefs, teacher interviews, student work, and my journal as a researcher and lesson designer.

Because algorithms govern such a wide array of media, we narrowed the focus of this case study to the realm of AI. AI represents a subset of digital algorithms that drive common applications such as entertainment, social media, search, and personal assistants. Narrowing the lessons to AI allowed for more contextually relevant learning experiences because AI drives many technologies that third and fourth-graders engage with daily, such as digital assistants, online games, search, and platforms such as YouTube and Instagram.

This research draws on the CAL framework (Cotter, 2020; Dasgupta & Hill, 2021; Wang et al., 2022). CAL seeks to empower students to evaluate, challenge, and construct algorithmically-driven media. In this study, I frame CAL as a nexus of computer science and critical media literacy (CML) as described by Kellner and Share (2019). CML seeks to develop analytical skills that "…examine the relationships between media and audiences, information, and power" (Kellner & Share 2019, p. 26). As digital algorithms serve as a form of communication technology akin to broadcasting and publishing (Gillespie, 2014), they should be incorporated into all conceptions of media literacy, which also encompasses traditional print literacy. I shall describe CML and CAL in greater detail later in this chapter.

This chapter frames CAL's epistemological underpinnings by defining media literacy and differentiating it from Kellner and Share's (2019) CML Framework. From there, I describe CAL, which I frame as an extension of CML. I then shine a light on the CAL model by defining digital algorithms and introducing the notion of algorithms as "sociotechnical systems" (Seaver, 2107, p. 1). This chapter then provides a brief overview of AI as it applies to the CAL lessons. I subsequently provide a rationale for introducing CAL instruction to elementary school students. From there, I identify gaps in current research addressed by this study. Finally, the chapter concludes with a statement of purpose, the research questions, and the significance of this research.

What is Media Literacy?

The concept of media literacy serves as an umbrella term which encompasses both CML and CAL. Media literacy education seeks to help students to make sense of the various media with which they interact. Commonly defined as the ability to "decode, evaluate, analyze, and produce both print and electronic media" (Aufderheide, 1993, p. 1), media literacy education remains virtually nonexistent within traditional K-12 classrooms (Buckingham, 2019; Hobbs, 2020; Share et al., 2019). At best, schools treat media literacy as an extra, often temporary, addition to K-12 school curricula (Hobbs, 2004; Kist, 2005; Redmond, 2012; Share, Mamikonyan, & Lopez, 2019). Media literacy education occurs even more rarely for students in grades K-6, where it can build foundational skills students will use throughout their lives (Herdzina et al.; 2020; Share, 2015).

Many scholars describe media literacy as an expansion of traditional literacy to "multiliteracies" that include various media such as music, film, video, and the Internet (Buckingham, 2007; Hobbs & Jensen, 2013; New London Group, 1996; Share, 2007). As digital algorithms make decisions on personal and societal levels, they influence how students understand themselves and relate to others. Accordingly, our notion of literacy education should expand to include students' critical consumption of, interactions with, and production of these powerful digital algorithms. The current study places digital algorithms as a medium to be included within this dynamic definition of literacy. Educational organizations such as The National Council of Teachers of English (2022) and the National Council for the Social Studies (2022), for example, have called for an expanded definition of literacy that includes digital media. The CAL framework provides a structure to address student needs by expanding traditional notions of literacy to include digital algorithms (Cotter, 2020; Dasgupta & Hill, 2021; Hautea et al., 2017; Trammell & Cullen, 2021; Wang et al., 2022).

Critical Media Literacy

Kellner and Share's CML Framework extends traditional literacy and media literacy models. CML (Kellner & Share, 2019) emphasizes that media literacy instruction should involve more than understanding and interpreting media messages— it should also challenge these messages. CML seeks to develop analytical skills that "…examine the relationships between media and audiences, information, and power" (Kellner & Share 2019, p. 26). CML endeavors to challenge dominant media representations and analyze power structures communicated through the various media with which we interact. The CML Framework consists of six conceptual understandings and corresponding questions (Table 1). Kellner and Share (2019) stress the importance of recognizing media's constructed nature, ideological interests, and audience influence. When designing the CAL lessons that are the focus of this study, I drew from Kellner and Share's CML as the primary conceptual framework.

Table 1

Critical Media Literacy Framework (Keller & Share, 2019)

1. **Social Constructivism**:	All information is co-constructed by individuals and/or groups of people who make choices within social contexts.
2. **Languages / Semiotics**:	Each medium has its own language with specific grammar and semantics.
3. **Audience / Positionality**:	Individuals and groups understand media messages similarly and/or differently depending on multiple contextual factors.
4. **Politics of Representation**:	Media messages and the medium through which they travel always have a bias and support and/or challenge dominant hierarchies of power, privilege, and pleasure.
5. **Production / Institutions**:	All media texts have a purpose (often commercial or governmental) that is shaped by the creators and/or systems within which they operate
6. **Social & Environmental Justice:**	Media culture is a terrain of struggle that perpetuates or challenges positive and/or negative ideas about people, groups, and issues; it is never neutral.

CML traces its roots to cultural studies and critical pedagogy. It emphasizes equity and social justice issues (Kellner & Share, 2019). Among its influences, critical media literacy has roots in Freire's (1970) ideas of "critical consciousness" as well as the Frankfurt School's description of media as a "culture industry" that shapes public perceptions (Horkheimer & Adorno, 1982). Borrowing from Freire and Macedo (1987), Kellner and Share (2019) describe CML as a "pedagogical approach that deepens literacy skills across all subject areas and empowers students to use multiple forms of media and technology to read and write the word and the world" (p. XVII). In other words, learners should move beyond decontextualized analysis and consider media's social, cultural, and political contexts. Central to its tenets, CML focuses learners on acknowledging that no media are neutral as they reflect the values and ideologies of those in power (Giroux, 1999).

Kellner and Share (2019) see the role of CML as expanding the concept of literacy and reconstructing education in order to prepare students to respond to the increase in media in every aspect of life. They posit that "literacies must constantly be evolving to embrace new technologies and forms of culture and communication, and must be critical, teaching students to become discerning readers, interpreters, and producers of media texts and new types of social communication" (p. 31). As such, this case study not only contributes to that evolving notion of literacy but also serves as a step forward in implementing the broader application of CML for elementary school students in the context of today's technologically-driven world.

Beyond media analysis, CML (Kellner & Share, 2019) seeks to empower students to create alternative media texts that challenge dominant, often hegemonic messages created and distributed by mass media. This production process engages students in questioning dominant narratives and finding their voices to communicate alternative viewpoints and representations. This emphasis on student production comprised a core focus of the CAL-integrated lesson design and the corresponding case study as production enhances students' media analysis skills (Buckingham, 2019; Kellner & Share, 2019; Redmond, 2019). I elaborate on the media production component of CAL later in this chapter.

Critical Algorithmic Literacy Defined

Grounded in CML, CAL seeks to expand education to provide students with skills that students "…can use to understand, interrogate, and critique the algorithmic systems that shape their lives" (Dasgupta & Hill, 2021, p. 1). Beyond students considering the effects of algorithms in authentic contexts, CAL invites students to develop a sense of agency to challenge how algorithms are used to establish and reinforce existing power structures (Trammell & Cullen, 2021). The critical examination of and interactions with these algorithmic effects empower students to assess the complex relationships between their lives and the multitude of media with which they interact. Drawing upon the foundation of CML (Kellner & Share, 2019) and the principles of computer science, CAL strives not only to empower students but to facilitate a shift in their mindset. By encouraging learners to act against inequitable power dynamics (Trammell & Cullen, 2021), CAL plays a pivotal role in transforming their media interactions and experiences.

In our increasingly digital and interconnected world, it is vital to create meaningful and permanent intersections between media literacy and computer science. To do this, I offer an updated definition of CAL building on Kellner & Share's (2019) CML Framework. Framing CAL with the CML Framework provides a valuable lens for addressing the interplay between technology, identity, society, and power. By using the CML Framework, CAL can be better understood as a tool for empowerment and social justice. It allows students to not only understand how algorithms work, but also how they can perpetuate or challenge existing power structures and societal norms. I see this framing as a means to empower students as active participants in their digitally-dominated culture.

Like CML, CAL traces its roots to critical pedagogy and cultural studies. The integration of algorithms into critical pedagogy was promoted by D'Ignazio & Bhargava's (2015) idea of Big Data Literacy. Drawing inspiration from Freire's work on empowering individuals through literacy education, Big Data Literacy emphasizes the need to counter disempowering effects of the large data sets used to store, analyze, and distribute individuals' data for commercial purposes. Also drawing on Freire's literacy education, Tygel and Kirsch (2016) posit that critical thinking and social engagement are well-suited for teaching students how to critically evaluate and use data. They view data literacy not as a technical skill but rather as a tool for social change.

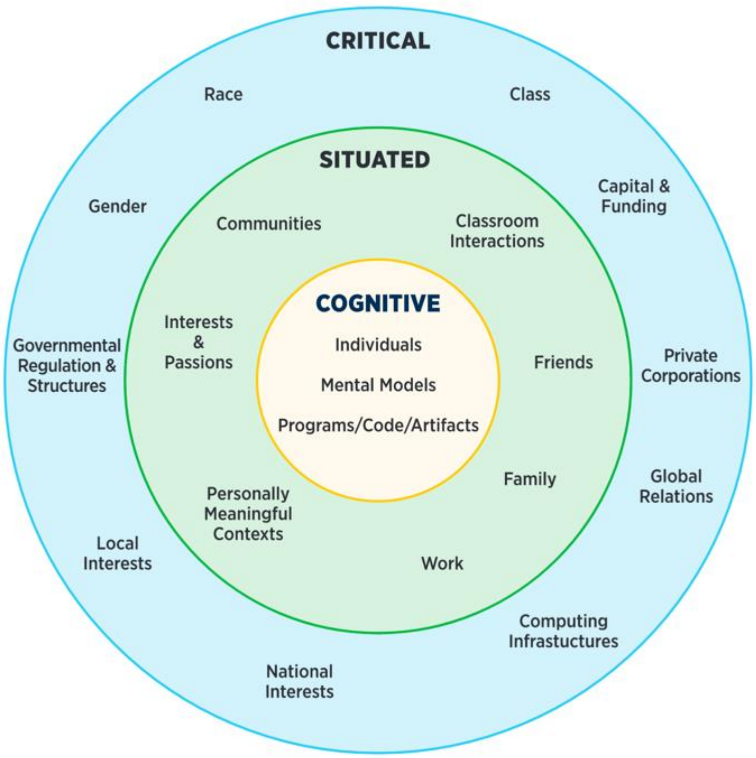
As many digital algorithms amplify power asymmetries in covert yet formidable ways, CAL reveals the nonneutral nature of algorithmically-driven media created by people for specific purposes in sociocultural contexts (Dasgupta & Hill, 2021; Hautea et al., 2017). Aguilera and Pandya (2021) argue that models such as CAL inform instructional practice "by rendering visible increasingly taken-for-granted issues of power, discourse, and ideology inherent in seemingly neutral computational technologies" (p. 106). CAL lessons implemented for this case study, for example, involved activities such as analyzing, questioning, and challenging Google Image results. In this way, students engage with "issues of power, discourse, and ideology" related to algorithmic outputs. CAL seeks to address fundamental questions about who or what has the power to determine what students see and can interact with, as well as the implications of that power.

For this study, I frame CAL as a nexus of CML and computer science. Currently, however, students learn computer science concepts almost exclusively within computer science-specific courses (Ciccone, 2021). Although extremely valuable, computer science courses rarely include examining the sociocultural effects of digital algorithms (Gebre, 2022; Ridley & Pawlick-Potts, 2021).

In an effort to expand the conversations about computer science education, Kafai and her colleagues (2020) differentiate between cognitive, situated, and critical perspectives in computer science education (Figure 1). The cognitive framing emphasizes computational concepts and programming practices intended to be helpful in college and future careers (Kafai et al., 2020). The vast majority of computer science courses emphasize cognitive framing (Gebre, 2022; Kafai et al., 2020). Technical knowledge alone, however, seldom provides information to predict the sociocultural impact of algorithmic outcomes (Kroll, 2018). The situated framing of computer science education emphasizes students' creative expression. Learners actively create and share digital applications with real audiences. The critical framing of computer science highlights the values and practices of computer science as it applies to social justice and critical pedagogy. This approach views computational thinking as a potential tool for grappling with political, moral, and ethical challenges. Kafai and her colleagues (2020) emphasize that the cognitive, situated, and critical perspectives are not mutually exclusive but inform each other to provide an epistemological framework for dialogue.

Figure 1

Framings of Computational Thinking (Kafai, et al., 2020)



The present study emphasizes the critical frame as it aligns with the contextual perspectives of CML. The critical frame "places students' computational thinking in the traditions of critical pedagogy, which emphasize both an examination of and resistance to oppressive power structures and production-oriented media literacy" (Kafai et al., 2020, p. 47). Emphasizing the critical perspective, CAL goes beyond the objective analysis of algorithms. CAL encourages students to explore the contexts and consequences of data-driven media platforms (Ching, 2012).

The analysis of algorithm-driven outputs requires some knowledge of computer science principles. Including technical computer science skills was integral to the CAL lesson design. For the CAL lessons, students engaged in fewer computer science specific activities than they would in more common computer science classes or activities that emphasize the cognitive frame. An area of inquiry for CAL is to what extent technical understanding of computer science (cognitive frame) supports students' capabilities to critically assess, question, and analyze the societal consequences of algorithms.

Algorithms Defined

Because computer science principles are integral to analyzing algorithm-driven outputs, it is important to place the word "algorithmic" in the context of CAL and this research. The word "algorithm" has many possible meanings and interpretations. Although the term algorithm, in the broadest sense, refers to "…instructions for solving a problem or completing a task" (Rainie & Anderson, 2017, p. 2), this study operationalizes the more current application of the word to refer to the increasingly powerful computer programs that autonomously make decisions based on data (Gillespie, 2014; Willson, 2017). Beyond purely technical definitions of computer algorithms, many further the term algorithm to include their sociocultural uses and effects (Gillespie, 2014). For example, Benjamin (2019), Noble (2018), and O'Neil (2017) describe algorithms as mechanisms that embed culturally-dominant ideologies. Seaver (2017) envisions digital algorithms "…as heterogeneous and diffuse sociotechnical systems, rather than rigidly constrained and procedural formulas" (p. 1).

O'Neil (2017) describes the nonneutral nature of algorithms by portraying digital algorithms as "opinions embedded in mathematics" (Kindle location 405). Despite their commercial purposes, recommendation engines such as Google, have become such a normative part of our interactions with technology that most people perceive their outputs are credible, accurate, depoliticized, and neutral (Noble, 2018). Nobel and many others emphasize the need for understanding and analyzing the nonneutral nature of algorithms in a broader sociocultural context. Aligning with the sixth conceptual understanding of CML, CAL activities strive to consider the producers' intentions and algorithmic biases in algorithmically driven media. The overarching goal of CAL is to provide students with the skills to examine the creators' intentions, biases, and purposes, as well as the collective effects embedded in these algorithms.

Artificial Intelligence

To support our goal of helping students understand algorithmic bias and its effects. I narrowed the focus of algorithms in general to AI. Even among experts, defining AI presents a challenge (Long & Magerko, 2020) as it represents a broad and evolving term (Register & Ko, 2020). Generally speaking, AI represents increasingly ubiquitous and complex algorithms that augment and often replace human decision-making (O'Neil & Gunn, 2020). For this research, I refer to AI's most common manifestation, supervised machine learning (Shane, 2019). Broadly speaking, this form of AI uses trial-and-error methods of deciphering large data sets to invent rules that help achieve specific outcomes (Shane 2019). As an example of this form of AI, imagine if one wanted to create a computer program that differentiated between cats and dogs. One could create a searchable database that lists the traits of each animal. Alternatively, AI would incorporate many examples of cats and dogs and "learn" their differences (Lane, 2021).

Conventional computer algorithms and AI are both fundamental components of computer science, but they interact and function in distinct ways. Conventional computer algorithms operate based on predetermined rules to solve problems or perform tasks. Given the same input, a conventional algorithm will always produce the same output (Taulli, 2019). AI, on the other hand, utilizes algorithms to create systems that can "learn" and make decisions or predictions based on data. AI algorithms, especially in the realm of machine learning, adjust themselves by interacting with data, deriving patterns, and continuously improving their understanding (Shane, 2019). This iterative learning process allows AI to handle complex tasks that involve uncertainty or variability. Although AI relies heavily on advanced algorithms, it represents a leap beyond traditional algorithmic processing, providing computers with the ability to perform tasks that normally require human intelligence such as interpreting natural language, recognizing patterns in data, or making predictions about future events (Shane, 2019).

AI systems make predictions, recommendations, and decisions that influence many aspects of students' lives (Yeung, 2020). AI recommends music, videos, friends, and products to children (UNICEF, 2020). The major technology platforms such as TikTok and YouTube deploy these powerful AI systems to exert this influence without fully considering the possible consequences to those affected (O'Neil & Gunn, 2020). Moreover, because AI content changes based on user interaction, many scholars emphasize the algorithmic effects caused by the interaction between users and AI algorithms (Bucher, 2018; Gillespie, 2014; Seaver, 2017; Zarouali et al., 2021). Examining the effects between AI-driven platforms and users adds another layer within the CAL that aligns with the CML Framework that calls for students to explore their roles in negotiating and contributing to meaning-making (Kellner & Share, 2019). As AI-driven media dominates students' lives through YouTube and other platforms, it is important to place artificial intelligence within the CAL framework. It is also necessary to note that this case study does not address generative AI. Tools such as ChatGPT were released after I finalized the design of this research.

Narrowing of the Problem

The Need for CAL

Each day, algorithmically-driven content takes a larger role in our lives. Because AI systems make decisions rooted in historical data, they may perpetuate and magnify existing inequities. Many examples exist of algorithms perpetuating negative stereotypes and societal injustices (Gran et al., 2021; Kantayya & Buolamwini, 2021; Noble, 2018; O'Neil, 2016). In one case of algorithmic bias, Amazon found that its AI-driven resume screening program negatively discriminated against women (Dastin, 2018). Benjamin (2019) and Noble (2018) also point out that Google Image searches for “Asian teenagers” or “Black teenagers,” for example, return images that reinforces sexualized and harmful stereotypes. In yet another example of AI reinforcing and perpetuating existing societal inequities, a facial recognition AI has been shown to be less effective in identifying images of with darker skin, especially women (Buolamwini & Gebru, 2018). These flaws in the AI sometimes lead to false arrests and incarcerations due to mistaken identity (Buolamwini & Gebru, 2018; Noble, 2018).

In addition to identifying and challenging algorithmically-driven biases, the critical perspective implicit in CAL becomes more vital for young students as their media environments expand and change exponentially. Since the 1950s, for-profit corporations have created a “cultural pedagogy” that influences students’ experience more than school, peers, parents, or even themselves (Steinberg and Kincheloe, 2004, p. 17). Consider the influences, for example, of Disney princesses, professional sports, and now social media “influencers” on the lives of many children. In addition, algorithmic-driven technologies such as YouTube and TikTok now personalize, expand, and intensify children’s immersion in this consumer-driven environment, that is, “…working twenty-four hours a day to colonize all dimensions of lived experience”

(Steinberg & Kincheloe, 2004, p. 131). This reality underscores the urgency of CAL in education. CAL empowers students with the tools to critically navigate, understand, and influence this pervasive, algorithmic-driven media landscape.

Currently, the attention economy drives digital surveillance, and algorithm-driven preference bubbles combine to create a profit-driven environment (Pariser, 2011) where many children spend much of their time and attention (Zuboff, 2019). Students require critical analysis skills as commercial entities seek to commodify all aspects of children's lives (Giroux, 2011). The enormous financial, cultural, and computational influence of these systems highlights the need for heightened awareness and individual empowerment in a world driven by algorithms.

CAL helps students counter the immense power wielded by the major technology platforms such as Google, TikTok, and Facebook. To keep us all captivated by these persuasive technologies, technology companies, in part, employ many of the same psychologically exploitive techniques used by designers of slot machines (Dow-Schüll, 2014). The success of slot machines, for example, is measured by "time on device." To increase time on device, many digital platforms combine persuasive psychology, variable rewards, and powerful reinforcers to connect rewards to the human need for approval. These elements combine to form a "personalized reward machinery" (Schüll, 2012, p. 71).

Because of the pervasive influence of algorithms, a power imbalance emerges between those trained in computer science and those who are not (Ciccone, 2021). While all students do not take computer science courses, all students would be well served to learn about algorithms in relevant contexts (Dasgupta & Hill, 2021; Hautea et al., 2017). Most students, after all, do not require programming skills to interact with algorithmic-driven media (Long & Magerko, 2020; Resnick & Silverman, 2005). Viewed from Kafai et al.'s (2020) framings of computer science, students benefit from a meaningful blend of the cognitive and critical frames of computer science knowledge. The CAL-integrated lessons in this study focused on a well-considered balance of the cognitive and critical frames to support a CML model that encompasses digital algorithms.

Production

Effective media literacy education, in general, includes both analysis of existing media as well as the thoughtful creation of media (Buckingham, 2007; Hobbs, 2019; Share, 2015). The cyclical process between production and analysis allows students to reflect on their creative work using their media analysis skills and then apply them to create new media products (De Abreu et al., 2017). A creator's perspective allows students to experience "…the clear connection between creative practice and criticality that exists in media education" (Connolly & Readman, 2017, p. 251). The enhanced creator's perspective empowers students as change agents. Student agency through authentic media production empowers "students to shape the world they live in and to help to turn it into the world they imagine" (Morrell, 2013, p. 302). By engaging in creative practices, students not only gain a deeper understanding of media but are enabled to critically engage with and influence the algorithmic structures that increasingly mediate our digital world.

Media production within media literacy education also provides students with the creators' perspectives needed to analyze media more effectively, such as considering purpose, audience, and embedded values (Buckingham, 2007; Dezuanni, 2015; Hobbs, 2019). Further, "If we ask the children to critique the world but then fail to encourage them to act, our classrooms can degenerate into factories of cynicism" (Bigelow et al., 1994). Student media production instills a sense of agency, inspiring them to apply their knowledge and insights to effect meaningful change.

Like other forms of media literacy education, CAL student production incorporates student agency through personally-relevant learning applied to real-world contexts (Lee et al., 2022). Relevant learning occurs when “the world around [students] can and should be used as text to build a curriculum that has significance in learners’ lives and that is developmentally sensible” (Vasquez, 2014, p. 6). CAL lessons designed for this case study, therefore, included opportunities for students to select and interact with media for analysis and as an impetus to authentic media production.

Moreover, authentic media production should incorporate Freire’s (1972) concept of “problem-posing education,” enabling students to develop their critical perception of their existence within the world they inhabit (p. 252). Like other critical pedagogies, CAL aims to empower all students, with particular emphasis on underrepresented groups and the economically disadvantaged. DiPaola and her colleagues (2020) emphasize that a CAL approach centers on stakeholders most vulnerable to harm during the design process. This focus on critical algorithmic literacy allows students to perceive the products they create as sociotechnical systems influencing their lives and those of others. Prior media literacy studies have examined student projects ranging from crayon drawings to media-rich productions (Redmond, 2019). However, there have been no studies that examine elementary school student projects that heighten their critical awareness of digital algorithms.

Student media production in and of itself, however, does not lead to enhanced media literacy skills. Educators throughout K-12 most often teach media production and media literacy separately (Buckingham, 2009; Redmond, 2019; Share, 2015). Students in media production classes, for example, rarely analyze media (Kellner & Share, 2019). Conversely, less than one-third of media literacy teachers focus on media production (Culver & Redmond, 2019). Students’ media production within media literacy education provides a more effective method for achieving its goals than focusing only on media analysis (Banerjee & Kubey, 2013).

From a critical media literacy perspective, Funk, Kellner, and Share (2016) argue that media production helps learners examine dominant ideologies and representations of those ideologies. Moreover, Redmond (2021) maintains that media literacy education without student media production tends to perpetuate the perspectives of the dominant cultures. To counter these dominant narratives, a typical CML activity engages learners in analyzing hegemonic representations of race, class, and gender and creating “counter-narratives” that challenge these portrayals from the learners’ perspectives (Share et al., 2019). Critical algorithmic literacy helps students see digital technologies’ potential to help them make a difference in their own life and the lives of others (Lee & Garcia, 2014). Despite this potential, many challenges exist in addressing CML tenets to CAL.

Challenges to Algorithmic Literacy

The nature of algorithms and AI increase the challenges to their critical examination. Effective CAL involves differentiating algorithms and AI from text, video, and other media to examine algorithms in the panoply of existing media. For example, algorithms remain mostly invisible to users, so their opacity requires inferring their effects. In addition, major digital platforms such as Google incorporate user data to personalize experiences, enhancing the platform’s persuasive powers and epistemic authority. These factors combine to contribute to digital platforms’ asymmetry of power that most people fail to perceive.

There exists a tremendous yet covert power imbalance between digital media platforms and their users. Former Google Design Ethicist Tristan Harris (2017) claims a “…handful of people working at a handful of technology companies … will steer what a billion people are thinking today.” Moreover, young people engage with these technologies at increasingly earlier ages (Rideout & Robb, 2020). This extreme asymmetry also exists in the relative privacy rights of companies and users. The technology platforms possess troves of data about their users, yet the users know comparatively little about the companies (Zuboff, 2019). Rushkoff (in Hobbs, 2019) notes, “[YouTube's] algorithms are watching us much more intently than we’re watching the videos” (p. vii). Pasquale (2015) describes the societal implications of this asymmetry: “To scrutinize others while avoiding scrutiny oneself is one of the most important forms of power” (p. 3). CAL seeks to address the power imbalance between digital platforms and K-12 students. Here again, CML’s focus on creators’ intentions and methods helps students to analyze major technology platforms’ perceived credibility without accountability.

The opacity of algorithms presents yet another challenge to examining their effects. Unlike other media, we do not observe the algorithms themselves but only their outputs. Many efforts exist to regulate these large platforms to increase algorithmic transparency. However, as Burrell (2016) and Pasquale (2009) point out, even if companies publicly shared their algorithms, it is unlikely that laypersons would understand these algorithms’ purposes, effects, and biases. In addition, even those who create algorithms lack a complete understanding of the algorithmic effects of their work (Rainie & Anderson, 2017). Finally, increased algorithmic transparency would not alter the asymmetry between these large technology companies and their users because the algorithms are dynamic, created by multiple programmers, and extremely complex (Burrell, 2016). Companies concealing their algorithms to protect their intellectual property amplifies the need for students to infer their effects.

In addition to algorithmic opacity, algorithmic epistemic authority complicates examining their individual and societal effects as the algorithms determine what can be known about them

(Cotter, 2020; Gillespie, 2014). The technology platforms arbitrate “truths” to which the users can see. Moreover, because digital algorithms control much of the information students are exposed to, they function as gatekeepers, essentially arbitrating what is important and true (Gillespie & Boczkowski, 2014). These scholars go as far to assert, “That we are now turning to algorithms to identify what we need to know is as momentous as having relied on credentialed experts, the scientific method, common sense, or the word of God” (Gillespie & Boczkowski, 2014, p. 2). Whether or not one considers algorithm-driven information as “momentous” as the word of God, our media-immersed environment requires specific skills involving critical analysis and production of algorithm-driven environments (Valtonen, 2019). Ito and her colleagues (2021) describe the social and moral imperative that students examine how algorithms are “shaped by and reflect historical inequities, problematic assumptions, and institutionalized power” (p. 3). CML informs CAL’s focus on considering the sources of media content, their purposes, and possible bias in algorithmically-driven systems.

Further complicating student analysis of algorithmically-driven systems, perceptions of algorithmic objectivity amplify the epistemic authority of algorithms. The belief in the impartiality of algorithms disguises the human subjectivity involved in their creation, application, and distribution (Gillespie, 2014; Noble, 2018). Gillespie (2014) refers to the perception of algorithmic objectivity as “… a carefully crafted fiction” (p. 13). The anthropomorphizing and personalization of intelligent agents such as Alexa and Siri require a “new sociotechnical understanding” of AI-driven tools (Choung et al., 2022, p. 3). Here, CML promotes this sociotechnical understanding by questioning nonneutral media to empower students to examine the relationships between media, their purpose(s), and context (Kellner & Share, 2019). As Noble (2018) and others point out, digital algorithms hide potential biases and harms behind a façade of objectivity and mathematical precision. Building on CML, CAL empowers students to look behind the façade by questioning what seems normal or natural in the algorithmically-driven media environment.

Despite the asymmetry, opacity, and subjectivity of digital algorithms, research suggests that most people, especially children, possess a high level of trust in AI and algorithms (Choung et al., 2022). Noble (2018) describes people's trust in search engines, for example, as "an object of faith" (p. 25). Many students assume intelligent agents think like humans and perceive them as credible and friendly (Long & Magerko, 2020). Students' trust in the effects of algorithms, moreover, minimizes the healthy skepticism that promotes critical inquiry (Gillespie, 2014; Hobbs, 2020). For example, most people consider Google's search results accurate, objective, and neutral. Therefore, most users don't search past the first result when using Google Search (DiPaola et al., 2020).

Although there are legislative (e.g., Algorithmic Justice and Online Platform Transparency Act, 2021) and private (Harris & Raskin, 2022; Neff, 2022) efforts to minimize the effects of potentially harmful algorithms on children, relatively few of those efforts focus on public education as a way of addressing the dominating influences of these digital algorithms. In part, the major digital platforms such as YouTube, Facebook, and Google dominate young people's lives by using detailed knowledge of them gathered from various sources (Alter, 2017; Eyal, 2019; McNamee, 2019). This personal information provides data that inform the addictive properties of these platforms. (Alter, 2017; Eyal, 2019; Lanier, 2018). In addition, the business models of companies such as Facebook, Netflix, and YouTube involve gaining and keeping attention by exploiting cognitive biases and other innate attributes (Alter, 2017). Yet, despite the role played in children's lives, very few efforts exist to help students make sense of these persuasive technologies**.**

There exist many challenges to CAL implementation. First, teachers often lack computer science knowledge to engage in CAL (Aleman et al., 2021). Further, school districts do not promote the study of algorithms beyond the objective explorations within computer science courses (Ciccone, 2021). In addition, teachers' fears of attracting backlash from parents, school administrators, or community members discourage some from pursuing any content perceived as political (Ciccone, 2021). CAL implementation may require educators to engage in challenging conversations around the impact of systems at the personal and community level. Finally, the many variations of media literacy education pose a challenge to teachers to pursue it as a new endeavor (Hobbs, 2022).

Multiple studies outline the obstacles students encounter when learning about computer science and AI. These perceptions can influence who pursues these mostly optional learning opportunities. Some high school students avoid computer science because of its perceived demands, especially math skills (Long & Magerko, 2019). By working with algorithms in authentic contexts, students can see relevant connections to their lives and the lives of others. Regarding a critical view of computer science, little exposure reaps positive effects (Resnick & Silverman, 2005). Media literacy education should now include some computational thinking (Valtonen et al., 2019). Recent case studies illustrate that relatively simple programming activities empower students to "uncover structures and assumptions in algorithmic systems" (Dasgupta & Hill, 2021, p. 20). It is here where CAL content provides students with content within context to maximize learning.

Gaps in the Research

Few scholarly studies exist documenting media literacy efforts for elementary school students (Hobbs, 2017; Kellner & Share, 2019; Rogow, 2021). Moreover, the United States government provides minimal effort and funding for media literacy education research (Lipkin, Culver, & Redmond, 2020). Most current media literacy research examines high school and post-secondary students (Share, 2015). As rare as investigations are for media literacy education, scholarly examinations of CML and CAL practices are even rarer. Wang et al. (2022) find that most educational research about children in the digital domain pertains to online safety and privacy issues. They argue for further investigation into critical algorithmic literacy that supports student agency and enhances student critical thinking skills regarding online content.

While a few studies of what could be described as CAL implementations exist (Breazeal and Payne, 2019; DiPaola et al., 2020; CCUNESCO, 2020; and Dasgupta & Hill, 2021), none have explored CAL implementation within the regularly scheduled school day. Some case studies of critical algorithmic literacy implementations have been conducted with high school and university-age students, but overall, research remains scarce. Chapter Two of this proposal describes some of these CAL implementations. These promising efforts informed this study of CAL implementations with third and fourth-grade students.

Statement of Purpose

The purposes of this study were threefold: 1) to examine the design process of critical algorithmic literacy instructional practices, 2) to describe challenges in the implementation of CAL lessons, and 3) to describe promising practices in the implementation of CAL lessons. This dissertation draws on the CML Framework (Kellner & Share, 2019) for introducing CAL instruction with third and fourth-grade students.

Just as books, videos, and music are media within the realm of multiliteracies (New London Group, 1996), my research places digital algorithms as a medium to include within the expanding definition of literacy. This case study examines the design, promising practices, and challenges in implementing nine lessons integrating the CAL framework with third and fourth-grade students. This dissertation draws on Kellner and Share's (2019) CML Framework for introducing critical algorithmic literacy instruction consisting of two groups of third and fourth-graders led by the same instructor. My inquiry seeks to contribute to the growing body of knowledge in various areas, including critical media literacy, algorithmic awareness, computer science education, and other disciplines that seek to incorporate some aspects of CAL.

Research Questions

This case study explored the following research questions:

1. How do a researcher and teacher design critical algorithmic literacy curricula for third and fourth graders for lessons conducted during the school day?
2. What are the challenges for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?
3. What are promising practices for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?

Study Significance

This study's significance stems from its contribution to the CAL framework that students "…can use to understand, interrogate, and critique the algorithmic systems that shape their lives" (Dasgupta and Hill, 2021, p. 1). Bridging the gap between CML and computer science, CAL bolsters the argument for the inclusion of digital algorithms within the concept of multiliteracies (New London Group, 1996). The present research extends the CML Framework by focusing on

CAL's capability to help elementary school students to analyze, question, and challenge these persuasive technologies that affect students' "…attitudes, beliefs, and behavior without their awareness" (Hobbs, 2020, p. 528). Currently, students' engagement with algorithms and computer science primarily happens in secondary classrooms, with an emphasis on technical aspects of analysis while often neglecting their sociocultural impacts (Ciccone, 2021; Gebre, 2021).

This study endeavored to extend the notion of literacy in K-12 education to encompass CAL as a traditional literacy component, given the profound effect of students' interactions with digital algorithms (Dignum et al., 2020; Valtonen, 2019). The findings examined the design process, promising practices, and challenges for teachers implementing CAL in elementary school—skills especially needed for children growing up in an age dominated by algorithmically-driven media.

Furthermore, enhanced algorithmic and media literacy skills not only improve students' critical thinking in real-world contexts but also promote an understanding of existing power structures (Wang et al., 2022). This research examined CAL lesson design, promising practices, and challenges in CAL instruction at the elementary level. The societal and personal implications of enhancing media literacy at this stage are substantial, establishing a foundation for children's media literacy throughout their lives.

CHAPTER 2: LITERATURE REVIEW

Instead of learning about our technology, we opt for a world in which our technology learns about us.

Douglas Rushkoff (2019)

This literature review provides a rationale and support for the use and study of critical algorithmic literacy (CAL) for elementary-school-age children. CAL represents a new area in K-12 education. This literature review begins by reviewing empirical research demonstrating the need for more general forms of algorithmic literacy, including low algorithmic awareness and unwarranted trust in algorithmic-driven media. Next, I explore emergent efforts to implement CAL education in various contexts. This literature review then highlights gaps addressed by the present research. Finally, I conclude this chapter by positioning the present study within a conceptual framework that combines the benefits of Kellner and Share's (2019) Critical Media Literacy (CML) Framework with basic computer science principles.

Need for Algorithmic Literacy

Low Algorithmic Literacy

As digital algorithms dominate the world's personal, economic, cultural, and social spheres, critical algorithmic literacy empowers students with the skills to question algorithmic representations of reality, thereby increasing their independence from the normative influences of dominant groups. These critical skills become more vital as students become immersed in digital technologies. In a pre-pandemic survey conducted by the Pew Research Center, 95% of teens reported having access to a smartphone, and 45% of those teens self-reported that they are "almost constantly" online (Rideout & Robb, 2020). Parents (Livingstone & Blum-Ross, 2021), psychologists (Twenge et al., 2020), and organizations such as the American Academy of

Pediatrics (2016) have expressed concerns about the effects of digital algorithms, particularly AI, that drive much of youths' interactions with technology.

With the increased focus on digital algorithms and AI, many terms and models have emerged that describe people's relationships with algorithms. The phrase "algorithmic awareness," for example, has been defined in various ways. Much of the variation centers on learning how algorithms work as opposed to their effects within specific contexts (DeVito, 2021; Dogruel et al., 2021; Zarouali et al., 2021). In the computer science realm, algorithmic awareness refers to discrete skills concentrated on computer programs' mathematical and computational aspects (Futsheck, 2006). The computer science-focused model, however, often ignores the sociocultural implications of the effects of algorithmically-driven content (Ridley & Pawlick-Potts, 2021).

An expanded view of literacy that includes algorithmic literacy should represent a priority in K-12 education. Low algorithmic awareness makes one more susceptible to data-driven manipulation, more likely to spread misinformation, and more accepting of stereotypes (Mohamed, 2020; Pariser, 2019). Because of the increasingly complex and changing nature of digital technologies, studies of the algorithmic awareness of adults are rare (Hargittai et al., 2020; Wang et al., 2022). For K-12 students, such research is virtually nonexistent (Wang et al., 2022). Moreover, most algorithmic awareness research has been limited to specific platforms such as Facebook, Google Search, and YouTube (Cotter & Reisdorf, 2020).

Multiple studies suggest that adults and children have low algorithmic awareness. In their research of more than 2,000 adults, for example, Zarouali and his colleagues (2021) found that many adults hold misconceptions about online algorithms. Surveying a representative sample of the Dutch population, the researchers found that misconceptions occurred more often with the less educated, lower socioeconomic status, and women. Cotter and Reisdorf (2020) found that socioeconomic factors similarly correlated with algorithmic awareness. Gran, Booth, and Bucher (2021) conducted an algorithmic awareness study with a nationally representative sample of more than 1,600 Norwegian adults. Their research found that 62% of the respondents perceive that they have little or no awareness of algorithms. The survey results also strongly correlate respondents' education level with algorithmic awareness. While studies of 1,600 Norwegian and 1,200 American adults may or may not generalize to K-12 students, there has been little research into the algorithmic awareness of school-age children.

In one notable exception, research by Wang and her colleagues (2022) found that 7-13-year-olds lacked opportunities to enhance their algorithmic awareness. These researchers interviewed 48 British school-aged children regarding their inferences about YouTube algorithms. While most of the children understood that YouTube collects their personal data, most believed that YouTube limited its data collection to prior videos viewed solely for the purpose of recommending videos. The interviews, however, identified gaps in students' perception of how their personal data are collected, which data are collected, and how that data are analyzed and monetized. Because the students lacked knowledge of the individual and sociocultural impacts of their technology use in real-world contexts, the authors advocate for increased critical algorithmic literacy so students "…engage in a critique of algorithmic systems reflexively" (p. 16). Long & Magerko (2020) suggest that educators can improve students' algorithmic awareness if students interact with and create algorithms in authentic contexts.

In Algorithms We Trust

Compounding the challenges of low algorithmic awareness, much research suggests that children and adults possess a high level of trust in algorithms. In their study of 3-10-year-olds, Druga et al. (2017) found that children tend to personify intelligent agents (such as Siri and Alexa) more than adults. Children in this study perceived these AI-driven technologies as “friendly,” trustworthy,” and “smarter” than themselves (p. 597). These technologies’ conversational abilities and other anthropomorphic features require a new level of critical awareness addressed within the CAL lessons. The rapidly evolving generative AI models further amplify this need.

Framed from a CML perspective, CAL entails analyzing various media’s credibility based on various information. In a study of over 7,800 students, however, the Stanford History Education Group (2016) described middle school, high school, and college students’ capacity to evaluate online information as “bleak” (Wineburg et al., 2020, p. 4). More specifically, many students could not distinguish between news stories and advertisements. In one example, more than 80% of middle school students misidentified an advertisement as a news story, despite the words “sponsored content” written within the ad. Considering information sources as part of the interpretation of any medium comprises an essential facet of critical pedagogies in general and CAL in particular.

AI-driven media make the evaluation of credibility even more challenging. In a widely cited study, researchers at MIT examined over 126,000 tweets and concluded that false news stories spread six times more readily than true stories (Vosoughi et al., 2018). The researchers surmised that the truth does not constrain false news, and incorrect information also includes the appeal of novelty. In sum, low algorithmic awareness, trust in opaque algorithms, and poor evaluative skills reflected in these studies highlight the need for increased algorithmic awareness in K-12 education.

CAL Implementations

As an emergent model, CAL implementations remain scarce. Although the following research informed the present case study, none of these implementations occurred within the traditional school day. Further, none of these researchers implemented efforts with students younger than fifth grade. The present research examined the implementation of CAL lessons into the regular school day for third and fourth-grade students. Although implementation efforts described below occurred in after-school and summer programs, these studies illustrate the potential benefits of CAL implementation with school-aged children during the school day.

Algorithmic Literacy Terminology

It remains important to discuss the diversity of terminologies describing recent models aimed at boosting student awareness of algorithms and their sociocultural impacts. Several concepts, including Big Data Literacy (D'Ignazio & Bhargava, 2015), Critical Computational Literacy (Lee & Soep, 2016), Critical Data Literacy (Hautea et al., 2017), Critical Machine Learning (Irgens et al., 2020), and Critical Computational Expression (Lee et al, 2022), each carry unique connotations but share a common objective. They seek to support learners' understanding of algorithms and their societal effects. The present study adopted and adapted the concept CAL, as defined by Cotter (2020), Dasgupta & Hill (2020), Aleman (2021), and Wang et al. (2022). This term best aligns with my aim of integrating computer science with the CML Framework (Kellner & Share, 2019) for third and fourth-grade students.

In recent years, several researchers have studied classroom implementations of what might be described as CAL. In one notable example of CAL implementation and research, Hautea et al. (2017) worked with 6-12 graders who interacted with simple algorithmic systems that led to meaningful questions and discussions regarding algorithms in relevant sociocultural contexts. Students interacted with and created computer programs to learn algorithms' limitations, assumptions, and biases. This experiential exploration included students' questioning and discussing data collection, using that data within digital algorithms, and their commensurate effects. The CAL lessons sought to create similar student learning outcomes.

More than 700 11-15 -year-old students in Hautea et al.'s (2017) case study used the visual computer programming tool Scratch. For this study, the researchers created additional programming functionalities known as Scratch Community Blocks. These computer coding/programming tools allowed students to access other Scratch users' data such as country of origin, number of followers, number of projects created, project views, and "love-its" received on their Scratch projects. Researchers conducted ethnographic observations of more than 700 users of the Scratch Community Blocks, examining over 1,600 student projects, their shared comments, and a special discussion forum created for the Community Block users.

The researchers found that these students' ability to access, analyze, and use others' data heightened their awareness of data privacy, data bias, and the real-world effects of these technologies (Hautea et al., 2017). For example, students described how they could create computer programs to shape others' behaviors. One student, for instance, expressed her concern about computer program creators using users' personal data to personalize content to increase engagement. These student statements reflect their awareness of the relationships between the author's purpose, the algorithm itself, and its effects on others.

The student projects in this case study also helped students develop insight into the subjectivity of algorithms. Some students used their collected data to create programs that ranked others' projects. For their project-ranking program, students created algorithms incorporating mathematical formulas based on their value judgments. Students later reflected that they based these algorithmic conclusions on their own perspectives as well as the data to which they had access. In this way, students internalized O'Neil's (2017) assertion that algorithms are "opinions embedded in mathematics" (Kindle location 405). Student insights from Hautea et al.'s (2017) case study inspired CAL activities reflected in the CAL lessons in my study. My inquiry builds on Hautea and her colleagues' study by describing CAL instruction during the school day with elementary school students.

Hautea, Dasgupta, and Hill's (2017) case study, perhaps, more than others, provided the initial inspiration and model for this case study. As in other forms of critical pedagogies such as CML, student media production provides students with insights into the nonneutral nature of algorithms and how those algorithms carry their creators' values and motivations. Although this single case study engaged students in critical analysis and production, further research is needed to determine to what extent these critical perspectives transfer to elementary student interactions with algorithms on other platforms and in different contexts. The lessons in the present research similarly sought to engage students to question relationships between algorithms and people affected by them.

Following up on this case study and other related research, Dasgupta and Hill (2021) described four design principles that support student attainment of critical algorithmic literacies: (a) Enable connections to data, (b) Create sandboxes for dangerous ideas, (c) Adopt community-centered approaches, and (d) Support thick authenticity (p. 2). These four design principles provided an overarching framework for the CAL lesson design in my case study. The authors describe the connection between the design principles and the core tenets of CAL:

> In our work, we see a similar phenomenon emerge where simple programming constructs, combined with data in straightforward ways, enable children to uncover structures and assumptions in algorithmic systems. This process allows children to raise

> questions and engage in conversations about algorithmic data collection (Dasgupta & Hill, 2021, p. 6).

Dasgupta and Hill's (2021) design principles align with CML's goals of empowering students to engage with the media they consume and create. Resnick and Silverman (2005) claim that "a little bit of programming goes a long way" (p. 119). The interactions with computer science principles provide a creator's perspective on the algorithmically-driven media with which they are immersed daily.

A case study by Irene Lee et al. (2021) involved middle school students focused on the implications of interactions with various AI-driven algorithms. Their research describes a summer workshop "designed to prepare middle school students to become informed citizens and critical consumers of AI …" (p. 1). As this study focused on the sociocultural implications of algorithms, I examine this workshop's focus on algorithmic bias. Much of the workshop involved students interacting with real-world problems affected by digital algorithms. Students, for example, engaged in "training" or providing raw data for AI systems such as the Google Teachable Machine.

The researchers point out that activities such as these "...help students build mental models of mechanisms and algorithms in action during machine learning and expose how bias can be embedded in AI systems" (p. 2). Training these AI-driven algorithms led to student discussions where they connected the activity and biases they encountered in their everyday interactions with algorithms. The researchers reported that students in the summer workshop searched for and found examples of algorithmic bias they had not previously considered. The student learning reflected in group discussions and researcher-student interviews demonstrated growth in CAL and, in fact, informs the present study. These student outcomes reflect the core tenets of CAL.

A case study by DiPaola et al. (2020) also informed my investigation. Using the same CAL curriculum as Lee and her co-researchers (2021), these researchers focused their efforts on a summer workshop for students in grades 5-9. Students reimagined digital media in more empathetic and inclusive ways as they prototyped new interfaces for YouTube. The researchers' results suggest that the student-production elements within the CAL curriculum transformed students' capacity to analyze critically and ethically design computer programs. Through this perspective-taking, students created interfaces that they considered more beneficial to the users. Here, the production components of CAL helped students take a producer's perspective and see the algorithms as nonneutral entities created with specific purposes.

In a case study that exemplifies the meaningful integration of Kafai et al.'s (2020) critical, situated, and cognitive elements, Lee and Soep (2016) worked with underrepresented 17-to-23-year-olds to create computer programs that empowered students to take action on issues affecting these young people's lives. Participants planned, developed, and distributed an interactive map of gentrification in a West Oakland neighborhood. The app was created for authentic audiences, spurring their audience to take action.

As an example of Lee & Garcia's (2014) Critical Computational Literacies, Lee and Soep's (2016) study combines critical pedagogy with computer science, where students … "learn design and coding not as ends in themselves, but as tools that allow our youth colleagues to make media that matters to them and makes a difference in their social and civic worlds" (p. 482). For their ethnographic study, the researchers collected observed learner interaction, reviewed student work, audio-recorded learner interactions, and conducted learner interviews.

More recently, Lee, Gobir, Gurn, and Soep (2022) conducted a study with 16 people between the ages of 15-19 in what the authors refer to as Critical Computational Expression (CCE). The authors describe CCE as a “theoretical and conceptual framework we have developed that integrates the three distinct traditions of critical pedagogy, computational thinking, and creative expression” (C. Lee et al., 2022, p. 7). The authors’ ideas align with and demonstrate Kafai et al.’s (2019) three framings of computer science. A young participant in the 2022 study aptly summarized a key principle of CAL, stating, “Because sometimes I see something and I’m like ‘that’s just there, and that just is,’ but then you can start to question it and understand what they are doing and how they’re affecting us” (p. 16). This remark reflects a critical perspective that they no longer merely accept digital technologies at face value but question their underlying mechanisms and societal implications.

C. Lee and his colleagues (2022) ultimately concluded that “by creating a learning ecology that centered the cultures and experiences of its learners while leveraging familiar tools for critical analysis, youth deepened their understanding of AI” (p. 1). Although their study placed greater emphasis on computer science and program creation than the CAL lessons in the present inquiry, the focus on algorithmic awareness and production was highly relevant to my work. I investigated how these crucial elements can be incorporated into CAL lessons that take place during the regular school day. Like the critical perspective espoused by CAL, the CCE approach proposed by Lee and his colleagues focuses on the analysis and creation of media aimed at engaging real audiences in order to challenge prevailing perspectives.

These five case studies demonstrate pioneering efforts in CAL and offer relevant insights for my research. The CAL implementations represent a meaningful blend of Kafai et al.’s (2020) cognitive and critical framings of computer science. The implementation-based studies entailed students examining algorithms from a critical perspective and creating products that reflected those analyses. These interventions formed the foundation of this dissertation's lessons and case study by emphasizing a synthesis of algorithmic awareness with a critical perspective. These cases illustrate that even relatively modest interactions with algorithms empower young people to think critically about the sociocultural effects of algorithms (Long & Magerko, 2020; Resnick & Silverman, 2005).

Through this enhanced perspective, students experience the nonneutral nature of media in general and algorithms in particular. The student production components helped students internalize that data requires interpretation and that people and entities shape the process of algorithmic creation and dissemination with their own purposes and biases (Dasgupta & Hill 2021). It is only through the critical examination of and interaction with these algorithmic effects that students examine the complex relationships between their lives and the multitude of media with which they are surrounded.

Present Study

The present study described the design, promising practices, and challenges in CAL lessons conducted during the school day. The present study drew primarily on Kellner and Share's CML Framework (2019) and embodied a critical analysis and production model as a lens for CAL. The design of the CAL lessons was also informed by Dasgupta and Hill's (2020) four design principles for critical algorithmic literacies.

Vasquez's (2014) critical literacy research also inspired the lesson design in my case study. Serving as an example of Dasgupta and Hill's (2020) "thick authenticity," many of Vasquez's ideas stemmed from classroom discussions and dialogues between teachers and her 3-5-year-old students. In Vasquez's preschool class, students analyzed a McDonald's Happy Meal as a textual artifact based on a student-initiated conversation. Specifically, the class scrutinized the normative gender roles promoted when McDonald's offered Hot Wheels (toy cars) for boys and Barbie dolls for girls in their Happy Meals.

The students investigated the influence of advertising in shaping their desires and preferences and gained a deeper understanding of the persuasive techniques employed by corporations such as McDonald’s. Drawing in part from the Reggio Emilia approach, which posits that teachers design activities based on children’s interests (Hewett, 2001), Vasquez’s project highlighted the power of young learners to engage in critical thinking and media literacy when content emerged from the students themselves. My investigation aimed to similarly incorporate students’ media experiences as texts for analysis and the basis for creative exploration.

CML provides a proper umbrella to examine digital algorithms in the nine CAL lessons. Digital algorithms govern a vast array of media processes, such as content generation, curation, filtering, and recommendation within almost all digital media forms (Valtonen et al., 2019). The need for critical examination of contextualized digital algorithms remains particularly true for children growing up in a world where digital media govern their social, intrapersonal, economic, and physical realities.

Perhaps more than any other subject learned in school, media literacy taps into students’ authentic experiences outside of school (Buckingham, 2003; Donohue, 2019). Moreover, CML provides a suitable framework for CAL, as CML seeks to challenge dominant media influences by analyzing the power structures communicated through the various media (Kellner & Share, 2007). Because digital algorithms often reinforce dominant perspectives (Beer, 2009; Kitchin, 2017; Noble, 2018), a critical viewpoint is warranted as CML examines relationships between information and power (Kellner and Share, 2019).

As media technologies change, models of media literacy change along with them. Some media literacy efforts, for example, focus predominately on broadcast media, where the media is transmitted to and received by the users (Cho et al., 2022). Print and broadcast media mostly lack the dominant digital platforms' data collection and personalization capacities. Because of the separation between producer and consumer, current media literacy models may lead to less personal analysis than those media that change based on user inputs. YouTube's algorithms, for example, manifest different user-producer relationships than Facebook and so on. Jandrić (2019) points out that newer technologies do not negate earlier forms of CML "…instead, it updates them for the digitally saturated world" (p. 34). The CAL model may update the current conception of media literacy education to develop skills more aligned with the world in which students live.

Conclusion

We live in a time where digital algorithms are woven throughout our society, often making vital decisions in areas including, but not limited to, education, commerce, politics, justice, and employment. Freire (1972) wrote, "No reality transforms itself" (p. 28). As educators, we should work to transform students' critical consciousness in the world in which they live. Because algorithms are not neutral entities, they may perpetuate injustices and structural inequities in powerful and covert ways. By helping students create connections between their computational thinking, personal experiences, and creative expression, the CAL lessons and case study seek to support student understandings of algorithms in authentic contexts. This study contributes to a body of knowledge that empowers teachers to help their students' journeys and transform their realities within the technologically-driven world in which they live.

Chapter 3: Methodology

We do not learn from experience. We learn from reflecting on experience.

John Dewey (1933)

Despite the pervasiveness of digital technologies such as artificial intelligence (AI), K-12 schools provide little opportunity for students to learn about these technologies and develop critical skills regarding how digital algorithms influence students' lives (UNICEF, 2020; Wang et al., 2022). The critical algorithmic literacy (CAL) framework provides a pedagogy and philosophy for students to examine the impact of digital algorithms, including AI, in their lives and the lives of others (Dasgupta & Hill, 2021). This dissertation presents my collaboration with an elementary school teacher to plan, design, and implement nine CAL lessons for third and fourth-grade students. I drew on Kellner and Share's (2019) critical media literacy (CML) Framework in the lesson planning and design. By describing the design, challenges, and promising practices of teaching CAL to elementary school students, findings from this case study contribute to our understanding of CAL implementations with elementary school students.

Research Questions

1. How do a researcher and teacher design critical algorithmic literacy curricula for third and fourth graders for lessons conducted during the school day?
2. What are the challenges for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?
3. What are promising practices for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?

Research Design and Rationale

My qualitative case study is a thick description of the planning, design, and implementation of nine critical algorithmic literacy lessons conducted with two classes of third and fourth graders. A qualitative case study also supported my inquiry as the classroom observation, teacher interviews, and artifact analysis allowed me to conduct a "richly descriptive" case analysis (Merriam, 2016, p. 37).

Through this qualitative case study, I addressed all three research questions regarding the CAL lessons' design, challenges, and promising practices. The CAL lessons occurred once a week over a period of 12 weeks. Because of Thanksgiving and the winter holidays, there was a one-week break between the first and second lessons and a two-week break between the fourth and fifth lessons. Ms. Sage and I wrote the CAL lessons to help students better understand how digital algorithms impact individuals and society. The lesson content integrated elements from various sources which included the CML Framework (Kellner & Share, 2019), Dasgupta and Hill's (2021) CAL design principles, and various curricula created for older students. The CAL objectives (Appendix B) represent my interpretation of the skills and knowledge for third and fourth-graders who are new to learning CML, CAL, and computer science. I offer CAL as an extended branch of the CML Framework.

Methods

School

I found no examples of research that investigated CAL instruction for elementary school students. Consequently, I selected third and fourth-grade classes as a focus for my research. My goal was to examine the design, challenges, and promising practices for CAL strategies for younger students. Dewey Elementary School represented a purposeful sample of a best-case classroom likely to engage in CAL constructs in daily practice. Dewey Elementary emphasizes a constructivist approach to organizing instruction that supports students' inquiry, exploration, and play. Teachers and staff at Dewey design and write the school's curricula. The school emphasizes interdisciplinary, authentic learning to empower student agency to affect change in the world. Moreover, Dewey's school culture encourages student and teacher risk-taking. Dewey Elementary also promotes authentic learning, which supports CAL's focus on real-world content and personally relevant student projects. The school's inquiry-based learning environments align with CAL's emphasis on student-centered learning. As such, Dewey's philosophy supports the tenets of CAL.

Dewey Elementary School's environment reflects its commitment to creating a positive atmosphere as well as its commitment to student-centered projects. The school's buildings are situated in a lush green setting, with trees, lawns, and gardens that create a peaceful and welcoming environment. Among the school's greenery, one finds student-created gardens and other student projects that reflect the school's commitment to authentic student work. The campus is clean, modern, and visually appealing, with plenty of space for students to learn, play, and grow.

Teacher

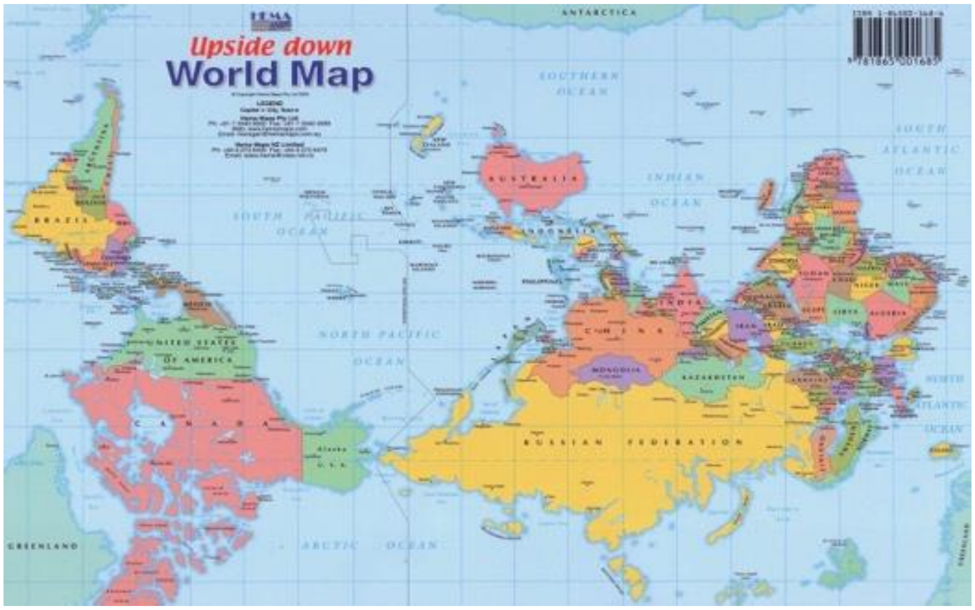
These nine CAL lessons were co-designed and taught by Ms. Veronica Sage (a pseudonym). Ms. Sage is a third and fourth-grade dual language immersion teacher at Dewey Elementary School in southern California. Ms. Sage has over a decade of teaching experience. Most of her career has centered on supporting dual language programs and emphasizing social justice. Ms. Sage began her career in Spain, teaching a full language immersion program for students in grades one through five. She then taught the third and fourth graders at a school on the East Coast. There, she was responsible for delivering an inquiry-based learning program as part of a dual-language curriculum. Ms. Sage's focus on social justice and inquiry-driven learning aligns with the philosophy and methods of CAL lessons within this study.

Classroom Environment

Ms. Sage's classroom was bright, colorful, and welcoming. Student artwork, pictures, and writing hung from the ceiling and decorated the walls. Ms. Sage's classroom contained a couch and beanbag chairs and was generally child-friendly and comfortable. In addition, one bulletin board displayed a "south-up" world map (Figure 2) labeled "perspectivas" (the Spanish word for "perspectives"). As a map is a form of media created by people with a purpose, an upside-down map exemplifies the effects of media on our perceptions of the world. Contemplating multiple perspectives aligns with CAL and CML in general, reflected in the CML question, "How would people view this differently?" (Kellner & Share, 2019, p. 8). The classroom environment, in general, reflects Ms. Sage's focus on student-centered learning as well as her emphasis on empathy and social justice.

Figure 2

Upside-Down World Map



Students

The necessity for young children to learn how to understand and engage with digital algorithms and AI drove my decision to study CAL implementation in third and fourth-grade classrooms. In today's algorithmically-saturated world, children of all ages are flooded with media that contain a wide range of content. Therefore, elementary school students should have opportunities to develop CAL skills to engage with and construct media messages in an informed way. Moreover, the critical aspect of CAL focuses on empowering students to address social injustices, especially for underrepresented populations. Some educators underestimate young children's capacity to address real-world issues and to "contribute to their own subjectivity" (Steinberg & Kincheloe, 2004, p. 7).

Each of the two classes was comprised of 18 students. All 36 student participants in this in this study were between 8-10 years old during the observations. The first group (heretofore, Room 1) had an even distribution of nine third graders and nine fourth graders. Room 2 had twelve third graders and six fourth graders. The ethnic breakdown of the student participants roughly mirrored the ethnic composition of students in Los Angeles County reported for the 2021-2022 school year (Education Data Partnership, 2023). Of the 36 student study participants at Dewey Elementary School, 25 are Latinx, 5 are White, 6 are multi-ethnic, and 3 are African-American. The reported family incomes of the students, however, did not closely reflect the incomes of families with students in Los Angeles County. Specifically, 16 of the 36 students' families reported income of over $200,000 per year, with three of those families reporting incomes of over $1,000,000 per year.

Lesson Design

Pre-planning Meetings

Before agreeing to participate in my research, Ms. Sage and I met to discuss CAL and the proposed case study. During our initial meeting, Ms. Sage appreciated the connection between CAL and her focus on teaching social justice issues and the relevance of this work to address the real-world needs of her students. Once we finalized the logistics of our collaboration, CAL lesson design commenced when Ms. Sage and I met during the summer before the 2022-2023 school year. In these pre-planning meetings, I provided an overview of CAL, and we discussed how CAL might be addressed with her third and fourth-grade students.

Ms. Sage and I met three times over the summer to plan lessons that address CAL concepts, her curricular goals, and my research questions. During these planning sessions, we created an outline of 10 lessons to address the CAL goals I shared with her. As CAL was a new concept for me, Ms. Sage, and the students, we agreed to develop one to two lessons each week.

This approach allowed us to be more flexible in terms of teaching methods, the pace of learning, and the content being taught.

As she has done throughout her career at Dewey, Ms. Sage wanted to continue integrating Social Justice Standards (Southern Poverty Law Center, 2018) into her curricula. Consequently, I shared example activities from Ko et al.'s (2022) Critically Conscious Computing curriculum as a possible way to adapt CAL to Ms. Sage's goals. The Critically Conscious Computing curriculum contains standards adapted from the Social Justice Standards (Southern Poverty Law Center, 2018) to infuse social consciousness into computer science. Although Ko and her colleagues created the Critically Conscious Computing curriculum for high school students, the adapted standards align with the tenets of CAL. Some of these adapted standards informed CAL lesson design and are listed within the CAL objectives in Appendix B. During our initial lesson design collaborations, Ms. Sage and I worked to integrate CAL curricular ideas to connect with her existing pedagogical goals and objectives.

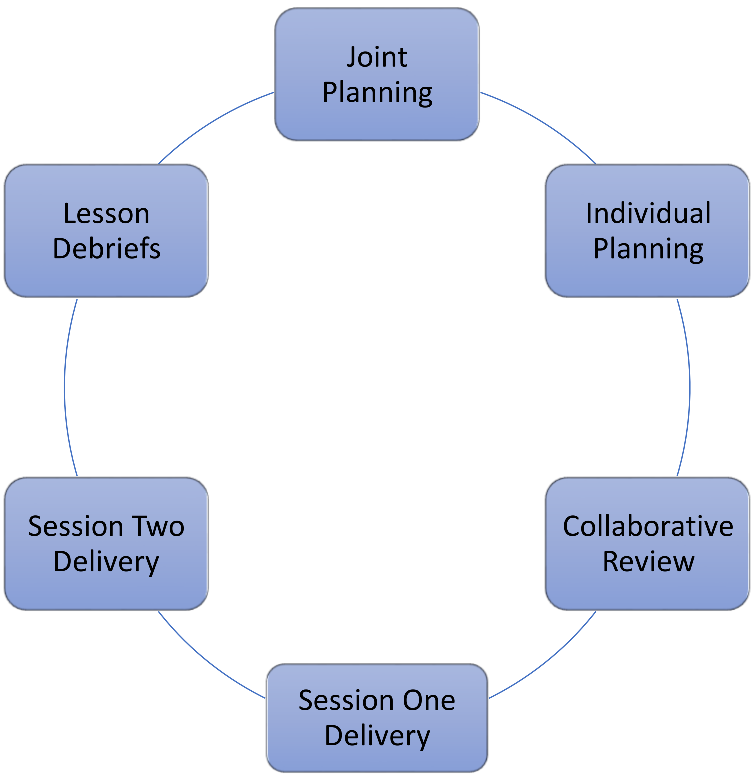
Planning Cycle

As we commenced the classroom observations, Ms. Sage and I scheduled weekly one-hour co-planning sessions. Throughout the planning process, I functioned primarily as a subject matter expert for CAL. My experience as an elementary school teacher also informed these planning sessions. Ms. Sage made numerous valuable contributions, such as her deep understanding of her students and the connections that would likely resonate with them. Additionally, she brought a wealth of pedagogical expertise, an emphasis on aligning the curriculum with social justice concepts, and effective classroom management skills. Ms. Sage had a strong understanding of media literacy and algorithmic bias based on her personal experience.

Figure 3 shows our lesson design process as a continuous cycle, where one planning phase informed the next. Reflections on each lesson played an integral role in shaping the design of the next week's lesson. This recursive design process fostered a flexible approach to best support students' achievement of the CAL goals and objectives.

Figure 3

Critical Algorithmic Literacy Lesson Design Cycle



Joint Planning

Our collaborative planning sessions began after the post-lesson debriefs (described in the data collection section below). Ms. Sage's post-lesson insights and my observation informed our planning. Her reflections helped us identify short-term goals, recognize specific student needs, and outline the necessary steps to meet our lesson objectives. The planning sessions became an essential platform for us to adapt and refine the CAL lessons.

Individual Planning

Following our lesson planning meetings, I reviewed the content from the debriefs and collaborative planning sessions. I also expanded my field notes, incorporating Ms. Sage's perspectives, our predefined lesson objectives (Appendix B), and CAL guiding questions (Table 2). In crafting the lesson draft, I prepared detailed slides that integrated multiple sources. Additionally, I included teacher prompts in the notes section of the slides to guide Ms. Sage during the lesson delivery. Finally, I emailed the draft slides to Ms. Sage for review. This allowed her to provide feedback or suggest changes before we finalized the lesson plan.

Collaborative Review

Two to three days before each lesson, Ms. Sage and I met in person or through Zoom to review and refine the upcoming lesson plan, slides, and additional resources such as videos. While we both played active roles in all aspects of the planning process, I usually contributed more to setting the lesson objectives and integrating the CAL content. Ms. Sage, with her firsthand knowledge of her students and expertise in teaching, led the pedagogical design of the lessons. She determined the pacing of the lessons and decided how much content to include in a single instructional period. Furthermore, she assessed the cognitive load of the lesson to ensure that it was appropriate for her students and would not overwhelm them. Ultimately, Ms. Sage had the final say in lesson design and implementation.

Changes Between Class Sessions

Ms. Sage implemented our jointly developed lesson during the first class session. Throughout the class, she maintained attentiveness to student engagement levels, monitored the pacing of activities, and assessed student understanding. By keeping track of these factors in real-time, she identified areas of the lesson to adjust for the second CAL session.

Based on the observations and insights gained from the first session, Ms. Sage adjusted the CAL lessons for the students in Room 2. These changes were intended to enhance the effectiveness of the lessons based on what worked well and to modify aspects that needed improvement. I described lesson adjustment changes in my field observation notes. Ms. Sage's adjustments and the resulting insights played a vital role in the design process of the CAL lessons. Recognizing that teaching and learning are dynamic processes, the ability to adapt and refine our approach was fundamental. This iterative process not only improved the immediate lessons but also provided significant information for our broader understanding of implementing effective CAL lessons.

Lesson Debriefs

Once the second CAL session was complete, Ms. Sage and I would convene for post-lesson debriefs. These sessions provided an opportunity for us to discuss the changes that were made for the second session. By talking through these adjustments, we could collectively evaluate their effectiveness, understand the reasons behind them, and consider how they could influence future lessons. The modifications made by the teacher provided us with invaluable insights into the teaching methods and materials utilized in the lessons. It revealed what strategies resonated with the students, which activities were most engaging, and how the pacing of the lesson affected student comprehension.

Lesson Goals

I used a variety of sources to create goals for the CAL lessons (Appendix A). I strove to incorporate Dasgupta and Hill's (2021) CAL design principles, such as ensuring students have authentic interactions with live data. I also adapted goals from existing curricula and resources, including Ko et al.'s (2022) Critically Conscious Computing curriculum, the Ethics of Artificial Intelligence Curriculum for Middle School Students (EAICMSS, Payne & Breazeal, 2019), and selected lessons from Project Look Sharp (2019). Drawing upon these resources and Kellner and Share's (2019) CML Framework, I formulated goals and guiding questions that incorporated algorithms as a medium within a broader understanding of literacy. The broad goals (Appendix A) address the six main topics of the CAL lessons: (a) understanding media influence, (b) understanding algorithms, (c) exploring data connections, (d) assessing consequences of algorithmic bias, (e) reflecting on personal experience, and (f) mitigating algorithmic bias. These broad goals drove the specific behavioral objectives (Appendix B) and the CAL lesson content, methods, and materials.

As described in Chapter 1 of this dissertation, neither CML nor CAL prescribes specific objectives or activities, rather they provide a structure for critical engagement. In my efforts to expand Kellner and Share's (2019) CML Framework, I adapted their questions to fit algorithms and algorithmically driven media (Table 2).

Table 2

Critical Algorithmic Literacy-Adapted Questions

CML Conceptual Understandings	CML Questions	CAL Questions
Social Constructivism All information is co-constructed by individuals and/or groups of people who make choices within social contexts.	**WHO** are all the possible people who made choices that helped create this text?	**WHO** are all the possible people who made choices that helped create recommendations?
Languages / Semiotics Each medium has its own language with specific grammar and semantics.	**HOW** was this text constructed and delivered/accessed?	**HOW** was this recommender[a] constructed and delivered/accessed? How is this recommender personalized? What techniques are used to capture and maintain my attention and interest? What information might have been used to customize this recommender?
Audience / Positionality Individuals and groups understand media messages similarly and/or differently depending on multiple contextual factors.	**HOW** could this text be understood differently	How could the results/outputs of this recommender be understood differently by people? How do my interactions with the algorithm affect the recommender? How do my interactions affect the recommender's creators?
Politics of Representation Media messages and the medium through which they travel always have a bias and support and/or challenge dominant hierarchies of power, privilege, and pleasure	**WHAT** values, points of view, and ideologies are represented or missing from this text or influenced by the medium?	**WHAT** values, points of view, and ideologies are represented or missing from this the working of this recommender? What bias(es) may be present in this recommender? What is presented as "normal"?

CML Conceptual Understandings	CML Questions	CAL Questions
Production / Institutions All media texts have a purpose (often commercial or governmental) that is shaped by the creators and/or systems within which they operate.	**WHY** was this text created and/or shared?	**WHY** was this recommender created and/or shared?

[a] For these CAL questions, I adopt the term "recommender" to describe algorithms that create recommendations based on data. Recommenders might include Google Search, YouTube, Spotify, and Netflix.

Lesson Objectives

Based, in part, on Kellner and Share's CML Framework (2019), prior CAL implementations, and overarching goals, I created a set of objectives to be addressed through the nine lessons (Appendix B). The learning objectives for all nine CAL lessons were derived and adapted primarily from three sources: (a) ISTE Hands-On AI Projects for the Classroom**:** A Guide on Ethics and AI (International Society for Technology in Education, 2021), (b) Critical Computer Science Curriculum (Ko, 2022), and (c) An Ethics of Artificial Intelligence Curriculum for Middle School Students (Payne & Breazeal, 2019). I curated and adapted the objectives from these sources based on my overarching goals, my planning conversations with Ms. Sage, and the CML Framework. Ms. Sage and I reviewed specific objectives for each week's lessons during our collaborative planning and review sessions. Table 3 shows the lessons goals with their associated learning objectives.

Table 3

Critical Algorithmic Literacy Lesson Goals and Aligned Objectives

CAL Goals	Associated Objectives
1. Understand Media Influence	• Describe the reasons why people create media. • Recognize and analyze how advertisements demonstrate bias or stereotyping. • Evaluate the elements in an image used to influence its audience. • Analyze the techniques used to capture and retain attention and interest in media.
2. Understand Algorithms	• Describe the components of an algorithm (input, processing, and output). • Summarize the three steps of algorithms. • Compare and contrast a cake recipe algorithm with YouTube's recommendation algorithm. • Explain how Google QuickDraw recognizes drawings.
3. Explore Data Connections	• Discuss the connection between the QuickDraw shoe data and Dr. Joy's experience with AI bias. • Analyze how limited training data can lead to bias in software.
4. Assess Consequences of Algorithmic Bias	• Evaluate potential biases in a recommender system. • Identify bias and identify algorithmic biases in search results. • Evaluate the consequences of algorithmic bias. • Analyze how algorithms can amplify injustice and inequity.
5. Personal Reflection	• Reflect on personal experiences and connections to lessons on media, algorithms, and bias.
6. Mitigate Algorithmic Bias	• Describe how incomplete or "bad" inputs can lead to poor outputs. • Discuss strategies for ensuring that a program or robot is not biased. • Evaluate the inputs used by an app and the potential biases and harms of the algorithm. • Discuss strategies for ensuring that the training data and output of an app is not biased.

Lesson Outline

Based on these overarching goals and the specific objectives (Appendix B), I created a broad outline of the nine lessons for this case study. As mentioned earlier, Ms. Sage and I finalized each lesson within the week prior to its implementation.

In addition to the nine scheduled lessons, I observed one 30-minute Council Circle session led by Ms. Sage. During Council Circles, the teacher and students share personal experiences, providing a relevant context for curricula or other topics (Ways of Council, 2023). Based on my request, Ms. Sage arranged a special session for the day before lesson seven: a Council Circle centered on students' media use. The purpose of Council Circles aligns with Vasquez's statement (2014) that "the world around [students] can and should be used as text to build a curriculum that has significance in learners' lives" (p. 6). By centering a discussion based on students' media experiences, we hoped to increase relevance and engagement for the students.

Table 4 includes a broad overview of the nine lessons and the single Council Circle session. In Appendix C, I have included a more detailed lesson summary that includes objectives, student activities, and guiding questions. Because we constantly revised and updated lessons, the summary below reflects the nine lessons as delivered to the students.

Table 4

Summary of Critical Algorithmic Literacy Lessons

Lesson	Topics	Objectives
1	• Media literacy • Gender bias in media	• Describe the reasons why people create media. • Recognize and analyze how advertisements demonstrate bias or stereotyping.
2	• Media literacy • Decoding media messages • Targeting specific audiences • Algorithmically-driven media bias [YouTube search]	• Evaluate the elements in an image used to influence its audience. • Analyze the techniques used to capture and retain attention and interest in media. • Evaluate potential biases in a recommender system.
3	• Introduction to algorithms • Flawed or incomplete input leads to flawed output • Connecting YouTube recommendations with input, processing, and output • Recommendation engines	• Summarize the three steps of algorithms. • Compare and contrast a cake recipe algorithm with YouTube's recommendation algorithm.
4	• Bias • Algorithmic bias- Google image search • Intro to possible consequences of algorithmic biases • Harms and benefits of technology • Introduce final project	• Identify algorithmic biases in search results. • Describe possible consequences of algorithmic biases. • Describe harms and benefits of technology.

Lesson	Topics	Objectives
5	• Final project • How programs use training data to identify images • Consequences of facial recognition bias • Connecting facial recognition to three step algorithm model	• Explain how Google QuickDraw recognizes drawings. • Describe consequences of facial recognition bias • Discuss the connection between the QD shoe data and Dr. Joy B.'s project. • Analyze how limited training data can lead to bias in software. • Evaluate the consequences of algorithmic bias. • Analyze how algorithms can amplify injustice and inequity.
6	• Bias • Gender bias • Bias in training data • Effects of facial recognition bias • Effects of other algorithmic biases • Final project	• Discuss the connection between the QD shoe data and Dr. Joy B.'s project. • Analyze how limited training data can lead to bias in software. • Evaluate the consequences of algorithmic bias. • Analyze how algorithms can amplify injustice and inequity
Council Circle	• Student-driven topics centered on media use	• Reflect on personal experiences and connections to lessons on media, algorithms, and bias.
7	• Project work time • Connecting project about the three-step model of algorithms • Focus on algorithmic inputs • Training data bias	• Analyze how limited training data can lead to bias in software. • Evaluate the inputs used by an app and the potential biases and harms of the algorithm. • Discuss strategies for ensuring that the training data and output of an app are not biased.

Lesson	Topics	Objectives
8	• Project planning • Algorithmic bias • Minimizing bias • Project prep	• Analyze how limited training data can lead to bias in software. • Evaluate the inputs used by an app and the potential biases and harms of the algorithm. • Discuss strategies for ensuring that the training data and output of an app are not biased.
9	• Summary of prior eight lessons • Project work time: video creation	• Create a one-minute video that describes you a hypothetical app, the intended audience and how the app avoided biased outputs.

For the final projects, we asked students to create planning documents and a one-minute video describing a unique application or robot they had envisioned. The primary goal was for students to design a technological application that could help others. We asked them to detail their target audience, how their application would assist that audience, and what kind of data their idea would need. In addition, we required students to explain how they would minimize algorithmic bias in their application. Optionally, we asked students to describe what they learned during these CAL lessons.

Data Collection

My data collection methods involved classroom observations, teacher interviews, and artifact analysis. Partly because there were no pre-established criteria for assessing students' CAL competencies, we did not create formal assessments to directly evaluate CAL learning. Both Ms. Sage and I, however, inferred student learning by comparing student work and behaviors with each lesson's objectives. Our perceptions and reflection regarding student learning informed the research questions regarding lesson design (RQ 1), challenges (RQ 2), and promising practices (RQ 3) of CAL implementation.

The multiple data sources supported the internal validity of the study's findings by reducing researcher bias and reactivity through various techniques of analysis and triangulation (Maxwell, 2013; Merriam & Tisdell, 2016). I cross-referenced the multiple data sources to infer connections between the planning documents, lesson materials, observation notes, interview transcripts, and student work. Observed student behaviors and teacher debriefs, for example, provided corroborating or contradictory data for student work. The observations also provided a context for discussions with Ms. Sage in subsequent interviews and planning sessions. The connections between the data sources addressed the research questions by providing a richer description from multiple perspectives. Further connections between data sources are described in this chapter's validity/reliability section.

Classroom Observations

The targeted lessons occurred after Dewey Elementary School's scheduled lunch period. Typically, students would filter into the classroom after lunch and sit at their tables. Often, students were called to the rug while another teacher or teaching assistant read a story to students. After 10 minutes or so, Ms. Sage would come in and begin the CAL lessons. During periods of individual and group work, I would circulate among the tables, observing and posing questions to the students. After the first 45-minute lesson in Room 1, Ms. Sage walked to Room 2 and delivered the lesson again with the second class of third and fourth graders.

I conducted a total of 18 45-minute classroom observations. I observed all nine CAL-integrated lessons, which Ms. Sage taught to two classes of students. I also observed the sole Council Circle session. Each observation lasted approximately 45 minutes. The classroom observations helped me explore my research questions. Observing the students' behaviors informed design decisions (RQ1), illustrated challenges (RQ 2), and promising practices (RQ 3) for CAL implementation within this case study. Using the observation field notes form (Appendix E), I documented Ms. Sage's methodology, student-teacher interaction, interactions between students, and independent student behaviors throughout the observed lessons.

The observation protocol instrument involved a three-column structured format. In the left column, I wrote objective, open notes reporting what I observed in the classroom. The middle column included direct quotes from the teacher and students. In the third column, I listed my thoughts, reflections, and questions. After the classroom observations, I expanded the field notes while the details of the observations were still clear in my memory. The expanded field notes often led to adding notes in a reflective journal and to the creation of analytic memos. As I carried out the analysis concurrently with data collection, I created analytic memos based on reflections related to the research questions, descriptive summaries, and emerging patterns from the classroom observations (Saldaña, 2021).

Teacher Interviews

The teacher interviews took two forms. I conducted three formal semi-structured interviews and nine informal post-lesson debriefs. The three formal, semi-structured interviews with Ms. Sage used open-ended questions (Appendix F) that facilitated a more flexible exploration of the teacher's reflections (Merriam & Tisdell, 2016). These three formal interviews with Ms. Sage occurred before, during, and after the nine-lesson observation period. The first interview occurred roughly two weeks before the first lesson. The second interview occurred after the fifth of the nine lessons. The final formal interview occurred after the completion of the ninth and final lesson.

Semi-Structured Formal Interviews. Each formal interview lasted 30-45 minutes and occurred in person in a private office adjacent to Ms. Sage's classroom. I recorded the interviews using a Sony ICD-PX470 portable digital audio recorder. Following each lesson, Microsoft Word transcribed the recordings. I checked and corrected all interview transcripts for accuracy by listening to the audio recording while reading the transcriptions. As a member check, I provided Ms. Sage with the reviewed transcripts to provide her the opportunity to verify their accuracy (Merriam & Tisdell, 2016). As an additional member check, I sent Ms. Sage specific interview excerpts that included my interpretation of her comments and asked her to confirm the fidelity of my interpretations.

As I framed CAL as an expanded context of traditional literacy, in the first teacher interview, I sought to understand Ms. Sage's overall philosophical approach to literacy education and her thoughts regarding how she conceptualizes CAL and her role in teaching it. The second interview explored her perceived successes and obstacles roughly halfway through the observed lessons by asking questions such as "Please describe specific challenges, if any, you've had to teach critical algorithmic literacy to this point." The third teacher interview explored Ms. Sage's perceptions regarding the design, promising practices, and challenges regarding co-planning and implementing the CAL lessons.

In the second and third interviews, I asked, "What changes or adjustments would you have made to the CAL lessons?" I also asked Ms. Sage to describe the rationale for some instructional choices, comment on the efficacy of these instructional practices, and share her perceptions of how students understood and applied intended CAL concepts. The final two interviews also sought the teacher's perceptions regarding the co-design process.

Post-Lesson Debriefs. In addition to the three formal interviews, I conducted post-lesson debriefs with Ms. Sage after the second of the two CAL lessons. These short, unstructured post-lesson debriefs were grounded in the observed events, behaviors, and instructional strategies from the observed lessons. The informal debriefs provided the teacher's timely perspectives concerning the research questions about promising practices and challenges of the CAL-integrated lessons. Our conversations lasted 10-20 minutes and evolved into the planning of future lessons. These post-lesson debriefs were audio-recorded and transcribed verbatim using the same methods as the formal interviews.

Artifact Collection

Artifact collection consisted of planning documents, lesson materials, my researcher design journal, and student work samples. The only student work samples were the project planning documents and the final student project, a one-minute video discussing a "never-seen-before" application they envisioned. Students were tasked with creating an idea for an application and/or robot of their choosing. They were also asked to describe the audience, how the application would help, and what data they need for their idea. For this final project, we requested that students describe how their application would avoid bias. Student progress reflected in hir final project videos informed all three research questions regarding design, challenges, and promising practices.

Final Video Projects. Students posted their final project videos to the teacher's password-protected Google Classroom site. I did not save or copy these videos. For data collection and analysis, I repeatedly viewed the final project videos from the Google Classroom site and did not make copies of them. I viewed each student video multiple times, copying quotes verbatim. These notes and transcriptions were anonymized, stored on a password-protected computer, and uploaded to secured cloud storage.

Planning Documents. Planning documents included lesson slides, notes from collaborative planning meetings as well as individual planning notes from my design journal. Instructional materials included lesson slide decks and supporting documents. The planning and lesson artifacts informed classroom observations and teacher interviews.

During the structured and unstructured interviews, the teacher referred to both lesson slides and observed students' behaviors to address the research questions about perceived successes and challenges within CAL lessons. The planning documents also informed the classroom observations regarding how the actual instruction compared to what was planned. Comparison between the lesson objectives and observed behavior framed the analysis and led to teacher reflections regarding promising practices and challenges. The researcher, teacher, and student-created artifacts were stored on a password-protected laptop, on the researcher's password-protected Google Drive, and on an external hard drive.

Design Journal. Throughout the case study, I wrote in a researcher's design journal. I used the journal to document, organize, and reflect on the research process and classroom observations. I used the same document for my individual planning sessions. In this way, the lessons and reflections informed plans and vice-versa. The journal enabled me to reflect on my experiences and feelings throughout the research process, which provided valuable insights to enhance the study's overall quality. At times, I recorded emerging themes, patterns, and insights in the journal, which supported my data analysis. When I associated a particular piece of data through the iterative analysis process, I created an analytic memo attached to that datum.

Data Analysis

I analyzed all data sources using the same iterative process. Data collection and analysis often occurred simultaneously. From the beginning of data collection, I uploaded interview transcripts, observation field notes, planning documents, and instructional materials to MaxQDA software. I created analytic memos to record my initial thoughts, questions, descriptive summaries, and patterns emerging from the various data sources (Saldaña, 2021). I associated these memos with specific data segments from classroom observations, teacher interviews, and other artifacts, ultimately leading to the development of broad categories or codes (Braun & Clarke, 2006). I continuously created, applied, and refined codes and categories throughout data collection, focused analysis, and dissertation drafting.

In this study, I employed a hybrid approach incorporating both inductive and deductive data analysis. I analyzed codes on a case-by-case basis to identify patterns and used queries within MaxQDA to provide context and detail to these patterns. Within MaxQDA, I categorized the data by source and created document sets organized by lesson. Initially, I adopted an inductive approach to identify themes not directly related to the CML Framework. This inductive coding allowed for a more comprehensive description of the data, as it was not limited by pre-existing theories (Braun & Clarke, 2006). Initial thematic codes included "design process," "teacher activities," "student learning," and "computer science."

As the analysis progressed, I identified new codes and sub-codes. For instance, within the "teacher activities" code, I identified sub-codes such as "teacher moves" and "teacher challenges." Furthermore, I established third-level codes under "teacher challenges," including "students lack background knowledge," and "student distraction," and "teacher connecting to students' experience."

After completing the initial stages of inductive analysis, I conducted a deductive analysis to uncover authentic connections to the CML Framework (Kellner & Share, 2019). I identified particularly illustrative examples, such as students recognizing algorithmic biases. Using deductive analysis, I facilitated a more in-depth examination of the research questions as they relate to the study's conceptual framework (Braun & Clarke, 2006). By the end of the iterative inductive and deductive analysis processes, I generated a total of 85 codes. The overview of codes (Appendix G) offers a detailed summary of the codes, sub-codes, and how frequently the codes connected to data. Once all the data were coded, I conducted frequency counts for each code. Such frequency counts helped me to understand how representative each code was concerning the rest of the data set. I also reviewed the data for content that is less frequent yet more salient to my research questions (Clarke & Braun, 2013).

Classroom Observations Analysis

Positionality

As the primary lesson designer and researcher, my positionality as the researcher exerted a considerable impact on this case study. Minimizing researcher bias was one of my greatest challenges in this study. I have worked as a K-12 teacher and technology coordinator for more than 30 years. I have taught elementary school for 10 of those years, including grades three and four. Throughout my career, I have specialized in educational technology. I earned a master's degree in educational technology in 1994, am a "Google Certified Innovator," and have focused my work on helping teachers with the purposeful integration of educational technology. Over the last 20 years, I have been a strong proponent of computer science education, speaking at dozens of conferences and conducting trainings on the topic.

Throughout my thirty-year career, I've worked to support teachers' integration of educational technology with core curricula. For 20 years, I have taught and promoted block-based coding with students in grades 3-8. As a classroom teacher, my students engaged in media production activities such as video creation, animation, and 3D modeling. Based on the length and nature of my education and work experience, some might consider me to be an expert in educational technology implementation.

As a classroom visitor, it was essential that the students and teacher felt as comfortable as possible. I carefully positioned myself first as a UCLA graduate student exploring a new topic to improve K-12 education. I then described myself as a former third and fourth-grade teacher. With these backgrounds, I portrayed myself as a passionate advocate and practitioner of critical pedagogies in a modern context.

Ethical Issues

No ethical issues arose during this study. I did not store any personally identifying information about participating students. I reminded the teacher and students of the confidentiality of their involvement in the study. The school site, teacher, and students have and will remain anonymous, and I used pseudonyms for the school, the teacher, and all students. I stored all research data on password-protected devices.

Reliability and Validity

Perhaps the biggest credibility threat to the validity of this study was my reactivity and bias. Naturally, I wanted these lessons to reflect the desired learning outcomes. Data analysis centered on the teachers' reflections and objective descriptions of student behaviors and served to minimize researcher bias, thereby minimizing my potential subjectivity. In addition, the triangulation of sources and methods, including the observation of multiple class sessions and member checks, helped me build a credible case study. I triangulated data from the teacher interviews, observations, and student artifacts to enhance validity and provide a more holistic view of the lessons and their effects.

Triangulation of data sources helped ensure a thick description on multiple levels. The teacher interviews illuminated classroom observation as the interviews shed light on teacher goals and methods related to classroom practices. Classroom observations informed the teacher interviews, particularly the informal post-lesson debriefs. The student behaviors witnessed during the classroom observations provided a context for student work analysis. The classroom observations enhanced document analysis by viewing the process, not just the final product.

Teacher interviews augmented the classroom observations as they provided a more nuanced view of the instructional goals than simply a planning document. Teacher interviews framed artifact analysis as it revealed to what extent student learning addressed the teacher's goals. These associations supported investigating connections between analytical and productive elements of student work. Student work also served as a discussion point in the final formal teacher interview. Finally, my reflective journal facilitated reflexivity, enabling me to examine my own biases, assumptions, and the potential influence biases may have on the research process and findings.

Teacher and Student Activity

In addition to my own biases, I was also concerned about the reactivity of the participating students and the teacher. The participating teacher knew that others would see the findings of this study. The students may have felt anxiety being observed by an older stranger. To gain the trust of the students, teachers, and administration, I attended three class sessions before the first observation. I presented myself as a former teacher conducting research seeking to learn from their teacher's expertise and experience. I explained to the students that the purpose of the study was to improve instruction in this new area of "digital literacy." By describing my background and purpose, I sought to facilitate trust and increase students' willingness to participate authentically in this research.

CHAPTER 4: FINDINGS

We shape our tools and thereafter they shape us.
John M. Culkin (1967)

Case Study Overview

The study examined the design, challenges, and promising practices of nine 45-minute lessons and one Council Circle session based on the CAL framework. One teacher, Ms. Sage, implemented these lessons with two grade 3/4 combination classes. The nine lessons extended over a 12-week span between November 2022 and late January 2023. I used multiple data sources to answer the research questions, including lesson slides, lesson planning materials, classroom observations, post-lesson debriefs, teacher interviews, student work, and my researcher/lesson design journal.

This chapter begins with a summary of the case study's findings, aligning them with my three research questions. I then describe the details of each finding. The chapter concludes with a summary of how these findings interact and build upon each other.

This study addressed the following research questions:

1. How do a researcher and teacher design critical algorithmic literacy curricula for third and fourth graders for lessons conducted during the school day?
2. What are the challenges for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?
3. What are promising practices for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?

Summary of Findings

In this chapter, I present the three main findings of my research. For the study's first finding, I examine the four primary purposes of modification of outside sources intended for older students. Through data analysis, I classified lesson modifications into four categories: (a) condensing content for time, (b) adding, reducing, or modifying lesson examples, (c) connecting to younger students' prior experiences, and (d) simplifying concepts and vocabulary. For the second finding, my data analysis highlighted the significance of providing high-quality educational examples that align with students' pre-existing knowledge and experiences. The instructional examples influenced the teacher and co-designer/researcher's design decisions, perceived challenges, and effective practices within CAL lessons. For the third finding, I discerned that many lessons required redesigning content to present in a new way. To allocate time for revisiting foundational concepts, such as bias and training data, we had to prioritize certain content and consequently omit other activities from lessons. These findings connect to all three of my research questions by explaining lesson design decisions and teacher practices that concurrently addressed a challenge and identified a promising practice for teaching CAL to elementary school students in this case study.

Finding #1: Adapting Lesson Materials Intended for Older Students

Throughout the study, Ms. Sage and I sought to address the lack of CAL at lower grades. While planning the CAL lessons, we adapted preexisting activities and ideas designed for older students. Based on my analysis of the lesson adaptations, I defined four purposes for these adaptations that aligned with the present case study's goals and objectives. The categories include (a) condensing content due to time constraints, (b) increasing or decreasing the number of examples, (c) connecting to students' prior experience, and (d) simplifying concepts and vocabulary. These categories often overlapped and influenced each other. For example, simplifying a lesson's vocabulary might also reduce the time required for its implementation.

The process of adapting content for younger learners involved reviewing the learning objectives, key concepts, and targeted skills of the outside content written for older students and assessing how they aligned with the intended objectives, concepts, and skills of the CAL lessons for third and fourth-graders. Next, I prioritized which borrowed content would be most relevant to the CAL lesson goals and objectives by evaluating the alignment of activities with objectives. Then, I simplified some complex concepts by streamlining or eliminating vocabulary words, scaffolding content, and modifying instructional format. Finally, I modified many instructional examples to better connect with younger learners' prior experience.

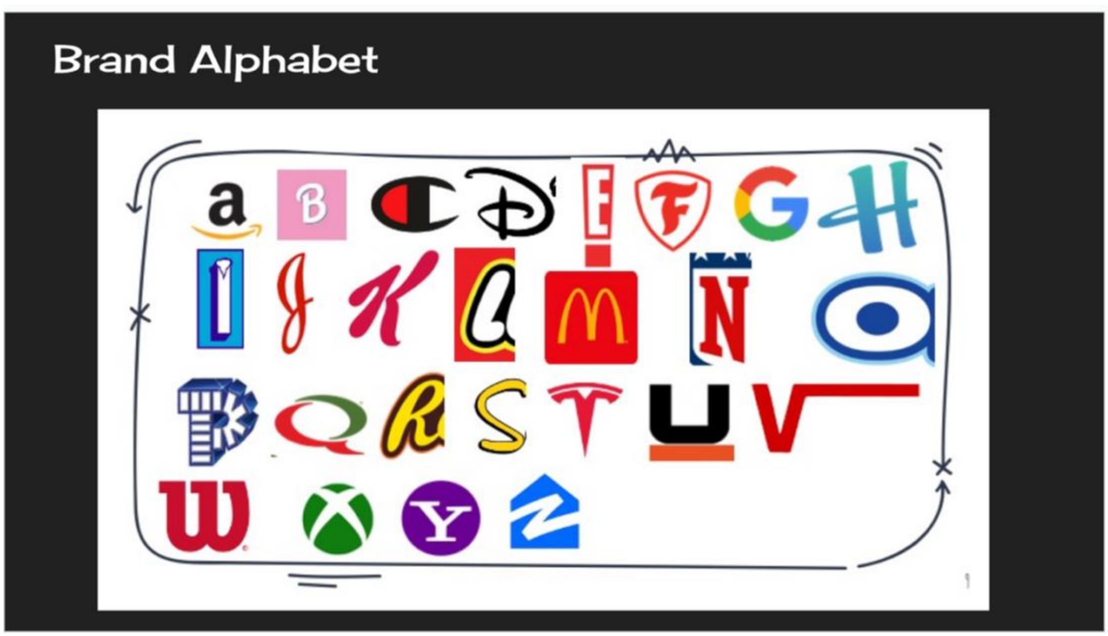
Condensing and Synthesizing for Time

Perhaps our greatest challenge in adapting existing materials was to address similar goals of the third-party lessons with much less class time to do so. Some of the CAL lessons were adapted, in part, from Payne and Breazeal's (2019) 107-page Ethics of Artificial Intelligence Curriculum for Middle School Students (EAICMSS). The EAICMSS curriculum guide states that all its activities require about 13 hours to complete. Our CAL lessons, in contrast, totaled 6.75 hours of class time for each student. One might safely assume that many of the activities intended for middle school students would require more time when attempted with third and fourth-graders. Furthermore, in addition to the EAICMSS, Ms. Sage and I also integrated other sources and created original content.

Ms. Sage often made time-saving adjustments for the second class session upon a brief reflection on the first CAL lesson of the day. As mentioned in the Methods chapter of this dissertation, the teacher's lesson adaptations between the first and second of the back-to-back sessions were an integral step in the design process for this case study. Classroom observations indicated, for example, Ms. Sage adjusted the first lesson's Branding Alphabet (Figure 4) lesson (McLaren, 2002) when facilitating it for the second group of students. The Branding Alphabet activity began with students identifying flower names from an image of 15 flowers. In the first iteration of this activity with Room 1, Ms. Sage accepted multiple student responses for students to guess the flowers. However, it was clear that the flower names were not common knowledge. Subsequently, the teacher asked the Room 1 students to identify 26 brand logos. The students instantly identified most, if not all, of these corporate logos. The activity was intended to illustrate the prevalence of media in all our lives. When facilitating this activity for Room 2 students, she provided just enough time for students to realize they did not know the names of the flowers so they could contrast that knowledge with how well everyone knew the corporate brands represented in the Branding Alphabet.

Figure 4

Branding Alphabet- Adapted from McLaren (2002)



During the first post-lesson debrief, Ms. Sage described the change between the first and second sessions. She remarked, “I think I noticed how the second lesson went better just because of the timing [of the Alphabet Branding activity]. I think that gave us more time for the Real Bugs discussion in the second class.” Here, Ms. Sage recognized the importance of the student discussion of gender bias in the commercials. She also acknowledged the function of naming the flowers in the Alphabet Branding (McLaren, 2002) activity as only to contrast with the Branding Alphabet.

These between-lesson modifications impacted the design of subsequent classes. During the collaborative planning after lesson one, Ms. Sage described the lesson timing she wanted to see in future lessons: “Ideally, we should be planning to do 10 to 15 minutes [with students gathered] on the rug, then give them some independent work time, and then end with reflection.” Her comments described the lesson structure we sought for the remaining eight CAL lessons. The alterations made to address the timing of activities between repeated lessons not only affected the second of the two daily sessions but also informed the planning and design of the remaining lessons.

Regarding the between-class adaptations in general, Ms. Sage quipped, “The second [class] is always better.” She repeated the sentiment in the lesson three debrief: “I think [adjustments we made between the first and second sessions] is something that we will be able to talk about every single session because the second session is always going to be better.” Ms. Sage’s second-lesson modifications, in fact, reflected design changes implemented throughout the lessons.

Another time-saving CAL lesson adaptation involved combining multiple lessons from content intended for older students. For the third of our nine CAL lessons, for example, I combined essential elements of two lessons from the EAICMSS curriculum. The EAICMSS curriculum guide suggests 45 minutes for each of these lessons. We strove to present the essence of both lessons in about 30 minutes of class time.

The “Introduction to Algorithms” lesson involved equating the three-step model of algorithms with the creation of building a peanut butter and jelly (PB&J) sandwich. To illustrate how algorithms can be customized for specific audiences, we attempted to extract the essence of the “Ethical Matrix” lesson of EAICMSS and integrate it with the “Introduction to Algorithms” lesson. The ethical matrix is comprised of a table with rows of potential stakeholders and columns that list the possible values a stakeholder might have. I similarly wanted students to gain the ethical perspective implicit in considering others’ values. Instead of having students complete the ethical matrix, however, I modified the lesson three slides to include only these questions: “Would your algorithm be different if it were for your parents? A doctor? Older people?” Although our students may not have learned the topic of stakeholder’s values as deeply as if they had completed the ethical matrix, we were hopeful they would begin to explore how algorithms, like various foods, can be targeted to specific audiences based on the user’s needs as perceived by the algorithm or sandwich creators.

My observation field notes indicate that after some students described their personalized sandwiches, Ms. Sage asked the group of seated students, “Would your algorithm be different if you were a doctor? One student replied, “They use a special kind of jelly.” In another exchange:

Cassie: They want you to put lettuce and Brussels sprouts [on your sandwich].

Teacher: Why?

Cassie: The doctor wants you to eat more vegetables.

The teacher/student exchange reflects the intended objective of seeing how media can be targeted based on the creator's perceptions of their audience. By synthesizing these two lessons into one shorter lesson, we addressed the time constraints while still providing an ethical perspective.

The focus on the ethical perspective in the condensed EAICMSS lessons was reflected in some students' final projects. Carlos, for example, proposed an application called *Animal-to-Human Translator*. In his final project video, Carlos stated that to avoid bias, his program "will make sure to have every type of animal and say it in any type of language." This seems to reflect the understanding that to avoid algorithmic bias, an AI's training data must strive to represent the population, even if that population is not human. Within the same video, Carlos also commented on how hard it would be to obtain every possible sound any animal might make. In this way, he seems to acknowledge the need for AIs to analyze massive amounts of data to better represent diverse populations.

It is likely that Carlos and many of his classmates learned how biased or incomplete training data can lead to flawed outputs during lesson six. Based on post-lesson-five reflections, I adapted part of MIT's Responsible AI for Social Empowerment and Education (RAISE) curriculum (2021) for lesson six. I modified the RAISE lesson entitled "How Do Machines Gain Intelligence?" (Massachusetts Institute of Technology, 2021) to take less class time than described in the original curriculum. In this lesson, students use Google QuickDraw to understand how training data impact the output of an AI system. QuickDraw uses artificial intelligence to recognize and classify a user's drawings in real-time. The prompts in QuickDraw (such as "draw a shoe") include a wide variety of objects and animals. As one draws, the AI system provides feedback in real-time, indicating whether the drawing is being recognized and classified correctly. One can view the AI's training data for the sketches, such as the thousands of user-submitted shoe drawings. The ability to view QuickDraw's training data as an algorithmic input help students internalize how AI training data influences its prediction capacity. Students interacted with QuickDraw in lesson five and those interactions formed the basis of a lesson six discussion.

Before engaging in the hands-on portion of the QuickDraw activity, this RAISE lesson includes scripted direct instruction that incorporates an activity where students verbally compare AI's predictions to predictions they've made in their lives. Following the discussion, students are directed to draw items on paper and guess each other's drawings. To save class time, I modified the activity to a briefer warm-up. Instead of having students guess each other's drawings, the lesson slides begin with the following prompts: (a) Close your eyes and picture a shoe. (b) Draw the first image of a shoe that pops into your head. (c) Did you all draw the same shoe? In my observation notes, I commented that this short warm-up task achieved its intended purpose of helping students consider the countless ways other people would represent the many variations of shoes. After this warm-up, students explored the QuickDraw tool, then came to the front of the room for a whole-class reflection. Ms. Sage told students that although Google QuickDraw contains huge amounts of training data to guess students' drawings, the AI could not represent every possible shoe.

The core CAL principle that the quality of an AI's training data affects the quality of its outputs was reflected in some students' final projects. Matthew's final project video, for example, reflected the knowledge that AI training data should be complete and representative to best avoid biased outcomes. His proposed robot, *Electrify*, locates and charges stranded electric cars. In his final project video, Matthew stated that his app "will avoid bias by giving it mixed information." Later in the video, he clarified that the app "will need many locations," acknowledging the need for ample and accurate training data to achieve the desired outcome of reaching the correct location. As with the other findings presented in this study, the success of modifying existing content hinged on the quality, frequency, and strategic deployment of instructional examples such as live AI training data.

Increasing or Reducing the Number of Examples

For complex concepts such as training data, bias, and algorithmic bias; the quality, frequency, and relevance of instructional examples are especially important. In some cases, learning objectives require a greater number of concrete examples than those required for older students. For the fourth CAL lesson, centered on algorithmic benefits and harms, I added more examples than provided in Project Look Sharp's (2019) lesson entitled "Google Image Searches – Do They Promote or Counter Stereotypes?" This lesson targeted sixth graders and had students compare Google image searches on the terms "working man" and "working woman." The intention of this activity was for students to perceive possible gender bias within Google's search algorithms.

Based on notes in my reflective journal and lesson objectives, I adapted Project Look Sharp's lesson in several ways. In addition to prompting students to search for "working man" and "working woman," the lesson slides also prompted students to do a Google Image search for "CEO" and "computer programmer" as well as "toys for boys" and "toys for girls." In addition, the lesson slide suggested that students conduct any other image searches that might demonstrate algorithmic gender bias. By interacting with more examples of algorithmically generated gender biases, students saw how Google's search algorithms might contribute to normalizing specific gender roles.

The students' discussions of the image search results seemed to reflect a clear understanding of algorithmic bias, in line with the lesson's objectives. Some students discussed to what extent the search results mirror reality and how much media-driven perceptions of gender roles influence them. In my observation field notes, I recorded Valerie's assertion regarding the "toys for boys" image search:

> If you look at Lego signs, you think they are for boys. They add black, yellow, and red; because they think those are colors boys would like. But that's not true. I personally love black. Girls like Legos. I have a friend who likes Legos.

This statement sparked a conversation about how much these search results truly represent reality and how much media-constructed views of gender roles influence them. Lyla, for example, observed, "Why are there only men CEOs and only a few women?" Following Lyla's questions, students' comments addressed the normalizing influences of biased media representation. Anthony, for example, commented on the differences he found in one image search: "Working men were carrying stuff – doing hard stuff. The women were mostly using electronics, not doing hard stuff. It's biased that women aren't strong." William added, "The working men were not smiling. The working women were smiling," to which Leah replied, "They're saying that men don't have feelings." This student exchange reflected their knowledge of how media may influence real-world perceptions and contribute to the normalization of specific gender-based roles.

Student perceptions of algorithmically-driven gender biases in the adapted Project Look Sharp (2019) lesson reflected students' attainment of the lesson's objective, "Describe how media perpetuates or challenges positive and/or negative ideas about people and groups." By increasing the number of image search examples, the activity demonstrated that algorithm bias can manifest in disparate areas such as toys, jobs, and normalizing perceptions of gender roles. In this way, students might perceive algorithmic bias as they encounter it in their lives.

Connecting to Students' Prior Experience

In addition to offering numerous high-quality instructional examples, connecting lesson content with students' previous experiences proved valuable throughout the CAL lessons. Indeed, tapping into a learner's existing knowledge should form the basis of almost every teaching methodology (Duffy & Johansen, 1992; Piaget, 1977; Vygotsky, 1978). From the very first lesson, Ms. Sage and I strove to connect to these third and fourth-graders' prior experiences, whether those experiences occurred in previous lessons or lived experiences outside of school.

Finding examples of algorithmic harms that connected to students' prior experiences proved to be a challenge. It seems unlikely, for example, that these students experienced real-world impacts of algorithmic bias, such as biased jail sentencing, unfair credit ratings, and employment discrimination. In the sixth CAL lesson, we focused on having students connect algorithmic bias to possible real-world consequences, in part, through a video entitled "Biases are being baked into artificial intelligence" (Axios, 2019). The tone and vocabulary of this two-and-a-half-minute video suggested that it was not intended for younger elementary students but addressed our objectives for this lesson. The video showed how biased algorithms "could amplify injustice and inequity." It included specific examples of the real-world impacts of algorithmic bias affecting areas such as creditworthiness, employment, no-fly lists, and automated jail sentencing guidelines.

As many of these examples may not have connected with the students' prior experience, I included a prompt in the lesson six slides for Ms. Sage to narrow this discussion to focus on how biased algorithms may affect employment. The lesson included a review of the story about

Amazon's hiring algorithm that demonstrated bias against hiring women (Dastin, 2018). In addition, this sixth lesson also included a three-minute summary (Moss Center, 2021) of the documentary *Coded Bias* (Kantayya & Buolamwini, 2021). This documentary film highlights the experiences of MIT researcher Joy Buolamwini, who discovered that widely used facial recognition models worked poorly on Black people, especially Black women. This video was integral to our instructional goals as the video provided a potentially relatable example of the real-world impact of algorithmic bias caused by incomplete and biased training data. The brief trailer to *Coded Bias* (Moss Center, 2021) included Dr. Buolamwini describing her findings that the training data for these facial recognition AI algorithms were trained mostly on White and Asian males.

By limiting the examples of algorithmic harms to Buolamwini's experience with facial recognition bias and the Amazon hiring example, students seemed to demonstrate knowledge of the impacts of algorithmic bias. Students, in fact, connected Buolamwini's story to flawed AI training data three weeks after lesson six. In response to the "What did you learn" question for the final project video, Marco recalled, "I learned about the college girl. [Her program] didn't work because there were a lot of White people in the training data." Marco's statement illustrates how the connection between computer science and real-world examples can be understood by elementary school students. His grasp of Joy Buolamwini's story underscores the importance of presenting complicated topics, like racial bias in AI, in an accessible manner.

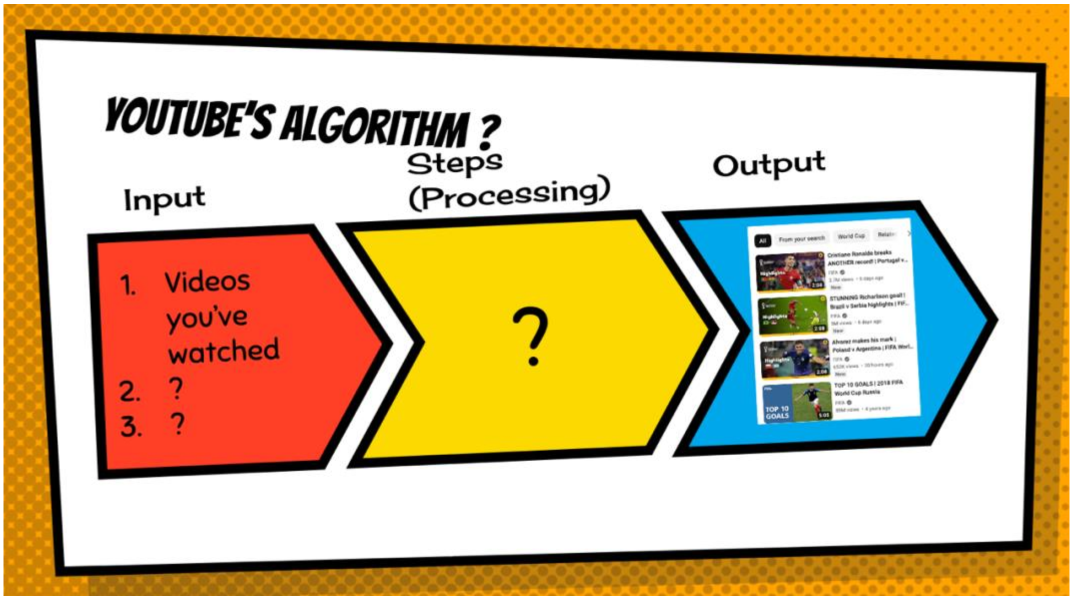
In another effort to connect with what we assumed to be students' prior experiences, I modified some of the lesson materials to be more familiar. In the very first lesson, for example, we introduced media literacy using the previously-mentioned Branding Alphabet lesson (McLaren, 2002). For this activity, I modified some of the logos within the Branding Alphabet so that they were more likely to be identified by third and fourth-grade students. For example, I replaced the Lysol logo with Lego, the Pinterest logo with Pez (candy), and substituted the Dawn dish soap logo with the Disney logo. In sum, I changed 14 of the 26 logos so that younger students might better connect with this activity.

Students in both groups, indeed, seemed extremely engaged, excited, and curious during this activity. My observation field notes illustrate how some student responses reflected the lesson's purpose. Lara remarked, for instance, "We always go to the Internet, but we don't see flowers that much." Building on that comment, Cyrus noted, "We are more interested in the internet than the flowers." The activity not only engaged the students but set the stage for connecting this "digital literacy" curriculum to their real-world experiences.

In addition to connecting with students' lived experiences, we also adapted some outside content to connect with prior CAL lessons. As mentioned earlier, computer science comprises an integral aspect of CAL. In lesson three, for instance, we wanted students to apply their understanding of computer algorithms and connect to their experiences with the recommendation features of YouTube. For this part of the lesson, I modified a lesson three slide by altering an EAICMSS representation of algorithms to include images and inputs within YouTube (Figure 5). For inputs, I provided scaffolding: "Videos you've watched," which prompted students to list other inputs that YouTube uses for recommendations. For the output, I used an image depicting a playlist of soccer videos.

Figure 5

Adapted slide from Payne and Breazeal's (2019) "Introduction to Algorithms" Lesson



During lesson three, after going through the slide comparing the peanut butter and jelly sandwich algorithm with YouTube's, the teacher led a discussion based on the following prompts:

1. How is your PB & J algorithm like YouTube's recommendation algorithm?
2. What bias(es) may be present in your algorithm?
3. What bias(es) may be present in YouTube's algorithm?

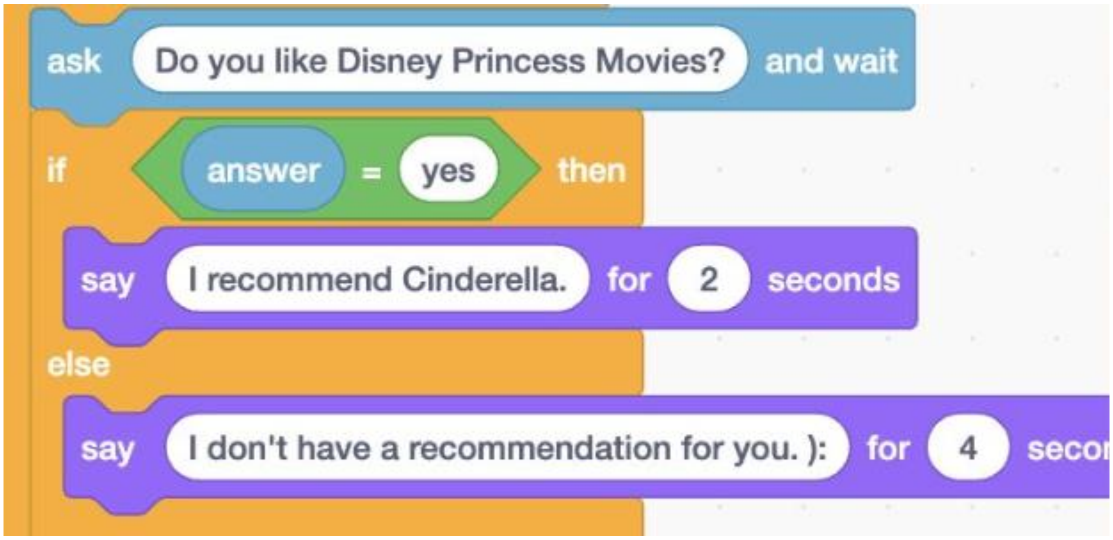
My classroom observation notes indicate that students expressed simple yet concrete connections between the new information about the three-step model of algorithms and their own experiences as YouTube consumers. In response to, "How is your PB&J sandwich like YouTube's algorithms?" Caleb replied, "They both have input, processing, and output." While anyone who uses YouTube likely knows that video recommendations are based on searches and previously viewed videos, this activity facilitated the connection between students' lived experiences and the three-step model of algorithms.

Simplifying Concepts and Vocabulary, Especially Computer Science

As students likely had little to no experience with computer science concepts, student comprehension of computer science principles presented an ongoing challenge. If these third and fourth graders struggled with computer science concepts and vocabulary, they would likely feel frustrated with and disengaged from the CAL lessons. To address this concern, I eliminated or modified some of the computer science content and vocabulary. Computer science encompasses an essential element of CAL. Addressing the second conceptual understanding of CML, "Each medium has its own language with specific grammar and semantics" (Kellner & Share, 2019, p. 8), computer science establishes the grammar of algorithms. Although we did not engage students with hands-on coding activities, a slide from lesson three showed an example of some block-based code to demonstrate computational logic and to offer a creator's perspective on algorithm-driven recommendations (Figure 6).

Figure 6

Scratch Recommendation Engine Code for Student Remixing. Adapted from Boomen, 2018



For this code block, I recreated a simple recommendation engine found in the coding tool known as Scratch. I found Recommendation Engine Starter Code (Boomen, 2018) on the Scratch website. As the name indicates, this is a simple program that asks the user one or two questions and then outputs one of ten movie titles or returns, “I don’t have a recommendation for you.” The original starter code contained 26 blocks of code and multiple levels of choices. In this final segment of lesson three, I leveraged this idea. I created a simplified version of this recommender program that contained only five coding blocks, filling it with the example with only one question and one recommendation. By adapting this Scratch “starter code” to show only one IF/THEM/ELSE (conditional) statement, we hoped to illustrate how algorithms form the building blocks of recommendation engines, such as YouTube’s.

Besides teaching students about block-based coding and recommendation engines, my planning notes indicate we intended to help students understand the program’s limitations and think about how they could improve a recommendation engine. Based on my observations and conversations with Ms. Sage, we observed no evidence that students attained those intended goals.

Aside from computer science, Ms. Sage and I were focused on not overwhelming students with excessive content or too much new vocabulary. The first of the CAL lessons introduced students to media literacy and included a viewing of the Introduction to Digital Media Literacy video from Media Smarts (2018). Some of the video's vocabulary and syntactic complexity, however, seemed too elevated for third and fourth-grade students. The video narration included, "Media are constructions. Media are created largely for social, political, or commercial purposes." I adapted the prompts on the lesson one slides to communicate the essence of those ideas while simplifying some of the video's language by substituting the student discussion prompts: (a) Who made it? (b) How does it work? (c) How do they make money? (The "they" in these prompts refers to those who created the content and the institutions that distribute them.)

In addition, the video also defined media literacy for students as "the ability to access, analyze, evaluate, and produce it." We did not attempt to reinforce this definition. In an effort to prioritize our goals and reduce students' cognitive load, Ms. Sage and I spared the children from many possible definitions, such as media literacy, algorithmic literacy, etc. In fact, we described these lessons to students as "digital literacy."

I also simplified the second lesson of the nine-lesson sequence. Building upon the first week's focus on media bias, one of lesson two's objectives tasked students to consider how YouTube recommends specific videos. I adapted this activity from Project Look Sharp's lesson entitled "YouTube Recommendations: Who's Steering Your View?" (2019). This lesson's activities are intended for high school students and adults. Tasks within the Project Look Sharp lesson include reading an editorial from the *New York Times* and an article from *Wired* magazine. These sources are written beyond the reading level of most third and fourth-graders.

Additionally, the Project Look Sharp lesson plan included twelve prompts separated into three categories. For the lesson two slides, I adapted three of the twelve prompts based on our instructional goals and time constraints. One of Project Look Sharp's prompts, "What questions should you ask when following Internet recommendations?" seemed too open-ended for students with less prior knowledge than the original lesson's intended audience. Instead, after students searched YouTube using the words "soccer" and "home cleaning tips," the lesson two slides included the prompt, "Why do you think you were shown that ad [that accompanied the video]?"

The Project Look Sharp lesson also included the prompt, "What are some strengths and weaknesses of YouTube recommendations?" To make this prompt less open-ended, I changed this question to "What do the companies assume about the audience of this video?" Also, because the lesson focused on introducing students to algorithmic bias, the lesson two slides included "What stereotypes may be present in this recommender?" and "What is presented as 'normal?'" With these two prompts, I strove not only to simplify the original content but to guide students to our specific lesson objectives, "Identify algorithmic biases in search results," "Evaluate potential biases in a recommender system," and "Describe how media perpetuates or challenges positive and/or negative ideas about people and groups."

Adapting existing activities and ideas intended for older students supported many of our goals and objectives. By condensing content, changing the number of examples, connecting to third-and fourth-grade students' prior experience, and simplifying concepts and vocabulary, we shaped the CAL lessons to better fit the needs of the students. I modified existing instructional activities, originally developed for older students, to address specific educational objectives for our third and fourth-grade students. I condensed some content more suited to time limitations and third and fourth-graders' comprehension abilities. When changing the number of examples, I sought to strike a balance between adequate information and avoiding cognitive overload. In addition, by connecting to students' prior knowledge and experiences, I looked to enhance comprehension and relevance. Lastly, I simplified the language and concepts, endeavoring to make the CAL content age-appropriate and readily understandable. As a result of these modifications, the CAL lessons may have been more effective and tailored to our students.

Finding #2: The Efficacy of Instructional Examples

Tailoring content to students' needs included using specific instructional examples aimed at helping students link the new information to their existing knowledge and personal experiences. We incorporated examples into the lessons to serve multiple purposes: encourage students to make connections with their pre-existing knowledge and personal experiences, provide context, help students to visualize complex ideas, and create opportunities for students to analyze and evaluate the implications of these complex ideas, such as algorithms, training data, and the societal impacts of algorithmic bias. For these nine CAL lessons, instructional examples, at times, helped students understand some of these new concepts, as demonstrated by their classroom discussions and the final project content.

Some Examples Supported Student Learning

The data from my classroom observation field notes and teacher debriefs suggested that incorporating examples from students' personal experiences enhanced their understanding of the lesson objectives. The Council Circle session, conducted with Room 2 students on the day before lesson seven, provided students the opportunity to connect CAL content with their lived experiences. Ms. Sage introduced the Council Circle session by asking students to consider their own media interactions.

> I invite you to think about everything we learned in our digital literacy lessons. I want you to think about your daily life. Have you seen or experienced anything that connects to our lessons

At first, students were silent. Ms. Sage then attempted to equate algorithmic recommendations with the categories found in a clothing store.

> So, when I was little, my mom would always get me clothes in the same store. One time, I really, really wanted a jacket that was the section for niños (boys). And my mom said, "That one is not for niñas. It's for niños. I wondered why I couldn't have that jacket. So, she ended up buying the jacket and I was so happy. But now that I'm older, that's making me think, "Why do stores still sell their clothes by niños and niñas?" And that also makes me think, "Who decides that? Who decides what are we supposed to wear or what we are supposed to watch?

In this example, Ms. Sage strove to connect algorithmic recommendations to clothing store categories by questioning their inherent assumptions. It highlighted how both systems make decisions about what people should want based on assumed characteristics or identities. As no students responded, she then asked the class, "Do you notice that in Netflix that you have to choose the user? Why?" I then observed students sharing their experiences with recommendation engines on Netflix, Hulu, etc. Serena described how when her cousin watched shows using her Netflix profile, the recommended shows changed to fit her cousin's preferences, which differed from hers. Other students were then eager to share similar stories about personalized Netflix recommendations. Callie added, "I actually use my mom's account on Netflix because I like murder shows. My dad's account is more political shows." Ms. Sage purposefully encouraged students to discuss their personal experiences with how recommendations they receive from Netflix and other platforms—affect their daily lives. By doing this, she successfully bridged their real-life experiences to the course learning objective, "Evaluate potential biases in a recommender system."

Later in the Council Circle session, Mario demonstrated a clear understanding of the potential impacts of algorithmically-driven recommendations: "Sometimes Netflix shows you … They might want to not [have you] watch the same thing, which is what I like to watch." Here, Mario describes how Netflix's AI-driven recommendations do not always align with his viewing preferences. Generally, when students created their own instances of how algorithm-based media doesn't meet their preferences, they appeared to gain a better understanding of how the results produced by algorithms are driven by incomplete or incorrect data. As the Council Circle concluded, Ms. Sage asked the group,

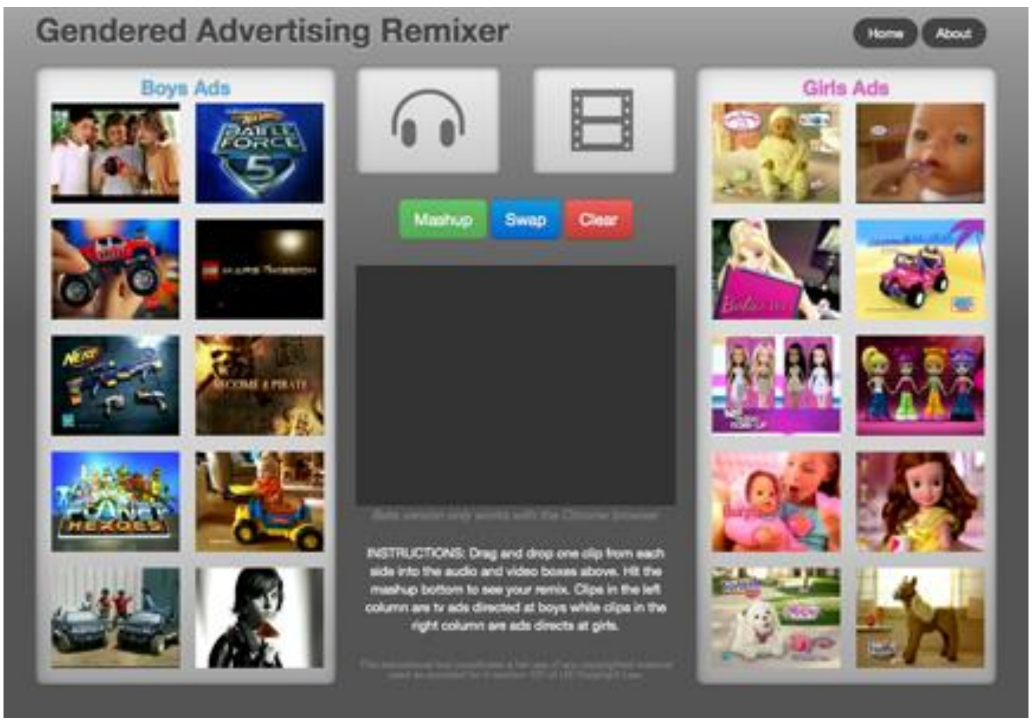
> From all these experiences you've shared, what impact would you say these experiences have in your lives or in your families' lives? What do you think is the impact -- maybe not today, but in a few years or in a few months?

Marco replied, "Well, maybe if someone watches a bunch of biased things all their life, maybe they might be biased." From this comment, it was not clear whether Marco was referring to biased content or biased recommendations. In either case, this statement reflects knowledge of the potential personal impacts of biased media. After complimenting Marco on his observation, Ms. Sage asked the class, "How are those experiences shaping us?" Serena replied. "I think that maybe when you're older, you'll think girls should watch this and boys should watch that." This statement reflects this student's awareness of the tremendous impact of media on shaping personal identities, including gender-normative behaviors. In sum, the opportunity for students to generate examples from their lives outside of school led to relevant discussions connecting algorithmic outputs to their potential real-world impacts.

Other examples from students' personal experiences seemed to help them connect to CAL content. During the first lesson, students interacted with television advertisements to illustrate media bias, particularly concerning the targeting and representation of normalized gender roles. In the first CAL lesson, for example, students explored media gender bias using the online tool Gender Advertising Remixer (Figure 7, McIntosh, 2011). This website allows one to re-combine the visuals from video ads directed at boys with the audio from ads directed at girls, and vice-versa. Students interacted with these examples by creating mash-ups intended to provide users with insight into gender bias in advertising.

Figure 7

Gender Advertising Remixer



After the gender remixing activity, students gathered on the rug to engage in a teacher-led discussion based on these prompts from the lesson one slides:

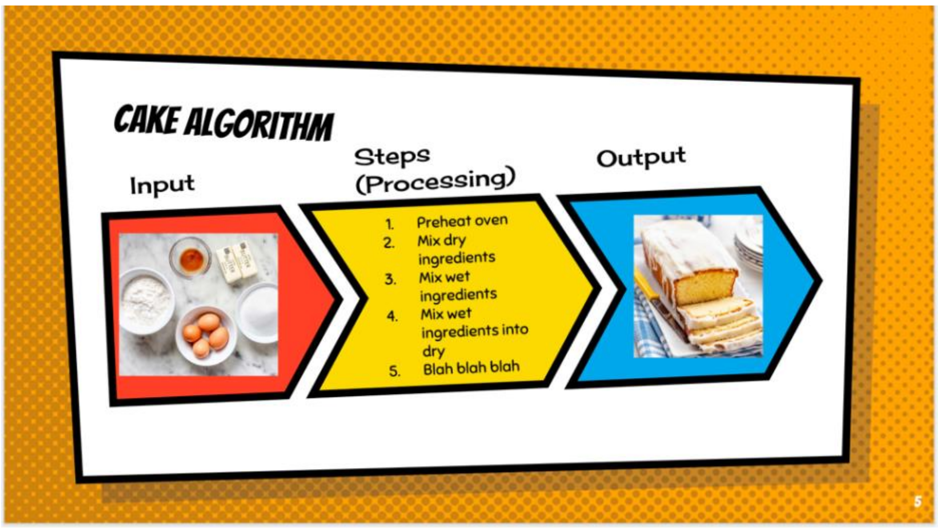
1. Can you think of examples of gender-targeted advertising?
2. How do these ads demonstrate bias or stereotyping?

My classroom observation field notes suggest the questions connected with some students. A student named Cassandra, for instance, replied that the remixed ads showed "skeletons and murder for boys and unicorns and sparkle and princesses for girls." This comment seemed to resonate with Cassandra's classmates, some of whom shared more examples and attributes of ads targeted at boys and ads targeted at girls. The student conversation then extended to real-world contexts. One student remarked that the ads were "sexist because some girls might like pirates and some boys might like pink stuff." The student responses seemed to suggest that the Gender Remixer examples supported one of the lesson's objectives: "Recognize and analyze how advertisements demonstrate bias or stereotyping."

As the lessons progressed from media bias to algorithmic media bias, I incorporated analogies to help students understand this complex topic. For students to understand algorithmic bias, they first needed some general computer science knowledge. The third CAL lesson, "What is an Algorithm?" contained two primary objectives: (a) Students will describe the components of an algorithm (input, processing, and output), and (b) Students will describe how incomplete or "bad" inputs can lead to poor outputs. As students likely had no computer science experience, we used an example comparing the making of a cake with the components of a digital algorithm (Figure 8, Payne & Breazeal, 2019). In this example, the cake's ingredients represented the input, the steps for making the cake represented the processing, and the finished cake represented the output. Beyond the lower-level description of digital algorithms, this extended metaphor allowed the teacher to make an immediate connection to how just as poor cake ingredients (input) would lead to a lesser cake (output), poor algorithmic input leads to less desirable outputs.

Figure 8

Slide from CAL Lesson #3, Payne & Breazeal (2019)



In the next phase of lesson three, students were tasked to design what they considered to be the "best" PB&J sandwich. The PB&J example extended the cake-making analogy. Just as one can customize sandwiches to target specific audiences, so can computer algorithms. To transition from the sandwich-making algorithm to algorithmic targeting, the lesson three instructions tasked students to consider how different creators and audiences might prefer different sandwiches. Ms. Sage asked the students, "Would your algorithm be different if the sandwich was made by a doctor?" Rebecca replied that a doctor would "want you to put the lettuce, cucumbers, and Brussels sprouts…because the doctor wants you to eat more vegetables." Connecting to lesson two's focus on audience targeting, this student comment reflects a cursory understanding of how different inputs produce outputs targeted for specific audiences. In the post-lesson debrief, Ms. Sage remarked, “I think [the lessons] went well. The [students] got the main idea for the parts of an algorithm.” Although we used no formal assessments, the teacher and researcher’s perceptions guided our views as to the attainment of the objectives of each lesson. However, throughout the CAL lessons, I observed students describing and applying the three-step model of algorithms.

Some Examples Distracted Students or Did Not Connect to Prior Knowledge.

Despite the positive impacts of these instructional examples, observation data and the post-lesson debriefs suggest that some instructional examples did not connect to any student experience or, at times, distracted the students from the tasks intended to address the lesson’s learning objectives. In the first CAL lesson, which focused on gender bias in popular media, students watched two commercials for a product called Real Bugs—a children’s toy comprising vibrating plastic insects. The students first viewed a 1997 advertisement featuring boys using the toy bugs to scare girls, followed by a more recent version depicting both boys and girls enjoying the toy insects and using them to frighten adults. The lesson two slides included these two questions: (a) How did the ads change over time? and (b) Why do you think the media creators changed it?

In both groups, students clearly summarized the differences between the two commercials. Amanda said, “The first commercial showed mostly girls being scared. The second commercial had no goo, and boys and girls were scared.” This student response addressed the first question, but no students addressed the question about the creators’ rationale for changing the second commercial. When the teacher asked, “Why do you think we are learning this?” no students in either group responded, except for a boy named Todd, who quipped, “I just want to watch some more cool commercials.” Other students concurred enthusiastically. In fact, many students talked about what they liked about the commercials, as opposed to our intended focus on the commercial representations of gender roles.

Neither Ms. Sage nor I observed any student actions or comments that suggested they understood the creators' intention to lessen gender while still trying to sell the toys. Although the advertisement comparison may have set the stage for future lessons related to media gender bias, the students did not demonstrate higher-level connections to the intended learning objectives. In several activities throughout the lessons, students appeared so excited by the less-traditional school content that they did not focus on the assigned tasks aligned with the lessons' objectives.

Students seemed similarly distracted during a lesson two YouTube activity. Students were tasked with comparing the advertisements displayed before soccer highlights on YouTube with the commercials shown before videos featuring home cleaning ideas. As I walked around the classroom, I documented that most students were watching soccer highlights and talking about soccer with their classmates. This class session took place during the 2022 World Cup. Students either skipped or ignored the advertisements. In fact, most of the students appeared so distracted by the soccer highlights that they completely ignored the assigned task of comparing advertisements. In the post-lesson debrief, Ms. Sage and I discussed how using commercial media could distract students in a classroom setting, particularly when the students may not perceive connections to more traditional school subjects.

> **Me**: Some students were not focusing on what you're teaching. They are focusing on the soccer itself, or whatever it is.
>
> **Teacher**: It's exciting for them because some of them are not even allowed to use YouTube at home. So, we should be more strategic about that.

Ms. Sage and I acknowledged the challenge in harnessing student excitement to ensure the educational objectives are not lost in their enthusiasm. In ensuing planning sessions, Ms.

Sage and I weighed the benefits of including certain instructional examples with their potential to detract from the lessons' goals and objectives.

The Sequencing of Examples Influenced the CAL Lessons' Effectiveness.

In addition to avoiding potentially distracting examples for students, we found that the placement of an instructional example affected students' learning. In the third week of the CAL lessons, we introduced students to the three-step model of algorithms. In this lesson, students designed their version of the "best" PB&J sandwich using pencil and paper. In the collaborative planning session prior to this lesson, Ms. Sage and I disagreed on whether students should see the slide showing various images of PB&J sandwiches (Figure 9) as a model before beginning work on their own sandwich algorithms. Based on my years of teaching, I felt that examples may reduce student creativity as students sometimes overly emulate the examples, reducing their creativity. Ms. Sage felt that students would greatly benefit from the pictorial examples. My field notes indicate that for the first class session, Ms. Sage followed my advice from the planning session and did not show students the various sandwich images before they began work designing their sandwiches. In the second session, however, she showed the image of the various sandwiches before students began working on their own PB&J algorithms.

Figure 9

Slide from "Algorithms as Opinions," Payne & Breazeal, 2019

In the post-lesson reflection, Ms. Sage commented that the sandwich algorithms created by the second group exhibited more depth and creativity than those created by the first group: "We showed the picture of the different types of peanut butter sandwiches before. I think that opened a wider range of possibilities for [students] to understand that we are unique and have differences." So not only is the relevance of examples support student learning but also where they are placed in the lesson. In this case, the placement of the example as a model for students helped students understand how algorithms can be targeted to specific audiences based on the creator's intentions.

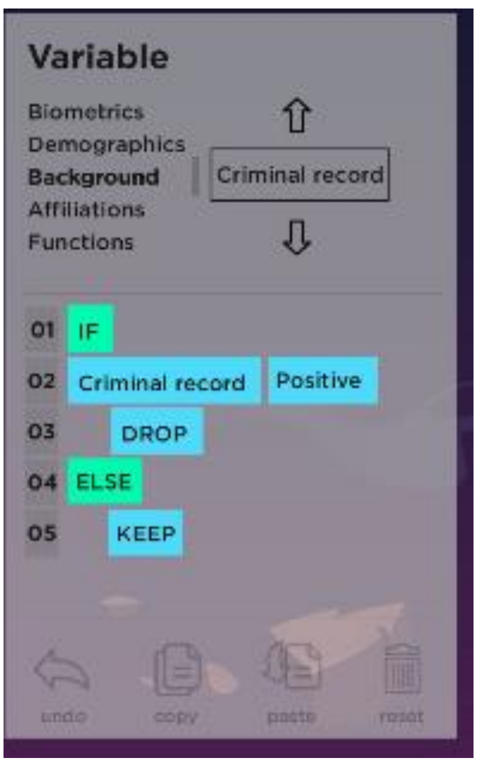
Less Effective Examples

Instructional examples should not only be sequenced correctly but should connect with students' prior experiences. On the lesson four slides, I included an example that failed to support its intended purpose of illustrating possible real-world consequences of a computer program. In this scenario, based on Aleman's (2021) Screening Bot activity, students were asked to imagine that they were starting a new planet, and their job was to let in only "good" people and prevent "bad" people from coming to their new planet. Ms. Sage projected the simple block-based code (Figure 10). The code consisted of a simple IF/THEN statement: "IF an applicant has a criminal record, THEN they are prevented from coming to that planet."

This activity was intended to spark a discussion questioning the algorithm's effectiveness in achieving its goals for the planet. Despite the algorithm's apparent objectivity, other factors may influence real-world outcomes.

Figure 10

Aleman's Screening Bot Activity (2021)



Observation notes indicated, however, that student comments in this discussion did not address the potential impacts of the algorithm but their own judgments on whether a person should be allowed to join this planet. Maria commented, “They have to be nice.” Omar added, “They should be good at their jobs.” Other student responses included “Over the age of 14,” “IQ over 90,” “How strong you are, and “You have to play one or more sports.” At the end of the session, Valerie pointed out, “It’s too hard of an answer to ask if you are a good person.” This comment could have illustrated the real-world challenges of algorithmic decision-making, but no one made the connections between the algorithm and human subjectivity.

The prompts connected to this example may have lacked the specificity to have students connect algorithms with consequential decisions, especially since students lacked experience in computer science. In the post-lesson debrief, Ms. Sage reflected on the need for examples to include more specific connections to the intended outcomes:

> I feel like I needed to find some better, stronger examples in the group activity for the colony and the planet, just in order to take them into the direction that we were hoping for. I feel like the question was too open, so they were just focusing on the fun idea of creating a new planet. So, there could be more work around there.

While I perceived that the Screening Bot example (Aleman, 2021) aligned with the CAL precepts, my observation notes and post-lesson debrief suggest the activity seemed ineffective in achieving our intended goals. Ms. Sage stated, “I think [we need more] specific examples because the deeper we are going, the more abstract this is becoming. So, I want to make sure that we don’t lose students.” Here, we see that about halfway through the nine lessons, the Screening Bot example revealed two challenges to achieving our objectives. First, the students lacked the computer science experience to make sense of the IF/THEN/ELSE statement presented in the Screening Bot example. Second, in the post-lesson debrief/planning session, Ms. Sage and I discussed that students should have more exposure and explorations to algorithmic bias and its potential effects.

As described in more detail later in this chapter, Ms. Sage and I felt the need to reinforce the concept of bias for the students. Lesson four began with a three-minute video entitled “What is Bias? - Intro for Young Kids” **(**Winter Bloomers, 2021). This video described an example of bias where students had to vote on the best student science presentation at school. In the video, one student demonstrated bias by voting for her friend, although she felt her friend’s presentation was not the best one. After the video, Ms. Sage asked students for other examples of bias that they had experienced or seen. No students replied.

Based on a lack of student response during the discussion of the video, Field notes from my observation of the lesson show Ms. Sage providing another example of bias. She offered a similar example of a student choosing their friends to be on their team for a sport such as kickball. The students then shared responses not related to the topic of bias, but about choosing teams for playground games. Marvin, for example, commented, “It feels bad being the last one picked.” Amanda added, “When you choose a partner in line, you choose your friend. But you might want to choose someone else instead.” Whether it was the nature of the example itself or the instruction surrounding the example, the case of voting for one’s friend instead of the best performer did not seem to enhance students’ understanding of bias.

Throughout the CAL lesson design, we employed specific instructional examples aimed at bridging new information with students’ existing knowledge and personal experiences. These examples served diverse purposes, including bridging new ideas with prior knowledge, supplying context, clarifying complex concepts, and fostering analysis as well as evaluation of topics like algorithms, training data, and algorithmic bias. For these nine CAL lessons, certain examples effectively aided students in grasping these new concepts, as evidenced by their classroom discussions and final project content. However, not all examples were equally successful in fulfilling their intended purposes.

Finding #3: Revisiting and Prioritizing Content

The less effective instructional examples, in part, represented the need to review, adjust, and sometimes omit content and activities throughout the CAL lessons. During our post-lesson debriefs, semi-structured interviews, and planning sessions, Ms. Sage and I discussed which areas might need to be reviewed based on students' inaccurate or incomplete responses to lesson prompts. The week-to-week planning allowed us to make lesson adjustments based on our perceptions of how to meet the lesson's objectives. In our collaborative planning sessions, for example, we agreed that students should not explore the concept of algorithmic bias until they possessed a strong understanding of the concept of bias in general. Revisiting content in upcoming lessons compelled us to prioritize and decide which previously planned activities we should omit to allocate time for revisiting foundational concepts.

Bias as a Fundamental Concept

Based on our observations of student replies, or lack thereof, the concept of bias seemed elusive to many students. In the lesson three activity, which introduced the concept of algorithmic bias, students examined which advertisements YouTube delivered based on video searches for "soccer" and "home cleaning tips." The lesson two slides included the question, "What kind of biases does YouTube have?" After no students responded, Ms. Sage described a personal example of targeted online advertising. She talked about searching for tea online and then receiving many tea ads on other web pages. In an effort to show potential flaws in targeted advertising, field notes from my observation of lesson indicated that she asked students, "But what if I was buying the tea for my mother?" Martin replied, "If you gave [the website] your email, you will receive more emails from [that company]." While the student's reply reflected a reality of online marketing, it did not address the concept of algorithmic bias.

In the post-lesson reflection, Ms. Sage expressed her desire for a deeper exploration of issues surrounding algorithmic bias.

> I would like to have more time to explore the concepts of stereotypes and bias by themselves so then [students] can bring that knowledge and create those connections here with the algorithm because I think we were only able to touch the surface today.

I concurred with the teacher's thoughts. In my designer reflection journal, I wrote about this lesson, "Some [students] may have gotten bias, but there wasn't enough time for more to 'get' bias and not enough time for students to make connections between algorithms and algorithmic bias."

Based on these concerns, Ms. Sage and I planned a review of bias. Toward this end, I added the video "What is Bias? - Intro for Young Kids" **(**Winter Bloomers, 2021) to the beginning of lesson four. We followed the video and whole-class discussion with the Google image search activity, where students searched images of working men and working women. We planned this lesson sequence so students would connect the concept of bias with possible gender biases present in Google's image search algorithms. Here, in the lesson four debrief, Ms. Sage described student progress in their understanding of bias while reinforcing that a greater number of relevant examples would further support students' understanding.

> I think [students] finally had the opportunity to delve deeper into the concept of bias. I think they were exploring examples that really related to them, so it was easier for them to understand it. The video was helpful. I want to make sure they have access to all the other different types of biases, right? Because they were focusing on the best friend [example from the video], and so getting out of that would be a process.

Ms. Sage highlighted how the relatable examples in the video facilitated students' learning and that additional relatable examples were still needed. In my lesson four reflection, I wrote, "The review of bias was helpful and necessary to make connections to algorithmic image search gender bias activity."

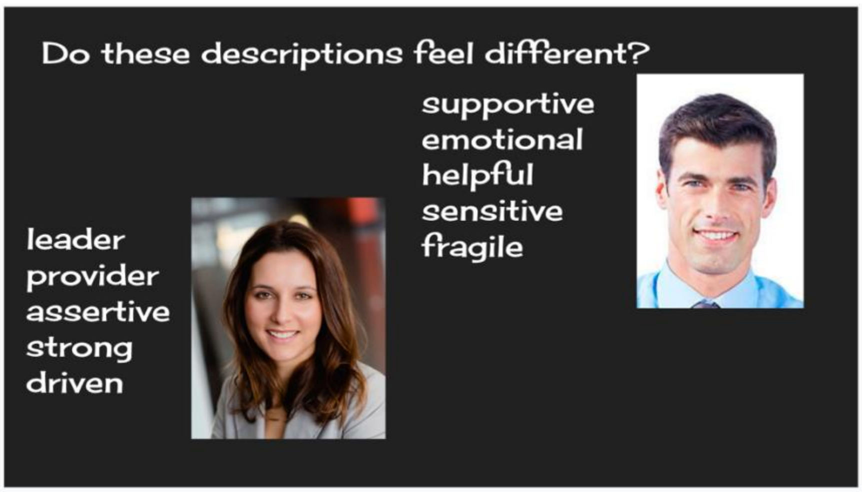
My lesson six observation notes revealed another example that reinforced the need for us to revisit algorithmic bias. During the lesson six discussion, students talked about why there were fewer pictures of Black people during the image searches for "CEO." One student replied, "I don't think it's [Google's] fault if they don't have pictures of Black people. Not as many Black people are doing important business. Maybe they don't have as many photos of Black people."

Ms. Sage paused to think about her reply to the student and to the group. She asked, "Where did you get your information?" After a seemingly uncomfortable pause, a different student remarked, "If it were me, I'd put 50/50," thus relieving the moment's tension. This interaction illustrates potential challenges inherent in having students connect their more limited life experiences with algorithmic bias.

Ms. Sage and I acknowledged student progress regarding the lessons' objectives regarding algorithmic bias. Based on our mutual classroom observations, post-lesson discussions, and planning sessions, we believed that students still lacked enough understanding of bias in general to conceptualize algorithmic bias and its potential consequences. To this end, for lesson six, I borrowed and modified an activity within a TEDx Talk video entitled, *Are You Biased? I Am!* (Pressner, 2017). In this video, the speaker engaged the audience in examining two images. One image showed a young man with the words "leader," "provider," "assertive," "strong," and "driven" next to that image. On the same slide was an image of a young woman next to the words "supportive," "emotional," "helpful," "sensitive," and "fragile." After reviewing those descriptors and images, the speaker showed the same images with the descriptors reversed (Figure 11). The perceived incongruity of the descriptors and images was intended to highlight our own biases if we, for example, find the terms “emotional,” “sensitive,” and “fragile” unfitting for a young man. For this sixth lesson, we included this activity to provide another concrete, perhaps more personal, example of potential gender biases.

Figure 11

Lesson Six Slide adapted from Karen Pressner’s TEDx Talk (2017)



Field notes from observation data field notes suggested that this activity stimulated the intended whole-group discussion regarding gender biases. Callie declared, “It’s unfair. Some girls can be leaders.” Another student remarked, “Not all girls are fragile.” In an unexpected development, another student pointed out that both images depicted White people, perhaps revealing my implicit biases. In our post-lesson reflections, Ms. Sage and I felt that this activity helped to reinforce the idea of bias, particularly gender bias. Again, in the post-lesson six debrief, Ms. Sage acknowledged progress in students’ understanding of bias but expressed concerns regarding finding suitable examples to help students internalize the real-world consequences of those biases.

> I think [students] are finally grasping the main concept of bias. The consequences - I think it's a little bit big. I think some of them are more exposed to real-life problems because they have different situations, economic situations at home, but some of them are so out of touch there that they I can see how it's hard for them to go there because this is something that's very new.

Ms. Sage also highlighted that diverse student backgrounds increase the challenge of finding examples that might connect to students' prior experiences. Here again, the quality and context of the instructional examples prove to play an integral piece in the perceived effectiveness of these lessons.

The Importance of Understanding Training Data

For students to understand how limited training data can lead to bias in software, it was important for them to comprehend the role of training data in AI systems. Based on our collaborative planning meetings, Ms. Sage and I felt that for students to grasp the potential consequences of biased algorithms, they must also examine how flawed training data, resulting from incomplete or biased inputs, can influence AI models' decision-making processes. To address this principle of "garbage in, garbage out," we reviewed the QuickDraw activity from lesson five.

As part of the fifth lesson, students engaged with the QuickDraw activity on their iPads. The students were very engaged and seemed to enjoy QuickDraw as a game where having it recognize their drawings counted as a "win." In lesson five, I observed that students didn't have time to connect the specific activity to the ideas of how the quantity and quality of training data affected the program's effectiveness at guessing the sketches. In the lesson debrief after the fifth lesson, I admitted to Ms. Sage,

> This is my fault for not having them pay attention to the wrong guesses. When you're trying to draw and you draw a sun and [QuickDraw] says, "I see a circle." "I see a face." --- It's guessing based on its huge collection of shapes and other drawings in the training data. So maybe we should revisit that.

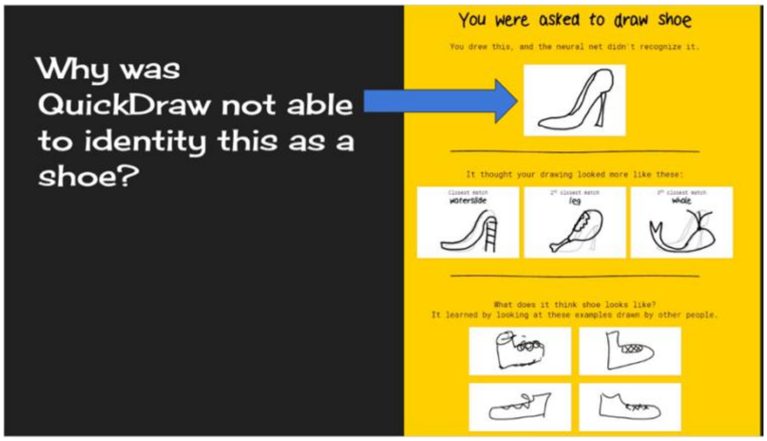
Students' incorrect guesses in QuickDraw were supposed to provide insight into the training data and the ways that incomplete or flawed data leads to flawed outputs. In lesson five, however, the session time ended before students could make that connection. In my reflective journal after the fifth lesson, I wrote,

> Seemed rushed again. Every item is hit and then left. Almost every aspect of the lesson would have benefitted from more time. I am concerned students are not seeing QuickDraw's wrong guesses, which should be an important part of the lesson.

Based on these data, Ms. Sage and I planned to have students spend more purposeful time with QuickDraw, which connected to the objective of identifying how incomplete training data impacts the program's output and results. To help us focus students' time with this AI tool during lesson six, I incorporated pieces of MIT's RAISE curriculum (2021). When we revisited the Google QuickDraw activity in lesson six, I included a slide that illustrated how at one time, QuickDraw could not identify a drawing of a high-heeled shoe as a shoe (Figure 12). Ms. Sage then showed students an image of some of the 115,749 samples of shoes in the program's training data. The image contained only a few high-heeled shoes in the data among the hundreds of examples viewed.

Figure 12

Slide From Lesson Six Incorporating a Screenshot from Google Quickdraw



When Ms. Sage asked why the AI could not properly categorize the high-heeled shoe, Callie replied, “So many people never thought about drawing the high heel.” Carlos added, “It’s shaped like a slide.” These observational data reflect the knowledge of how image recognition AI compares its training data to the user input. During the second session of lesson six, Ms. Sage and the students had the following interaction:

> **Mario**: It thinks a shoe is flat.
> **Ms. Sage**: Why?
> **Mario**: It’s assuming.
> **Ms. Sage:** Why is it assuming?
> **Amanda**: It only had flat shoes in the data.

In this somewhat more nuanced reflection of student understanding, Amanda described a connection between the training data and the effectiveness of the program. The students’ interactions with and reflections about AI training data yielded some rich responses aligned with the lesson’s objective, “Analyze how limited training data can lead to bias in software.”

Many students addressed this objective in the final projects. In her final project video, for example, Rebecca described how her app, *Emotions Solutions*, would avoid algorithmic bias. This proposed “online therapist” would need to “[listen to people’s problems] lots of times until it works.” She added that to avoid bias, the app’s “Training data need to know the solutions to all feelings.” These comments illustrated Rebecca’s awareness of a cause algorithmic bias, and the need to include comprehensive training data to minimize it.

Prioritizing Lesson Content

Because of the additional time needed to review foundational concepts from lesson to lesson, we were compelled to decide which of the tentatively planned concepts and activities we needed to omit from future lessons. During our collaborative planning sessions, we reviewed the existing activities and weighed the time required to complete the activity as compared to its role in our overall lesson goals.

In addition to reviewing the Google QuickDraw activity to help students better understand the workings of training data. It was our hope that students would connect these examples with the training data flaws in the Google QuickDraw activity where students interacted with powerful, yet sometimes flawed AI based on incomplete training data. During the lesson six debrief, Ms. Sage commented on how pairing of the QuickDraw activity with the *Coded Bias* trailer (Moss Center, 2021) supported students’ connections to algorithmic bias and possible real-world impacts.

> They are making real-world connections. So, I think there’s a lot of progress with that. The Google QuickDraw was powerful to fully understand, plus the *Coded Bias* video to understand the importance of the inputs that we implement. I think this lesson was a turning point where I can see a lot of independence and a deep understanding of what we are trying to achieve.

Based on my observation notes and reflective journal, I concurred that revisiting the QuickDraw activity helped students understand AI training data’s flaws and potential impacts. The connection between students’ interactions with the live data, coupled with a powerful example of real-world consequences of biased training data, may have led to the connections we sought.

Having students understand algorithmic impacts and possible biases proved integral to students completing their final projects. During our planning meetings, Ms. Sage and I also discussed introducing the students' final project as early as possible, providing students with ideas for their proposals for a hypothetical application or robot. We also wanted to give students enough time to consider possible algorithmic biases in those applications. To this end, we introduced the project to the students during lesson five and provided other examples of student-created programs designed to help others. After viewing the example programs, the teacher asked students about potential biases that might exist in the example programs they saw. Because this activity and the other lesson five content consumed so much time, we decided to move the computer science activities to lesson six. Between lessons five and six, however, my designer's journal included the following notes that informed the planning of the next lessons:

- Prioritize Bias
- Torn about following up on AI training data bias vs. Tynker [student coding program]
- Let's devote 30 minutes to Tynker's "Candy Quest" tutorial.
- Idea: Make a video showing the AI for Oceans activity [to save time]
- Idea: Skip the coding, and I can volunteer to support during community time.

Despite our desire to have students interact with algorithms using Tynker or code.org's AI for Oceans activity, we thought it was still vital to prioritize the foundational concept of bias. (In AI for Oceans, students use a simple AI model to differentiate images of marine organisms from trash for the purpose of training an AI to remove trash while protecting sea life.)

In the post-lesson-four debrief, Ms. Sage commented on a student remark that startled her and influenced our decision regarding prioritizing content: "Mario surprised me when he said, 'But I don't understand what you are saying? [about bias].' So that's a message for me as a teacher, saying, "OK, I didn't scaffold enough." The passion and content of Ms. Sage's reaction as she recounted this student's comment led us to revisit bias, even if it meant reducing some computer science components of the lessons. Not until I wrote "skip coding?" in my lesson six design journal did I first consider eliminating the primary hands-on computer science activities that we considered integral to these CAL lessons. In my individual planning for lesson six, my design journal concludes, "Planning is getting harder as time is getting tighter."

Based on Ms. Sage's post-lesson four comments such as, "I feel like [some of the content on bias] was very superficial," we still wanted to review gender bias in the lessons. As mentioned, we included an updated version of a bias-recognition activity from Pressner's (2016) TED Talk. Lesson six included many different topics and activities. This lesson included an introduction to the societal consequences of algorithmic bias, reviewing how training data affects AI outputs, a short video on how bias is "baked into" algorithms (Axios, 2019), and examples of student-created projects.

Because we revisited and provided additional scaffolding for the content about bias, algorithmic bias, and its potential impacts, we eliminated much of the student interaction with computer science. We made this choice, in part, as I observed that for the hands-on QuickDraw activity, most students needed 10 or more minutes of the 45-minute lesson time to get their iPads, find the right iPad application, navigate to the website, and get started on the activity. Students had not used the iPads in class to this point in the school year, so we were concerned that some students would struggle just to begin the subsequent hands-on iPad activities. We speculated that the planned activity, where students remix simple block-based computer code to create their own basic recommendation engine, would encompass almost all of one 45-minute lesson. Another factor contributing to our choice to exclude the hands-on computer science activities was our position that students should also have time to explore the children's coding program (Tynker) before beginning the remixing activity.

As described throughout this dissertation, student interaction with computer science comprises a vital component of CAL. These computer science interactions were integral to lessons' overarching goals as described in lesson objectives and planning documents. Before deciding to eliminate many of the interactive computer science activities, we strove to somehow fit students' interaction with computer science into a lesson. In fact, as late as the planning for lesson five, Ms. Sage and I talked about having the AI for Oceans activity in lesson five and the coding remix activity in Tynker for lesson six.

During the collaborative planning session preceding lesson five, I described how we would incorporate computer science in the following lesson:

> First, Tynker and the project. So that is also may be a good place to revisit the planet discussion because that's based on an IF/THEN statement [students will be using in the remixing activity]. So that's like if they have a prison record, then they're out. So that's a really good example.

Clearly, this code remixing activity would have entailed a more detailed exploration of algorithms than the three-step model presented in prior lessons. Moreover, we intended to reinforce the connection between Aleman's (2021) planetary exclusion algorithm activity and other real-world examples of algorithmic harm. In this pre-lesson five planning session, I stressed the importance of teaching the students about IF/THEN statements (aka "conditionals"). For example, I suggested "unplugged" activities whereby students interact with computer science concepts without using a computer.

> [Using conditional logic] is something we do all the time. IF it's cold, then you wear and jacket, and so on. So, you could play a game where you hold up a card. IF the card is red, THEN put it face up. IF the card is black, THEN put it face down. With IF/THEN statements, you could do anything just so they get the idea of that. That's the piece of

> computer science that – It's got to be small - but that’s really important: the IF/THEN statement. That kind of ties everything together.

Because the computer science concept of conditionals seemed foundational to students’ understanding of algorithms and algorithmic bias, I suggested the benefits of “just talking” about the concepts without having students interact directly with their iPads. I then proceeded to show Ms. Sage the example (Figure 6) and the template I created for the planned student remixing activity.

Despite our desire to include deeper explorations involving student interaction with algorithms, by lesson five of the nine lessons, we acknowledged the time constraints prevented us from addressing all the components for students to describe the effects of algorithmic bias and its societal impacts. In the planning session before lesson five, I proposed a set of goals for the four remaining lessons, reflecting an ambitious plan that provided little time for inquiry learning, reflection, or hands-on activities:

> Lesson five is the Oceans for AI activity and talks more about bias and how algorithms become biased based on training data. Then lesson six is the Tynker and the IF/THEN statements. And then, for lesson seven, we will introduce some more effects of algorithmic bias and have more time for the project. And then for lesson eight, would be more project time. And for those students who are ahead, they could do peer feedback, and those who need more time just to work. Then, hopefully, in lesson nine, we could do some share out. Obviously, we will adjust as we go, but that's an overview.

After this planning meeting, I reflected in my journal, “Although I taught third and fourth graders [more than 10 years ago], I am starting to remember how to teach them again.” I realized that I was attempting to include too much content for these learners in too short a time.

To achieve greater continuity between lessons, I planned lessons five and six simultaneously. In my design journal for lesson five, I wrote about the significant amount of content and activities for the next two lessons and noted the beginning of the end of the planned computer science activities: “Time will be a challenge. Project introduction, two videos, Google

QuickDraw, and project examples. - Thinking about eliminating or reducing the Oceans for AI activity." The realization that we would not have the class time required for these student interactions with algorithms prompted us to reprioritize our objectives and consider how to address our overarching goals within the limited time remaining.

Teacher Lack of Computer Science Experience

Another factor influencing our decision to eliminate many of the hands-on activities with computer science was the teachers' self-described lack of background in this area. It's important to note that at no time did this study seek to evaluate the teacher in any way. Both Ms. Sage and I knew that she lacked experience teaching media literacy and computer science. Throughout the study, however, Ms. Sage mentioned her lack of computer science background as a challenge in implementing these lessons. In the first formal interview, conducted more than a week before the first lesson, Ms. Sage expressed concern about her lack of computer science knowledge:

> Something that is on my mind – It's pretty new to me, and I feel like I don't know enough about the algorithms myself. I fear I might not be able to teach to the point, right? All the conversations that we've been having -- I really appreciate. So, the scaffolding and the steps, and the website that you're preparing will help me prepare for the lessons. I think it's going to be an exciting journey for me. I hope I can transfer that to my students, too, because the truth is that I didn't grow up with technology, but [the students] are growing up with technology, and there are a lot of unknowns. I feel a responsibility to provide a space for them to hopefully become more aware - more than what I am right now.

In this comment, Ms. Sage articulates not only her apprehension regarding her limited computer science experience but also her determination to implement the CAL lessons despite these reservations. Driven by her passion for ensuring students acquire knowledge about algorithms influencing their daily lives, she expressed a willingness to engage in a domain outside of her comfort zone.

During the lesson three debrief, which introduced algorithms, Ms. Sage also commented,

> I need to know the subject matter even more deeply in order for me to probe my students or guide them into a certain direction, and for that, I will need research time to read about everything out there. This is a new topic for me too. I think the students will benefit from the teachers having this time. I feel like I know some of it only. I'm on the surface.

During this post-lesson debrief, Ms. Sage expressed her concern about her lack of computer science knowledge and generalized her concerns for other teachers who might teach CAL in their classrooms.

Part of our planning sessions included talking through CAL, specifically explicit media literacy and computer science concepts. Once again, Ms. Sage expressed a positive attitude toward these lessons, despite lacking confidence in her computer science background. In the midpoint interview, when asked about CAL implementation challenges to this point (between lessons four and five), Ms. Sage expressed:

> Now that I'm in the middle of this project, if I could go back in time, I would love to have more training myself and deeper conversations with you, reading articles together, and reading research so I can be more prepared to translate. At the same time, I feel like since we are just planting the seeds, that's not a big obstacle. But I could see how that could become an obstacle if we continued progressing. I will definitely have to continue learning about [computer science].

Despite her admission that she would appreciate more background knowledge, once again, she expressed confidence in delivering the lessons successfully.

In the formal interview after the final lesson, Ms. Sage enumerated the many things she had more time. Among those, she wished that she had more time for preparation: "[I wish I had more] time for myself, for professional development, all that pre-reading to be able to do the front-loading for my students in a more meaningful way." One can reasonably conclude that some of this professional development would have included increased knowledge of computer science concepts that are so integral to the design and implementation of CAL lessons.

It is also reasonable to assume that a higher level of computer science knowledge might have resulted in better examples for designing and implementing the CAL lessons. The use of effective instructional examples was essential in all aspects of lesson design, including modifying content taken from other sources.

Conclusion

I derived the three major findings from an extensive analysis of all data sources. The first finding described ways that modifying content from outside sources supported the needs of younger learners throughout the CAL lessons. I categorized these modifications into four areas: condensing content for time, adjusting lesson examples, connecting to students' prior experiences, and simplifying concepts and vocabulary. For the second finding, my interpretation of the data emphasized the significance of high-quality, effective student examples and their impact on design decisions, perceived challenges, effective practices, and students' demonstration of CAL objectives. Less effective examples, on the other hand, failed to resonate with students or distracted them from the intended lesson objectives.

In the third finding, my analysis highlighted instances where the co-designers felt compelled to revisit certain content and, subsequently, omit some originally planned content in order to accommodate the necessary revisions. Overall, this conclusion synthesizes the key findings of the case study, shedding light on the importance of effective examples, adapting lesson content, and addressing students' needs to foster skills and knowledge described in the lesson objectives. These insights can guide future research and practice in this evolving field.

CHAPTER 5: DISCUSSION

Media literacy fits everywhere. Therefore, you find it nowhere.
Theresa Redmond (2022)

Digital algorithms, including artificial intelligence (AI), pervade almost every aspect of human existence, making consequential personal, economic, cultural, and social decisions. Many of these algorithmically-driven decisions reinforce existing dominant hierarchies and adversely impact underrepresented groups (Benjamin, 2019; Noble, 2018; O'Neil, 2017; Wu, 2018). Despite the pervasiveness and influence of algorithmically-driven technologies, opportunities for K-12 students to learn about algorithms and their broader implications remain limited (UNICEF, 2020; Wang et al., 2022). This disparity between the need for critical algorithmic literacy and its scarcity underscores the urgent need for more comprehensive and authentic approaches to algorithmic education.

In this context, educators must equip future generations with the knowledge and tools to prepare students for the algorithm-driven world in which they live. The critical algorithmic literacy (CAL) framework seeks to prepare students with the analytical tools to question representations of reality constructed by algorithms. These skills enhance student autonomy and resistance to the normative influences exerted by prevailing power structures.

Chapter Two of this dissertation examined several efforts that combined the practical application of digital algorithms and critical analysis of their societal implications. Some of these contextualized computer science initiatives involved students developing computer programs for authentic purposes (C. Lee et al., 2022) or collecting and analyzing data (Hautea et al., 2017). In other instances, students engaged with AI models to broaden their understanding of AI and its collective impact (DiPaola et al., 2020; I. Lee et al., 2021). The CAL lesson designs draw from and are inspired by these implementations' synthesis of algorithmic awareness and critical perspective. However, none of these endeavors took place during regular school hours or involved elementary school-age students. This inquiry sought to bridge the existing research gap by exploring the implementation of CAL for younger students within the standard school day.

Description of the Study

The study's three research questions sought to address the design (RQ1), challenges (RQ2), and promising practices (RQ3) of a nine-lesson CAL implementation with two grade 3/4 combination classes. Ms. Veronica Sage led the lessons during regular school hours. The CAL lessons integrated concepts from CML and computer science to help students understand computer algorithms, their potential biases, and the possible sociocultural effects of those algorithmic biases. The study offers a first step to the potentially transformative approach of integrating CAL within the regular school day.

In this chapter, I reflect on the study's significance, organized by research questions, and relate them to prior research. I subsequently describe the implications for potential new implementation and research opportunities suggested by the study's findings. I then review the study's limitations and describe how I will disseminate this work. I end with a brief conclusion.

RQ 1: Designing CAL Lessons

The first research question asks, "How do a researcher and teacher co-design critical algorithmic literacy curricula for third and fourth graders for lessons conducted during the school day?" In our roles as co-designers, Ms. Sage and I discovered that one of our biggest design challenges was presenting complex content in a manner accessible to 8-10-year-old children who were encountering CAL content for the first time. We wanted to ensure students understood multiple interdependent concepts, such as “bias” and “training data.” As the findings suggest, the necessity for us to revisit some of the content and modify lessons highlighted the essential components needed to support students in comprehending algorithmic bias, its potential real-world consequences, and heightening awareness about such biases.

For instance, Ms. Sage and I agreed that students should understand the concept of bias to better understand consequences of algorithmic bias. In addition, to help students understand that biased or incomplete training data can result in biased outputs, they should first comprehend the input-processing-output model of algorithms. The three-step algorithm model then supported students’ comprehension of how training data influences the functioning of AI systems. Furthermore, if we aimed for students to be aware of the real-world implications of algorithmic biases, they should be exposed to relatable examples that demonstrate these impacts. Lastly, to encourage student agency concerning algorithmic bias, we must offer opportunities for students to engage with and create content driven by algorithms.

The complexity and interdependence of these objectives emphasize the design challenges in fostering students’ understanding of algorithmic bias within the context of CAL. This framing of the lesson sequence influenced our design decisions to revisit what we considered to be vital content, such as bias in general and the effects of algorithmic bias. The lesson sequence and its foundational concepts also impacted how I adapted pre-existing curricular materials to support the third and fourth graders.

Four Design Principles

Dasgupta and Hill’s (2021) four CAL design principles profoundly influenced my lesson design choices. I sought to adapt and extend these principles for elementary school students with little or no computer science experience. Dasgupta and Hill’s design principles emerged from their work with middle school-aged students who had access to a customized feature of the block-based coding tool Scratch (Hautea, Dasgupta, & Hill, 2017). Student participants anonymously mined other Scratch users' data and integrated it into their Scratch programs. Although the younger students in my study had neither the tools nor the time to engage in such robust interactions with computer science using real-world data (Hautea et al., 2017), I sought to adapt the four design principles to the present study.

In the lesson design, I sought to incorporate the primary design principle suggested by Dasgupta and Hill (2021), which is to "enable connections to data" (p. 1). During the CAL lessons, for instance, students analyzed and questioned gender biases present in Google's image search algorithms. Additionally, the guided reflection following the Google QuickDraw activity enabled students to understand how incomplete or biased training data can lead to flawed results. We strengthened this understanding by linking the QuickDraw discussion to Joy Buolamwini's experience with facial recognition bias (Buolamwini & Gebru, 2018). This connection emphasized the relationship between deficient AI training data and its potential societal implications. This design strategy of connecting image search and QuickDraw activities with examples of and consequences of algorithmic bias inspired students to identify instances where biased algorithms reinforced dominant power hierarchies, especially concerning normalizing gender roles. Ms. Sage described the students' discussion of the implications of AI bias caused by incomplete training data as a "turning point" in the CAL lessons. Here the connections to live data, coupled with examples of the algorithmic impacts described in the *Coded Bias* summary video (Moss Center, 2021), presented students with concrete examples of the causes of algorithmic bias and its possible effects in the real world.

My observations of students' interactions with algorithms also support Irene Lee et al.'s (2021) conclusion that interactive AI tools such as QuickDraw and Google Teachable Machine "...help students build mental models of mechanisms and algorithms in action during machine learning and expose how bias can be embedded in AI systems" (p. 2). The middle schoolers in their study created and tested their own training data using Google Teachable Machine. The third and fourth graders in my study only viewed the QuickDraw tool training data. In my study, younger students engaged in less complex interactions than middle schoolers in Hautea et al.'s (2017) and Irene Lee et al.'s (2021) studies. The findings in my study suggest that interactions with live data supported student progress toward achieving the CAL objectives, such as analyzing how limited training data can lead to bias in software and evaluating the consequences of algorithmic bias.

To a limited extent, my investigation addressed Dasgupta and Hill's (2021) second design principle: "Adopt community-centered approaches" (p. 2). Each lesson included whole class discussions of media bias. In these discussions, students' personal and group values regarding gender and racial equity often emerged. Most notably, students' values surfaced in the design of their final projects for those students who expressed how their hypothetical application would minimize algorithmic bias. Student projects included applications and robots for aiding the homeless, locating lost animals, conserving water, helping mothers, cleaning the ocean, inspiring artists, assisting job seekers, feeding the hungry, providing parenting tips, removing trash, planting flowers, and supporting aspiring singers. The varied project ideas represented students' authentic interests. Future CAL lesson design could emphasize group work and the integration of students' media experiences to further enhance community-centered approaches to CAL.

The initial CAL lesson design sought to adapt Dasgupta and Hill's (2021) "Create sandboxes for dangerous ideas" design principle (p. 2). A "sandbox" in this context is a secure space for programmers to test code without impacting other computer systems. The middle school students in Hautea et al.'s (2017) study created programs, for example, to rank other Scratch users within a closed system. One young participant in their study discussed the potential harm of a program they developed, which could enable surveillance, discrimination, and other negative outcomes. One might contend that the grade three and four students' application planning served as an early stage of a computer programming sandbox. Program planning without production, however, does not provide students with the feedback and consequences of interactions a true sandbox would provide.

Although students lacked the opportunity to create counter-hegemonic media through their participation in the CAL lessons, their interaction with computer science principles supported their progress toward our stated CAL objectives, such as describing personal and societal consequences of algorithmic bias. Through these interactions with and decisions about biased algorithms, students progressed in their ability to "uncover structures and assumptions in algorithmic systems" (Dasgupta & Hill, 2021, p. 6). While the third and fourth graders in the present case study did not interact with algorithms to the extent of students in the Hautea et al. (2017) or C. Lee et al.'s (2022) case studies, student interaction with data empowered students to analyze and question automated biases such as those found in artificial intelligence-powered media.

Throughout the design process, we strove to "support thick authenticity," as described in Dasgupta & Hill's (2021) third design principle. The broad concept of "authenticity" in education usually involves providing students with personally relevant activities connected to real-world issues (Shaffer & Resnick, 1999). In our CAL lesson design, we included activities authentic to students' media-saturated world, such as conducting a Google image search, playing a computerized guessing game, and making sense of advertisements. As algorithms become more common in various contexts, numerous settings offer opportunities to promote algorithmic literacy through meaningful, authentic experiences. The Council Circle session perhaps most demonstrated authenticity when students discussed algorithmic targeting and bias as they related to their personal experiences with Netflix and other streaming services.

RQ 2: Challenges of CAL

This investigation's second research question asked, "What are challenges for implementing critical algorithmic literacy during the school day in the context of this specific elementary school case study?" As described throughout, many of the lessons did not include components originally considered central to its implementation. Most notably the media production and student interactions with computer science were reduced or eliminated. Additionally, the original vision of these lessons included time for student inquiry-learning, reflection, and cooperative activities. This section examines those challenges and offers suggestions for minimizing them for future researchers and practitioners seeking to implement CAL with elementary-school-aged students.

My motivation for this study came, in part, from books such as *Algorithms of Oppression* (Noble, 2018), *Race After Technology* (Benjamin, 2019) and films such as *Coded Bias* (Kantayya & Buolamwini, 2021) and *The Social Dilemma* (Exposure Labs, 2020). While acknowledging the positive impacts of technology, these media depict the formidable societal consequences of algorithmic bias, perceptions of algorithmic objectivity, and increasing reliance on algorithms to govern many parts of our lives. However, because these books and films contain mature content, they are not suitable for children between the ages of 8 and 10 to watch or read.

These books and films detail numerous societal consequences of biased algorithms. However, this study's findings suggest that few of those consequences resonated with the experiences of third and fourth graders at an elementary school in southern California. Imperfect algorithms have been found to negatively impact underrepresented and socioeconomically disadvantaged groups in areas such as creditworthiness, prison sentencing, immigration, policing, and employment (Benjamin, 2019; Noble, 2018; O'Neil, 2017). Few third and fourth graders have direct experiences in any of these areas.

This study's second finding highlights the importance of selecting appropriate examples that connect with students' prior experiences. For instance, after the sixth lesson, Ms. Sage discussed the relative success of a video that illustrated Amazon's discovery of gender bias in its AI-driven hiring program (Dastin, 2018). However, the teacher also recognized that many students may not have fully understood the examples of algorithmic impacts due to their diverse backgrounds and experiences. To maintain academic engagement, it is crucial to select examples that are relatable and comprehensible for the target audience.

Relevance is particularly important here, where the goal is for students to see the impacts of algorithmic bias on themselves and others. Upon reflection, using examples such as AI-based medical technologies, known to disproportionately impact ethnic minorities (Qeadan et al., 2021), may have served as a more relevant illustration of the consequences of algorithmic bias. Examples such as racist soap dispensers (NBC News, 2021) might also have provided a more suitable example for these third and fourth graders.

Introducing popular media into the regular school curriculum poses another challenge for CAL implementation. In lesson two, students were both delighted and surprised to be asked to explore YouTube during school hours. The objective of this lesson was for students to compare advertisements shown before soccer highlights videos with those played before home cleaning tips videos. As I observed the students, I noticed that only 2-3 students in each group engaged in the assigned task.

Students appeared to be similarly distracted when asked to contrast two different commercials for the Real Bugs toy. This observation suggests that popular media can trigger a non-academic response from students, underscoring the need for them to critically analyze such media. Based on my experience as a teacher, I have found that distractions arising from the classroom use of popular media tend to diminish over time. However, I also discovered that when students love a particular movie, for example, it is especially challenging for them to take a more objective analytical perspective.

The extent to which students find popular media distracting in a school setting likely hinges on several factors, such as students' prior experiences, the established classroom culture, and the inherent characteristics of the media. I would recommend that teachers gradually integrate popular media into their curriculum, with the goal of students viewing a website, app, movie, or video game as another educational resource. Although this process might not follow a linear trajectory, the endeavor could significantly enhance the authenticity of media analysis in CAL implementations.

Although I have extolled the use of real-world connections to promote authenticity, the practical implementation of this strategy can present significant challenges for teachers. As described in the Findings chapter, during a discussion about image search bias, one student replied, “I don’t think it’s [Google’s] fault if they don’t have pictures of Black people [as CEOs]. Not as many Black people are doing important business. Maybe they don’t have as many photos of Black people.” This interaction illustrates a significant potential challenge of bringing real-life experiences to the classroom, specifically for younger students. Many teachers worry about facing criticism from parents, school administrators, or community members, deterring some educators from introducing content viewed as political (Ciccone, 2021). Implementing CAL likely involves conducting difficult discussions about subject matter related to identity-based oppression and discrimination.

Upon reflection, most of the lesson activities and examples focused more on gender bias and less on racial bias. My decision to focus on gender biases in algorithms was influenced by a primary school CML practitioner (Medina, 2022) who simplified students’ analysis of media biases to suit their age and understanding. However, CAL follows in the CML tradition of challenging biases. Considering today’s challenging political environment for many teachers, it could be essential for teachers to get approval from administrators and parents to tackle issues of algorithmic bias more extensively.

As CAL represents a nexus of CML and computer science, the latter comprised a core component of these nine lessons. Most elementary school students, however, have little to no experience with computer science education (Code.org, 2022). Hautea, Dasgupta, and Hill’s (2017) implementations using Scratch Community Blocks illustrated how authentic interactions and production with computer programming tools empower students to “uncover structures and assumptions in algorithmic systems” (Dasgupta & Hill, 2021, p. 20). Through students applying block-based programming tools such as Scratch to real-world contexts, students not only learn computer programming but also gain a deep understanding of the underlying structures and assumptions in algorithmic systems. This work enhances students' agency, potentially empowering them to shape the world that aligns with their aspirations.

To support this authentic hands-on interaction with computer science, I created an activity to simplify and abbreviate the student interaction with coding tools. Aligning with Dasgupta & Hill's (2021) design principle of creating "sandboxes" for student ideas, the Tynker remixing would have provided students with a low-risk environment where they could adapt and customize already existing code without making changes to the original program. In this way, students would have engaged in hands-on programming, despite their limited background in computer science. Time constraints compelled us to eliminate this activity. Although Ms. Sage showed students this simple block of code, without hands-on interactions, students cannot see the effects of modifications to these algorithms. Various studies support the use of code remixing for students new to computer coding (Amanullah & Bell, 2019; Vourletsis & Politis, 2023; Yalcinkaya et al., 2022). For CAL implementation, students could begin by remixing code that connects with CAL concepts, such as the simple recommendation engine example shown to students during lesson three.

In addition to providing more time to remix code blocks, students would have benefitted from more frequent and robust interactions with interactive AI models. In certain instances, tools such as Google QuickDraw and Teachable Machine (not used in these lessons) allow users to view or create training data for an AI system. Possessing access to this training data and general comprehension of the three-step algorithm model (input-processing-output) enables students to make more informed deductions about the algorithms' functioning. Given more time, I would have included student interactions with Google Teachable Machine as it empowers students to create their own training data (images, movement, or sound), train the AI (by clicking a button), and test the effectiveness of the AI to identify the images, sound, or movements. Irene Lee et al.'s (2021) case study described middle school students' benefits from their interactions with Google Teachable Machine. Given the opportunity to train and test their own AI models, the third and fourth-grade students might be empowered with a more robust understanding of how training data influence AI outputs.

It is not surprising to state that many of the challenges associated with CAL lesson implementation could be addressed with more time. Time limitations, for example, limited the amount of student reflection during the CAL lessons. Reflection, as defined in the classroom setting, refers to the act of thinking about how new knowledge fits with what we already know (Douillard, & Labbo 2002). Reflection facilitates connections between recent learning and past experiences. It involves students interacting with new information by making observations, asking questions, and comparing their understanding with others. Incorporating reflective activities in the classroom makes thinking more visible, enabling students to learn from each other and gain deeper insights into their own thinking and learning processes (Schön, 1983).

In the second session of lesson seven, students had more time than usual to reflect on the day's lessons. After this class session, Ms. Sage commented on the value of student reflection time:

> We haven't been able to include [time for students to reflect on their learning] in our past sessions, and I see how valuable that space is. We could even be adding an extra layer every time a student shares out. We could be asking questions and giving suggestions for how to make it better. So that will add a whole other layer, listening to each other. There's a lot of value in that.

Ms. Sage's enthusiasm for the brief yet sustained reflection time highlights its value. As young students confront complex, interrelated issues like identity, media bias, algorithms, and their personal media experiences, it is crucial to allocate ample time for them to engage in discussions and reflections on these multifaceted subjects.

Time limitations, however, impacted almost every aspect of the CAL lessons. In the final interview, Ms. Sage specified the various time challenges throughout the lessons and study. What follows is Ms. Sage's final answer to the question, "What would you consider to be the biggest challenges as you implemented these lessons?" I have provided this quote in full as it thoroughly outlines the key challenges that future researchers and practitioners may face when implementing CAL for elementary school students.

> If I would have to say just one word, then I would say "time." Because it affects everything, it's like the big umbrella. We could be talking about time to be more thoughtful with planning time for you and I to meet more often with more time. Not having a limited time. Because I know that's been my challenge since I need to leave at 3:45.
>
> Time during the lessons itself. The 50-minute blocks were a challenge for us to identify what content to include in each lesson.
>
> Time to reflect I feel like these lessons have been very powerful, but they could have been even more powerful if we would have had more time to allow our students to discuss with each other.
>
> Time for myself, for professional development all that pre-reading to be able to do the front-loading for my students in a more meaningful way.
>
> Time for us to read articles together to discuss. Even that short meeting that we had with [another teacher at Dewey] was so powerful, but at the same time, I felt limited because I knew I had to go. I feel like right like I'm just saying "time," but it just means everything.

Ms. Sage's reflections on the challenges related to the time limitations in CAL lesson implementation offer valuable insight for future research and practice for CAL implementations. Further research could focus on identifying practical strategies to optimize the usage of available time in teaching environments. These strategies might include increased planning and reflection time, professional development, as well as student discussion opportunities. Ms. Sage's concluding thoughts reinforce the notion that time is not merely a logistical constraint but a critical factor that impacted the CAL implementation. Increasing time for the matters Ms. Sage shared would likely enhance the effectiveness of future CAL lesson implementations.

RQ 3: Promising Practices for CAL

My study's findings address the third research question by describing promising practices that support students' understanding of the non-neutrality of algorithmically-driven media. The teacher's skill in linking CAL content to students' previous media experiences represented promising practices observed throughout the CAL lessons. Embodying Vazquez's (2014) idea that "the world around [students] can and should be used as text" (p. 6), the CAL lessons endeavored to connect with students' worlds. CAL activities, such as The Branding Alphabet (McLaren, 2002), image search, and television advertisement analyses, reinforced the student-media-world connection enhancing the relevance of the content. This promising practice of connecting students' media habits could be further enhanced by designing lessons to have students self-select media for analysis and discussion.

Some students demonstrated their progress toward CAL objectives in the final project planning. When Ms. Sage asked Carlos how he could ensure his animal translator application would be equitable, the student replied, "I would have lots of different voices." This seemingly simple response reflects the knowledge that a large and varied set of training data reduce the chances of biased outputs. Perhaps because he was able to extrapolate from examples such as the facial recognition bias presented in Joy Buolamwini's (2019) work to his own application, it is possible that the student will be empowered to generalize these ideas when encountering other AI systems throughout his life.

In addition to analyzing media for bias, the student production of counter-hegemonic media remains central to CML and, therefore, CAL. While C. Lee et al.'s (2022) critical computational expression served as a partial inspiration for the present study, neither time nor context permitted students to create counter-hegemonic media that might have empowered them to address concerns about problematic biases perpetuated by large media platforms such as YouTube and Google. Apart from the final project videos describing the hypothetical applications or robots, students did not generate media as part of the CAL lessons.

Students in the CAL lessons planned but did not create computer applications that served others. Building on DiPaola et al.'s (2020) study of middle schoolers engaging with Payne and Breazeal's (2019) EAICMSS, my investigation's findings suggest that the media design process represented a step toward enhancing students' ability to analyze computer programs critically and ethically. Through conceptualizing hypothetical applications, the third and fourth-grade students adopted a creator's viewpoint, reinforcing the social constructivism tenet of CML and recognizing algorithms as nonneutral entities.

The application design project represented a first step to approaching C. Lee et al.'s (2022) critical computational expression for students to have "the capacity, and responsibility, to design systems in dynamic and critical ways" (p. 15). Although current technologies such as Tynker and Scratch empower younger students to create computer programs for authentic audiences, students in our case study did not create such media that might "question, challenge, and disrupt the hegemonic algorithmic AI practices of large corporate institutions that profoundly affect our daily lives" (p. 23). Student application planning, informed by their knowledge of algorithmic bias, supported initial progress toward challenging and disrupting hegemonic media.

I recommend that future researchers and educators build on these promising practices for CAL. By directly exploring data and algorithmic processes, students can gain a deeper understanding of how algorithms, including AI, can produce biased outcomes. Understanding the real-world implications of algorithmic bias helps students become more critical consumers and enhances their agency to challenge algorithmic bias wherever they find it.

Implications for Researchers

This study emphasized the importance of effective examples, adapting lesson content, and addressing students' needs to foster CAL competencies. As this investigation likely represents the first case of CAL implementation at the elementary school level, this study points to several directions for continuing inquiry. The findings suggest many areas to explore for future researchers.

Before beginning the discussion on research for future CAL implementations, it is important to consider the wide range of models, literacies, and frameworks that address contextualized algorithmic education such as CAL. In my view, research on implementations such as critical computational literacy (Lee & Soep, 2016) and critical data literacies (Aguilera & Pandya, 2021; Irgens et al., 2020) should be regarded as within the same broad category of contextualized algorithmic education as CAL. It is important to note that some researchers emphasize the sociocultural components of computer science education in their framings of algorithmic literacy (Thumlert et al., 2022) and AI literacy (Long & Magerko, 2020). These efforts align with the goal of improving students' understanding of algorithms and their impact on society. Like CAL, these models also emphasize authentic student production to enhance their agency in our algorithmically immersed environment. Some argue that the many variations of media literacy education pose a challenge to its wider implementation (Hobbs, 2022). As many models and frameworks exist, it is important not to let the relatively small, sometimes semantic, differences detract researchers and educators from common goals.

One of the many challenges of all media literacy models is the rapidly changing media landscape. Although the present investigation did not include generative AI such as ChatGPT, future investigations could determine to what extent a CAL-centered curriculum applies to generative AI technologies. Just as CAL involves analyzing and critiquing the outputs of AI recommenders such as YouTube and Google Images, students could analyze, critique, and challenge the outputs of generative AI tools. Other CAL foci, such as ethics, representation, and bias, could be applied to these analyses of generative AI.

Although many iterations of what I describe as contextualized computer science education exist, measuring student outcomes in these efforts remains a challenge. This study contained no formal assessments to measure student attainment of the CAL objectives. Although there have been multiple efforts to evaluate media literacy skills in general (Hobbs, 2017), no established CAL evaluation criteria yet exist. As CAL does not prescribe specific competencies, it becomes more difficult to establish generalized evaluation criteria. Researchers could build on or adapt the objectives for the CAL lessons within the present study (Appendix B). Alternately, researchers might create their own agreed-upon evaluation criteria before embarking on a case study that might involve pre-and post-testing.

Other researchers and educators may choose to use, adapt, or discard the sequence of topics we explored in the nine lessons. The CAL lessons followed the following sequence of topics: Media bias, bias, media targeting, introduction to algorithms, targeting algorithmic outputs, algorithmic bias, consequences of algorithmic bias, and the final project to design a product with minimal algorithmic biases. The findings indicated that the lessons proceeded somewhat recursively, but we established this sequence so that one concept informed the next.

In addition to altering the lesson sequence, researchers, teachers, technology coaches, curriculum writers, or perhaps commercial interests could create CAL final project videos, instructional materials, and activities specifically for lower grade levels. My research highlighted my need as a co-designer to adapt lesson content and classroom materials intended for older students. Most of the videos viewed by students in the CAL lessons were not explicitly intended for CAL implementations with elementary school students. We adapted not only curricular items such as the EAICMSS (Payne & Breazeal, 2019) but also abbreviated and scaffolded learning materials such as instructional slides, images, and videos. When looking for materials and videos, we found none specifically for addressing CAL for elementary school students.

In future research, it would be valuable to investigate the extent to which increased student involvement in computer program creation enhances their CAL skills. CAL and similar frameworks include some technical understanding of algorithms. Kafai's et al.'s (2019) framings of computer science (Figure 1) place the cognitive component as central to the situated and critical elements. A vital question for further inquiry is how much technical computer science knowledge students need to enhance their critical perspective on algorithms and AI. In the present study, we introduced third and fourth-grade students to fundamental computer science concepts. As the findings indicate, students did not have the opportunity to work with a "sandbox for dangerous ideas" (Dasgupta & Hill, 2021, p. 2).

In order to explore the role of computer science in CAL, future researchers could conduct randomized controlled trials that involve comparing different CAL implementations, specifically comparing students with prior computer science experience versus those without such experience. Although CAL does not require extensive knowledge of computer science, much could be learned by studying CAL implementations with elementary school students who have some computer science experience. Initiatives such as The Hour of Code (Code.org, 2023) and Google's CS First (Google for Education, nd), coupled with the increased interest in computer science education, have increased the number of students exposed to computer science and coding. Similar studies could be conducted with teachers possessing computer science education experience.

Researchers might also gain valuable insights by exploring the intersection of computer science education and CML (Kellner & Share, 2019). Moreover, researchers looking to explore CAL as an extension of CML might conduct more detailed explorations of all six of CML's conceptual understandings as they pertain to CAL. As stated throughout this dissertation, the lesson design and study drew from and sought to expand Kellner and Share's (2019) CML Framework. This present study, however, did not thoroughly address all six conceptual understandings of the CML Framework.

The first CAL lesson, which focused on media bias in TV advertisements, addressed the first and fifth tenets of the CML Framework (Table 1). The first CAL lesson focused explicitly on having students consider media creators' choices and purposes for the media they produce. Throughout the subsequent lessons, class discussion of creators' decision-making formed a foundation for other content. These lessons, however, did not explore the economic factors driving what Wu (2018) has described as the attention economy. Researchers might want to examine how a more detailed student analysis of algorithmic-media producers' purposes impacts student CAL learning.

One of the strengths of the CML Framework lies in its flexibility for educators to apply its conceptual understandings to virtually any iteration of every medium. The second key concept of CML posits that "each medium possesses its own unique language, complete with specific grammar and semantics" (Kellner & Share, 2019, p. 8). Understanding the semantics and grammar of algorithms, more so than other media, presents distinct challenges. Firstly, the content mediated by algorithms remains largely hidden from all but a select few of their creators (Burrell, 2016). Moreover, comprehending the grammar and semantics of commercially developed digital algorithms is nearly unattainable without an extensive background in computer science and proficiency in particular programming languages. Finally, algorithmic-driven media often function as gatekeepers by determining what can be known about them (Cotter, 2020; Gillespie, 2014).

To address these challenges, the CAL lessons in this investigation included some technical computer science knowledge. The three-step model of algorithms explored in the CAL lessons represents an important yet cursory understanding of the "specific grammar and semantics" (Kellner & Share, 2019, p. 8) of digital algorithms. While the three step-model and students' limited interactions with computer science supported students' understanding of algorithmic bias, a more thorough understanding would better support the language/semiotics category of the CML Framework. It is worth repeating that a key avenue for future inquiry is examining to what extent the technical knowledge of computer science supports students' critical analysis of digital algorithms.

The third conceptual understanding of CML states, "Individuals and groups understand media messages similarly and/or differently depending on multiple contextual factors" (Kellner & Share, 2019, p. 8). The CAL lessons within this case study rarely addressed positionality. The idea that media are interpreted differently by different people, however, emerged organically in many discussions of gender bias. Several class discussions centered on the gendering of children's toy advertisements. This perspective was reflected by student comments such as, "Some girls might like pirates and some boys might like pink stuff." Future studies and implementation may address the concept of positionality more explicitly. For instance, one could offer guided exercises that show how a person's unique positionality affects how they interpret media.

Recognizing and analyzing media bias is an integral component of the fourth conceptual understanding of CML: "Media messages and the medium through which they travel always exhibit a bias and either support or challenge dominant hierarchies of power, privilege, and pleasure" (Kellner & Share, 2019, p. 8). The CAL lessons overtly targeted the fourth principle of the CML Framework centered on the politics of representation and media bias. Throughout the nine lessons, students identified, analyzed, and often challenged potential biases in media driven by algorithms. In fact, all nine CAL lessons centered on media bias, algorithmic bias, the impacts of algorithmic biases, and/or bias in general. As described in the findings chapter, we prioritized ideas surrounding the various biases over computer science and production components that we had considered essential to the CAL lessons.

The analysis of invisible algorithms informs future applications of the fourth conceptual understanding within the CML Framework. CAL specifically addresses the sometimes ignored "medium through which media messages travel" aspect of the CML Framework (Kellner & Share, 2019, p. 8). Historically, media analysis has concentrated on what is explicitly visible and audible within the media. However, algorithmic opacity introduces an additional layer to both

CML and media literacy in general. Kellner and Gennaro (2022) bring clarity to this challenge of differentiating media content from the means by which they travel:

> In basic grammar, medium is the plural of media, but for a more in-depth analysis, the two terms need to be separated so that medium provides for a description of the container that houses the content and media takes on the definition of the content itself (p. 293).

This distinction between medium and media opens possibilities for future research in algorithmic literacy, as it encourages a closer examination of how the characteristics and biases embedded within the container (medium) can shape and influence the content (media), particularly in the context of algorithmic systems.

Clarifying differences between media and medium may provide more nuance to the fifth tenet of the CML Framework (Kellner & Share, 2019), which states, “All media texts have a purpose (often commercial or governmental) that is shaped by the creators and/or systems within which they operate” (p. 8). This conceptual understanding emphasizes that all media texts possess a purpose, often influenced by creators and the systems they operate within. The focus on creator’s purpose was exemplified in students’ final projects. My findings suggest that students, by considering media creators’ perspectives, enhanced their awareness of product design. In this way, CML’s focus on purpose helped them to achieve CAL objectives such as “Discuss strategies for ensuring that the training data and output of an app are not biased.” Researchers seeking to implement CAL in elementary should maintain or perhaps increase their focus on individuals’ and institutions’ purposes as it is an integral element within all forms of media literacy.

As mentioned in the first chapter of this dissertation, CML’s focus on social justice differentiates it from other models of media literacy education. Consequently, much of the CAL lesson design centered on the sixth tenet of CML, which states, “Media culture is a terrain of struggle that perpetuates or challenges positive and/or negative ideas about people, groups, and issues; it is never neutral" (Kellner & Share, 2019. p. 8). Throughout the lessons, we strove to design activities that engaged students in identifying and analyzing algorithmically-driven examples of sexism and racism. From the first lesson, in which students used the Gender Advertising Remixer tool, to discussing racist algorithms shown in a *Coded Bias* summary (Moss Center, 2021), the lesson design consistently highlighted the nonneutral nature of media and its impact on society. This study contributes to the existing research on implementing Kellner and Share's (2019) CML Framework by describing how elementary school students engaged in a critical analysis of algorithmic consequences, thus highlighting the non-neutrality of algorithmically-driven content.

While the students in the present study seemed to comprehend the nonneutral nature of media, they only minimally entered the "terrain of struggle that perpetuates or challenges positive and/or negative ideas about people, groups, and issues" (Kellner & Share, 2019, p. 8). As highlighted in the literature review, student production activities would have likely reinforced the core notion that algorithms are "opinions embedded in mathematics" (O'Neil, 2017, Kindle location 405). The findings suggested that more relevant instructional examples would have enhanced the social justice focus of the CAL lessons. I also recommend that researchers investigate the impacts of student-created counter-hegemonic media to enhance the social justice component of CAL.

This classroom case study contributed to the expansion of Kellner and Share's (2019) CML model by specifically exploring the evolving CAL model. By encompassing all six conceptual understandings of CML, this study highlights the potential of CAL to support an extended notion of CML. This investigation opens numerous opportunities for researchers to further examine how CAL can enhance and reinforce the broader understanding of CML.

Implications for Practitioners

Many of the implications outlined for researchers could also benefit teachers, curriculum writers, and administrators who are looking to implement CAL with elementary school students. For instance, educators could alter the order of topics, develop CAL-specific evaluations, and encourage students to incorporate their personal media experiences into CAL lessons. Future case studies will likely involve both lesson and study design, as these two aspects mutually influence each other.

Time for Planning

Weekly planning and adjustments, as conducted in this case study, may not be practical for broader CAL implementation. This study's findings regarding lesson design, however, suggest that teachers can benefit from the flexibility and additional planning time for CAL lesson implementation. Additional planning time would increase the likelihood that teachers would connect CAL to core content and create CAL-integrated cross-disciplinary units of study. Additional planning time for curricular integration might also support enhancing the student media production element that was lacking in this case study.

As a basic understanding of computer science comprises an integral component of CAL, it follows that teacher implementing it would benefit from al at least some computer science training. Because of the increased demand for computer science education, many public and private initiatives now exist that focus on providing computer science training for teachers. Organizations such as the International Society of Technology in Education (ISTE) and code.org provide computer science training and certification for teachers. It is my view that to implement

CAL, elementary school teachers need only a basic understanding of computer science and the ability to create simple programs using block-based tools such as Tynker and Scratch.

CAL integration may also spark student interest in computer science. In K-12 education, most student interactions with algorithms occur in computer science courses (Ciccone, 2021). Moreover, most efforts to persuade students to enroll in computer science electives often focus on describing possible future economic benefits. Some students reason that if they don't want to work in the computer science field, there is no need for them to learn computer science. CAL, on the other hand, places computer science in authentic contexts. Analyzing, questioning, and challenging algorithmically-driven in authentic contexts media may increase some students' interest in computer science. Further, because CAL involves learning a little computer science, this exposure could spark students' curiosity for further explorations. As many efforts exist to increase participation in computer science-specific courses and content, introducing computer science in authentic contexts is worthy of further investigation.

Core Content

In addition to bringing CAL to computer science courses and content, CAL should integrate within core content areas. Algorithmically-driven media should be considered as another form of text within educators' ideas about "traditional" literacy. The application of CAL in my research occurred as supplemental instruction, separate from core content areas such as language arts or science. Although these lessons likely aligned with some Common Core standards, our planning process did not include addressing specific academic content standards. Integrating CAL within core content would offer numerous advantages. For instance, applying reading, writing, listening, and speaking standards could seamlessly integrate within CAL instruction. Additionally, the mathematical logic and problem-solving skills inherent in computer science aspects of CAL align with mathematical standards. CAL can also relate to social studies topics; for example, the influence of AI systems on immigration could be linked to third-grade standards on immigration. In science, CAL's emphasis on evaluating evidence can strengthen students' scientific inquiry skills. The possibilities for cross-disciplinary connections are extensive.

This integrative approach not only optimizes instructional time by addressing multiple learning objectives concurrently, but it also enhances the relevance and authenticity of core content. By incorporating CAL into core subjects, educators make core subject areas more applicable to students' experiences in a digitally-driven world.

Future CAL implementation should prioritize the relevance and real-world applicability of the content and tasks assigned to students. For example, encouraging students to analyze media they regularly interact with could emphasize the practical relevance of the learning materials. Furthermore, focusing on projects that tackle real-world issues of importance to the students could further bolster the authenticity of the learning experience.

Research Limitations

The results of this study are not intended to be prescriptive due to its qualitative design and small sample size. Classroom contexts vary. Those seeking to study similar implementations can build on this study's lesson and the research design. This study's limitations take nothing essential away from its findings. Some limitations may, in fact, be strengths regarding future CAL implementations. One notable limitation of this study, for example, was the lack of time for cooperative planning as well as the brevity of the lessons themselves. The time constraints that reduced students' inquiry learning, interaction with computer science, and media production activities limited what could be learned from this study. All schools, however, face time constraints on planning and class time. In this way, this research applies to the realities of most K-12 public schools.

Future researchers could expand the methodology to include student interviews or focus groups. The present study involved classroom observations in ascertaining students' behaviors and attitudes. Incorporating students' perceptions could help identify potential challenges and successes. Increased student data would provide a more holistic understanding of the CAL implementations, which in turn will inform the development of subsequent research and implementation efforts.

Dissemination

I am in a unique position to disseminate this research in a variety of contexts for researchers and practitioners. In my role as Instructional Technology Outreach Coordinator for the Los Angeles County Office of Education, I am in a position where I can support educational technology use for the 80 school districts within Los Angeles County.

With the public release of ChatGPT and other generative AI tools in late 2022, the interest in AI in education has soared. For many schools and interests, the fear of rampant cheating is now paired with the desire to teach with and about these new generative technologies. I feel this study informs my support for schools and districts to address AI literacy and equity issues. In my role as a technology coordinator, I intend to create free online CAL workshops and offer them to educators in Los Angeles County. These overviews could evolve into training sessions for interested schools and districts.

Conferences for Practitioners

I would also like to disseminate this work at teacher conferences. I have already presented about CAL at the National Council of Teachers of English (NCTE, Share, Gambino, and Moss, 2022) and the 2023 Computer Using Educators (CUE) conference (Moss, 2023). In July of 2023, I am scheduled to present at the International Society of Technology in Education (ISTE) and National Association of Media Literacy (NAMLE) conferences. I will continue to share this work at teachers' conferences in an effort to support educators in the field and to increase CAL implementations at all grade levels.

Scholarly Journals

I also intend to disseminate my work through scholarly journals. An article based on this dissertation's literature review was published in *The Journal of Media Literacy* (Moss, 2022). I presented a variation of that paper at the 2023 America Educational Research Association conference (Moss, 2023). Beyond media literacy and computer science journals, most subjects and role-specific journals are interested in the impacts of new generative technologies and how to leverage generative AI to support their goals. Once again, I believe my study's critical stance may generate interest from various areas. As with computer science in general, most of the current, initial efforts on student algorithmic literacy focus on its technical aspects.

Conclusion

The significance of this study's findings stems from its contribution to the continuous exploration of strategies that enable students to comprehend the algorithms influencing their lives and the lives of others. By bridging the gap between media literacy and computer science, this research bolsters the argument for including digital algorithms within the concept of multiliteracies (New London Group, 1996). Moreover, this study advances the CML Framework (Kellner & Share, 2019) by empowering elementary school students with a critical perspective to analyze, question, and challenge algorithmic representations of reality. As a first research effort implementing CAL with third and fourth-grade students, this case study not only corroborates the results of previous research with older students but also lays the groundwork for new avenues of CAL investigation and implementation. Because of the number of variables regarding content, schools, teachers, and students, future efforts in CAL implementations will differ from the present study. This research can contribute to those examining CAL in different contexts.

APPENDICES

Appendix A: CAL Lesson Goals

These overarching goals informed the selections and creation of the more specific CAL lesson objectives (Appendix C).

1. Understand Media Influence: Learn about the reasons behind media creation, the techniques used to retain audience interest, and identify instances of bias and stereotyping.

2. Understand Algorithms: Understand the steps of algorithms, with an emphasis on comparing algorithms in different contexts. Recognize biases in algorithms and search results.

3. Understand how limited training data can lead to software bias.

4. Assess Consequences of Algorithmic Bias: Evaluate the societal impacts of algorithmic bias, including the amplification of injustice and inequity.

5. Personal Reflection: Reflect on personal experiences related to media, algorithms, and bias, and make connections to classroom lessons.

6. Explore Data Connections: Investigate relationships between different data sets and projects.

7. Mitigate Algorithmic Bias: Learn strategies for preventing and identifying bias in programs, robots, or applications, including evaluation of inputs and training data.

Appendix B: CAL Lesson Objectives

The objectives for all nine CAL lessons were derived and adapted from three sources: (a) ISTE Hands-On AI Projects for the Classroom**:** A Guide on Ethics and AI (International Society for Technology in Education, 2021) (b) Critical Computer Science Education Pedagogy (Ko, 2022), and (c) An Ethics of Artificial Intelligence Curriculum for Middle School Students (Payne & Breazeal, 2019).

Students will:

- Describe the reasons why people create media.
- Recognize and analyze how advertisements demonstrate bias or stereotyping.
- Describe the components of an algorithm (input, processing, and output).
- Describe how media perpetuates or challenges positive and/or negative ideas about people and groups.
- Evaluate the elements in an image used to influence its audience.
- Analyze the techniques used to capture and retain attention and interest in media.
- Explain the three-step model of algorithms (Input-Processing-Output).
- Compare and contrast a cake recipe algorithm with YouTube's recommendation algorithm.
- Identify potential biases in a recommender system.
- Describe how incomplete or "bad" inputs can lead to poor outputs.
- Explain how Google QuickDraw recognizes drawings.
- Discuss the connection between the Google QuickDraw shoe data and Dr. Joy B.'s discovery about facial recognition bias.
- Analyze how limited training data can lead to bias in software.
- Describe personal and societal consequences of algorithmic bias.
- Analyze how algorithms can amplify injustice and inequity.
- Reflect on personal connections to lessons on media, algorithms, and bias.
- Evaluate the inputs used by an app and the potential biases and harms of the algorithm.
- Discuss strategies for ensuring that the training data and output of an app are not biased.
- Describe an application and/or robot help to help others while minimizing algorithmic bias with the application.

Adapted Social Justice Standards (Southern Poverty Law Center, 2018) from Critically Conscious Computing (Ko et al., 2022)

- Explain how software excludes groups marginalized by their gender, race, ethnicity, language, and ability.
- Examine power imbalances in the design of computing systems that create, amplify, and reinforce inequities and injustices in society.
- Demonstrate ways a given algorithm impacts different groups, communities, and disciplines in unequal ways.
- Recognize how data and algorithms stereotype and explore how to respect people as individuals in computation.
- Apply CS practices in ways that center equity and justice for marginalized groups.
- Apply CS practices in ways that center equity and justice for marginalized groups.
- Explain how software excludes groups marginalized by their gender, race, ethnicity, language, and ability.
- Describe how artificial intelligence can automate complex human decisions, while also encoding and amplifying bias.

Appendix C: Detailed CAL Lesson Summary

Lesson	Topics	Objectives	Activities	Guiding Questions
1	Media Literacy Gender Bias in media	Describe the reasons why people create media. Recognize and analyze how advertisements demonstrate bias or stereotyping.	Alphabet Branding Gender Advertising Remixer Real. Bugs ad comparison	Why do people create media? How do ads demonstrate bias or stereotyping?
2	Media Literacy Decoding media messages, Targeting specific audiences Algorithmically-driven Media Bias [YouTube Search]	Evaluate the elements in an image used to influence its audience. Analyze the techniques used to capture and retain attention and interest in media. Evaluate potential biases in a recommender system.	McDonald's print ad analysis YouTube Ad Comparison	What in the image is used to influence its audience? Which ads are recommended on YouTube? What techniques are used to capture and keep my attention and interest? What bias(es) may be present in this recommender? What is presented as "normal"? Who might benefit from this message and who might be harmed by it?
3	Introduction to Algorithms Flawed or incomplete input leads to flawed output Connecting YouTube recommendations with input, processing, and output Recommendation Engines	Summarize the three steps of algorithms. Compare and contrast a cake recipe algorithm with YouTube's recommendation algorithm.	PB & J sandwich design	What are the three steps of algorithms? Would your algorithm be different if it were for someone else? How is your PB&J algorithm like YouTube's recommendation algorithm? What bias(es) may be present in your algorithm? What bias(es) may be

Lesson	Topics	Objectives	Activities	Guiding Questions
				present in YouTube's algorithm?
4	Bias Algorithmic Bias- Google Image search Intro to possible consequences of algorithmic biases Harms and benefits of technology Introduce final project	Identify bias and identify algorithmic biases in search results.	Google Image search activity Start a new planet screening activity	What is Bias? What algorithmic biases (stereotypes) did you find in the search results? How can apps create harms? What data inputs will you use to determine if people should be included or excluded? Think about a never-seen-before app that you would like to create for final project after the break).
5	Final Project How programs use training data to identify images Consequences of facial recognition bias Connecting facial recognition to three step algorithm model	Explain how Google QuickDraw recognizes drawings.	Google QuickDraw activity Coded Bias video	How can your app help others? What problem are you trying to solve? How does Google QuickDraw recognize the things you are drawing? what's the connection with the shoe data and Dr. Joy B.'s project? How did the faces in training sets lead to bias in the software? Can you think of other examples when limited training data might lead to bias? Examples: Does YouTube know everything you like and dislike? What are possible consequences of algorithmic bias? How can your app help others?

Lesson	Topics	Objectives	Activities	Guiding Questions
6	Bias Gender Bias Bias in training data Effects of facial recognition bias Effects of other algorithmic biases Final project	Discuss the connection between the QD shoe data and Dr. Joy B.'s project. Analyze how limited training data can lead to bias in software. Evaluate the consequences of algorithmic bias. Analyze how algorithms can amplify injustice and inequity.	Gender descriptor comparison Quickdraw review	What is bias? Why was QuickDraw not able to identity this [high-heeled shoe] as a shoe? What kinds of decisions are made by computers? How can your app help others? What are potential benefits of your program or robot? What are potential biases & harms of your program or robot? How can algorithms amplify injustice and inequity?
Council Circle	Student-driven topics centered on media use		Whole group free form discussion regarding media use, algorithms and bias.	Have you seen or experiences anything that connects to our lessons?
7	Project Work Time Connecting project about the three-step model of algorithms Focus on algorithmic inputs Training data bias	Reflect on personal experiences and connections to lessons on media, algorithms, and bias.	Final project planning	What problem are you trying to solve? How will it help people? Who is your audience? What is the output(s) of your program or robot? What does it do? How do make sure your app is not biased? Reflect on what you learned during these lessons.

Lesson	Topics	Objectives	Activities	Guiding Questions
				What did you learn? How might you use what you learned outside of school? Does the data represent all possible users without bias?” and “Is there enough data to accurately train the computer?
8	Project Planning Algorithmic bias Minimizing bias Project prep		Project work time	What does your app/robot do? How do you make sure it’s not biased? Reflect on what you learned during these lessons. What did you learn? How might you use what you learned outside of school? What is algorithmic bias? Which input(s) does your app use? How will you be sure that your apps training data is not biased? How can you be sure that the output of your app is not biased? What are potential biases & harms of your algorithm?

Lesson	Topics	Objectives	Activities	Guiding Questions
9	Summary of prior eight lessons Project work time: video creation	Discuss strategies for ensuring that a program or robot is not biased. Evaluate the inputs used by an app and the potential biases and harms of the algorithm. Discuss strategies for ensuring that the training data and output of an app is not biased.	Thank you Lesson review Video recording	What does your app/robot do? How do you make sure it's not biased? What did you learn during these lessons?

Appendix D: Final Project Rubric

Criterion	Awesome	Good	Developing
Describe your application or robot	Describe the program output and who it will help	Describe the program output or who it will help	Cannot yet describe program output or who it will help
How will your app/robot avoid bias and ensure fairness for users?	Describes the program's input and how it will avoid bias	Describes the program's input or how it will avoid bias	Cannot yet describe the program's input or how it will avoid bias
Describe what you learned in the digital literacy lessons. Is there anything you will use in your life outside of school?	Describe what you learned in two or more areas, such as media literacy, steps in an algorithm, bias, media targeting, potential harms of algorithms, and/or training data.	Describe what you learned in one area, such as media literacy, steps in an algorithm, bias, media targeting, potential harms of algorithms, and/or training data.	Cannot yet describe what you learned in one area, such as media literacy, steps in an algorithm, bias, media targeting, potential harms of algorithms, and/or training data.

Appendix E: Field Notes Observation Protocol

Classroom Observation for Class #x - Date

Observed	Quote	Comment

Appendix F: Teacher Interview Questions

<u>Interview #1</u>

1. Please describe your overall approach to literacy in the classroom.

2. Please describe specific successes you've had teaching and implementing social justice/critical pedagogy (SJ/CP).

3. Describe how your SJ/CP implementation connected to a standards-based core curriculum.

4. Describe your concerns and other thoughts as you prepare to engage your student in critical algorithmic literacy.

<u>Interview #2</u>

1. Please describe your perceptions regarding the critical algorithmic literacy lessons to this point.

2. Please describe specific successes, if any, you've had teaching critical algorithmic literacy to this point.

3. Please describe specific challenges, if any, you've had teaching critical algorithmic literacy to this point.

4. What changes or adjustments would you make to the CAL lessons to this point?

5. Describe how, if at all, the CAL lessons have connected to a social justice-based curriculum

6. Describe how, if at all, the CAL lessons have connected to a standards-based core curriculum

<u>Interview #3</u>

1. Please describe your perceptions regarding the critical algorithmic literacy lessons.

2. Please describe specific successes, if any, you've had teaching critical algorithmic literacy to this point.

3. Please describe specific challenges, if any, you've had teaching critical algorithmic literacy.

4. What changes or adjustments would you have made to the CAL lessons

5. Describe how, if at all, the CAL lessons have connected to a social justice-based curriculum

6. Describe how, if at all, the CAL lessons have connected to standards-based core curriculum

7. Do you anticipate teaching CAL in the future? Why or why not?

Appendix G: Overview of Codes Report

This Overview of Codes report generated by MaxQDA represents shows all 85 codes used for data analysis. The codes are organized in descending order by the number of coded segments associated with each code.

Overview of Codes

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
RQs	Student Learning	67	8.98	24	4/22/23 20:39:09	12/22/22 09:51:14
Design Process	Revisited content (+)	57	7.64	17	4/6/23 17:41:06	3/5/23 12:06:08
	Computer Science	33	4.42	19	3/11/23 12:57:33	12/22/22 08:52:12
	Design Process	28	3.75	11	4/6/23 19:59:25	12/22/22 07:41:44
Design Process	Omitted ideas	26	3.49	13	4/6/23 20:08:19	1/17/23 11:12:16
	Quotable	25	3.35	14	4/9/23 07:53:11	1/18/23 17:47:34
Design Process	Time Constraints	25	3.35	11	3/28/23 22:34:11	12/22/22 08:36:33
Student Learning	Student Misconceptions & Lack of Knowledge	24	3.22	12	3/27/23 13:00:32	12/22/22 10:24:16
Teacher moves	Changes after Lesson #1	20	2.68	11	2/11/23 16:18:46	12/22/22 08:53:37
Teacher challenges	Teacher lacks ML Experience	19	2.55	9	2/1/23 07:45:01	12/11/22 19:01:32
Student Learning	Personal Connection	18	2.41	9	2/28/23 13:39:59	12/22/22 08:22:23

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Representation/Bias	Student Knowledge of Bias	17	2.28	9	2/19/23 15:16:03	12/22/22 08:24:45
CML Framework	Semiotics	16	2.14	3	2/24/23 14:28:46	12/11/22 18:49:29
RQs	Teacher moves	16	2.14	9	4/22/23 20:39:09	12/22/22 10:23:22
Teacher challenges	Student Distraction	15	2.01	11	1/27/23 18:54:12	12/11/22 19:02:08
Student Learning	Student Engagement & Excitement	12	1.61	7	2/28/23 13:15:11	12/22/22 09:52:08
	Autocode - ANY: bias	11	1.47	5	3/11/23 12:57:33	12/11/22 13:25:56
Computer Science	Algorithmic Bias	11	1.47	2	2/24/23 14:27:46	2/7/23 16:22:43
Computer Science	Training Data	11	1.47	3	3/5/23 12:11:26	2/7/23 16:24:51
Teacher challenges	Time	11	1.47	9	1/30/23 09:21:03	1/3/23 14:20:05
Teacher moves	Teacher promising practices	11	1.47	9	1/27/23 19:16:56	12/11/22 14:38:59
	S Training data identification	10	1.34	9	3/11/23 12:57:33	2/3/23 17:22:06
CML Framework	Representation/Bias	10	1.34	7	2/26/23 10:36:22	12/11/22 18:51:00
Design Process	Core content	10	1.34	7	3/11/23 12:57:33	12/28/22 21:15:02
Student Learning	Student prior knowledge	10	1.34	6	3/10/23 22:39:48	1/25/23 22:22:10

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Design Process	Teacher knowledge of students	9	1.21	6	3/11/23 12:57:33	1/11/23 16:24:23
Design Process	Teacher suggestions	9	1.21	5	3/11/23 12:57:33	1/17/23 11:40:11
Teacher challenges	Students lack prior knowledge	9	1.21	6	2/1/23 07:44:41	1/3/23 14:14:25
Teacher Learning	Teacher attitude	9	1.21	6	4/6/23 20:02:39	12/22/22 08:33:51
Adapted material	Condensing/Synthesizing for time	8	1.07	1	4/2/23 10:19:40	4/2/23 09:24:42
Design Process	Logistics	8	1.07	6	3/11/23 12:57:33	1/17/23 11:15:56
Student Learning	S not making connection	8	1.07	6	3/28/23 22:16:39	2/28/23 13:15:11
Teaching Activities	Student Reflection/Connection	8	1.07	6	2/26/23 10:41:49	2/26/23 10:19:12
Computer Science	Input-Processing-Output	7	0.94	5	3/11/23 13:08:13	2/7/23 16:24:13
Design Process	Researcher ideas	7	0.94	3	3/11/23 12:57:33	1/25/23 22:19:34
Design Process	Borrowed sources	7	0.94	5	3/11/23 12:57:33	1/25/23 22:28:35
RQs	Researcher Learning	7	0.94	4	4/22/23 20:39:09	12/11/22 18:53:16
Student Learning	Media Literacy	7	0.94	4	2/28/23 13:15:11	1/25/23 22:47:28
Teaching Activities	Teaching Algorithmic Bias	7	0.94	4	2/26/23 10:46:02	2/26/23 10:15:01
Adapted material	Connecting to students' prior experience (+)	6	0.80	1	4/23/23 15:17:52	4/2/23 09:20:27

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Design Process	Plan while reflecting	6	0.80	5	3/11/23 12:57:33	1/17/23 10:48:13
Student Learning	Student Centered	6	0.80	5	2/28/23 13:15:11	12/22/22 08:23:57
Teaching Activities	Student Hands-on activity	6	0.80	6	2/26/23 10:47:08	2/26/23 10:21:25
Teaching Activities	Project Prep	6	0.80	4	2/26/23 10:45:02	2/26/23 10:28:58
Teaching Activities	Connecting project to other content	6	0.80	3	2/26/23 10:46:53	2/26/23 10:41:49
	S Avoid Bias	5	0.67	5	4/6/23 17:39:10	2/3/23 17:17:53
Adapted material	Simplifying and reducing vocabulary and content-including CS (	5	0.67	1	4/23/23 15:18:12	4/2/23 09:22:15
Design Process	Design flaws	5	0.67	5	3/11/23 12:57:33	1/4/23 18:54:46
Design Process	Teaching CAL while planning	5	0.67	3	3/11/23 12:57:33	1/4/23 17:15:20
Student Learning	General Bias	5	0.67	2	2/28/23 14:25:26	2/7/23 16:40:50
Teaching Activities	Teaching Media Bias	4	0.54	2	2/26/23 10:41:49	2/26/23 10:17:58
Teaching Activities	Teaching consequences	4	0.54	2	2/26/23 10:41:49	2/26/23 10:15:54
Adapted material	EXAMPLES!	3	0.40	1	4/2/23 10:18:32	4/2/23 09:32:05
CML Framework	Social Justice	3	0.40	3	2/24/23 14:28:46	12/11/22 18:51:57

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
RQs	Teacher challenges	3	0.40	2	4/22/23 20:39:09	12/11/22 14:38:28
Teacher moves	Inquiry learning	3	0.40	2	1/25/23 22:52:24	1/25/23 22:40:39
Teaching Activities	Teaching Algorithms/CS	3	0.40	3	2/26/23 10:44:46	2/26/23 10:14:32
Teaching Activities	Teaching Media Literacy	3	0.40	2	2/26/23 10:41:49	2/26/23 10:13:26
Teaching Activities	Teaching Bias in General	3	0.40	3	2/26/23 10:41:49	2/26/23 10:14:11
	S Self-reported learning	2	0.27	2	3/11/23 12:57:33	2/3/23 17:30:31
	Multiliteracy	2	0.27	1	3/11/23 12:57:33	12/22/22 07:43:03
	Constructed	2	0.27	2	3/11/23 12:57:33	12/11/22 18:49:07
CML Framework	Audience/Positionality	2	0.27	2	2/19/23 10:32:31	12/11/22 18:50:14
Design Process	Changes to planning	2	0.27	1	3/11/23 12:57:33	1/3/23 14:23:57
Design Process	Planning Time	2	0.27	2	4/6/23 17:41:57	1/30/23 09:00:50
Design Process	Adapted material	2	0.27	2	4/1/23 10:34:23	3/4/23 11:46:39
Design Process	Identified area of S need	2	0.27	2	3/11/23 12:57:33	3/10/23 22:34:00
Student Learning	Student stress and confusion	2	0.27	1	3/4/23 09:31:41	1/24/23 22:52:32
Teacher challenges	Other T challenges	2	0.27	2	1/24/23 22:55:51	1/17/23 19:43:09
Teaching Activities	Teaching Training data	2	0.27	2	2/26/23 10:45:18	2/26/23 10:15:37

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
	Classroom Environment/Context	1	0.13	1	3/11/23 12:57:33	12/22/22 09:59:58
	Social Justice	1	0.13	1	3/11/23 12:57:33	1/17/23 19:52:46
Adapted material	Scaffolding/guidance	1	0.13	1	4/2/23 10:19:40	4/2/23 09:24:13
Computer Science	Omitted CS	1	0.13	1	2/24/23 14:27:46	2/11/23 10:32:13
Computer Science	Recommendation engines	1	0.13	1	2/24/23 14:27:46	2/11/23 16:24:16
Design Process	Collaborative Reflection changes/moves	1	0.13	1	3/11/23 12:57:33	3/4/23 13:54:19
RQs	Teacher Learning	1	0.13	1	4/22/23 20:39:09	12/11/22 18:53:32
Scaffolding/guidance	Too open-ended	1	0.13	1	4/2/23 10:19:40	4/2/23 09:19:12
Student Learning	Media Bias	1	0.13	1	2/28/23 13:15:11	2/11/23 16:19:42
Student Learning	Varied Student Experience	1	0.13	1	2/28/23 13:15:11	2/11/23 10:18:05
Teacher moves	T-Provided examples	1	0.13	1	1/25/23 22:52:33	1/25/23 22:52:24
	CML Framework	0	0.00	0	3/11/23 12:57:33	12/11/22 14:37:37
	Teaching Activities	0	0.00	0	3/11/23 12:57:33	2/26/23 10:12:32
	RQs	0	0.00	0	3/11/23 12:57:33	12/11/22 14:37:57
CML Framework	Purpose/ Production	0	0.00	0	2/24/23 14:28:46	12/11/22 18:51:28

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
	Computer Science	33	4.42	19	3/11/23 12:57:33	12/22/22 08:52:12
	Design Process	28	3.75	11	4/6/23 19:59:25	12/22/22 07:41:44
	S Self-reported learning	2	0.27	2	3/11/23 12:57:33	2/3/23 17:30:31
	CML Framework	0	0.00	0	3/11/23 12:57:33	12/11/22 14:37:37
	S Avoid Bias	5	0.67	5	4/6/23 17:39:10	2/3/23 17:17:53
	Teaching Activities	0	0.00	0	3/11/23 12:57:33	2/26/23 10:12:32
	Autocode - ANY: bias	11	1.47	5	3/11/23 12:57:33	12/11/22 13:25:56
	Quotable	25	3.35	14	4/9/23 07:53:11	1/18/23 17:47:34
	Classroom Environment/Context	1	0.13	1	3/11/23 12:57:33	12/22/22 09:59:58
	Multiliteracy	2	0.27	1	3/11/23 12:57:33	12/22/22 07:43:03
	S Training data identification	10	1.34	9	3/11/23 12:57:33	2/3/23 17:22:06
	Social Justice	1	0.13	1	3/11/23 12:57:33	1/17/23 19:52:46
	RQs	0	0.00	0	3/11/23 12:57:33	12/11/22 14:37:57
	Constructed	2	0.27	2	3/11/23 12:57:33	12/11/22 18:49:07
Adapted material	EXAMPLES!	3	0.40	1	4/2/23 10:18:32	4/2/23 09:32:05
Adapted material	Connecting to students prior experience (+)	6	0.80	1	4/23/23 15:17:52	4/2/23 09:20:27

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Adapted material	Condensing/Synthesizing for time	8	1.07	1	4/2/23 10:19:40	4/2/23 09:24:42
Adapted material	Scaffolding/guidance	1	0.13	1	4/2/23 10:19:40	4/2/23 09:24:13
Adapted material	Simplifying and reducing vocabulary and content- including CS (	5	0.67	1	4/23/23 15:18:12	4/2/23 09:22:15
CML Framework	Representation/Bias	10	1.34	7	2/26/23 10:36:22	12/11/22 18:51:00
CML Framework	Semiotics	16	2.14	3	2/24/23 14:28:46	12/11/22 18:49:29
CML Framework	Audience/Positionality	2	0.27	2	2/19/23 10:32:31	12/11/22 18:50:14
CML Framework	Purpose/Production	0	0.00	0	2/24/23 14:28:46	12/11/22 18:51:28
CML Framework	Social Justice	3	0.40	3	2/24/23 14:28:46	12/11/22 18:51:57
Computer Science	Omitted CS	1	0.13	1	2/24/23 14:27:46	2/11/23 10:32:13
Computer Science	Input-Processing-Output	7	0.94	5	3/11/23 13:08:13	2/7/23 16:24:13
Computer Science	Algorithmic Bias	11	1.47	2	2/24/23 14:27:46	2/7/23 16:22:43
Computer Science	Training Data	11	1.47	3	3/5/23 12:11:26	2/7/23 16:24:51
Computer Science	Recommendation engines	1	0.13	1	2/24/23 14:27:46	2/11/23 16:24:16

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Design Process	Plan while reflecting	6	0.80	5	3/11/23 12:57:33	1/17/23 10:48:13
Design Process	Changes to planning	2	0.27	1	3/11/23 12:57:33	1/3/23 14:23:57
Design Process	Teacher knowledge of students	9	1.21	6	3/11/23 12:57:33	1/11/23 16:24:23
Design Process	Researcher ideas	7	0.94	3	3/11/23 12:57:33	1/25/23 22:19:34
Design Process	Logistics	8	1.07	6	3/11/23 12:57:33	1/17/23 11:15:56
Design Process	Revisited content (+)	57	7.64	17	4/6/23 17:41:06	3/5/23 12:06:08
Design Process	Planning Time	2	0.27	2	4/6/23 17:41:57	1/30/23 09:00:50
Design Process	Borrowed sources	7	0.94	5	3/11/23 12:57:33	1/25/23 22:28:35
Design Process	Design flaws	5	0.67	5	3/11/23 12:57:33	1/4/23 18:54:46
Design Process	Teaching CAL while planning	5	0.67	3	3/11/23 12:57:33	1/4/23 17:15:20
Design Process	Teacher suggestions	9	1.21	5	3/11/23 12:57:33	1/17/23 11:40:11
Design Process	Omitted ideas	26	3.49	13	4/6/23 20:08:19	1/17/23 11:12:16
Design Process	Time Constraints	25	3.35	11	3/28/23 22:34:11	12/22/22 08:36:33
Design Process	Collaborative Reflection changes/moves	1	0.13	1	3/11/23 12:57:33	3/4/23 13:54:19
Design Process	Adapted material	2	0.27	2	4/1/23 10:34:23	3/4/23 11:46:39
Design Process	Identified area of S need	2	0.27	2	3/11/23 12:57:33	3/10/23 22:34:00

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Design Process	Core content	10	1.34	7	3/11/23 12:57:33	12/28/22 21:15:02
Representation/Bias	Student Knowledge of Bias	17	2.28	9	2/19/23 15:16:03	12/22/22 08:24:45
RQs	Teacher Learning	1	0.13	1	4/22/23 20:39:09	12/11/22 18:53:32
RQs	Researcher Learning	7	0.94	4	4/22/23 20:39:09	12/11/22 18:53:16
RQs	Teacher moves	16	2.14	9	4/22/23 20:39:09	12/22/22 10:23:22
RQs	Teacher challenges	3	0.40	2	4/22/23 20:39:09	12/11/22 14:38:28
RQs	Student Learning	67	8.98	24	4/22/23 20:39:09	12/22/22 09:51:14
Scaffolding/ Guidance	Too open-ended	1	0.13	1	4/2/23 10:19:40	4/2/23 09:19:12
Student Learning	Student prior knowledge	10	1.34	6	3/10/23 22:39:48	1/25/23 22:22:10
Student Learning	Media Bias	1	0.13	1	2/28/23 13:15:11	2/11/23 16:19:42
Student Learning	Media Literacy	7	0.94	4	2/28/23 13:15:11	1/25/23 22:47:28
Student Learning	Varied Student Experience	1	0.13	1	2/28/23 13:15:11	2/11/23 10:18:05
Student Learning	General Bias	5	0.67	2	2/28/23 14:25:26	2/7/23 16:40:50
Student Learning	Student stress and confusion	2	0.27	1	3/4/23 09:31:41	1/24/23 22:52:32
Student Learning	S not making connection	8	1.07	6	3/28/23 22:16:39	2/28/23 13:15:11
Student Learning	Student Misconceptions	24	3.22	12	3/27/23 13:00:32	12/22/22 10:24:16

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
	& Lack of Knowledge					
Student Learning	Personal Connection	18	2.41	9	2/28/23 13:39:59	12/22/22 08:22:23
Student Learning	Student Engagement & Excitement	12	1.61	7	2/28/23 13:15:11	12/22/22 09:52:08
Student Learning	Student Centered	6	0.80	5	2/28/23 13:15:11	12/22/22 08:23:57
Teacher challenges	Teacher lacks ML Experience	19	2.55	9	2/1/23 07:45:01	12/11/22 19:01:32
Teacher challenges	Student Distraction	15	2.01	11	1/27/23 18:54:12	12/11/22 19:02:08
Teacher challenges	Time	11	1.47	9	1/30/23 09:21:03	1/3/23 14:20:05
Teacher challenges	Other T challenges	2	0.27	2	1/24/23 22:55:51	1/17/23 19:43:09
Teacher challenges	Students lack prior knowledge	9	1.21	6	2/1/23 07:44:41	1/3/23 14:14:25
Teacher Learning	Teacher attitude	9	1.21	6	4/6/23 20:02:39	12/22/22 08:33:51
Teacher moves	T-Provided examples	1	0.13	1	1/25/23 22:52:33	1/25/23 22:52:24
Teacher moves	Changes after Lesson #1	20	2.68	11	2/11/23 16:18:46	12/22/22 08:53:37
Teacher moves	Inquiry learning	3	0.40	2	1/25/23 22:52:24	1/25/23 22:40:39
Teacher moves	Teacher promising practices	11	1.47	9	1/27/23 19:16:56	12/11/22 14:38:59
Teaching Activities	Teaching Algorithms/CS	3	0.40	3	2/26/23 10:44:46	2/26/23 10:14:32
Teaching Activities	Student Hands-on activity	6	0.80	6	2/26/23 10:47:08	2/26/23 10:21:25

Parent code	Code	Coded Segments	% Coded Segments	Documents	Modified	Created
Teaching Activities	Teaching Media Bias	4	0.54	2	2/26/23 10:41:49	2/26/23 10:17:58
Teaching Activities	Project Prep	6	0.80	4	2/26/23 10:45:02	2/26/23 10:28:58
Teaching Activities	Teaching Media Literacy	3	0.40	2	2/26/23 10:41:49	2/26/23 10:13:26
Teaching Activities	Teaching Training data	2	0.27	2	2/26/23 10:45:18	2/26/23 10:15:37
Teaching Activities	Teaching Algorithmic Bias	7	0.94	4	2/26/23 10:46:02	2/26/23 10:15:01
Teaching Activities	Student Reflection/Connection	8	1.07	6	2/26/23 10:41:49	2/26/23 10:19:12
Teaching Activities	Teaching consequences	4	0.54	2	2/26/23 10:41:49	2/26/23 10:15:54
Teaching Activities	Connecting project to other content	6	0.80	3	2/26/23 10:46:53	2/26/23 10:41:49
Teaching Activities	Teaching Bias in General	3	0.40	3	2/26/23 10:41:49	2/26/23 10:14:11

Appendix H: Lesson Summary for Dewey Elementary School

Study Summary

Critical Algorithmic Literacy: Bridging Computer Science and Critical Media Literacy in the Elementary Classroom

From November 2022 until February 2023, researcher Scott Moss of the Educational Leadership Program (ELP) in the School of Education & Information Science will collaborate and co-design curriculum with demonstration teacher Veronica Sage for her third and fourth-grade students in rooms 1 & 2 to implement a series of lessons in critical algorithmic literacy (CAL). Critical algorithmic literacy seeks to expand media literacy education to provide students with skills that help them understand, interrogate, and critique the algorithmic systems that shape their lives. The goal of this research is to describe how students demonstrate critical algorithmic literacy skills and knowledge. The research will also describe the teacher/researcher co-design process.

The researcher will observe every scheduled CAL-integrated lesson implemented to describe how students demonstrate CAL competencies. In addition, students' work samples, such as reflection journals and projects, will be used to explore the effectiveness of the curriculum. By helping students create connections between their computational thinking, personal experiences, and creative expression, the CAL lessons seek to support student understandings of algorithms in authentic contexts. As this research study is part of the planned curriculum, any parent/students who wish to opt-out of the study would still learn and participate in the classroom without any data or research being collected. Participation in this study is voluntary and will remain confidential. Any questions about the project can be directed to the principal investigator, Scott Moss.

REFERENCES

Aguilera, E., & Pandya, J. Z. (2021). Critical literacies in a digital age: Current and future issues. *Pedagogies: An International Journal*, *16*(2), 103–110. https://doi.org/10.1080/1554480X.2021.1914059

Aleman, E., Nadolny, L., Ferreira, A., Gabetti, B., Ortíz, G., & Zanoniani, M. (2021). Screening bot: A playground for critical algorithmic literacy engagement with youth. *Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play*, 198–202. https://doi.org/10.1145/3450337.3483478

Ali, S., Payne, B. H., Williams, R., Park, H. W., & Breazeal, C. (2019). Constructionism, ethics, and creativity: Developing primary and middle school artificial intelligence education. In *International workshop on education in artificial intelligence K-12 (EDUAI'19)* (pp. 1-4).

Alter, A. (2017). Irresistible: the rise of addictive technology and the business of keeping us hooked. Penguin Press.

Amanullah, K. and Bell, T. (2019) Evaluating the use of remixing in scratch projects based on repertoire, lines of code (loc), and elementary patterns. *2019 IEEE Frontiers in Education Conference (FIE)*, Covington, KY, USA, 2019, pp. 1-8, doi: 10.1109/FIE43999.2019.9028475.

American Academy of Pediatrics. (2016). Media use in school-aged children and adolescents. *Pediatrics*, *138*(5), e20162592. https://doi.org/10.1542/peds.2016-2592

Anderson, M., & Jiang, J. (2018). Teens, social media & technology. Pew Research Center. http://publicservicesalliance.org/wp-content/uploads/2018/06/Teens-Social-Media-Technology-2018-PEW.pdf

Aufderheide, P. (1993). Aspen institute program on communications and society., & national leadership conference on media literacy. *media literacy: A report of the National Leadership Conference on Media Literacy, the Aspen Institute Wye Center, Queenstown Maryland, December 7-9, 1992*. Washington, D.C: Communications and Society Program, the Aspen Institute.

Axios (2019). Biases are being baked into artificial intelligence. [YouTube video]. https://youtu.be/NaWJhlDb6sE

Banerjee SC, Kubey R. (2013) Boom or boomerang: A critical review of evidence documenting media literacy efficacy. In: Scharrer E, editor. *Media effects/media psychology.* Wiley-Blackwell Publishers; 2013. pp. 2–24.

Beer, D. (2009). Power through the algorithm? Participatory web cultures and the technological unconscious. *New Media & Society*, *11*(6), 985–1002. https://doi.org/10.1177/1461444809336551

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the new Jim code*. Social Forces.

Bigelow, B., Christensen, L., Karp, S., Petersen, B. (Eds.) (1994). *Rethinking our classrooms: teaching for equity and justice*. Rethinking Schools.

Boommen. 2018. Recommendation engine starter code. [Shared computer program]. https://scratch.mit.edu/projects/208662938/

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Breakstone, J., Smith, M., Wineburg, S., Rapaport, A., Carle, J., Garland, M., & Saavedra, A. (2021). Students' civic online reasoning: A national portrait. *Educational Researcher*. https://purl.stanford.edu/cz440cm8408

Bucher, T. (2018). *If... then: Algorithmic power and politics*. Oxford University Press.

Buckingham, D. (2007). Digital media literacies: Rethinking media education in the age of the Internet. *Research in Comparative and International Education*, *2*(1), 43-55

Buckingham, D. (2019). *The media education manifesto*. Polity.

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. In *Conference on fairness, accountability and transparency* (pp. 77-91). PMLR.

Burrell, J. (2016). How the machine 'thinks': Understanding opacity in machine learning algorithms. *Big Data & Society*, *3*(1), 2053951715622512. https://doi.org/10.1177/2053951715622512

Canadian Commission for UNESCO. (2020). Algorithm literacy education guide. https://www.algorithmliteracy.org/data/resources/en/Algorithm-Literacy-Education-Guide.pdf

Ching, C.C. (2012). Introduction: Part I: Developmental perspectives. In R. Foley & C Ching (Eds.) *Constructing the self in a digital world* (p. 17-25*)*. Cambridge University Press.

Cho, H., Cannon, J., Lopez, R., & Li, W. (2022). Social media literacy: A conceptual framework. *New Media & Society*, 14614448211068530. https://doi.org/10.1177/14614448211068530

Choung, H., David, P., & Ross, A. (2022.). Trust and ethics in AI. *AI & Society*, 1–13.

Ciccone, M. (2021). Algorithmic literacies: K-12 realities and possibilities. In *Algorithmic rights and protections for children*. https://doi.org/10.1162/ba67f642.646d0673

Clarke, V. & Braun, V. (2013). *Successful qualitative research*. SAGE Publications.

Code.org. (2023). Hour of code. https://hourofcode.com/us

Code.org, CSTA, & ECEP Alliance (2022). 2022 State of computer science education: Understanding our national imperative. https://advocacy.code.org/stateofcs

Connolly, S. and Readman, M. (2017). Towards 'creative media literacy' in *International handbook of media literacy education* [Eds De Abreu, B. Mihailidis, P., Lee, A.Y.L., Melki, J. and McDougall , J.] Routledge.

Cotter. K.M., (2020). *Critical algorithmic literacy: Power, epistemology, and platforms.* [Doctor of Philosophy]. Michigan State University.

Cotter, K., & Reisdorf, B. (2020). Algorithmic knowledge gaps: A new horizon of (digital) inequality. *International Journal of Communication*, *14*, 21. https://ijoc.org/index.php/ijoc/article/view/12450

Creswell, J. W., & Creswell, J. D. (2017*). Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Culkin, J. M. (1967). A schoolman's guide to Marshall McLuhan. https://static1.squarespace.com/static/5a6135761f318d1d719bd5d9/t/5b2536342b6a2886441759d5/1529165365116/JOHN_CULKIN.pdf

Culver, S. H. & Redmond, T. (2019) Media literacy snapshot. National association for media literacy education. https://namle.net/publications/somlr/

Dasgupta, S., & Hill, B. M. (2021). Designing for critical algorithmic literacies. In *Algorithmic rights and protections for children*. https://wip.mitpress.mit.edu/pub/designing-for-critical-algorithmic-literacies/release/1?readingCollection=646d0673

Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. In *Ethics of data and analytics* (pp. 296-299). Auerbach Publications.

De Abreu, B., Mihailidis, P., Lee, A.Y.L., Melki, J. and McDougall , J. (2017). Arc of research and central issues in media literacy education in *International Handbook of Media*

Dezuanni, M. (2015). The building blocks of digital media literacy: Sociomaterial participation and the production of media knowledge, *Journal of Curriculum Studies*, *47*:3, 416-439, DOI: 10.1080/00220272.2014.966152

Dewey, J. (1933). *How we think*. Heath & Co.

Dewey, J. (1938). *Experience and education*. Macmillan.

D'Ignazio, C., & Bhargava, R. (2015). Approaches to building big data literacy. *Bloomberg Data for Good Exchange Conference.*

Dignum, V., Pigmans, S., Vosloo, S., & Penagos, M. (2020). *Policy guidance on ai for children." UNICEF, the office of global insight and policy." The United Nations children's fund*. https://www.unicef.org/globalinsight/media/1171/file/UNICEF-Global-Insight-policy-guidance-AI-children-draft-1.0-2020.pdf

DiPaola, D., Payne, B. H., & Breazeal, C. (2020). Decoding design agendas: An ethical design activity for middle school students. *Proceedings of the interaction design and children conference*, 1–10. https://doi.org/10.1145/3392063.3394396

Dogruel, L., Masur, P., & Joeckel, S. (2021). development and validation of an algorithm literacy scale for internet users. *Communication Methods and Measures*, 1–19. https://doi.org/10.1080/19312458.2021.1968361

Douillard, K., & Labbo, L. D. (2002). Going past done: Creating time for reflection in the classroom. *Language Arts*, *80*(2), 92.

Druga, S., Williams, R., Breazeal, C., & Resnick, M. (2017). "Hey Google is it OK if I eat you?": Initial Explorations in Child-Agent Interaction. *Proceedings of the 2017 conference on interaction design and children*, 595–600. https://doi.org/10.1145/3078072.3084330

Duffy, T. M., & Jonassen, D. H. (2013). *Constructivism and the technology of instruction: A conversation*. Routledge.

Education Data Partnership. (2023). Cumulative enrollment by race/ethnicity. *Ed-Data*. https://www.ed-data.org/county/Los-Angeles

Exposure Labs. (2020). *The social dilemma*: Discussion and action guide. https://drive.google.com/file/d/1Z9KysBogheudj2L02s8LFyYlyNYNeS_M/view

Eyal, N. (2019). Indistractable: how to control your attention and choose your life. BenBella Books.

Freire, P. (1972). *Pedagogy of the oppressed*. Herder and Herder.

Freire, P., & Macedo, D. (1987). *Literacy: Reading the word and the world*. Bergin & Garvey.

Funk, S. S., Kellner, D., & Share, J. (Eds.). (2019). *Critical Media Literacy as Transformative Pedagogy*. IGI Global. https://doi.org/10.4018/978-1-5225-8359-2

Futschek, G. (2006). Algorithmic thinking: The key for understanding computer science. In *Informatics education–The bridge between using and understanding computers: International conference in informatics in secondary schools–Evolution and Perspectives, ISSEP 2006,* Vilnius, Lithuania, November 7-11, 2006. Proceedings (pp. 159-168). Springer Berlin Heidelberg.

Gebre, E. (2022). Conceptions and perspectives of data literacy in secondary education. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13246

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. J. Boczkowski, & K. A.Foot (Eds.), *Media technologies* (pp. 167-194). Cambridge, MA: MIT Press.

Gillespie, T., Boczkowski, P. J., & Foot, K. A. (Eds.). (2014). *Media technologies: Essays on communication, materiality, and society*. MIT Press.

Giroux, H. A. (1987). Critical literacy and student experience: Donald Graves' approach to literacy. *Language Arts*, *64*(2), 175–181. http://www.jstor.org/stable/41961590

Giroux, H. (1999). Rewriting the discourse of racial identity: Towards a pedagogy and politics of whiteness. *Harvard educational review* 67 (2), 285-321

Google for Education. (nd). Teach computer science & coding to kids - CS first. https://csfirst.withgoogle.com/s/en/home

Gran, A.-B., Booth, P., & Bucher, T. (2021). To be or not to be algorithm aware: A question of a new digital divide? *Information, Communication & Society*, *24*(12), 1779–1796. https://doi.org/10.1080/1369118X.2020.1736124

Hargittai, E., Gruber, J., Djukaric, T., Fuchs, J., & Brobach, L. (2020). Black box measures? How to study people's algorithm skills. *Information, Communication & Society*, *23*(5), 764–775. https://doi.org/ 10.1080/1369118X.2020.1713846

Harris, T. (2017, April). *How a handful of tech companies control billions of minds every day*. [Video]. TED Conferences. https://www.ted.com/talks/tristan_harris_how_a_handful_of_tech_companies_control_billions_of_minds_every_day

Harris, T. and Raskin, A. (2022) Center for humane technology. https://www.humanetech.com/

Hautea, S., Dasgupta, S., & Hill, B. M. (2017). Youth perspectives on critical data literacies. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 919–930. https://doi.org/10.1145/3025453.3025823

Herdzina, J., & Lauricella, A. R. (n.d.). *Media literacy in early childhood report*. 54.

Hewett, V. M. (2001). Examining the Reggio Emilia approach to early childhood education. *Early childhood education journal*, 29, 95-100.

Hobbs, R. (2017). Measuring the digital and media literacy competencies of children and teens. In Fran C. Blumberg and Patricia J. Brooks (Eds.), *Cognitive Development in Digital Contexts* (pp. 253 – 274). Academic Press.

Hobbs, R. (2019). Media literacy foundations. *The international encyclopedia of media literacy*, 1-19.

Hobbs, R. (2020). Propaganda in an age of algorithmic personalization: Expanding literacy research and practice. *Reading Research Quarterly*, *55*(3), 521-533.

Hobbs, R. (2022). Assessing media literacy measures, presentation to the 2022 international communication association. April 11, 2022. [YouTube Video]. https://www.youtube.com/watch?app=desktop&v=GDaQgSDMX-s.

Horkheimer, M., & Adorno, T. W. (1982). *Dialectic of enlightenment*. Continuum.

Ito, M., Cross, R., Dinakar, K., & Odgers, C. (2021). *Algorithmic rights and protections for children*. https://wip.mitpress.mit.edu/pub/intro-algorithmic-rights-and-protections/release/1

Irgens, G. A., Knight, S., Wise, A. F., Philip, T. M., Olivares, M. C., Vakil, S., Marshall, J., Parikh, T., Lopez, M. L., Wilkerson, M. H., Gutiérrez, K., Jiang, S., & Kahn, J. B. (2020). Data literacies and social justice: Exploring critical data literacies through sociocultural perspectives. *The Interdisciplinarity of the Learning Sciences, ICLS 2020 - Conference Proceedings*, 8.

Jandrić, P. (2019). The postdigital challenge of critical media literacy. *The International Journal of Critical Media Literacy*, *1*(1), 26–37. https://doi.org/10.1163/25900110-00101002

Kafai, Y., Lui, D., & Proctor, C. (2020). From theory bias to theory dialogue: embracing cognitive, situated, and critical framings of computational thinking in k-12 cs education. *ACM Inroads*, *11*(1), 44–53.

Kantayya, S. (Director) & Buolamwini, J. (Writer). (2021). *Coded Bias* [Film]. Shalini Kantayya, p.g.a. (Producer).

Kellner, D. & Gennaro, S. (2022) Digital culture, media, and the challenges of contemporary cyborg youth. In Kellner, D., *Critical theory and pedagogy: Towards the reconstruction of education.* Peter Lang. Kindle Edition.

Kellner, D., & Share, J. (2019). *The critical media literacy guide: Engaging media and transforming education.* Brill.

Kist, W. (2005). *New literacies in action: Teaching and learning in multiple media* (Vol. 75). Teachers College Press.

Kitchin, R. (2017). Thinking critically about and researching algorithms. *Information, Communication & Society*, *20*(1), 14–29. https://doi.org/10.1080/1369118X.2016.1154087

Ko, A.J., Beitlers, A. Wortzman, B., Davidson, M. M. Oleson, A., Kirdani-Ryan, M., Druga, S. (2022). *Critically conscious computing: Methods for secondary education*. [Online book]. https://criticallyconsciouscomputing.org/.

Kroll, J. A. (2018). The fallacy of inscrutability. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2133), 1-14. https://doi.org/10.1098/rsta.2018.0084.

Lanier, J. (2018). *Ten arguments for deleting your social media accounts right now*. Random House.

Lauricella, A. R., Herdzina, J., & Robb, M. (2020). Early childhood educators' teaching of digital citizenship competencies. *Computers & Education*, *158*, 103989.

Lee, C. H., Gobir, N., Gurn, A., & Soep, E. (2022). In the black mirror: Youth investigations into artificial intelligence. *ACM Transactions on Computing Education*, *22*(3), 1-25.

Lee, C. H., & Soep, E. (2016). None but ourselves can free our minds: Critical computational literacy as a pedagogy of resistance. *Equity & Excellence in Education*, *49*(4), 480–492. https://doi.org/10.1080/10665684.2016.1227157

Lee, I., Ali, S., Zhang, H., DiPaola, D., & Breazeal, C. (2021). Developing middle school students' AI literacy. *SIGCSE '21 Conference Proceedings*, Toronto, Canada March 17 - 20, 2021, Lipkin, M.C., Culver, S.H. & Redmond, T. (2020). Snapshot 2019: The state of media literacy education in the US. *National Association of Media Literacy. https://namle.net/wp-content/uploads/2020/10/SOML_FINAL.pdf*

Livingstone, S., Blum-Ross, A. (2021). *Parenting for a digital future: How hopes and fears about technology shape children's lives*. Oxford university press.

Long, D. and Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the *2020 CHI Conference on Human Factors in Computing Systems* (CHI '20). Association for Computing Machinery, New York, NY, USA, 1–16. https://doi.org/10.1145/3313831.3376727

Massachusetts Institute of Technology. (2021). Responsible AI for social empowerment and education upper elementary: Teachable machines | 2021-22 Day of AI Educator Guide. [Instructional unit plan]. https://docs.google.com/document/d/1uCxfgaHYpLbPaL5ahrgAOs9ldR2JOnuBvIosIP8kDPw

Maxwell, J. A. (2013). *Qualitative research design: An interactive approach*. United Kingdom: SAGE Publications.

McLaren, C. (2002). The branding alphabet. Center for Media Literacy. https://www.medialit.org/reading-room/branding-alphabet

McIntosh, J. (2011) The gendered advertising remixer: A media literacy web application [Curriculum]. https://genderremixer.com/curriculum/

McNamee, R. (2019). *Zucked: Waking up to the Facebook catastrophe*. Penguin Press.

Media Smarts. (2018). An introduction to digital literacy | Digital Literacy 101 [YouTube video]. https://youtu.be/8o96ey4jCgE

Medina, A. (2022). Critical media literacy brings environmental justice into the classroom. [Conference presentation]. *International Media Literacy Symposium*. June 28, 2022. Madison, Wisconsin.

Merriam, S. B., & Tisdell, E. J. (2016). *qualitative research: a guide to design and implementation* (4th ed.). San Francisco, CA: Jossey Bass.

Mohamed, S., Png, MT. & Isaac, W. (2020). Decolonial AI: Decolonial theory as sociotechnical foresight in artificial intelligence. *Philos. Technol.* 33, 659–684. https://doi.org/10.1007/s13347-020-00405-8

Morrell, E. (2013). 21st-century literacies, critical media pedagogies, and language arts. *The Reading Teacher*. 66 (4).

Moss Center (2021). *Coded bias* trailer. [YouTube video]. https://youtu.be/xy8iVg7shjI

Moss, S. (2023a). Critical algorithmic literacy: Addressing algorithmic epistemological authority for K-12 students [Paper]. American Association of Research in Education. April 2023.

Moss, S. (2023b). The prevalence of artificial intelligence, surveillance capitalism, disinformation, and biased algorithms amplify the need for critical skills applied to media. *The Journal of Media Literacy*. September 1, 2022.

National Council of Teachers of English (2020). Literacy is more than just reading and writing. *Literacy & NCTE* [Blog]. https://ncte.org/blog/2020/03/literacy-just-reading-writing/.

NBC News (2021). Automatic soap dispensers are racist. | A little late with Lilly Singh. Aired April 27, 2021. https://www.nbc.com/a-little-late-with-lilly-singh/video/automatic-soap-dispensers-are-racist-a-little-late-with-lilly-singh/4352246

New London Group. (1996). A pedagogy of multiliteracies: Designing social futures. *Harvard Educational Review*, 66(1), 60–92.

Noble, S. U. (2018). *Algorithms of oppression: How search engines reinforce racism*. University Press.

O'Neil, C. (2017). *Weapons of math destruction*. Penguin Books.

O'Neil, and Gunn, H. (2020) Near-Term Artificial Intelligence and the Ethical Matrix In *Ethics of Artificial Intelligence*. Edited by: S. Matthew Liao, Oxford University Press.

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. Viking/Penguin Press.

Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Cambridge, MA: Harvard University Press.

Payne, B. H., & Breazeal, C. (2019). *An Ethics of Artificial Intelligence Curriculum for Middle School Students*. [Curriculum document]. MIT Media Lab. https://docs.google.com/document/d/1e9wx9oBg7CR0s5O7YnYHVmX7H7pnITfoDxNdrSGkp60/

Piaget, J. (1977). *The construction of reality in the child*. Routledge.

Pichai, S. (2018) World Economic Forum. Davos, Switzerland. June 20, 2018.

Pressner, K. *Are you biased? I am*. [YouTube video]. TEDx Talks, Basel. https://youtu.be/Bq_xYSOZrgU

Project Look Sharp. (2019). Google image Searches – Do they promote or counter stereotypes? [Lesson Plan]. Ithaca College. https://www.projectlooksharp.org/download.php?resource_entry_id=2188

Project Look Sharp. (2019). YouTube Recommendations: Who's Steering Your View [Lesson Plan]. Ithaca College. https://projectlooksharp.org/front_end_resource.php?resource_id=464

Qeadan, F., VanSant-Webb, E., Tingey, B., Rogers, T. N., Brooks, E., Mensah, N. A., & Rogers, C. R. (2021). Racial disparities in COVID-19 outcomes exist despite comparable Elixhauser comorbidity indices between Blacks, Hispanics, Native Americans, and Whites. *Scientific reports*, *11*(1), 1-11.

Rainie, L., & Anderson, J. (2017). *Numbers, facts and trends shaping the world*. Pew Research Center.

Redmond, T. (2012). The pedagogy of critical enjoyment: Teaching and reaching the hearts and minds of adolescent learners through media literacy education. *Journal of Media Literacy Education*, 15.

Redmond, T. (2019). Unboxed: Expression as Inquiry in Media Literacy Education. *Journal of Literacy and Technology*. Special Edition. Volume 20, Number 1: Winter

Redmond, T. (2021). The art of audiencing: Visual journaling as a media education practice. *Journal of Media Literacy Education Pre-Prints.* Retrieved from https://digitalcommons.uri.edu/jmle-preprints/17

Redmond, T. (2022). Post-Secondary Media Integration with Dr. Theresa Redmond. Hosted by Diana Maliszewski. [Podcast]. https://voiced.ca/podcast_episode_post/post-secondary-media-integration-with-dr-theresa-redmond/

Register, Y., & Ko, A. J. (2020). Learning Machine Learning with Personal Data Helps Stakeholders Ground Advocacy Arguments in Model Mechanics. *Proceedings of the 2020 ACM Conference on International Computing Education Research*, 67–78. https://doi.org/10.1145/3372782.3406252

Resnick, M., & Silverman, B. (2005). Some reflections on designing construction kits for kids. *Proceeding of the 2005 Conference on Interaction Design and Children - IDC '05*, 117–122. https://doi.org/10.1145/1109540.1109556

Rideout, V. J. & Robb, M. B. (2020). The Common Sense census: Media use by kids age zero to eight, 2020. San Francisco, CA: Common Sense. https://www.commonsensemedia. org/research/the-common-sense-census-media-useby-kids-age-zero-to-eight-2020.

Rideout, V. J., Peebles, A., Mann, S., & Robb, M. B. (2022). Common Sense census: Media use by tweens and teens, 2021. San Francisco, CA: Common Sense. https://www.commonsensemedia.org/research/ the-common-sense-census-media-use-by-tweens-and teens-2021

Ridley, M., & Pawlick-Potts, D. (2021). Algorithmic literacy and the role for libraries. *Information Technology and Libraries*, *40*(2). https://doi.org/10.6017/ital.v40i2.12963

Rogow, F. (2021). Challenging the messages of identity in the media with elementary students: Promoting identity exploration and student engagement through critical media literacy. [Conference presentation]. *Critical Media Literacy Conference of the Americas*. October 16, 2021.

Rushkoff, D. (2019). Forward In Hobbs, R. *Mind over media: Propaganda education for a digital age*. W. W. Norton & Company.

S.1896 — 117th Congress (2021-2022). Algorithmic justice and online platform transparency act.117th Congress (2021-2022). (2021, May 27). https://www.congress.gov/bill/117th-congress/senate-bill/1896/

Saldaña, J.M. (2021). *The coding manual for qualitative researchers*. [Kindle Edition] 4th ed., SAGE Publications, 2015.

Schön, D. (1983). *The reflective practitioner: How professionals think in action*. Basic Books.

Schüll, N.D. (2012). *Addiction by design: Machine gambling in Las Vegas*. Princeton University Press.

Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data & Society*, *4*(2), 2053951717738104. https://doi.org/10.1177/2053951717738104

Seidman, I. (2019) *Interviewing as qualitative research a guide for researchers in education and the social sciences*. Teachers College Press.

Shaffer, D. W., Resnick, M. 1999. “Thick” authenticity: New media and authentic learning. *Journal of Interactive Learning Research*. 10(2):195–215.

Shane, J. (2019). You look like a thing and I love you. Hachette UK.

Share, J. (2015). *Media literacy is elementary: Teaching youth to critically read and create media* (Second Edition). Peter Lang Publishing.

Share, J., Gambino, A., and Moss, S. (2022). Critical media literacy brings social and environmental justice into the classroom. Presented at the National Council of Teachers of English (NCTE). November 17, 2022.

Share, J., Mamikonyan, T., & Lopez, E. (2019). Critical media literacy in teacher education, theory, and practice. In J. Share, T. Mamikonyan, & E. Lopez, *Oxford Research Encyclopedia of Education*. Oxford University Press. https://doi.org/10.1093/acrefore/9780190264093.013.1404

Southern Poverty Law Center. (2018). Social justice standards. *Learning for Justice*. https://www.learningforjustice.org/frameworks/social-justice-standards

Steinberg, S. R., & Kincheloe, J. L. (2004). *Kinderculture: The corporate construction of childhood*. Boulder, Colo: Westview Press.

Thompson, N. (2018). When tech knows you better than you know yourself: Historian yuval noah harari and ethicist tristan harris discuss the future of artificial intelligence with wired editor-in-chief nicholas thompson. *Wired* [Online magazine]. (October 4, 2018). https://www.wired.com/story/artificial-intelligence-yuval-noah-harari-tristan-harris/

Thumlert, K., McBride, M., Tomin, B., Nolan, J., Lotherington, H., & Boreland, H. (2022). Algorithmic literacies: Identifying educational models and heuristics for engaging the challenge of algorithmic culture. *Digital Culture & Education*, *14*(4), 19–35.

Taulli, T. (2019). *Artificial intelligence basics: A non-technical introduction*. Apress.

Trammell, A., & Cullen, A. L. (2021). A cultural approach to algorithmic bias in games. *New Media & Society*, *23*(1), 159–174. https://doi.org/10.1177/1461444819900508

Twenge, J. M., Haidt, J., Joiner, T. E., & Campbell, W. K. (2020). Underestimating digital media harm. *Nature Human Behaviour*, *4*(4), 346–348. https://doi.org/10.1038/s41562-020-0839-4

United Nations Children's Fund (UNICEF) (2020). Policy guidance on AI for children. https://www.unicef.org/globalinsight/media/1171/file/UNICEF-Global-Insight-policy-guidance-AI-children-draft-1.0-2020.pdf

Valtonen, T., Tedre, M., Mäkitalo, Ka., & Vartiainen, H. (2019). Media literacy education in the age of machine learning. *Journal of Media Literacy Education*, *11*(2). https://doi.org/10.23860/JMLE-2019-11-2-2

Vasquez, V.M. (2014) *Negotiating critical literacies with young children* (Language, Culture, and Teaching Series). Taylor and Francis. Kindle Edition.

Vosoughi, S., Roy, D., & Aral, S. (2018). The spread of true and false news online. *Science*, *359*(6380), 1146-1151.

Vourletsis, I., & Politis, P. (2023). Developing computational thinking practices in primary education. outcomes from a school-year instructional intervention. In A. Reis, J. Barroso, P. Martins, A. Jimoyiannis, R. Y.-M. Huang, & R. Henriques (Eds.), *Technology and innovation in learning, teaching and education* (Vol. 1720, pp. 354–369). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-22918-3_27

Vygotsky, L. S., van der Veer, R. E., Valsiner, J. E., & Prout, T. T. (1994). *The Vygotsky reader*. Basil Blackwell

Wang, G., Zhao, J., Van Kleek, M., & Shadbolt, N. (2022). Don't make assumptions about me!': Understanding Children's Perception of Datafication Online. *Conference on Computer Supported Cooperative Work and Social Computing*, 1–20. https://www.tiffanygewang.com/publication/paper-placeholder-8/paper-placeholder-8.pdf

Ways of Council (2023). Council in schools. https://waysofcouncil.net/council-in-schools/

Willson, M. (2017). Algorithms (and the) everyday. *Information, Communication & Society*, *20*(1), 137–150. https://doi.org/10.1080/1369118X.2016.1200645

Wineburg, S., Breakstone, J., Ziv, N., & Smith, M. (2020). How approaches to teaching digital literacy make students susceptible to scammers, rogues, bad actors, and hate-mongers (p. 22). The Stanford History Education Group.

Winter Bloomers (2021). *What is bias? - Intro for young children.* [YouTube Video]. https://www.youtube.com/watch?v=EdEQmH65ybQ

Wu, T. (2018). Blind spot: The attention economy and the law. *Antitrust LJ*, *82*(711).

Yalcinkaya, R., Sanei, H., Wang, C., Zhu, L., Kahn, J., & Jiang, S. (2022). Remixing as a key practice for coding and data storytelling. In *Proceedings of the 15th International conference on computer-supported collaborative learning-CSCL 2022, pp.* 407-410. International Society of the Learning Sciences.

Yeung, K. 2020. Recommendation of the council on artificial intelligence (oecd). International Legal Materials 59, 1 (2020), 27–34.

Zarouali, B., Boerman, S. C., & de Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the algorithmic media content awareness scale (AMCA-scale). *Telematics and Informatics, 62*, 101607. https://doi.org/10.1016/j.tele.2021.101607

Zuboff, S. (2019) *The age of surveillance capitalism*. Public Affairs.