Johnson
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Administrative Science Quarterly
2021, Vol. 66(4)1173–1212

DOI: 10.1177/00018392211016755
journals.sagepub.com/home/asq
SAGE

When Knowledge Work and Analytical Technologies Collide: The Practices and Consequences of Black Boxing Algorithmic Technologies

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Abstract

Analytical technologies that structure and process data hold great promise for organizations but also may pose fundamental challenges for how knowledge workers accomplish tasks. Knowledge workers are generally considered experts who develop deep understanding of their tools, but recent observations suggest that in some situations, they may black box their analytical technologies, meaning they trust their tools without understanding how they work. I conducted a two-year inductive ethnographic study of the use of analytical technologies across four groups in an investment bank and found two distinct paths that these groups used to validate financial analyses through what I call ''validating practices'': actions that confirm whether a produced analysis is trustworthy. Surprisingly, engaging in these practices does not necessarily equate to understanding the calculations performed by the technologies. In one path, validating practices are partitioned across junior and senior roles: junior bankers engage in assembling tasks and use the analytical tools to perform analysis, while only senior bankers interpret the analysis. In the other path, junior and senior members engage in co-construction: junior bankers do both assembling and interpreting tasks, and senior bankers engage in interpreting and provide feedback on junior bankers' reasoning and choices. Both junior and senior bankers in the partitioning groups routinely black boxed the algorithms embedded in their technologies, taking them for granted without understanding them. By contrast, bankers in the co-construction groups were conscious of the algorithms and understood their potential impact. I found that black boxing influenced the knowledge outputs of these bankers and constrained the development of junior members' expertise, with consequences for their career trajectories.

Keywords: knowledge work, expertise, technology, work and occupations, task allocation

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Our economy is driven by knowledge, but the nature of knowledge work is changing. With the digital revolution in full swing, computer-based analytical technologies—those that structure, format, and process data—are spreading across many domains of knowledge work, including legal advice, medical diagnosis, and strategy making (Maslach et al., 2018; Kluttz and Mulligan, 2019; Lebovitz, 2019). These technological tools, which contain embedded algorithms that codify procedures to transform data (Gillepsie, 2014; Kellogg, Valentine, and Christin, 2020), can meaningfully shape the process and outcomes of this work. Though such tools enable considerable data-processing power, they also can subsume key practices, which may affect knowledge outputs.

In some contexts, this may even affect firms' reported financials and influence the stock prices of large, publicly traded companies. Consider this August 2019 quote from Adam Aron, CEO of AMC Entertainment, on why the firm's stock price fell 63 percent:

> If you look at our stock, there's something very specific that's gone on that really has nothing to do with the movie business. . . . Factset, Capital IQ, as they interpreted [our operating leases] . . . took our debt level at AMC from $5 billion on March 31 to $12 billion on April 1 when there was no change in our interest obligations, there was no change in our cash flows, there was no change in our real leverage, there was no change in our business. . . . This has caused . . . our stock [price to drop] markedly. . . . [Some experts] say what I'm saying just now . . . [others] just see the data . . . and they act accordingly.

As evidenced by this reflection, one risk is that users may not question or understand how embedded algorithms within analytical technologies work. For instance, some knowledge workers treated the shift in interpretation of AMC's operating leases by Factset and Capital IQ—two analytical technologies—as a real change in the company's level of debt rather than as a reporting change, much to the peril of AMC's stock price. The consequences of such reliance without understanding are amplified by the trust society puts in expert knowledge workers (Giddens, 1990), especially when knowledge outputs are quantitative, as users tend to treat numbers as objective and "true" (Porter, 1996; Mazmanian and Beckman, 2018).

An extensive body of literature has found that knowledge workers—those who think for a living (Drucker, 1957)—seek to be experts in their work. This includes developing deep understanding of their technologies' inner workings to ensure that produced knowledge is analytically sound (Dodgson, Gann, and Salter, 2007; Bailey and Barley, 2011) and to develop and maintain unique expertise and skill (Vincenti, 1990; Lave and Wenger, 1991; Alvesson, 2004). Indeed, expertise and produced knowledge are inextricably connected with tools (Galison, 1997; Knorr Cetina, 1999; Kaplan, 2011). While non-experts, such as managers, newcomers, and outsiders, may be lured to trust tools without question (Shackley and Wynne, 1996; Bailey, Leonardi, and Barley, 2012; Barley, Treem, and Kuhn, 2018), prior literature has assumed that knowledge workers actively toil to avoid such outcomes, lest the quality of their knowledge products be questioned or doubted and their status as experts be threatened. How, then, do we account for some knowledge workers' lack of understanding of analytical technologies, as we see with the confusion around AMC's debt? More broadly, how might knowledge workers come to rely on their analytical technologies without understanding how they work—and with what consequences?

To answer this question, I draw on an in-depth, two-year comparative ethnographic study of four groups of knowledge workers in an investment bank. Leveraging eight months of fully immersive fieldwork, interviews, and archival data, I examine the use of Factset and Capital IQ (''CapIQ''), which contain different algorithms and thus produce different numbers in the construction of financial analysis. While all four groups engaged in ''validating practices''—actions that established their knowledge outputs as trustworthy—two groups came to conclusions without understanding their tools, whereas two groups developed awareness and understanding of how the tools worked. Such awareness had significant consequences for the consistency of knowledge outputs and the development of junior members' expertise.

This study makes several important contributions. First, I challenge existing literature on knowledge work by showing that, at times, expert knowledge workers may black box their technologies, taking them for granted without understanding how they work, even when engaging in efforts to validate analyses and develop expertise. Thus, knowledge workers may conclude that their knowledge outputs are trustworthy without understanding their tools. In addition, this study contributes to research on junior members' participation in knowledge work by demonstrating how task allocations can lead to differences in expertise, with career consequences. Finally, counterintuitively, I find that hierarchical authority may actually be helpful for reproducing expertise in knowledge work, especially when analytical technologies are in use.

KNOWLEDGE WORKERS' USE AND UNDERSTANDING OF ANALYTICAL TECHNOLOGIES

Knowledge workers are highly educated employees who work on intellectual tasks (Alvesson, 2004). They draw on unique expertise and practices in their work to produce knowledge outputs that often solve a concrete problem. These outputs might include scientific papers, engineered structures, advice, and medical diagnoses (Vincenti, 1990; Berg, 1997; Knorr Cetina, 1999; Alvesson, 2004; DiBenigno, 2020). While education and formal training are central to developing knowledge workers' expertise, research has emphasized that the ongoing accomplishment of work is also key to fostering unique expertise and skill (Lave and Wenger, 1991; Wenger, 1998).

Knowledge workers strive to be experts in their work—''expert knowledge is the sine qua non'' of knowledge-based work (Gorman and Sandefur, 2011: 278). This is because expertise and skill afford these workers control over the problems they solve, allow their privileged position in relation to clients and within organizations, and enable their claims to status (Abbott, 1988; Bechky, 2003; Huising, 2015). Knowledge workers are trusted because of their expertise; they accomplish complex tasks and solve problems that others cannot (Zetka, 2001; Collins and Evans, 2007; Bechky, 2020). Further, their expertise is what allows them to produce quality knowledge outputs or solve problems in ways deemed superior.

To produce knowledge outputs, these workers often draw on the ongoing use of specialized tools and instruments (Berg, 1997; Galison, 1997; Knorr Cetina, 1999). Such tools can even help to foster knowledge workers' unique expertise. For example, arbitrage trading is performed with Bloomberg terminals (Beunza and Stark, 2004), ship navigation with nautical charts (Hutchins, 1995), and experimental physics with detection devices (Galison, 1997). Thus, knowledge workers' expertise and skill are often formed in relation to the ongoing use of technologies.

In the digital age, these tools are evolving into computer-based analytical technologies, which contain embedded algorithms that can meaningfully shape constructed knowledge (Murray, Rhymer, and Sirmon, 2020). Algorithms—"encoded procedures for transforming input data into a desired output, based on specified calculations" (Gillespie, 2014: 168)—can significantly enhance analytical capabilities by enabling more complex and efficiently performed analysis. For instance, the arrival of analytical technologies into drug discovery science enabled new measurements and analyses, as well as the ability to model compounds, diseases, and human biology. These measurements, analyses, and models would not exist without such digital analytical technologies (Dougherty and Dunne, 2012).

Yet these tools enable such analyses because they also subsume knowledge workers' practices and replace them with the technology designers' assumptions and beliefs (Introna, 2016). As a consequence, knowledge workers can become distanced from key tasks that would have historically been accomplished with more manual tools and techniques. For instance, how buildings are designed and constructed evolved as engineers transitioned from using slide rules to computer-aided design (CAD) software. While the calculations performed using CAD enabled the design of buildings too complex to design using slide rules, such distance from designing and performing these calculations meant that engineers risked overlooking errors or problems in their designs (e.g., Petroski, 1985).

The benefits of these tools therefore may be accompanied by considerable risk for expertise and knowledge outputs (e.g., Nelson and Irwin, 2014; Bechky, 2020). Research has shown that to help offset these risks, knowledge workers strive to develop deep understanding of the inner workings of their technologies to maintain their expertise and ensure consistent quality in their work. For example, Scarselletta (1997) found that to avoid false positives and false negatives on blood test results, medical lab workers had to thoroughly understand how their machines worked in order to spot errors. Similarly, Mazmanian, Cohn, and Dourish (2014) found that teams navigating the trajectories of spaceships cultivated collective understanding of the algorithms in their complex software program tools to trace the crafts' orbit, movements, and position in space.

This expertise is developed by employing comparative practices and configuring social interactions to question how a technology works. To scrutinize outputs of analytical technologies, knowledge workers compare outputs with other data, artifacts, and their own expectations (Knorr Cetina, 1999). This pattern has been repeatedly demonstrated across a host of knowledge work contexts; for instance, traders compare their own analysis to competitors' estimates in order to spot errors in their predictions (Beunza and Stark, 2012), scientists compare their analysis to physical lab specimens to ensure conclusions are sound (Barley and Bechky, 1994), structural engineers draw on the laws of physics to examine assumptions in their modeling software (Bailey and Barley, 2011), and fire safety engineers compare their simulation models with hand calculations and data from real fires to validate model assumptions (Dodgson, Gann, and Salter, 2007).

In addition, knowledge workers configure social interactions to develop and maintain expertise. These include informal interactions to monitor each other's work and share experiences, collectively question outputs, and configure tasks (e.g., Orr, 1996; Cohen, 2013). For instance, technicians at EquipCo informally helped develop collective expertise and decrease errors in their knowledge products by checking one another's work and communicating best practices (Bechky and Chung, 2018). Knowledge workers also leverage meetings to enable questioning and public scrutiny (e.g., Owen-Smith, 2001; Kaplan, Milde, and Cowan, 2017). For example, Owen-Smith (2001) found that scientists used meetings to subject one another's findings to doubt in order to ensure their methods and techniques produced ''good science'' and also to help junior scientists develop expertise in what ''good science'' entailed. Finally, social interactions are often a way to organize, assemble, and disassemble tasks across workers, which can shape the development and distribution of expertise (e.g., Cohen, 2013, 2016). Interactions may also lead to different task bundles, even when these jobs carry the same label (e.g., Chan and Anteby, 2016; Wilmers, 2020). Through the configuration of social interactions, expertise is both developed and collectively maintained—and understanding and judgment regarding technology use are fostered.

There are, however, instances in which technologies can be black boxed or taken for granted without understanding how they work (Latour, 1987; MacKenzie, 1990; Anthony, 2018). Research on the social construction of technology has found that actors who are socially distant from the technology may be more likely to trust its objectivity without understanding its inner workings. These actors include broader societal members who express certainty about the capabilities of such a technology (MacKenzie, 1990), clients who trust that knowledge workers have developed appropriate systems of expertise (Shackley and Wynne, 1996), and managers who may be overconfident about the reliability of these technologies *without* scrutiny by knowledge workers (Bailey, Leonardi, and Barley, 2012). In all of these situations, those who trust technologies in this way are not knowledge workers themselves.

In addition, literature on communities of practice has found that newcomers who have not yet developed expertise are more likely to trust analytical technologies as accurate without examination (e.g., Turkle, 2009), though they ultimately develop expertise by participating in knowledge work with more experienced colleagues (Brown and Duguid, 1991; Lave and Wenger, 1991; Wenger, 1998). For newcomers, ''participation involving technology is especially significant because the artifacts used . . . carry a substantial portion of that practice's heritage'' (Lave and Wenger, 1991: 101). Thus, as junior members develop expertise through ''legitimate peripheral participation,'' the black box ultimately becomes a ''glass box'' through which they develop understanding of a tool's inner workings (Lave and Wenger, 1991: 102). To ensure the quality of outputs is not undermined, participation in tasks may also be monitored by senior members. Hutchins (1995) found that junior navigation trainees would first learn how to take bearings on distant objects, then record these from another person taking those bearings, and then plot the position and headings based on another person's records. These tasks enabled the development of expertise in how to use nautical charting technologies and how they shaped navigation while also facilitating the detection and correction of errors.

Both of these research streams suggest that whether or not a technology is black boxed can be explained by actors' structural position relative to the technology—whether or not they are knowledge workers and whether they are new to knowledge work. Prior research would indicate that for expert knowledge workers, black boxing is antithetical to knowledge work itself. How, then, and why might expert knowledge workers come to trust their analytical technologies without understanding how they work, especially given the risks to their knowledge outputs, expertise, and status as experts more broadly (Giddens, 1990; Alvesson, 2004)? My study explores this question.

METHODS

Research Context and Site

To generate a grounded understanding of how knowledge work is accomplished by using and verifying analytical technologies, I conducted an inductive study through ethnographic fieldwork in the investment banking department of a global investment bank, which I call GLOBAL Bank.[1] Investment banks provide capital market services to companies, including trading, research coverage, and strategic advisory services.[2] Advisory services are housed in investment banking departments.[3] Members of these departments (hereafter referred to as ''bankers'') work privately with companies on major corporate transactions by producing analyses and evidence for what deals ought to be made, such as mergers, acquisitions, and changes to capital structure and corporate governance. These departments are arranged into groups that specialize by product, or type of transaction, and by industry. Typically, departments house around three to five product groups, including those that work on mergers and acquisitions, leveraged finance, and equity. In addition, departments usually have between seven and nine industry groups, such as consumer retail, industrials, and healthcare.

The analyses, distribution of tasks, and nature of the work performed by investment bankers have remained largely stable since the 1970s. In small teams that typically include junior bankers (one to three analysts and/or associates) and senior bankers (one to two vice presidents, directors, and/or

[1] All identifying information has been disguised.

[2] Investment banks differ from other financial institutions in important ways. First, unlike commercial and retail banks, investment banks do not take deposits. Instead, their focus is on advising on and executing the market activities of firms. Second, they are not ''buy side'' investment firms that invest in companies, like private equity funds, hedge funds, and mutual funds. Rather, they earn revenue through deal fees, which are calculated as a percentage of the value of the corporate transactions they advise on and execute.

[3] Research departments estimate value and, based on this analysis, issue investment recommendations such as ''buy,'' ''hold,'' and ''sell.'' In sales and trading, traders use Bloomberg terminals to buy and sell securities—including shares, bonds, and derivatives—of publicly traded companies. Traders sit together in open floor plans, are on the cutting edge of shifting technologies and financial models, and use the same technologies across hierarchical roles. While much has been written on how traders ''make'' the financial markets, their outcomes are often market-focused (MacKenzie and Millo, 2003; MacKenzie, 2008), and given the structure of their work, issues surrounding hierarchy, expertise, and changes to analytical technologies may be less salient (Beunza and Stark, 2004).

managing directors), members work together to create documents called ''pitch books'' that contain advice to clients on major corporate transactions. Pitch books are the primary output that codifies the knowledge work performed by bankers. Junior bankers produce the quantitative analyses and construct the pitch book. After a process in which senior bankers comment on the analyses and revisions are completed, the pitch book is then presented by senior bankers to a client firm's top management team. If the clients are interested in pursuing the action suggested by the bankers, the investment bank is then given authority to execute.[4]

The way in which analysis is performed in investment banking has evolved considerably. Historically, junior bankers collected physical copies of public filings mailed to the bank from the U.S. Securities and Exchange Commission (SEC). Junior bankers would read through financial statements and other filings to manually calculate key metrics using paper ledgers. This required junior bankers to perform calculations by hand. When computers became widely adopted in the industry, spreadsheet technology replaced pencil and paper. Physical filings were also digitized, as the SEC began publishing filings online, enabling quicker access to key documents. Yet even with spreadsheets and digital access to filings, junior bankers still collected and read through financial statements manually, inputting data and calculations into spreadsheets and using those numbers as a basis for their analysis. The person doing analysis made assumptions about how to calculate key metrics based on their interpretations of filings and codified their beliefs into formulas.

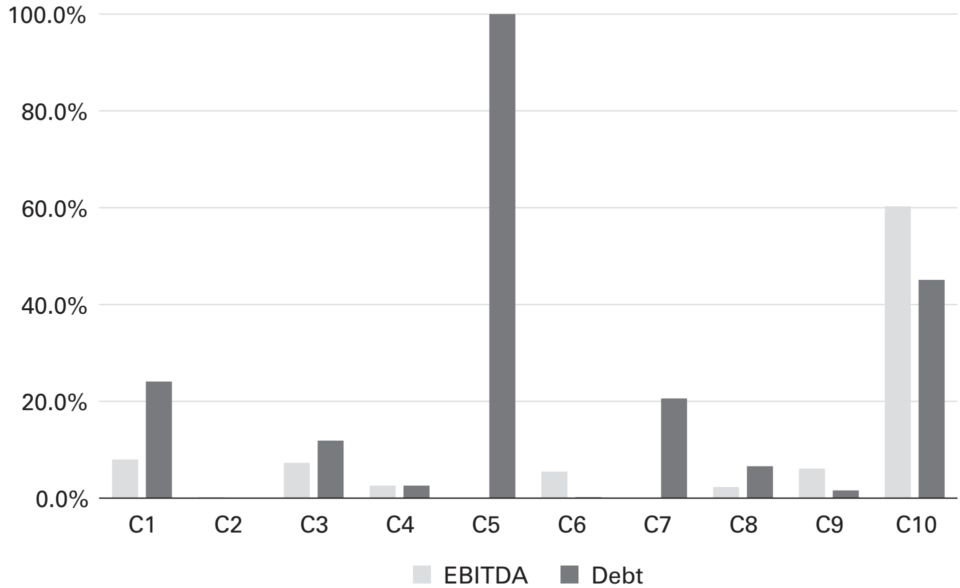
More recently, two technologies, Factset and CapIQ, have subsumed many of the manual calculations historically performed by junior bankers.[5] These tools gather financial data from public filings and automatically populate numbers into spreadsheets. Spreadsheets still are used to perform calculations, but they now also interface with these analytical technologies that provide precalculated metrics. Further, while analysis still relies on the same source—public filings—junior bankers are no longer required to collect, read, and analyze these documents or to manually enter and calculate numbers.

Factset and CapIQ share many of the same technical features: they both interface with spreadsheet technology and perform calculations of the same metrics. But importantly, they house different algorithms for how standard metrics are calculated. For instance, one utilizes the treasury stock method for share count, which takes into account employee stock option plans. By contrast, the other uses basic share count. Depending on a company's stock option plans, these equations may give very different results. Differences like these can be seen across many standard metrics. For example, EBITDA (earnings before interest, tax, depreciation, and amortization) and debt are metrics commonly utilized in analyses. Yet, as is evidenced in Figure 1, because of the different assumptions embedded in their algorithms, these two tools often calculate different numbers for these metrics. The magnitude of such differences can vary over time, but they can differ meaningfully; see Figure 2. For instance, C8's total debt number in 2011 would differ by more than $1.5 billion depending on whether one used Factset or CapIQ for the calculation.

[4] There are typically many meetings between bankers and clients during the development and execution of a prospective transaction.

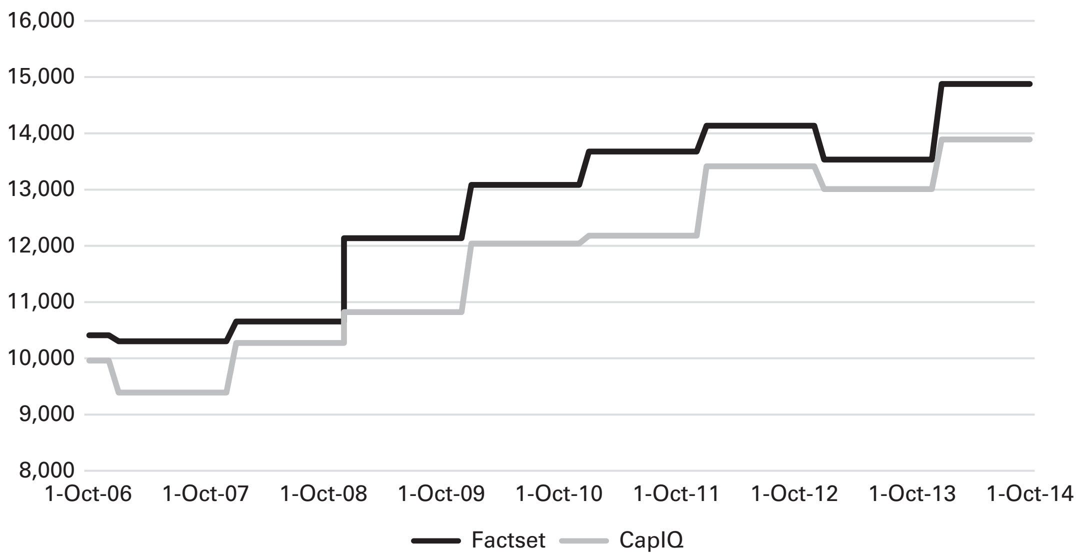
[5] Nearly every major bank in the world uses at least one of these technologies, and many use both.

Figure 1. Absolute Difference of Factset and CapIQ Calculations across Ten Randomly Selected Publicly Traded Companies*



* Absolute difference calculated as a percentage of Factset's metric.

Figure 2. Differences of C8's Debt Calculation over Time*



* In US$ millions.

Because bankers are constantly generating knowledge and rely on analytical technologies with different algorithms, I suggest that banking offers an ideal setting for theory building (Small, 2009) about how knowledge workers come to understand (or not) and trust their tools, and with what consequences.

Sample

I sampled multiple cases within GLOBAL Bank at the group level. I followed what Bechky and O'Mahony (2016: 171) referred to as a ''matched pair approach,'' which is based on the selection of ''cases that invite comparison on the basis of some type of similarity.'' This matching strategy allowed me to control for environmental and contextual variation that could influence differences between sites and also to focus my sampling to isolate select differences (i.e., Barley, 1986; Kellogg, 2009). Even though groups had slightly different strategic orientations, group members largely performed the same work: they calculated similar metrics, and they all had access to Factset and CapIQ for producing analyses. In addition, at the junior level, new members were hired into GLOBAL Bank from the same elite undergraduate and MBA programs, participated in the same multi-week training program, and subsequently were sorted into groups. Junior bankers were not sorted by ability, and my conversations with members of the human resources department indicated that junior bankers arrived into groups with similar GPAs and backgrounds. This controls for differences in selection at the group level. The analysis presented here includes data from four groups. See Table 1 for an overview of these groups.

Table 1. Comparison of Groups

	Group 1	Group 2	Group 3	Group 4
Firm	GLOBAL	Same	Same	Same
Work structure	1–2 seniors, 2–3 juniors	Same	Same	Same
Analytical tools	Factset, CapIQ	Same	Same	Same
Group orientation	Product	Industry	Product	Industry
Group size*	35–40	15–20	30–35	10–15
Approximate proportion of senior to junior bankers	1:3	1:4	2:5	1:3
Approximate percent of juniors from undergraduate business programs	90%	100%	95%	95%
Female senior banker(s)?	Yes	Yes	Yes	No
Female junior banker(s)?	Yes	Yes	Yes	Yes
Hiring	Juniors hired to firm, subsequently sorted into groups	Same	Same	Same
Formal training	New hires participate in multi-week firm-wide training	Same	Same	Same

* Group size is presented in approximate ranges. This is because there was attrition across my fieldwork. In addition, to further protect the identities of my informants, I have used ranges to limit how identifiable the groups are.

Data Collection

I collected data through ethnographic fieldwork during 2014 and 2015. This method is well suited to gathering data on daily work practices from the perspective of informants (Barley and Kunda, 2001), as well as to observing knowledge work (Orlikowski, 2002). The bank required that to gain access I had to be employed as a part-time intern. This method of entry held considerable benefits for my data collection. As described by Tripsas (2009), the benefits of employment in ethnographic studies of organizations include significant visibility of how work is performed, ease of asking informants questions about tasks and interactions, and unique access to archival materials. Further, because of norms surrounding contribution to work goals (Ho, 2009), working was especially important to gaining access to my informants' perspectives and experiences and developing deep involvement with my field site (Anteby, 2013). I was introduced to members of the department, including each group, as an academic researcher interested in studying technology use in investment banking. My informants thus saw me primarily as a researcher.

I completed eight months of immersive fieldwork over an 18-month period. This required approximately 70 to 90 hours of fieldwork per week and included observation, participant observation, ongoing informal conversations, and semi-structured interviews. While many ethnographers gather data a few days a week over more extended time periods, bankers often work long hours and are known to have strong norms about face time (Ho, 2009; Michel, 2011), so being present was crucial for my data collection. But with grounded theory, ongoing theoretical iteration and analysis is also important for sound emerging theory (Strauss and Corbin, 1990), and such immersive fieldwork was a challenge for iterating between analysis and sampling. I thus took time outside of the bank to analyze my data and revise my protocols, completing my fieldwork in two blocks of four months. In total, I spent roughly 1,100 hours with Group 1, 350 hours each with Groups 2 and 3, and 700 hours with Group 4. Between periods of immersive fieldwork, I remained "in the field" by attending group events and social gatherings and by continuing to conduct interviews. I recorded my observations and conversations in notebooks and in e-mails to myself written on a personal smartphone (which was easiest in meetings and social gatherings). During evenings and weekends, I expanded my notes.

Observation. I observed daily practices and meetings, which included bankers collaborating on and responding to analyses. I was given a seat with a computer terminal and access to Factset and CapIQ. I had access to shared drives that contained historical and emergent work, allowing me to observe the analysis being performed across pitch books.

Participant observation. My participant observation included maintaining lists of ongoing projects and assisting with deal tracking. Importantly, following Bechky (2003), I did not partake in the design of any tasks or make suggestions as to how tasks should be done; I followed the instructions given to me. In addition to these formal tasks, I participated in new hire training. Finally, I participated in social gatherings including coffee breaks, lunches, dinners, and social events when invited.

Interviews. I engaged daily in informal conversations with informants about their work. I used these conversations to gather data and to refine my emerging findings. Following the tenets of ethnographic interviews, I took extensive notes on these conversations (Spradley, 1980). In addition, I conducted 86 semi-structured interviews with 83 individuals. I interviewed all members of Groups 1 and 4, including interviewing a senior banker in each group twice and a junior banker in Group 1 twice. I interviewed more selectively the members of Groups 2 and 3, largely to confirm what I had learned in my informal conversations and observations and to compare across groups. In total, I interviewed roughly half of the bankers in these two groups. Twelve of my interviews were with members of senior management, HR, and other groups.

The semi-structured interviews lasted between 30 and 90 minutes. I began interviews by asking broad, descriptive, grand-tour questions and then probed more deeply into statements or descriptions of tasks that included interacting with analytical technologies. These included structural questions like ''How do you do x analysis?'' as well as contrast questions and prompts like ''So tell me about how you use this tool when doing x and this other tool when doing y.'' As I began to recognize patterns in technology use, I brought data from the analytical technologies to interviews to confirm these patterns. I asked informants in each group to describe the data, how they compared, and how they were used.

Archival data. This study also draws on multiple types of archival data including the written materials groups used to perform their work, such as training materials, manuals, junior bankers' personal notebooks, and printouts of analyses and marked-up work. In addition, I coded 80 pitch books to triangulate the patterns found in observations and interviews. These books are a random subset produced by these groups during the time of my study. Finally, I gathered information from LinkedIn on the career trajectories of the junior bankers in this study.

Data Analysis

Data analysis was iterative and inductive (Strauss and Corbin, 1990). Because I had sampled these groups for matched comparison, my data analysis followed the steps of comparative ethnographic analysis (Barley, 1996; Bechky and O'Mahony, 2016). This analytic strategy revolved around comparing data across groups over several iterations with particular attention paid to the similarities and differences in knowledge production. I engaged in multiple readings and coding of field notes and interview transcripts, which were coded using a constant comparative, grounded approach (Glaser and Strauss, 1967; Locke, 2001). Throughout my data collection, I wrote memos about emerging salient themes and verified theoretical categories to confirm emerging categories and focus my study.

I began by laying out the descriptive process within each group from start to finish of preparing a pitch book, including when a meeting with a client was set, how analysis was drafted, reactions and revisions to drafts, and finally when the pitch book was considered finished. Following Strauss (1978), I turned my analytical focus to group members' actions and interactions. This included coding the use of analytical technologies, the interactions among group members in revising analyses, and the steps of revisions.

Next, I began to systematically compare groups' processes and used charts and tables to facilitate that comparison (Miles and Huberman, 1994). I mapped processes, looking for commonalities and contrasts, and my analysis led me to refine my coding structure again in order to build theoretical explanations for what I found (Bechky and O'Mahony, 2016).

Significant differences and similarities emerged. For instance, who decided that an analysis was accurate, and how, varied by group. It also became clear that differences in the expertise surrounding product and industry specialty were not shaping the patterns I saw; rather, groups had different task allocations across hierarchical roles, which appeared to be shaping how groups validated their analysis in surprising ways. At this point, I pooled data across groups with similar patterns and consequences: Groups 1 and 2, and Groups 3 and 4. Though both sets of groups ultimately produced analyses they considered trustworthy, the implications of differences in how trustworthiness was established were unexpectedly shaping group members' awareness of algorithms, knowledge outputs, and expertise.

During these steps, I iterated with theory in order to translate my analysis into more generalizable categories that were present in each group and would transfer to other contexts as well. I reanalyzed all of my field notes, memos, transcripts, and documents as I engaged in conversations with colleagues and considered various literatures. This enabled me in my theory building to consider the transferability of my findings outside of my immediate context.

FINDINGS

I found that all four groups configured their work around producing knowledge they considered to be trustworthy, spending considerable effort ensuring their outputs were sound. My analysis uncovered that this was accomplished through "validating practices": actions that establish outputs as trustworthy. Validating practices included *establishing reliability*, which occurred when junior bankers helped each other prepare outputs; *assessing accuracy*, which focused on ensuring that their analysis was "correct" and reflected beliefs about economic reality; and *correcting analysis*, which occurred when feedback interactions between junior and senior bankers led to revising outputs as needed.[6]

Although all four groups engaged in these seemingly similar validating practices, a deeper examination revealed that across groups, junior bankers' roles in these practices varied considerably. In particular, I found that the ways

[6] My use of these terms differs from their stricter meaning within engineering, where reliability is defined as consistency and validity as factual soundness, or measuring what it's supposed to measure. However, my use of these terms shares important similarities with these definitions, including with their logical ordering, as well as with how organizational scholars have picked up the terms (e.g., Rerup and Zbaracki, 2021). First, like these definitions, establishing reliability is a necessary but insufficient condition for achieving validity. In other words, to produce valid analysis, the process of assembling the analysis must first be reliable. Second, March, Sproull, and Tamuz (1991: 6) suggested they reflect socially established belief systems: "If individual beliefs converge to an accurate understanding of reality, then they become simultaneously shared and valid," and when enacted, produce reliability and validity.

in which senior bankers included junior bankers in validating practices differed, and the differences shaped the ways groups understood and used their tools. Groups 1 and 2 partitioned validating practices across junior and senior roles, and thus I refer to these groups as *partitioners*. In Groups 3 and 4, junior and senior bankers co-constructed validating practices, so I use the label *co-constructors*. Because of these differences, not all groups were equally aware of the algorithms embedded in their analytical technologies, and groups' level of understanding of how their analytical technologies worked had significant consequences for knowledge outputs and the development of junior bankers' expertise. I unpack validating practices first for partitioners and then for co-constructors. Table 2 presents additional evidence of such practices.

Validating Practices by Partitioners

Validating practices among partitioners (Groups 1 and 2) involved splitting tasks across roles: junior bankers engaged in assembling tasks and were responsible for using technologies to perform analysis, while senior bankers interpreted the analysis. The assembling work included creating spreadsheets, using analytical technologies to pull numbers into these spreadsheets for analysis, and printing the analysis to give hard copies to senior bankers. Senior bankers believed analytical technologies influenced this assembling work by ''[making] it easier for [the junior bankers] to do the analysis faster.'' Thus in Groups 1 and 2 these tools were not seen as fundamentally changing the nature of the work but as improving efficiency. Senior bankers believed that by performing analysis, junior bankers would ultimately develop expertise. As a senior banker explained:

> At first you're just doing it because someone told you to do it. Then you do it. . . . ''Oh, I've done this before. Yeah, I think I understand what he's getting at.'' And then you do it again, and then the third time you've done it it's like, ''Okay, yeah, okay.'' And you just do it again, and again, and again; and then you really just gain a much better appreciation for what it is that you're trying to do and what the important answers are to that.

Senior bankers therefore believed that junior bankers should have autonomy over how analysis was produced: ''If you're talking about . . . how that analysis comes to be, it still very much resides in the hands of [junior bankers].'' Junior bankers thus participated in knowledge work by focusing on technical steps to construct analysis, while senior bankers focused on tasks related to interpreting analysis. This was reflected in the task allocations and interactions across establishing reliability, assessing accuracy, and correcting analysis.

Establishing reliability. For partitioners, establishing reliability meant performing consistent operational steps, and it was junior bankers' responsibility. Importantly, junior bankers achieved reliability by following guides laid out by one another; since they had autonomy over analytical work, various junior bankers had developed the spreadsheets and steps by which analysis was produced. Junior bankers would thus teach each other how to use the spreadsheets that Factset and CapIQ interfaced with, and often the person who created the spreadsheets would shepherd their use. For instance, a junior banker who had built the spreadsheet noticed that another junior banker was

Table 2. Additional Evidence of Validating Practices across Groups*

	Partitioners	Co-Constructors
Establishing reliability	**Junior bankers responsible; reliability means taking consistent operational steps:** A junior banker explained that preparing analysis is ''a very standard process . . . [we] have . . . instructions on how you go about these things.'' **Helping interactions between juniors focused on stable assembly:** When a junior banker asked how to change EBITDA, another junior banker explained the steps: ''EBITDA is approximately $1 billion. Search EBITDA, control F.'' JB5: Stop. Undo . . . Go down, copy format . . . No, you can't do it that way because it's not the format. Copy from N54 and copy exactly . . . Make sure there are consistent decimal places. JB6: One copy or two? JB5: Just one.	**Junior bankers responsible; reliability means preparing defendable analyses:** A junior banker explained, ''I'm not just [knocks on the table] pressing keys, and getting things done, I can think about how . . . my [senior], well how would he think about this . . . and do what he would do.'' **Helping interactions between juniors focused on interpreting analysis:** A junior banker explained, ''Other [junior bankers] can share insights or . . . are also pretty deep into the data with you when we're doing these analyses. So, I think between those two things we kind of get an understanding of what you should be doing.'' JB7: Is EBITDA positive? I see a 4% margin. I thought EBITDA was negative. JB8: It's right around neutral. JB7: [Pauses and leans back] Yeah, that's right.
Assessing accuracy	**Senior bankers check for internal consistency:** After looking over an output, a senior banker exclaimed ''Whoa! They're matching [the numbers on the page]! Can we just take a minute to appreciate this!'' A senior banker assured another senior banker that the work was accurate by saying ''It's consistent.'' **Senior bankers judge accuracy based on expert wisdom:** A senior banker explained, ''Some things just don't look right. After being in the business for almost 25 years I can look at basic information . . . about a deal and say something doesn't look right about something. . . . So, some of it is just instinct based on what I've seen over the years.'' A junior banker explained that analysis is correct when it ''work[s] out perfectly according to the way he [the senior banker] has . . . in his mind.''	**Senior and junior bankers ensure analysis has appropriate embedded assumptions:** A senior banker questioned a junior banker, asking, ''Why'd you use Factset numbers for EV [enterprise value] and market cap? We said we're not doing that.'' JB9: Hey, can you double check this number? JB10: Are you in an old version? The number ties to the PowerPoint. JB9: [Opens the spreadsheet, looks through formulas] This looks good. . . . We've had this issue with [another client's analysis], and the [calculations] changed. [Starts changing the formula in CapIQ] [They] changed a little, 2.8 to 2.9, and 10.4 to 10.5. A junior banker explained that ''CapIQ is better for . . . capitalization, meaning enterprise value, equity value. Factset is better for [other calculations].''

(continued)

Table 2. (continued)

	Partitioners	Co-Constructors
Correcting analysis	Senior bankers evaluate junior bankers' outputs: A senior banker explained, ''You know from my vantage point I don't see the sausage being made. . . . I tend to mark this stuff up by hand, and it's given to [junior bankers] to process.'' Feedback interactions focused on senior bankers dictating changes for junior bankers to execute: A senior banker approached the desk of a junior banker, motioning between the marked-up output and the junior banker's computer screen: ''So they'll be 10%. Clean that. This is debt to market cap. Open this up. . . . This is the wrong calc, [we] need to override. It's the wrong EBITDA. . . . Type equals 233 divided by pro forma EBITDA. So debt is 32%.'' A senior banker directed a junior banker to make changes to analysis: ''Do an 'if, then' formula. If this number, then all caps, if no, no. Here [pointing to the spreadsheet on the junior banker's screen]—comma, greater of, colon.''	Senior bankers scrutinize junior bankers' process: A senior banker explained, ''If I ask [a junior banker], 'why are the numbers doing that?' they look at you like a deer in headlights. Like, if P/E [price to earnings] multiples are up, and there are less earnings. You [don't want to] get 'I don't know, that's what [the analytical technology] pulled in.' . . . So automation is good, it helps production, but it's only good if people understand where anything is from and the issues are understood.'' Feedback interactions focused on senior bankers explaining reasoning behind analysis and corrections: A senior banker called a junior banker into his office. ''Remove [lists the companies], and leave the public companies. . . . The point of this page is to say in the public markets, what matters is growth and free cash flow. The client doesn't have growth, and trades and 5.2 times [earnings]. . . . Did we look at combined growth rates? Did we make any changes to this?'' The junior banker confirmed that he had made changes by combining growth rates. The senior banker continued, ''When you look at historical, we should have historical EBITDA and cash flow.'' A senior banker and junior banker are standing around a filing cabinet discussing an analysis, the senior banker explaining that this analysis is meant ''to show a track record. . . . So, for example, if debt is $100 million, the returns would be higher. What's the transaction value from 2014?'' The junior banker does not know and returns to his desk to find the answer.

* This table combines evidence from interviews and observations.

making changes to it and reprimanded him in front of others, loudly exclaiming, ''You shouldn't change this. This is standard.'' Even though they consistently handed off analyses to senior bankers that required corrections, the junior bankers saw the construction of analyses as ''consistent and standard'' because they followed similar steps as one another.

Senior bankers rebuffed participation in and guidance of these tasks. For example, a new junior banker tried to ask a senior banker for help with using an analytical technology. The senior banker responded, "What do you mean? Isn't this just data pulling? This is up to you. You're scaring me." Motioning to another junior banker, the senior banker continued, "Can you check this? I've got a lot of stuff going on." He walked away, and then the other junior banker shared, "The less details, the better. [Senior bankers] freak out."

Thus, helping conversations among junior bankers ensured consistent steps to import numbers from Factset and CapIQ into spreadsheets and largely pertained to spreadsheet commands. The content of these conversations included instruction around the location of focus on a spreadsheet (which rows and which columns), as well as the keystroke actions themselves. For instance, a senior banker approached the desks of two junior bankers looking for a piece of analysis: "I don't know if there's a way to do that; we are just trying to understand the sector. . . . If it's not set up and automated the way you usually do it, will you have time to do it this morning?" After the senior banker left, the junior bankers (JB1 and JB2) engaged in conversation to walk through the operational steps to assemble the analysis:

> **JB1:** Copy this row, drag it down. Go back and grab the next one . . . we should delete [these] rows.
>
> **JB2:** Let's do that after.
>
> **JB1:** Maybe we should paste these in [motioning to his screen]. But when we open . . . won't it populate?
>
> **JB2:** Do we copy and paste now? So control c, control v? Should we copy and paste this data to here? Should I copy to get this box, and then paste over it? Control c . . .

In this interaction, JB1 helped JB2 take particular operational steps in the appropriate order. This work was left to the junior bankers, who helped to correct each other's steps.

Helping also took the form of written instructions created by junior bankers for other junior bankers to act as guides for completing analyses. Instructions were often printed and pinned up inside junior bankers' cubicles, and they would be taken down and followed, especially when junior bankers were new. The instructions were incredibly detailed, some containing over 40 granular steps, such as "Go to BV19 through CC19 and see if any of the numbers there are not 0s, if so that means there are rows that need to be deleted or updated" (step 21); and "Click sort (Alt A SS), and click OK without changing the sorting criteria" (step 32).

Both forms of helping—conversations and written instructions—fostered and maintained collective norms about the operational steps for completing analysis. Therefore, the meaning of reliability for junior bankers in partitioning groups was focused on assembly steps and keeping them stable across members. Assumptions and interpretations were not part of establishing reliability.

Assessing accuracy. In partitioning groups, accuracy was assessed primarily by senior bankers—not junior bankers—and was accomplished through two means: internal consistency and fit with expert wisdom. This included questioning whether the numbers on a page "made sense" and, if not, coming to an understanding as to why they did not. Because the senior bankers assessed correctness by interpreting numbers on a printed page, they did not go ''backwards'' into the spreadsheets or analytical technologies in order to ''check.'' Rather, they considered the interrelationships between the numbers on the page and calculated the numbers that other numbers implied. This work could be done without understanding how the numbers were calculated. As one senior banker described, ''having that hard copy in front of me, I will then use a calculator . . . if I find an error up top then I know I need to dig deeper. . . . I can then call the [junior banker] and say, 'You made a mistake. This is exactly where you made it,' as opposed to having them waste a ton of time trying to figure it out on their own.'' This senior banker's methodology of calculating implied values on a page allowed him to spot what he perceived to be errors and then communicate them to the junior banker. During a feedback interaction with junior bankers, a senior banker performed his math out loud while motioning to the page: ''This amount plus D&A of fixed stuff? That should lever your EBITDA. . . . Start with EBITDA. . . . This is a total? So 130 minus 42 would be . . . so we're off by 5.''

This methodology of assessment fostered the principle of correctness as one of internal consistency. As a junior banker explained, ''there's no right way; it's just be consistent.'' Making sure that ''the numbers all match'' ensured that the analysis was trustworthy. Indeed, as long as the numbers were consistent, they were generally seen as accurate: ''It's important to be consistent . . . as long as you're consistent with it, at least you're being accurate.''

Senior bankers in partitioning groups also assessed the correctness of analysis by relying on their intuition or ''expert wisdom'' for when numbers seemed ''off.'' As one explained, ''you get a sense that things basically they seem right, they smell right, you know?'' Senior bankers used this sense of numbers ''smelling'' right or wrong—their gut feeling about numbers—to assess whether the directionality of numbers did not seem probable, such as if numbers seemed too high, too low, or ''too good to be true.'' They described this gut sense as coming from years of experience. One senior banker said that ''a lot of senior guys on our team will just know when something is off because they'll feel it in their bones and from experience that it's kind of crazy. You know, I tell [junior bankers], 'You wouldn't believe it but I've got guys who just know in a 50-page pitch book the chart on page 27 is going to be wrong and they can do that just by flipping through it.'''

Experts' gut sense came to define how junior bankers thought about accuracy as well. One junior banker explained that ''[senior] people generally know where things lie,'' so if a junior banker were to ''plug in a bunch of inputs . . . and come up with like a crazy number,'' he expected the senior banker to recognize any inaccuracy. He said with a sarcastic tone, ''The [senior banker] is going to be like, 'Wow, I didn't know your model produced that number. I guess we should use that number. I guess we should be selling for 30 times [earnings] instead of 10.''' Further, junior bankers came to see their role as validating senior bankers' intuition rather than validating the technologies: ''the numbers are already sort of predetermined so you're not really finding out stuff, you're just kind of validating an existing view.'' Another junior banker explained that he saw his job as pulling numbers ''directly from CapIQ, or directly from Factset, and then show[ing] them to a [senior banker].'' Whenever a senior banker told him to go back and make changes, he believed doing so was ''not [about] the thinking; it's the verification almost that they're [the senior banker] right.''

Through internal consistency and expert wisdom, senior bankers assessed the correctness of numbers without searching beyond the printed page in front of them. Junior bankers were not generally involved in this work.

Correcting analysis. For partitioners, artifacts—paper printouts of analysis—were central to the process of correcting analysis. The printouts bridged the barrier between analysis construction and interpretation and provided a medium for communicating revised numbers. One junior banker explained that to prepare for interactions with senior bankers, producing printouts (versus explicating the process of assembling, including the use of analytical technologies) was most important: ''I'm more concerned with the output . . . it's gonna be printed out for someone anyways who's gonna have no idea where it's sourced from.''

Junior bankers produced the paper printouts and handed them off to senior bankers, who then handed them back with their changes marked for the junior bankers to feed back into the spreadsheets. The printed analyses underpinned senior bankers' interpretations and enabled them to exercise their hierarchical authority over the content of the analyses and the junior bankers' work. A senior banker explained, ''I tend to mark this stuff up by hand, and it's given to [junior bankers] to process.'' Senior bankers believed that printed analyses made it easier for them to spot any issues with the numbers. As one said, ''I've found that I am much better at catching mistakes if it's printed out in front of me on a hard copy than if I'm looking at it on the screen. . . . I get the feeling that certainly most of my generation and older are big believers in editing on paper. Certainly the MDs [managing directors] are. I don't know if there's any MD that actually looks at anything on a screen unless they absolutely have to.''

Armed with their paper markups, senior bankers would dictate changes to junior bankers without explaining the logic behind the changes. For example, a senior banker brought marked-up pages with him to a junior banker's desk, explaining that some numbers needed to be adjusted. The senior banker leaned his hip on the junior banker's desk, pointed at the computer screen, and said ''let's change that. So press 'goalseek.' And refresh the pages. Okay, send it out.''

Importantly, these steps never suggested which technology should be providing financial data. The senior bankers were intending to show the junior bankers that their analyses had problems, but they avoided direct instruction around how to alter their process.

Validating Practices by Co-Constructors

Work in Groups 3 and 4 involved what on the surface appeared to be a similar set of validating practices: establishing reliability, assessing accuracy, and correcting analysis. As their partitioner colleagues in Groups 1 and 2 had done, senior bankers in these co-constructing groups avoided assembling work and distanced themselves from the use of analytical technologies. But tasks were integrated within co-constructing groups, meaning the junior bankers did both assembling and interpreting tasks as opposed to just assembling. And instead of exerting authority over outputs, senior bankers exerted authority in their interactions with junior bankers by questioning junior bankers' processes, including their reasoning and choices.

This approach to involving junior bankers appeared to result from the perceived challenge that analytical technologies posed for developing and maintaining expertise. As one senior banker explained, "Here's the problem: there is a direct relationship between automation and knowledge. The more you automate, the more you use tools to automate, the less they [junior bankers] know why things are going on. This includes Factset and CapIQ." Thus, instead of seeing analytical tools as only marginally affecting the work of assembling analysis—which was senior bankers' perspective in partitioning groups—senior bankers in co-constructing groups saw the use of these technologies as potentially hurtful to the development of expertise. As a result, they chose to hold junior bankers' work to a higher standard, insisting that junior bankers learn how to create "client-ready" analyses.

Establishing reliability. As in the partitioning groups, junior bankers in co-constructing groups were responsible for establishing reliability and did so through helping conversations. But in these groups, reliability had a different meaning: instead of being about following consistent technical steps, reliability meant that analyses could be defended. Thus, in helping conversations, junior bankers tried to help each other clarify senior bankers' assumptions and requests. Rather than talk primarily about technical steps, junior bankers helped ensure their work was ready for senior bankers to see. They focused on the importance of being able to "predict what your higher-up people are gonna ask, so that you're one step ahead of them."

One junior banker described seeing another junior banker get reprimanded by a senior banker for not articulating the origins of his numbers:

> Factset and Cap IQ are great, but you can't just pull in stuff, because if it's wrong you can't just say [that's where you got your numbers]. . . . This happens, right? [SB was] like, "Why is this number so off?" [and JB said], "Oh, it's Factset." It's like, "Well, you didn't see that this was off? You should have gone into the estimates, and you could have seen that one estimate was way off, and you should have clearly removed it because it's an outlier and now this multiple is way off from the trend."

To avoid situations like this, the junior bankers helped each other prepare numbers and produce analyses that were defendable to skeptical senior bankers. For instance, after receiving an e-mail from a senior banker, a junior banker turned to another junior banker for help.

> **JB3:** [Senior banker] wants to know how REITs [real estate investment trusts] are valued [in this pitch book].
>
> **JB4:** I've done this before. Here, let me pull the reports for you.
>
> **JB3:** We need to send him the answer and then attach a report. So it looks like they're valued by FFO [funds from operations]. Look at the first report on page 42. Multiple of funds from operations. Free cash flow? No, not free cash flow. Funds from operations.
>
> **JB4:** Wait, are you paying attention just to REITs? Data center REITs look at free cash flow because they constantly reinvest versus data center companies that don't reinvest.

> **JB3:** Well, are all three reports for data centers?
>
> **JB4:** First two are data centers, third is switching to REIT. Do you know the difference between a regular data center and REIT?

After they came to an agreement, the first junior banker sent an e-mail to the senior banker with the answer. Such helping interactions focused on making sense of the numbers and analysis to help establish the reliability of analytical outputs. Importantly, they were geared toward preparing each other for interactions in which senior bankers would question how junior bankers arrived at their calculations.

Assessing accuracy. To assess accuracy, co-constructors ensured that their interpretations and choices were analytically sound. In contrast to partitioning groups, in which only senior bankers assessed accuracy, both junior and senior bankers were involved in these tasks in the co-constructing groups. The definition of accuracy used by Groups 3 and 4 included the assumptions made within calculations, which resulted in matching technology use with collectively held preferences. Assessing accuracy this way directly affected how these groups used CapIQ and Factset. As a junior banker explained, ''due to accuracy . . . you obviously wanna show the client the most accurate thing you can, and Factset [for some calculations], and CapIQ is always on point with [other calculations], well, you just use that.''

These groups assured accuracy by embedding it in the preferences for—and use patterns of—the analytical technologies themselves. As a result, interactions surrounding mistakes were rare; conversations about assumptions in the numbers were integrated throughout analytical construction. In fact, using the technologies differently than what was collectively agreed upon was considered a source of error. As a senior banker explained, errors stemmed from ''incorrect'' assumptions becoming embedded in analysis, which came from using Factset and CapIQ outside of what each had been deemed good for: ''That's usually where the error comes in . . . if a project gets passed on from one person to another person, or gets dug up from a year or two ago, and it might've been from someone else, you know, a different analyst [junior banker] who did it [using the tools] a different way.'' Recognizing that the junior bankers occasionally worked on transactions with senior bankers from other groups or offices that might have different preferences, one senior banker explained that ''sometimes they [junior bankers] forget. . . . I don't fault them for not keeping it all straight, but I remind them at the outset.''

When there were questions about calculations, junior bankers drew on their own intuition and also looked for internal consistency. For example, as one junior banker explained:

> If you're getting 20 times EBITDA for a legacy business, that's definitely not right, so that doesn't make sense, right? That's not saying the analyst did work wrong. The data is not wrong. For example, this company (motioning toward his analysis) had revenue growth from 100 million to 400 million just within a year. But if you look back, the growth rate is only 10, 20 percent, then all of a sudden they have this crazy 400 percent growth, there must be something wrong. But it's not wrong because they made [an] acquisition. Then when you're calculating the revenue growth you have to find the pre-acquisition revenue.

When numbers looked "off," however, ensuring internal consistency did not absolve any potential inaccuracy. Instead, steps were taken to examine assumptions. For example, when two junior bankers worked together to assemble some analysis, one of them noted that a number didn't look right. In this instance, the junior bankers looked into the assumptions within the calculation to resolve the problem. Rather than changing the numbers to match, the bankers worked to understand what was causing discrepancies.

Correcting analysis. Analysis in co-constructing groups was corrected during feedback interactions that centered around junior bankers being subjected to senior bankers' skepticism. Questions such as "how did you get this number?" put junior bankers in the position to explain their analysis. These interactions were multi-modal, involving conversations, e-mails, and sometimes paper printouts of the analysis. But unlike in Groups 1 and 2, which split the tasks of assembly and interpretation, the printouts (and any other elements of these interactions) did not serve as objects to facilitate translation and conversation.

To get at necessary corrections, senior bankers exercised authority over junior bankers' reasoning and expected junior bankers to explain their analysis. As one senior banker explained, "if they have conviction in something, [they should] not just cower to a scary [senior banker] who says like, 'Where's this from?' If they know where it's from, and they know it's right, I want them to be able to sort of speak up in that situation." Speaking up in this case was not indicative of psychological safety that mitigates hierarchical differences (Edmondson, 1999). Instead, it was about being able to explain how numbers were calculated. Making mistakes was embarrassing, and when junior bankers did not catch those mistakes, senior bankers displayed frustration. For example, venting after having noticed an issue with a number, a senior banker said under his breath, "you should have known this was wrong. It looks off." Junior bankers had internalized this expected response, explaining that "you can't have things that are wrong, so I mean you . . . will kind of [get] chew[ed] out if there are things that are wrong with your data or if you didn't check things."

To ensure correct analyses, junior bankers interacted with senior bankers by laying out their reasoning. For example, when a junior banker got an e-mail from a senior banker with questions about a piece of analysis, he leaned back in his chair and stared at the ceiling. "Hmm . . . I need to think about this," he said. He then printed out the e-mail and began opening various spreadsheets to make changes. When the changes were made, he looked at his revised results. "Hmm, holy sh*t," he said looking at the new numbers. He then opened up CapIQ. "What's going on here? Whoa. What's going on here?" he said, continuing to speak to himself under his breath. He then began typing a CapIQ formula into a spreadsheet. He flipped between the CapIQ calculation and the analysis on another tab. "It looks like they also announced new financials. With the new financials, the share price is up 20 percent. Just on earnings, 20 percent in one day." He reflected on whether the analysis still made sense to show the client, and he sent an e-mail to the senior banker with his findings, attaching the supporting analysis. In this feedback interaction, the junior banker effectively constructed his interpretations and suggestions for the client and avoided scrutiny over his choices.

If senior bankers were not satisfied with junior bankers' reasoning, they would suggest changes and explain why. Importantly, blaming the tool was not acceptable reasoning. After a senior banker asked a junior banker why he used gross margin in his analysis, the junior banker responded by saying he had used CapIQ. This reasoning fell short of expectations, prompting the senior banker to reply, ''So, don't use CapIQ here.'' He explained why conceptually he thought it was problematic before asking the junior banker to make the change: ''with gross margin, the difference is [the company] recognizes net revenue, but there are $1.5 billion in transactions that they've done that they don't use. See what I'm saying?'' After the junior banker asked a follow-up question about the kinds of products the company makes, the senior banker responded, ''For a manufacturer, yes, but for [this kind of company], no. . . . Transactions took place, so that's net revenue. Now that's what we want. Okay, cool.'' The junior banker then responded with further questions about the calculation, and the senior banker continued to explain: ''Gross margin doesn't tell you about CapEx [capital expenditure].'' Notably, just as in Groups 1 and 2, senior bankers did not use the analytical technologies; the technical tasks remained in the purview of junior bankers. Thus, after the senior banker finished his explanation, the junior banker walked back to his desk to make changes to the analysis.

Consequences of Partitioning and Co-Constructing Validating Practices

Across all four groups, validating practices assured group members that their analyses were trustworthy. Yet different modes of task involvement held important consequences for whether or not group members developed awareness and understanding of the algorithms in analytical technologies. Further, differences in validating practices resulted in significant consequences for the content of produced knowledge and development of junior members' expertise.

Consequences for the group: Awareness of algorithms in analytical technologies. An important consequence of how junior bankers were involved in validating practices was whether group members understood the algorithms embedded in analytical tools and, as a consequence, used them intentionally or routinely took them for granted.

Because of how partitioners established the validity of knowledge outputs using analytical technologies, neither senior nor junior members were aware that the algorithms embedded in Factset and CapIQ differed. When I asked bankers to help me make sense of the differences in the outputs of their calculations—like those found in Figure 2—regardless of hierarchical role, bankers in partitioning groups were surprised and confused at the chart. Responses to the differences included questions like ''Which one is right?'' In one instance, a junior banker asked me if I had made an error and accidently formatted calculations on different axes in the spreadsheet. Many noted that in some instances, these differences could have led them to different conclusions. Senior bankers doubled down on the importance of their expertise in correcting analyses and validating the knowledge output, saying, ''This is why we can't trust these tools.'' One even took out a pen to mark changes on the paper for me to make.

This lack of awareness reflected the task splitting in the partitioning groups: senior bankers examined outputs, not technologies; and junior bankers were users of technologies who were not charged with making sense of or evaluating the numbers. In addition, senior bankers had authority over what was seen as accurate and exerted this authority over outputs. Thus, even though junior bankers were responsible for choosing and using these technologies, they had not developed an understanding of their inner workings. Junior bankers assumed these technologies would produce the same answers, since they used the same source data.

As a consequence, junior bankers saw these tools as interchangeable. And because junior bankers had autonomy over the production of analysis, the choice about which tool to use was left entirely up to them. Underpinning that choice were familiarity with and preferences for the tool interface, not the embedded algorithms. As a junior banker explained, ''if you like Factset better, then I guess you just use Factset. If you like CapIQ better, you use CapIQ.'' The choice between the two was not seen as important: ''I think everybody . . . for the most part is pretty indifferent.''

In addition, although senior bankers had idiosyncratic preferences in their assessments of analyses, I never observed a senior banker in a partitioning group directing a junior banker to use one technology over the other or questioning a junior banker about this choice. Instead, senior bankers were unaware of how junior bankers used Factset and CapIQ. For example, when asked whether he preferred junior bankers to use one technology over the other, a senior banker explained that it was not his job to know: ''I think that's probably happening more at kind of the [junior banker level], and I'm getting the final output of it. . . . You'd have to ask them [what's] more efficient and more helpful for them, but from my perspective I haven't seen anything kind of positive or negative.'' In these groups, validating practices alienated members from their technologies while also making their work unknowingly subject to the technologies' differing algorithms.

While validating practices also assured co-constructors that their analysis was trustworthy, junior bankers' involvement in both interpretative and assembling tasks enabled understanding of the algorithms in analytical technologies. Members of co-constructing groups actively worked against black boxing Factset and CapIQ by being attuned to the assumptions embedded in their analytical tools. For instance, when I asked members of these groups about the different numbers produced by the two technologies (as in Figure 2), they were not surprised. Each member could explain not only how the algorithms differed but also the implications these differences held for the way the tools were used in the group, as well as instances in which differences could influence conclusions drawn about analyses. Over the course of my fieldwork, these groups' members articulated preferences for Factset or CapIQ, why these technologies differed, and their perceptions as to why the differences mattered for their knowledge outputs.

These collectively held preferences for how calculations should be performed disciplined the use of analytical technologies. As a junior banker explained, ''I know it gets complicated, but . . . we use different things for different purposes.'' He noted that ''we use CapIQ in our comps; we'll take out the Factset formulas, put in CapIQ formulas for market cap and enterprise value. . . . Factset does something [different] . . . and that's not the way we do it.'' Though senior bankers never used the technologies, they learned about the tools' different assumptions through feedback interactions when junior bankers explained their choices and reasoning. As a result, senior bankers had developed awareness of the tools' algorithms and could instruct junior bankers on which technology to use in a given situation.

Consequences for knowledge outputs: Content and consistency. As I have noted, Factset and CapIQ contain algorithms with different assumptions about key metrics. Depending on which one is used, a banker could get different numbers for the same analysis. In partitioning groups, because of how junior bankers were involved in validating practices, this is just what happened: some pitch books contained one set of assumptions and other pitch books another set of assumptions. I found that once a technology was selected by a junior banker, it was used to perform all calculations in a pitch book. In the sample of pitch books constructed by these groups during my study period, Factset was used to perform calculations in 33 percent of them; in 67 percent of pitch books, CapIQ was used. As a result, the analyses produced contained unobserved variance driven by the equations embedded in each technology's algorithms.

These differences could be important. When I asked bankers about the differences between the numbers in Figure 2, they considered the magnitude of the differences to be significant to analytical conclusions and advice. Members of the partitioning groups noted how, depending on which numbers were produced, they might advise clients differently. For example, in response to the debt numbers, one senior banker said that the difference between the two could have a material impact on the ''leverage/capital structure. It looks like a full turn [of EBITDA].'' He explained that this could mean the difference between proceeding with a transaction or not—or at least how much debt a company could take on. Although the magnitude and directionality of these differences may vary across scenarios, the broader point is that the validating practices in these groups resulted in meaningful variance that neither junior nor senior bankers were aware of. These differences could influence conclusions and advice.

By contrast, junior bankers' participation in assessing accuracy and correcting analyses in co-constructing groups resulted in consistent equations between analyses. Not only were knowledge outputs created by co-constructors consistent, but their contents were intentionally constructed. In analyzing the patterns across the sample of pitch books created by these groups, I found that Factset and CapIQ were consistently used for the same calculations in every book. For example, whenever enterprise value was calculated, CapIQ was used. Pitch books often combined calculations from Factset and CapIQ: in 45 percent of books produced by these groups, both technologies were used. When a technology was not used, it was because calculations associated with that tool were not present in the analysis; this was the case in 55 percent of books, in which only CapIQ was used. Co-constructors' knowledge outputs thus had less unobserved variance, meaning that across pitch books, variance in the quantitative analysis that might influence conclusions and advice was intentionally constructed.

This matters because, like partitioners, members of co-constructing groups also saw the differences between the CapIQ and Factset calculations to be substantive. For example, as one senior banker explained, "I think where Factset gets it wrong is they average share counts over periods as opposed to taking a snapshot of share counts, which is more accurate. And it usually comes into play in the company's IPO. Or if a company does a stock split. . . . It can be off materially." Thus, regardless of which junior or senior banker was working on the analysis, the conclusions and the algorithms that drove them were known and were consistent. This meant that the equations driving the final knowledge output were more stable, and by extension, so was the advice given to clients.

Consequences for junior bankers: Development of expertise. As a result of how junior bankers participated in validating practices, junior bankers in partitioning groups did not develop key professional expertise but instead developed deep understanding of operating spreadsheets. The task allocations and hierarchical oversight in these groups did not enable junior bankers to develop the ability to assess financial analyses. When asked how he interprets the numbers produced by the analytical technologies, one junior banker said, "I think that's more something that people would do at higher levels. I don't think I know enough about the markets or any particular industry to look at it and be like, 'Hmm, I'm questioning CapIQ right now.'" When another junior banker noted that calculations from Factset and CapIQ are not always "right," I asked how he might know that. He explained that "for stuff like that, that's honestly something that I usually don't catch, just 'cause, you know, I wouldn't be like, 'Oh, you know, this random bond isn't 450, it's 400.' I wouldn't know that. But usually, as it goes higher up, those guys kinda know the space that, whatever this deal's embedded in, they say, 'Think this looks weird.'" Therefore, even though senior bankers in the partitioning groups believed that junior bankers' task involvement would help them develop expertise related to assessing analyses, it did not.

Some senior bankers recognized that junior bankers were not developing this expertise. Yet they did not consider it a problem related to task allocation or how they interacted with junior bankers; they considered it a problem with the way junior bankers chose to use analytical technologies in their assembling tasks. One senior banker described seeing "a weakening of really understanding the trends and what's going on with the business." Senior bankers blamed this lack of understanding on the junior bankers' reliance on Factset and CapIQ for calculations: "I think they tend to rely on the technology so much that they don't know how to do math." This created a self-reinforcing dynamic: senior bankers continued to correct analyses, thinking they were helping the junior bankers correct their analytical processes, and junior bankers focused on their spreadsheets and continued to believe the senior bankers were the ones with the answers.

By contrast, junior bankers in co-constructing groups participated in validating practices in ways that enabled the development of expertise by improving their understanding of what drove their analyses. This dynamic was shaped by how senior bankers exerted their hierarchical authority during feedback interactions. One junior banker said that "at the end of the day you're going to have to explain this to someone. So, if your [senior banker] starts asking you questions, you're going to explain where the data came from and how you got to the numbers.'' Whereas junior bankers in partitioning groups frequently received comments and corrections on their analyses, junior bankers in co-constructing groups found it embarrassing if senior bankers corrected their work: ''once it goes up the ladder, if your MD [managing director] finds something that's wrong it's even more of an issue.'' As another junior banker explained, senior bankers ''don't expect you to give them work that's half right or half done. So, if you're a good [junior banker] you shouldn't get that many comments on your work.''

Differences in the expertise developed by junior bankers across these groups appeared to be reflected in promotion and turnover rates. Partitioners had notably lower rates of promotion and higher rates of turnover compared with co-constructors, as shown in Table 3. The differences in turnover were even more pronounced when taking into account whether junior bankers who departed the bank took jobs at other investment banks and thus continued to progress in the profession, or whether they pursued careers outside of investment banking altogether. As Table 3 illustrates, junior bankers in partitioning groups tended to leave investment banking when they departed the firm, whereas those in co-constructing groups tended to remain in the profession if they left the firm.

Junior bankers who were promoted in partitioning groups also appeared to face considerable hurdles in establishing themselves as senior bankers. For instance, someone who was promoted from junior to senior banker during my study period seemed to lack the expertise to assess the accuracy of an analysis and provide corrections to junior bankers. He relied heavily on internal consistency, which was noted by other senior bankers who described him as lacking judgement and focusing too heavily on ''copy and paste.'' As a result he was not entrusted to develop independent relationships with clients. Within a year of his promotion, he left the profession. This was not an isolated incident—during my study period, around one-third of those promoted in these groups ultimately departed after becoming senior bankers. By contrast, I did not observe the same doubting of promoted bankers' expertise in co-constructing groups, where task allocations followed a pattern of integration and senior bankers exerted authority over reasoning. Instead, these bankers were entrusted to speak with clients independently and forge their own client relationships.

Table 3. Junior Bankers' Promotion and Turnover across Groups

	Partitioners		Co-Constructors	
	Group 1	Group 2	Group 3	Group 4
Promotion*	38%	17%	83%	60%
Turnover from the firm†	73%	83%	50%	57%
Turnover from the profession†,‡	54%	67%	33%	14%

* Calculated based on which junior bankers were eligible for promotion.

† Calculated before and after promotion windows; includes turnover events within five years of this study.

‡ Excludes junior bankers who left to take lateral jobs at other investment banks.

Table 4. Summary of Validating Practices and Their Consequences

	Partitioners	Co-Constructors
Beliefs about the impact of technology on core tasks	Efficiency	Transformative
Nature of involvement		
Task allocations	Task splitting: Junior bankers are responsible for assembling tasks Senior bankers engage in interpretation	Task integration: Junior bankers are responsible for assembling tasks and also engage in interpretation Senior bankers engage in interpretation
Task oversight	Senior bankers exert authority over outputs	Senior bankers exert authority over junior bankers' process (i.e., decisions and choices)
Validating practices		
Establishing reliability	Junior bankers focus on consistent operational steps	Junior bankers focus on defendable analysis
Assessing accuracy	Senior bankers check for internal consistency and assess fit with expert wisdom	Junior and senior bankers ensure "correct" assumptions used in particular calculations
Correcting analysis	Senior bankers evaluate outputs, dictate changes that junior bankers execute	Senior bankers scrutinize junior bankers' process, explain reasoning behind corrections that junior bankers execute
Consequences		
Algorithms in analytical technologies are black boxed	Yes	No
Knowledge outputs	Inconsistent and contain unobserved variance	Consistent and contain intentionally constructed variance
Junior bankers develop key expertise and progress within the profession	No	Yes

While patterns in turnover and promotion are descriptive, and I cannot say whether these bankers were selected out or chose to leave, the data suggest that how junior bankers participated in validating practices held consequences for their career trajectories—namely, whether they progressed in investment banking or departed the profession.

Table 4 summarizes my findings, showing that how junior members were involved in validating practices informed how reliability was established, accuracy defined and assessed, and analysis corrected. Ultimately, their involvement in validating practices influenced whether these knowledge workers black boxed (or not) the algorithms in their tools and held important consequences for the content of their knowledge outputs, as well as for junior members' development of expertise and their progression.

DISCUSSION

This study demonstrates how junior members' involvement in validating practices may significantly affect the way analytical technologies are used and understood by knowledge workers. The results of my comparison of four groups in an investment bank reveal that how junior members are included in these practices can influence whether knowledge workers develop understanding of their technologies' embedded algorithms or inadvertently black box them. Further, I find that relying on analytical technologies without understanding their embedded algorithms can shape the content of knowledge outputs—sometimes in ways that are not obvious to knowledge workers themselves. It may also influence the reproduction of expertise in junior members, with consequences for their career trajectories.

Analytical technologies, therefore, may pose unique challenges for how knowledge workers configure practices to validate their analysis and hold significant consequences for knowledge outputs and expertise. These findings advance research on technology use in knowledge work and in new member participation.

Contributions to Our Study of Technology Use in Knowledge Work

This study contributes to literature on knowledge work by demonstrating the conditions and mechanisms through which knowledge workers might come to black box their analytical technologies. To date, research has focused on how knowledge workers achieve unique expertise, including in the inner workings of their technologies. Whereas those who are distant from the use of technology, such as policy experts and managers (e.g., MacKenzie, 1990; Shackley and Wynne, 1996), or those who are new to knowledge work and yet to be socialized (e.g., Petroski, 1985; Turkle, 2009) may trust technologies without understanding, such black boxing seems antithetical to knowledge work and to our images of experts. Knowledge workers are assumed to question their technologies in order to develop and maintain expertise, as well as to ensure the quality of knowledge outputs (Hutchins, 1995; Orr, 1996; Knorr Cetina, 1999; Dodgson, Gann, and Salter, 2007; Bailey and Barley, 2011).

My study challenges these findings, revealing how knowledge workers may rely on their tools without understanding how they work. In groups in which validating practices were partitioned across roles and junior bankers participated only in tasks related to assembling analysis, members failed to unveil the inner workings of analytical technologies. This occurred because junior bankers did not encounter algorithms as they assembled outputs, and senior bankers focused on interpreting and correcting these outputs, remaining distanced from how tools figured into analytical tasks. By contrast, groups in which validation was co-constructed and junior members interpreted their analysis as they produced it avoided such black boxing; junior bankers had to defend their reasoning to senior bankers, requiring an assessment of assumptions embedded in tools and ultimately analysis. Thus, my findings suggest that while expertise may be necessary, it is not sufficient for understanding algorithms embedded in technologies.

Interestingly, I find that when knowledge workers rely on their technologies without understanding their embedded algorithms, they still engage in practices to validate their work to ensure that they consider it trustworthy for clients. This reveals a new form of black boxing that is fundamentally different from existing research. Prior literature has suggested that when technologies are taken for granted, they are not questioned (Latour, 1987; Marx, 2010). However, I find that when knowledge workers black box their technology, these workers do what we expect knowledge workers to do: they scrutinize outputs and engage in interactions with one another to weigh in on whether or not the analysis is trustworthy. The groups I studied that were unaware of the algorithms still worked constantly to establish reliability, and senior bankers were continuously assessing accuracy and correcting analyses. Yet my findings show that splitting technical work from interpretive tasks may result in validating practices that are focused on creating consistent operational steps and correcting outputs based on internal consistency and fit with expert wisdom—not based on the examination of analytical technologies. Further, because these groups went through steps to validate their work, these knowledge workers were seemingly unaware that they were relying on the algorithms embedded in their tools. Whether knowledge workers fostered understanding of technologies rested not in the presence or absence of validating practices but rather in how key technical and interpretive tasks were allocated (or not) to junior roles.

The analytical technologies studied here are similar to many other tools used in knowledge work settings that contain algorithms and assist with big data analytics. The algorithms in these tools could be questioned and understood by their users, and thus black boxing in my context emerged through tasks, interactions, and practices. Yet the materiality of some emerging analytical technologies may make it difficult, if not impossible, to understand how they work (Faraj, Pachidi, and Sayegh, 2018; Christin, 2020). For example, some of these tools are embedded with algorithms that are not transparent, such as some types of artificial intelligence and machine learning. My findings suggest that expert knowledge workers can still deem outputs as trustworthy without understanding the algorithms in their tools, but doing so may result in the creation of knowledge outputs containing inconsistent assumptions and may thwart the reproduction of expertise in junior members. This suggests that inscrutable technologies may pose fundamental risks for knowledge work. Clearly, more research is needed on the intersection of knowledge work and algorithmically-driven analytical technologies.

Focusing on knowledge outputs in my setting, it was not obvious that the recommendations bankers gave to clients based on different algorithms were "wrong" per se. As in many forms of knowledge work, the quality of outcomes is difficult to assess (e.g., Alvesson, 2004). But bankers' analysis was not always purposefully constructed, and knowledge workers in the groups that black boxed their analytical technologies were unaware of key assumptions. While research has suggested that organizations need to analyze data in their decision making (Teece, 2007; Kaplan and Orlikowski, 2013), I find that knowledge workers can analyze data without knowing what it says, which may unknowingly shape knowledge outcomes. In some settings, this may have profound consequences. For instance, economists who used databases to study African development recommended policy without realizing how key measures—including population, agricultural production, and national income—reflected different tactics taken by colonial rulers (Jerven, 2013). This led to scholarly misinterpretations, divergent conclusions, and political controversy. My study points to what may make such outcomes more likely, suggesting that how knowledge workers structure validating practices systematically shapes knowledge outputs.

The knowledge workers in my setting are members of a high-status occupation and cultivate trusting relationships with clients. As a result, they are not subject to the same scrutiny that other occupations may be, and they tend to enjoy more authority (Giddens, 1990). This suggests that we may see more unpacking of how technologies work where relations with clients are different and occupations are lower status. Thus, a potentially important area for future work to explore may be how occupational status and client relationships affect practices for validating analytical technologies, influencing knowledge work more broadly. For instance, it could be that lower-status occupations fare better than higher-status occupations in their scrutiny of analytical technologies and reproduce expertise in their junior members more consistently as a result.

This study contributes to research that examines how knowledge workers respond to technologies that may threaten their expertise. Prior literature has found that workers may avoid these new technologies or may reframe their expertise to accommodate the technologies (e.g., Nelson and Irwin, 2014; Lifshitz-Assaf, 2018; Bechky, 2020). Yet all of this work assumes that knowledge workers are aware of how a tool might challenge expertise, and none considers what happens when workers lack such awareness. Adding to a growing body of literature that points to intra-occupational sources of heterogeneity in response to new technologies (Mazmanian, 2013; Howard-Grenville et al., 2017), I find that knowledge workers may differ in how consequential they perceive new technologies to be for expertise, which may ultimately shape how technologies are used and expertise is developed. For instance, senior members in groups that engaged in partitioning viewed analytical technologies as improving efficiency by simply speeding up work, believing that junior bankers would develop expertise through using the tools to perform analysis just as they had. By contrast, senior bankers in co-constructing groups saw these tools as more transformative and thus as having the potential to hurt junior bankers' expertise. Surprisingly, those who perceived technologies as potentially threatening did not avoid the technologies or reframe their own expertise but rather engaged more deeply with the assumptions in their tools through task allocations and oversight than those who perceived them as marginally affecting work. Ironically, groups in which senior members believed that analytical technologies would speed up otherwise stable practices produced knowledge outputs that were largely driven by the algorithms embedded within the technologies.

Contributions to Our Study of Participation in Knowledge Work

This study demonstrates that how junior members participate in validation matters for how knowledge workers accomplish their work. As scholars have long found, reproducing expertise in newcomers is of paramount concern for occupations because it enables the continuation of knowledge work across generations. To enable this continuity, junior members typically are included through legitimate peripheral participation, working alongside experts to develop expertise and ultimately become senior members (Lave and Wenger, 1991; Hutchins, 1995; Wenger, 1998; Brown and Duguid, 1991). While prior research has noted that senior members' expectations may shape forms of participation (Wenger, 1998; Gomes, 2019), this research has largely assumed that such differences coincide with occupational and environmental factors (Bailey and Barley, 2011), including technological barriers and economic challenges (e.g., Marshall, 1972; Beane, 2019). For instance, differences in the allocated tasks and interactions with senior members across newcomer tailors and midwives are explained by what form of participation would best allow them to develop expertise in light of environmental constraints (Goody, 1989; Jordan, 1989). By contrast, I find that how junior members participate may differ even within the same knowledge work occupation based on more locally held beliefs about how new technologies affect core practices.

My study thus introduces an emerging literature on task allocations (e.g., Cohen, 2013; Chan and Anteby, 2016; Cohen, 2016; Wilmers, 2020) to research on newcomers' participation in knowledge work. These studies have found that task allocations emerge based on local beliefs and social structures and may result in unequal task distributions within the same role. For instance, Chan and Anteby (2016) found that female transport security workers were disproportionately required to do pat-downs of passengers, which led to less job satisfaction and higher rates of turnover. Like this research, I too found that tasks assembled within the same role can differ depending on local beliefs, and the allocation of tasks can lead to unequal outcomes. However, my study suggests a new pattern in allocations leading to negative consequences. In my case, the *lack* of particular tasks in the work of junior bankers—rather than the incorporation of additional tasks—resulted in unequal job experiences and career outcomes. This suggests that the nature of what tasks are included or excluded in allocations may matter significantly for knowledge work outcomes.

Further, the importance of different task allocations in junior members' participation moves beyond prior literature, which has largely assumed that newcomers do not develop expertise if they do not participate (Lave and Wenger, 1991; Wenger, 1998) or if they participate only in "crappy tasks"—the work no one wants to do—like getting coffee (Becker, 1972: 97). Instead, all four groups in my study enabled junior members' participation in important tasks—namely, the assembly of core analysis that underpinned advice to clients—and junior members in all four groups engaged in ongoing interactions with senior bankers. But not all junior members successfully developed expertise through this work, with implications for their careers. Only those junior members whose reasoning was scrutinized by senior members and who thus interpreted their analysis as they produced it developed key expertise while using analytical technologies. Thus, while prior literature has presumed that participation and access to senior members provides equal opportunity for newcomers, I find that *how* participation unfolds is also significant for knowledge work. Further, senior members, while believing they facilitate opportunities for junior members to learn, may undermine the reproduction of expertise through task allocations and interactions, ultimately perpetuating unequal expertise across otherwise similar new members.

Differences in junior members' participation may also be important because of a trade-off that is typically presumed between risks to knowledge outputs and the inclusion of junior members in the work. Prior literature has suggested that newcomers may be excluded from key tasks to protect the quality of outputs. For instance, junior butchers were forced to wrap meat instead of cut it because of the cost associated with ruining an expensive cut of beef (Lave and Wenger, 1991), and junior surgeons were unable to practice robotic surgery because of risks posed to the patient (Beane, 2019). Yet I find that junior members' participation may not necessarily add risk to knowledge outputs, depending on how they are included. And, counterintuitively, groups in which junior bankers were involved in more tasks—namely, assembling and interpretation to justify their analysis—developed awareness of how their analytical technologies worked, resulting in the production of consistent analyses for clients. Groups in which junior bankers did not interpret their analysis faced considerable consequences: they black boxed analytical technologies and as a result produced knowledge outputs with unintentionally inconsistent analysis. Therefore, including junior members may in some cases benefit knowledge outputs rather than add risk. This may be especially true in contexts in which analytical technologies disrupt the core tasks typically allocated to junior members.

My study also reveals that hierarchical authority may play a surprisingly valuable role in social interactions that help develop and maintain expertise. Previous literature has largely painted a picture in which hierarchy is negative for knowledge work. Indeed, members may focus on maintaining and improving their social positions over the accomplishment of work (Owens and Sutton, 2001), avoid asking questions for fear of vulnerability (Lee, 1997, 2002), and unequally engage in knowledge sharing (Brooks, 1994). Further, less hierarchy has been found to be better for knowledge creation and learning (Adler, 1993; Lee and Edmondson, 2017). For instance, Edmondson, Bohmer, and Pisano (2001) found that practice innovation in surgical teams was successful when teams behaved more collaboratively and less hierarchically. Similarly, Barley (1986) found that institutionally entrenched status differences challenged interactions across technicians and radiologists when technicians had more expertise than radiologists.

However, I find that the role of hierarchy may be more complicated than what previous literature has allowed. For co-constructors, hierarchical authority was key to passing on expertise, and junior bankers' concerns about their social position were helpful for the pursuit of work goals. In particular, how authority was exercised during validating practices—namely, over junior bankers' choices and reasoning—influenced the development of expertise. To avoid the embarrassment of substandard work and to demonstrate judgment, junior bankers who were subject to scrutiny of their choices and who feared the embarrassment of mistakes remained attuned to the assumptions in their tools and worked to understand the implications of their analyses for clients. Yet in partitioning groups, hierarchy undermined the development of expertise in junior members, ultimately resulting in inconsistent knowledge outputs. In addition, junior bankers were not developing key professional expertise, which appeared to shape their career trajectories. This suggests that hierarchical authority can, under certain conditions, be positive for knowledge work outcomes, particularly when algorithmically-driven technologies are in use.

Opportunities for Future Research

In this research, I focused on how knowledge workers might come to black box their technologies, but an open and critical question remains as to why such different pathways for involving junior members in validating practices emerged in the first place. Although I was unable to disentangle the cause of these differences in this study, my findings suggest a few fruitful areas for future inquiry. First, partitioning and co-constructing appeared linked to senior members' beliefs about how analytical technologies affected the core work of junior bankers. This was surprising, because research has found that members of the same collective meaning system—like an occupation—tend to have similar beliefs about what a technology is good for (e.g., Orlikowski and Gash, 1994; Benner and Tripsas, 2012; Mazmanian, 2013; Anthony, Nelson, and Tripsas, 2016). Yet some senior bankers saw this new technology as incremental, not affecting core junior practices, while others saw it as fundamentally reshaping the way analysis was assembled. Future research might explore what influences differences in beliefs about technology, especially by those in positions of authority over newcomers' learning, as it might lead to differences in task allocation and oversight.

In addition, future research might consider how the tenure of senior knowledge workers could play a role in shaping junior members' involvement. For instance, those in positions of authority who have more experience guiding the work of junior members without technologies may be more attached to older ways of accomplishing work (e.g., Barley, 1990). Further, differences in tenure can shape interaction norms across hierarchies (i.e., Bailey and Barley, 2011), which might also shape how junior members are included. Clearly, more research is needed to uncover the origins of different modes of involvement, since they can meaningfully impact knowledge work—and those who perform it—in important ways.

Conclusion

Because knowledge is trusted by consumers and shapes the competitiveness of organizations, the consequences of its production are key for economic life and society more broadly, especially as algorithms continue to be integrated and relied upon for things like medical diagnosis, strategic decision making, and even courtroom sentencing. Thus awareness of how algorithms work, the production of knowledge, and the development of expertise in junior members matters profoundly for knowledge work occupations as well as for organizations. Someday, junior members will become senior and will be responsible for developing expertise in others and vetting produced knowledge, which is central to the survival of occupations (Abbott, 1988). Yet the challenges posed by new analytical technologies for theories about how these processes unfold are significant, and classic images of expertise as tied to tenure may not hold (Blasi, 1995). Instead, participation in validating practices may play a central role in developing expertise, using and verifying technologies, and producing knowledge—but how, and with what consequences, remain fundamentally important questions.

Acknowledgments

I am deeply grateful for the invaluable and unwavering support of Mary Tripsas, Mary Ann Glynn, and Andrew Nelson throughout the development of this work. Jean Bartunek, Beth Bechky, Curtis Chan, Eliana Crosina, Anne-Laure Fayard, Colby Green, Gillian Gualtieri, Matthew Hall, Sarah Kaplan, Wesley Koo, Michael Lee, Christian Mealey, Wanda Orlikowski, Mike Pratt, Zach Rodgers, Melissa Schilling, Susan Silbey, Lee Watkiss, Mark Zbaracki, and members of the NYU Qualitative Group also shared constructive comments on earlier versions of this manuscript. Special thanks to Mary Benner and three anonymous reviewers who provided excellent feedback and guidance during the review process and to Joan Friedman who suggested helpful improvements.

Funding was graciously provided by the Strategic Research Foundation and Social Sciences and Humanities Research Council. Finally, I am grateful to members of GLOBAL Bank for allowing me to learn about their work. All errors are my own.

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