

1 *Introduction*

Tyra nervously refreshed her browser after completing her latest project on TalentFinder and received the following feedback from her manager, “She was fast, accurate, and easy to work with.” It was a succinct, positive review. But now Tyra had to wait. She clicked “refresh” again, waiting to see when and how TalentFinder’s algorithm would update her rating evaluation score. So much hinged on the algorithm’s verdict: receiving a higher wage, being noticed by more prestigious clients, and gaining visibility in search results, for starters.

The problem, however, was that Tyra had no way of knowing how the algorithm controlling her visibility and success on TalentFinder behaved. She had virtually no access to what the algorithm’s criteria were, how its criteria were weighted, or even when the algorithm would update her score. After refreshing her page for the tenth time to no avail, Tyra closed out of the window and ruminated on the unknowable algorithm controlling her fortunes. Frustrated, she turned to express her predicament in the best way she knew, by writing a poem:

The Algorithm,
None can explain;
To attempt to decipher,
Is an effort in vain.

It's up, or it's down,
With no reason in sight;
Accept or do not,
You won't win the fight.

So work and work,
Leave the mysteries be;
To ponder the Algorithm,
Is a path to misery.¹

Tyra's poem was not an exaggeration. Experienced workers, new workers, workers with high and low rating scores, workers located in different countries—all reported similarly befuddling experiences with TalentFinder's algorithm. Sometimes the algorithm increased their rating evaluation score, sometimes it decreased it, and sometimes it did nothing at all. These outcomes had significant ramifications for workers' ability to find work on TalentFinder, but deciphering how the algorithm arrived at its decision was maddeningly impossible—it was, as Tyra put it, “a path to misery.”

Inside the Invisible Cage examines how organizations' use of algorithms is reconfiguring our understanding of control for Tyra and millions of other high-skilled workers who use online labor market platforms (e.g., Upwork, TopCoder, Gigster) to find their work. An explosion of online labor market platforms has transformed the nature of work in the past two decades.² In 2021, over forty million people used an online labor platform to find work in the United States.³ To put that number in context, according to recent estimates, retail,

the industry with the most employees in the United States, had 3.6 million workers.⁴ In fact, if the five largest occupations in the United States were combined, that still would not equal as many people as those who use online labor platforms to find work.⁵

The issue is not just that lots of people use online labor platforms to find work; it is that these platforms have transformed how organizations and workers find and work with each other.⁶ The goal of these platforms is to create an Amazon for labor: a platform that provides organizations and individual clients with instant access to top talent from around the world with the click of a button.⁷ Organizations, for example, can use online labor platforms to hire high-skilled workers, such as software engineers, graphic designers, data scientists, engineers, architects, and even lawyers and doctors, from around the world to complete primarily unstructured, knowledge-intensive projects.⁸ The appeal of online labor market platforms increased with the dramatic rise of remote work precipitated by the COVID-19 pandemic.⁹

Algorithms power the growth of online labor market platforms. Millions of participants are registered on platforms, and it would be impossible for a platform to individually match each job opportunity with workers whose skills, wages, and scheduling fit the position. Instead, these platforms use algorithms to match organizations and clients with workers, much like YouTube or Netflix use algorithms to match viewers' interests with video content.¹⁰ Yet, I argue that platforms use these algorithms to do much more than match jobs with workers.

This book argues that algorithms enable platforms to control high-skilled workers within an “invisible cage”: an environment in which organizations embed the rules and guidelines for how workers should behave in opaque algorithms that shift without providing notice, explanation, or recourse for workers. The invisible cage provides platform organizations with predictability because they can use algorithms to more efficiently collect data and monitor, evaluate,

and categorize which workers are rewarded and sanctioned on a global scale. At the same time, the opaque, dynamic algorithms in the invisible cage make life more *un*predictable for workers because they do not know which actions will be rewarded or punished.¹¹ I show that workers remain enmeshed in the invisible cage because the platform organization's algorithms control a worker's ability to get jobs within and outside the platform. As a result, workers like Tyra largely see their attempts to comply with its opaque algorithms as the only option they have, even though they can theoretically leave the platform at any time. The invisible cage concept thus reflects how workers must contend with an ever-changing and opaque set of algorithms that control their job opportunities and success within and between labor markets.

Platforms maintain the invisible cage by leveraging the weak institutional oversight and regulations¹² that govern their activities to cultivate and harness power and information asymmetries through concealed data collection, processing, and experimentation.¹³ These asymmetries have significant implications for platform organizations and workers. A major finding of this book is that algorithms can prove especially disruptive to the way workers find and complete work; this is especially the case for workers with college and advanced degrees—precisely those workers who have long been thought to be immune to technological disruption. This argument is primarily derived from six years of ethnographic data collection conducted on one of the world's largest online labor market platforms for high-skilled work, TalentFinder (a pseudonym).

More broadly, the invisible cage signals a profound shift in the way markets and organizations try to categorize and ultimately control people. Previously, markets and organizations classified people into categories based on group-level characteristics such as education, gender, location, and age (e.g., females with an engineering degree in their 20s living in Chicago).¹⁴ However, my analysis shows that organ-

izations can use algorithms to categorize them based on more granular, individual-level data in an attempt to “know” people in the invisible cage better than they know themselves. I show that the act of defining what algorithms should “know” about workers is an organizational decision that reveals what an organization prioritizes and what it wishes to (de)value. Whereas high-skilled workers traditionally had some degree of control over how they were evaluated and ranked, in the invisible cage organizations use algorithms to transfer this control to themselves, all the while removing workers’ ability to influence or contest the consequences of this transfer of control. In particular, organizations collect people’s data, dynamically classifying them using various algorithmic ratings, rankings, and categories. People cannot verify what data are collected and may struggle to understand how or why an algorithm categorizes them in a given way. Unlike previous forms of control used in bureaucratic organizations or market settings, the invisible cage is ubiquitous yet opaque and shifting, making it difficult for workers to break free from it.

By examining the implications of using algorithms to control high-skilled work, this book moves beyond existing scholarship, which has mostly focused on how platforms’ algorithms facilitate lower-paying work (e.g., Uber, Instacart, and Amazon Mechanical Turk).¹⁵ In lower-paying contexts, organizations use algorithms to nudge workers towards standardized behavior, revealing an enhanced form of Taylorism.¹⁶ In contrast, in the invisible cage the platform organization does not want workers to think about the algorithm or which behaviors are desired; rather, it encourages workers to behave “naturally” so that it can “objectively” categorize, rank, and recommend workers depending on their actions. In choosing which information is objective, measured, and valued, the organization’s algorithm reifies certain worker characteristics and choices while stripping out the complexity and unpredictability inherent in high-skilled work. Thus, as organizations increasingly use

algorithms to make consequential decisions¹⁷ for people inside the invisible cage (such as deciding who can rent and buy property,¹⁸ who goes to jail,¹⁹ and whom to hire²⁰), this form of control increasingly determines our opportunities without allowing us to understand or respond to the factors that govern our success.

To understand how the nature of control has changed with organizations' use of algorithms in online labor market platforms, I first provide a theoretical overview of the iron cage, the dominant metaphor that has shaped managerial and sociological theories of control.

The Iron Cage Metaphor for Control

Control—the ability to dictate someone else's actions to conform with your own goal—is described as management's "fundamental problem."²¹ Any manager who has tried to control an employee, or really anyone, can relate to this diagnosis. Even if a manager technically has the power and authority to compel a worker to comply with their directives, trying to coerce someone to adhere to a manager's expectations can backfire. Some of the earliest studies of foremen controlling factory workers document how workers resist coercive attempts to control their behavior.²² This resistance contributes to ongoing tensions between workers and management.

The sociologist Max Weber observed that bureaucratic organizations deal with management's fundamental problem in a way that largely reduces the tensions between workers and management. Bureaucracies, he argued, provide a rational system and rule-based hierarchy that outlines clear guidelines for how workers should behave.²³ Bureaucracies, for instance, prescribe rules and processes for how workers should be hired, evaluated, and promoted. Weber demonstrated that bureaucracies' systematic rules provide organizations with worker compliance without having to rely on individual managers' constant oversight and rule enforcement.

Although some groups of workers experience systematic discrimination that impedes their ability to advance in bureaucratic organizations,²⁴ it is generally theorized that if a worker complies with these seemingly rational rules, they will receive promotions and advance in their careers.²⁵ As a result, Weber argued that bureaucracies' rational systems enmesh people within an organization as if they were in an "iron cage"²⁶ because workers comply with the organization's rules without perceiving that they are formally being controlled. The iron cage concept of control thus converts immaterial bureaucratic decisions into a material reality that is very difficult to escape. Therein lies the effectiveness of the iron cage: unlike other attempts to control people, workers largely see their compliance with bureaucratic rules as the right thing to do, not as a direct attempt of a manager to control their behavior.²⁷ Thus, for both workers and organizations, the iron cage provides much-desired predictability and stability.

Since Weber, many scholars have suggested that organizations have implemented different forms of control, but at their core they reproduce the rational, rule-based compliance captured by the iron cage metaphor.²⁸ For instance, scholars view many companies that are celebrated for providing employee benefits as modern examples of "tightening the iron cage"²⁹ or even more subtly embedding workers' compliance within an organization's culture. The free meals, massages, and nap rooms that organizations like Google, Facebook, and Airbnb provide for workers also encourage them to remain at work for longer hours. Why go home when you can eat dinner while you "voluntarily" continue working on a project and continue conversations with colleagues? In short, the iron cage metaphor has proved to be an enduring metaphor to understand how organizations elicit compliance from workers without resorting to managers having to overtly direct and monitor them.

This understanding of control rests on the assumption that organizations employ workers full-time because that was the dominant

employment relationship in the twentieth century, when bureaucracies proliferated.³⁰ This arrangement gave organizations the power to set rational rules and procedures to align worker behavior with their expectations. In return for worker compliance, organizations provided workers with benefits tied to their employment, such as a regular salary, healthcare insurance, and paid time off.³¹ In the last few decades, however, organizational shareholders have come to view full-time employees as costly resources that decrease an organization's profitability.³² Beginning in the 1980s and accelerating in the decades thereafter, organizations that could outsource or hire temporary workers realized the economic benefits of accessing high-skilled workers without having to provide them with the costly benefits afforded full-time employees.³³ Further, when organizations need to cut costs, these temporary employees can be fired with relative ease compared to full-time employees, who may require severance pay. As the stock market continues to reward organizations that relied on temporary workers, methods of hiring temporary workers have multiplied. Even large companies championed as worker friendly, such as Google, employ more temporary workers than full-time employees.³⁴

Although organizations cannot legally dictate how temporary workers should behave, eliciting compliance from temporary workers is relatively straightforward when these workers are colocated with full-time employees.³⁵ Temporary workers are not typically subjected to formal evaluation in organizations. However, through various policies and cultural practices, organizations establish clear expectations for how they should behave, whom they should interact with, and how long they should work.³⁶ It is not uncommon, for example, for organizations to provide temporary workers with separate badges, workspaces, and equipment.³⁷ These measures visually and physically reinforce their temporary status within an organization. Further, deviating from an organization's rules and norms could re-

sult in the termination of a temporary worker's contract and ruin any chances that the organization might offer them full-time employment. In some respects, then, for the duration in which temporary workers are colocated on a project, they are enmeshed in an organization's iron cage with even more rigid rules than those exerted on full-time employees.³⁸

What happens, however, when temporary high-skilled workers are remote, are no longer colocated with other full-time employees, and can work for multiple clients? In this situation, organizations cannot rely on temporary workers' adherence to the rules and norms established on-site. Further, the threat of being fired is diminished when temporary workers can more easily find other clients to work for. These conditions characterize online labor market platforms, providing new challenges to how organizations exert control. Given the dramatic rise in the number of people using online labor market platforms to find work, understanding how control functions in the conditions specific to online platforms provides insight into larger dynamics in our society as algorithms are used to manage the way we work and interact in an increasing number of domains.

Ratings as a Mechanism of Control in Online Labor Market Platforms

Billions of people rely on online platforms to work, socialize, and buy products (a reliance that has increased significantly during the COVID-19 pandemic), activities that were deemed risky just a few decades ago because they involved transacting with unknown strangers from around the world. Scholars credit eBay with pioneering the approach that allayed many users' concerns about the legitimacy of online goods and services.³⁹ In the mid-1990s, eBay introduced a rating system in which buyers numerically rate sellers after they receive a product. These ratings serve as the "shadow of the past": they

provide other buyers with an easy, quantified measure of how people who previously interacted with the seller rated their experience. High ratings signal that the seller has a history of delivering quality products in a timely manner for multiple people, while low ratings signal that buyers have had trouble transacting with the seller. Much like performance evaluations in the iron cage, which serve as a key mechanism of control because they encode a formal rubric by which workers are evaluated, compared, and rewarded, ratings encode a platform's expectations for how sellers should behave and how they will be rewarded.

The genius of eBay's solution to facilitating remote transactions between strangers on a global scale was that eBay did not have to hire sellers, create elaborate rules for them, or individually vet and verify every transaction. Ratings are ostensibly a measure of quality, but they are also a mechanism of control in online markets and beyond. While ratings provide a sense of transparency and accountability for external audiences,⁴⁰ sociologists have consistently demonstrated that because people are heavily influenced by ratings (when is the last time you bought something or transacted with someone online who had a low rating?), those subject to ratings will do whatever it takes to get the best rating possible.⁴¹

Ratings in online labor markets thus function as a significant mechanism of control. Each time a client finishes a project with a worker, the platform asks them to rate the worker, which provides a formal rubric by which workers are judged, sorted, and matched. Online labor markets' algorithms, for instance, aggregate these ratings and provide workers with a rating score that other clients can use to determine whether they want to hire a worker for a project.⁴² Much like with eBay, ratings have enabled online labor markets to operate on a global scale without overseeing every interaction between clients and workers. Clients cannot observe a worker's actions in the same way they could if a worker were physically colocated, but workers are

aware that clients will provide a rating evaluation once the project is completed. The conventional wisdom therefore suggests that workers will adhere to the online labor market's and the client's expectations to ensure they receive the highest rating evaluation possible.⁴³

Recent scholarship focused on online labor markets that facilitate lower-paying work, such as ride hailing (e.g., Uber and Lyft),⁴⁴ routine tasks (e.g., Amazon Mechanical Turk),⁴⁵ and short-term domestic tasks (e.g., TaskRabbit),⁴⁶ provides evidence that ratings function as a mechanism of control. These algorithms can monitor, measure, and rate workers' minute activities at a greater speed and scale than human managers, and they can nudge workers to perform their tasks to the platform's desired expectations.⁴⁷ This scholarship thus highlights how online labor markets' algorithmic ratings can align workers' actions with organizations' expectations without explicitly dictating how workers should behave.

In fact, mainly to avoid liability, online labor market platforms go out of their way to state explicitly that they have no formal employment relationship with workers and do not dictate how workers should behave; they claim workers are theoretically free to choose their own schedule, whom they work with, and how they work.⁴⁸ Sociologists, however, demonstrate that these claims belie workers' lived experiences in which, much like the iron cage of bureaucracies, an online labor market's rating embeds a rational system of expectations that workers follow to ensure they are rewarded with more work opportunities.⁴⁹ In ride hailing, for example, if workers do not work in the areas, at the times, and for the duration that the online labor market's algorithms suggest, they may not receive subsequent ride assignments.⁵⁰ As a result, workers assimilate the criteria of algorithmic ratings into their daily actions without direct managerial oversight.⁵¹

The expectation that online labor markets' ratings can serve as an efficient, effective control mechanism, however, is being undone in

many settings. Most rating systems have transparent criteria. This transparency is key to communicating expectations without explicitly dictating how workers should behave. That is, if workers understand the ratings' criteria, they will adjust their behavior to be in line with the ratings' criteria so that they can receive the highest rating. But this transparency also makes it easier for workers to game the rating system.⁵² Instead of aligning their behaviors to achieve the highest possible ratings, workers can devise alternative tactics to achieve the highest rating.

One prominent example of the ease with which someone can game relatively transparent online rating systems came to light in 2017. A person was hired by restaurants to help increase the restaurants' ratings on TripAdvisor. In the process of helping these restaurants, the worker gained enough of an understanding of how TripAdvisor's algorithmic rating system operates that he decided to open his own restaurant. Within just six months of starting the restaurant, it became the top-rated restaurant in London. The catch: the restaurant was fake. The address listed led to the person's backyard.⁵³ The person had proved their point: it takes relatively little effort to game an algorithmic rating system on one of the most popular online platforms in one of the biggest cities in the world, which at that time had over eighteen thousand restaurants listed and rated on the platform.

One outcome that occurs when it is easy to game a rating system is rating inflation.⁵⁴ Rating inflation in online markets can be problematic because if most users have high ratings, ratings convey less information because people are unable to use them to differentiate the best-quality users.⁵⁵ Imagine if every product on Amazon had a five-star rating: how useful would ratings be at differentiating the products? Ratings cease to reliably signal quality or serve as a mechanism of control if everyone has a similar rating.

Online labor market platforms have been unable to control gaming behavior in part because they classify workers as independent

contractors. This classification means that there is no legal, recognized employment relationship between platform organizations and workers.⁵⁶ Platforms are not allowed to dictate how workers should act.⁵⁷ As a result, platforms theoretically (and legally) cannot explicitly prohibit workers from engaging in actions that contribute to rating inflation because doing so could jeopardize the employment relationship between platforms and workers. Further, unlike online labor market platforms that facilitate lower-paying work, labor platforms that facilitate higher-skilled work cannot as easily specify how workers should behave. Higher-skilled work involves unclear and shifting timelines, changing priorities, and iteration, making it more difficult to observe and quantify workers' activities. Creative project work, for example, may involve reading, brainstorming, and speaking to people from different disciplines—tasks that may appear unproductive but are necessary to spark new ideas to meet a client's expectations.⁵⁸ Yet although it may seem that platforms that facilitate high-skilled work have fewer options to control workers, they in fact have devised methods to control workers, which thus far have been underexplored in this context. Opaque, speculative algorithms are their chief tool for exerting control.

Toward a New Definition of Algorithms

Algorithms are everywhere. They are responsible for advances in artificial intelligence. Yet the use of algorithms in different contexts changes the definition of an algorithm. The *Oxford English Dictionary* defines an algorithm as “a procedure or set of rules used in calculation and problem-solving; a precisely defined set of mathematical or logical operations for the performance of a particular task.” This definition of an algorithm reflects its use primarily in mathematical and engineering domains. Throughout most of history, the word “algorithm” was employed when mathematicians and engineers

formalized the relationship in “objective” natural phenomena.⁵⁹ Algorithms developed to understand these phenomena, such as the steps to calculate the area of a square or the process to determine the mass of an object, are not subject to change.⁶⁰ These algorithms are independently verifiable, and the procedures identified by them are definitive. For example, once the algorithm for calculating the area of a triangle was established, the algorithm continues to capture a relationship between different factors (height and length of the triangle) that can be verified, reproduced by anyone under any circumstances, and that will not change. I refer to the use of algorithms in such contexts as “deterministic algorithms” to clearly demarcate algorithms that capture enduring relationships between objectified phenomena.

Applying the definition of deterministic algorithms to *social* phenomena—such as calculating anything from a worker’s reputation to someone’s happiness—is problematic for at least two reasons. First, relationships between social phenomena are, in reality, subjective, probabilistic, and changing, but algorithms calcify them into fixed constructs.⁶¹ For instance, an algorithm created to calculate a person’s propensity to get diabetes would involve specifying relationships between diet, age, gender, and other similar factors. These relationships, however, are not definitive, universally held, or reproducible in a group of people who are not represented in the data by which the algorithm was created. Furthermore, the relationships between these factors are subject to change. As just one example, as lifestyles have dramatically changed in the last few decades, especially during the COVID-19 pandemic, the factors predicting whether someone will get diabetes have also changed.⁶² Nevertheless, in social domains algorithms mainly use past data to establish a *probabilistic* relationship between variables. Once an algorithm has been created and deployed, however, it treats relationships between social factors as static.⁶³ Even advanced machine learning algorithms that

dynamically change must specify a relationship between social factors when they are implemented. The fact that an algorithm can update almost instantaneously does not “solve” the fact that algorithms in social contexts use correlations to intuit probabilistic relationships between social constructs, which are not constant, universally held, or logically explained in nature.⁶⁴

Second, because algorithms applied to social phenomena can never perfectly specify the relationship between different factors, algorithms inevitably involve decisions that reflect people’s beliefs, interests, and biases about the relationships between social phenomena.⁶⁵ These beliefs and interests are not fully reflected in the algorithm itself. That is, when the steps in an algorithm are formalized, the algorithm itself cannot express the countless implicit and explicit human thoughts, conversations, deliberations, and decisions that were made when determining the relationship between different factors in an algorithm. Numerous studies have revealed how seemingly “objective” algorithms used by companies prioritize narrow interests, maximizing immediate profit and, frequently, exacerbating existing biases and racism.⁶⁶ Even when biases in algorithms are revealed, it is unclear if they were intentionally specified by the people who constructed the algorithm, if they were the result of biased data, or if they were produced by any number of other factors that are obscured when one observes only the algorithm’s underlying formula.⁶⁷ The only things that can be examined are the abstract, technical procedures in an algorithm. As the media scholar Ed Finn eloquently explains, every algorithm’s formula “has a shadow, a puddled remainder of context and specificity left behind in the act of lifting some idea to a higher plane of thought.”⁶⁸

Given the glaring incompatibilities between algorithms used in mathematical and those used in social contexts, I offer “speculative algorithm” as a more apt term for algorithms used in social contexts broadly and for the purposes of this book specifically. For the sake of

simplicity, I define a speculative algorithm as a set of procedures used to accomplish a task by establishing a probabilistic relationship between social phenomena, thereby reifying algorithmic designers' implicit and/or explicit beliefs and interests. Unless otherwise noted, all references to “algorithms” in this book refer to speculative algorithms.

I use the term “speculative” to distinguish algorithms used in social contexts from deterministic algorithms used primarily in mathematical and engineering domains. I use the term “probabilistic” to emphasize that any relationship between social phenomena is a “best-guess” approximation that mostly relies on past data. Additionally, my definition forces researchers and readers to more closely examine the extent to which the result of an algorithm used in social domains is speculative, including how organizations collect the data to train an algorithm, how the relationships between procedures in an algorithm are forged, whose interests are embedded when an algorithm is constructed, what impact an algorithm has in practice, which elements captured by algorithms are more or less accurate and why that may be, and when an algorithm's parameters should change. Such an approach is sorely lacking from contemporary scholarship, especially with the rise of “generative” artificial intelligence models (most prominently ChatGPT), which, at their core, use speculative algorithms.⁶⁹ That is, there is nothing inherently artificial or intelligent about artificial intelligence and the speculative algorithms undergirding AI.

Note, while at times it may seem that I am using dynamic, opaque, and speculative interchangeably, each term provides an important distinction as it relates to describing algorithms. Specifically, *dynamic* refers to the ability of algorithms to evaluate input and make decisions in real-time, including when encountering new data or situations. *Opaque* refers to the extent to which an algorithm's

inputs, processing, and output are known to both the algorithm's designers and those subject to algorithms. *Speculative*, as discussed earlier, refers to algorithms that use a set of procedures to accomplish a task by establishing a probabilistic relationship between social phenomena.

Studying the Intersection of Platform Algorithms, Control, and Workers

Inside the Invisible Cage focuses on one of the largest online labor market platforms for high-skilled work: TalentFinder. As alluded to earlier, at its core TalentFinder sought to build a platform for high-skilled labor akin to Amazon, on which clients could search for a software engineer or graphic designer, and the results would return a list of people from around the world with the requisite skills. Much like on Amazon, clients can filter the results by different criteria, including ratings and location. A central component of TalentFinder's operations are its algorithms. While subsequent chapters will delve into its algorithms in more detail, briefly, TalentFinder's algorithms provide the digital infrastructure for facilitating a labor platform at a global scale by, among other things, curating search results, rating workers, and controlling workers' visibility on the platform.

Collecting data to study the platform's algorithms and its effect on workers was not straightforward. First and foremost, workers who use TalentFinder are distributed around the world. Second, TalentFinder considers its algorithms to be a proprietary secret. Much as with Google, Amazon, and other online platforms, most employees within the organization do not have access to how its algorithms work. Third, as will become apparent throughout this book, there is a huge power imbalance between TalentFinder and workers. Establishing a relationship with TalentFinder, even an informal one, could

jeopardize workers' trust in me as an impartial researcher and prevent them from sharing their experiences.

To overcome these challenges, I chose to collect data in two primary ways. First, I developed an in-depth understanding of TalentFinder's social context and the impacts its algorithms have on worker control primarily by collecting ethnographic data. For readers unfamiliar with ethnographic data collection and analysis, taking such an approach involves becoming immersed in the experiences of the people being researched to provide a richer understanding of the "how" and "why" behind social phenomena, which are difficult to measure and quantify with standard data collection and analysis techniques.⁷⁰ To complement and enhance the ethnographic data, I used computational social science methods to assist in my data collection and analysis. While the Methodological Appendix provides a more in-depth explanation of my methods, I briefly explain these approaches here.

To gather the ethnographic data, I registered as both a client and as a worker on the platform in 2014. Becoming a registered user provided me with access to exclusive platform communication, features, and firsthand experiences of using the platform. As a registered user, I kept a detailed account of the emails, notifications, and platform changes I observed through my accounts. Using my client account, I posted jobs for workers, paid them for their time and effort, and left feedback and evaluations after projects ended. These steps enabled me to gain firsthand insight into how TalentFinder communicates with clients, and it showed me what it was like to use TalentFinder's algorithms to search for, hire, and rate workers. As a registered worker, I collected information on what TalentFinder formally communicated during registration and when the organization made changes to its platform.

I also collected data by interviewing workers and clients.⁷¹ I conducted 118 interviews with workers (93) and clients (25) between

2014 and 2020. I used a variety of ways to recruit and interview workers and clients. To collect interview data from workers, for example, I created a paid job on the platform to which anyone could apply, used the platform's search engine to find workers with a specific background (e.g., workers with a specific specialty), found workers on the discussion boards, and met people who used TalentFinder in my local community. To collect data from clients, I used a snowball sampling approach, primarily based on recommendations from existing workers and clients. Combining these sources ensured that I heard from workers with diverse experiences, skills, ratings, locations, and genders. I asked both workers and clients open-ended questions about their careers, their paths to finding and getting started on TalentFinder, the benefits and challenges of using the platform, and their experiences with the platforms' algorithms. Many of the workers and clients kept in touch with me after our interviews, sending me updates about their experiences.

The third source of data was primary source material found on the platform between 2004 and 2020, including data from the platform's discussion boards, terms of service, announcements, help articles, and blog posts. These data allowed me to track changes on the platform over time, triangulate my data from my own observations and interviews, and understand TalentFinder's public stance toward the algorithms and the changes it introduced to the platform. Given the remote, distributed nature of the relationships between TalentFinder, workers, and clients, the discussion boards are the primary way that these parties communicate with each other. Any registered user can post on the discussion boards, and I was thus able to access a much wider and more diverse set of worker and client experiences. In addition to qualitatively analyzing these data, I used natural language processing (NLP) techniques to discover new themes, triangulate the qualitative analysis, and guide subsequent qualitative data

collection and analysis. The Methodological Appendix expands on how I used NLP and ethnographic data collection analysis in symbiotic ways.

A note on anonymizing TalentFinder and the people I interviewed is in order: some readers may quickly be able to discern TalentFinder's real identity and wonder why I chose to anonymize the company. First, anonymizing workers and clients provided the confidentiality needed for them to openly share their experiences without the fear that the platform or other people would be able to take any action against them. Unfortunately, there have been countless examples of platform organizations retaliating against workers who share their experiences with the public.⁷² Providing and honoring the anonymity I promised workers and clients minimizes the chances that the data I use in this book can be traced back to them. Secondly, I chose to study TalentFinder because I believe it provides insight into larger dynamics that are increasingly at play across our society and that will impact the future of work as speculative algorithms proliferate. For better and worse, organizations that have created platform markets, such as eBay and Amazon, have had an outsized influence on how traditional organizations operate and are regulated. As I will show, the same holds true for TalentFinder in how organizations are increasingly treating high-skilled workers in ways that were once thought unlikely.⁷³ As a result, anonymizing the company encourages readers to focus less on the specific platform and to relate the theoretical insights I have uncovered to their own experiences and to institution-level dynamics occurring within organizations, platforms, and even governments. Too often, specific company names elicit strong reactions based on shaky evidence. This book insists on taking the necessary step of asking how the phenomenon uncovered in TalentFinder relates to broader industry and society dynamics that will influence the future of work.

Book Outline

The book is structured as nine chapters that track how TalentFinder developed and honed its algorithms and examine the consequences of that process. Broadly, Chapter 2 provides an overview of the factors that led to TalentFinder creating one of the first online labor market platforms for high-skilled work. Chapters 3 and 4 investigate how TalentFinder tried to initially exert control on the platform as it quickly grew and the problems it encountered with this growth. The next two chapters (Chapter 5 and Chapter 6) reveal how TalentFinder responded to the problems it encountered by asserting enhanced control over workers through using new opaque, dynamic algorithms and how being subject to these algorithms created an invisible cage for workers with detrimental consequences. Chapter 7 explains why workers seemingly chose to stay inside the invisible cage, despite the negative consequences they encountered within it. The final two chapters summarize the book's main theoretical and practical contributions for scholars, organizations, workers, and policy makers (Chapter 8) and provide predictions about how the future of control in the age of algorithms may unfold beyond what is commonly discussed today (Chapter 9).

In more detail, Chapter 2 shows how the confluence of social, economic, and technological factors in the early 2000s set the stage for TalentFinder's founding. I highlight how TalentFinder's origins can be traced back to the start of the internet, which offered new methods of catering to organizations and clients looking for cheaper, outsourced, trustworthy, and reliable high-skilled labor. Taking inspiration from eBay, TalentFinder decided to launch an online labor marketplace platform that enabled anyone in the world to join. This move introduced a paradigm shift from existing approaches, such as traditional staffing firms, to facilitating high-skilled work on a global scale. This chapter also draws on interviews to describe the types of

workers and clients who use the platform and what initially motivated them to join TalentFinder. The last section of the chapter analyzes a portion of TalentFinder's terms of service, which reveals how TalentFinder was able to launch an innovative global online labor platform while limiting its legal liability. Specifically, I show how the platform established an amorphous, ill-defined, multiplex employment relationship involving workers, clients, and an unknown number of third-party organizations. I argue this amorphous employment relationship provides the foundation for the platform to exert control while limiting its liability on a global scale.

In the next chapter, I show how TalentFinder created and initially relied on a five-star rating evaluation algorithm to connect workers and clients on a global scale. The platform's initial rating algorithm relied on transparent calculation processes that provided detailed explanations about how workers' evaluations were calculated. However, this setup exacerbated two outcomes that impacted workers, clients, and the platform. First, the platform's reliance on rating evaluations worsened what is called the "cold start" problem for new workers because the platform's algorithm had difficulty recommending workers who had no prior rating evaluations or data for the algorithm to base a recommendation upon. It also exacerbated rating inflation. I show how, over time, workers were able to game the platform's transparent rating algorithm such that nearly all workers had identical ratings on the platform. Although workers individually benefited from this arrangement, it created a "tragedy of the commons," which refers to situations in which individuals act in their self-interest, but their actions ultimately lead to a suboptimal outcome for everyone.⁷⁴ In this case, everyone having an almost perfect rating impeded the platform algorithms' ability to match clients with workers.

Chapter 4 analyzes how the platform responded to these problems by testing a major change that addressed the tragedy of the commons created by rating inflation. TalentFinder partially intro-

duced an opaque rating algorithm but did not provide workers with information about the change, including whether the opaque rating algorithm was just a test or would be rolled out more broadly. I further show that because the organization withheld key information about whether the change was simply a temporary test or a permanent change, workers began to develop unverified theories about the potential algorithmic change and the impact it could have on their platform activities and success. In the second half of the chapter, I argue that TalentFinder’s ability to roll out a potential change and exert control in this manner is enabled by “digital boilerplate agreements”: a shifting terms of service that enables an organization to implement any change that further entrenches its power and information asymmetries over workers. I share how my own account became sanctioned due to a new condition added to the platform’s terms of service, which was not originally present when I first joined the platform. The chapter thus argues that digital boilerplate agreements establish the foundation for the invisible cage and subsequent changes on the platform.

In Chapter 5, I show how TalentFinder decided to permanently implement its opaque algorithms across the platform. I detail how the platform’s use of opaque data collection, processing, and experimentation was essential to the platform’s ability to implement and sustain its algorithms and control over workers, but it also resulted in workers experiencing pervasive unpredictability. Workers were uncertain how their actions on the platform or with clients could impact their platform visibility and success. This chapter thus exposes how the platform sustained and preserved its algorithms undergirding the invisible cage by using various practices to exploit its information and power asymmetries. This created predictability for TalentFinder but unpredictability for workers.

Building on the findings and arguments presented in Chapter 5, Chapter 6 identifies the long-term cognitive and behavioral

consequences workers experienced inside the invisible cage. Workers reported negative cognitive outcomes such as having difficulty learning how they could improve their performance, experiencing pervasive anxiety from not knowing which actions impacted their platform success, and changing their perception of TalentFinder from a natural facilitator to a controlling, authoritarian platform. In terms of behavioral consequences, workers changed the way they interacted with clients; rather than focusing on producing the best-quality work, they attempted to interact with clients in ways that they hoped would maximize their chances of appeasing the platform's algorithms. I also unpack how workers' reactivity to the platform's rating algorithm varied: some experimented with ways to improve their rating scores while others constrained their activity on the platform. Their reactivity differed based not only on their general success—whether they received high or low ratings—but also on how much they depended on the platform for work and whether they experienced setbacks in the form of decreased ratings. Chapter 6 illustrates a stark departure from the freedom and flexibility that initially drew workers to TalentFinder, as described in Chapter 2.

Although leaving the platform theoretically seems easy, in Chapter 7 I identify a novel mechanism, reputational interdependence, to explain why workers stay enmeshed inside the invisible cage and platforms more broadly. Reputational interdependence refers to the fact that platforms' algorithms are increasingly interconnected and share people's ratings with each other without worker consent, decreasing a worker's ability to control their own reputation. Reputational interdependence captures how platforms' opaque algorithms enhance both the visibility and permanence of a worker's reputation between platforms, organizations, and labor markets, beyond worker control. As a result, even if workers wanted to stop using TalentFinder, they found that their information was accessible on Google, social media, and other platforms. Workers were thus confronted with a choice that

exemplifies the paradox between autonomy and control on platforms: while workers could theoretically leave at their own discretion, if they left, the algorithms undergirding the invisible cage would downgrade and continue to publicly share their ratings across other online platforms, jeopardizing their employment prospects off-platform.

Chapter 8 draws together the book's empirical insights to argue that the invisible cage represents a novel form of control because its underlying logic, outcomes, and the mechanisms sustaining it rely on dynamic, opaque, speculative algorithms. I highlight the theoretical implications of the invisible cage for sociologists, management scholars, and labor researchers working at the intersection of control, evaluations, and labor markets. The chapter also discusses the practical implications of the invisible cage for organizations, workers, and policymakers. In particular, I highlight crowd-sourced accountability and worker-initiated alternatives to the current platform model as two paths forward that could redress the power and information asymmetries that currently favor platforms. These potential reforms will be of interest to policymakers, labor organizers, and platforms hoping to create more equitable relationships between actors.

Chapter 9 aims to go one step further than looking at possible reforms available in the present by providing a framework for predicting how the future of control in the age of algorithms will unfold. Rather than falling for the kind of simple utopian or dystopian predictions common in the media, I argue that the future of control in the age of algorithms is not foretold. Rather, it will be defined by the decisions we—institutions, organizations, and individuals—make today. Drawing on the “tetrad” framework, which philosopher and media studies scholar Marshall McLuhan developed to anticipate the hidden and unobserved impact of a technology in the future,⁷⁵ I predict four possible scenarios that may unfold with organizations' increased use of and reliance on algorithms.⁷⁶ Each scenario forces us

to grapple with the changes to our current legal, political, organizational, and individual institutions and routines that need to occur (or be prevented from occurring) for such scenarios to come to fruition.

The Methodological Appendix provides a detailed overview of how I collected and analyzed the data for the book and the lessons I learned along the way. I detail how I adapted traditional participant observation and ethnographic interview techniques to a digital platform setting as well as how I leveraged computational social science techniques to aid in collecting and analyzing large-scale textual data and triangulating the insights gleaned from the other qualitative data collected.

. . .

When I first began studying TalentFinder and online labor market platforms, they represented an emerging phenomenon with unclear implications for whether using algorithms to control the way people work was a fad or represented the future of work. Today, however, it is clear that organizations and even governments have embraced speculative algorithms to control, evaluate, and monitor an increasing number of workers and people. As a result, the findings and arguments I present in this book provide important insight into how the invisible cage concept of control may permeate an increasing number of organizations and parts of our society, and I offer them with the hope that they will spur productive actions and policies that create more equitable outcomes for workers, organizations, and society more broadly.

For ease of reference, Table 1 summarizes the arguments I advance with the corresponding chapter in which the specific argument is elaborated (Chapter 8 and Chapter 9 are concluding chapters and as a result are not included in the table below).

TABLE 1. Overview of Invisible Cage Concept

Invisible Cage Characteristics	Description	Chapter
Underlying logic	Dynamic opacity enabled by speculative algorithms	5, 6
Key outcomes	Predictability for organization, unpredictability for workers	4, 5, 6, 7
Mechanisms sustaining control in invisible cage	Opaque algorithmic data collection, data processing, and experiments	5
Role of evaluations (beyond control)	Organization: use algorithms to evaluate workers from “within” so that they are easily differentiated Worker: public, permanent measure of reputation and expertise to attract clients and stand out from the crowd	3, 4, 5
Reactivity to evaluations	Experimental reactivity	6
Institutional and legal context	Constrained reactivity Weak institutional and legal framework governing employment relationships, leading to amorphous employment relationship and lack of recourse pathways	2
Why do workers stay?	Reputational interdependence, network effects, and lack of market alternatives	7