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They Work with Data and Do Some Science: How Identity Conflict Turns Data Professionals away from Data Science

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Short Paper

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Abstract

Data science is widely perceived as an attractive, lucrative, and prestigious emerging occupation. Research so far has focused on understanding data scientists' practices and identity work associated with establishing and legitimizing this new occupation. This work, however, is not sufficient to explain a phenomenon we observed whereby professionals rejected the opportunity to adopt this new occupational identity. To understand why professionals may not want to be labeled data scientists, we analyzed 43 interviews with data professionals at an educational measurement company in the U.S. Despite a clear steer from management towards the data science label, many interviewees stuck to their established professional identities. In our preliminary findings, we use the literature on identity conflict as a lens to make sense of our observations. By identifying three types of conflicts: 1) task conflict, 2) role conflict, 3) tool conflict, we begin to explain what turns professionals away from data science.

Keywords: data science, data scientists, identity conflict, occupational identity, identity work

Introduction

Data science is an occupation that is gaining popularity at an unprecedented rate, with numerous organizations hiring data scientists or upskilling their existing workforce (Davenport 2018; Davenport et al. 2010). In consequence, data scientists, those with the "skills and ability to extract actionable knowledge from large data sets with the use of sophisticated digital technologies such as the programming languages, visualization techniques, or Artificial Intelligence" (Vaast and Pinsonneault 2021, p. 1087) are increasingly in demand. For this reason, the occupation is often seen as an attractive, lucrative, and prestigious career (Avnoon 2021; Vaast and Pinsonneault 2021), to the extent that data science has been called "the sexiest job of the 21st century" (Davenport and Patil 2012).

Research around data science as an occupation focuses on its emerging status, that is, how data science and data scientists differentiate themselves from other, more established occupations with similar skill sets and work duties (Ghasemaghaei et al. 2018; Ghasemaghaei and Turel 2021; Joshi 2020; Kery and Myers 2017; Vaast and Pinsonneault 2021). For example, Vaast and Pinsonneault (2021) showed how data scientists maintain their occupational identity through a balancing act between the optimal distinctiveness and persistent extinction of their roles against ever-changing organizational contexts and digital technologies. Avnoon (2021) discussed how data scientists construct their elite and prestigious identities through bridging the gap between science and engineering, drawing from multiple theories, engaging in intensive professional development, bringing together technical and social skills, and acquiring domain expertise. Waardenburg and colleagues illustrated how data scientists behind the Dutch police predictive system maintained their differing occupational identities since they "were located in a different building, far removed from daily police operations" and as they were hired for their specific data science expertise they "considered algorithmic predictions fundamentally different from police occupational knowledge" (2021, p. 64).

In sum, data scientists engage in identity work (Avnoon 2021; Stein et al. 2013) to evolve and maintain their occupational identity as an elite career different from other information technology, engineering, or technical occupations. One of the main reasons why such a high degree of identity work is required is the persistent ambiguity of the terms data science and data scientists (Parmiggiani et al. 2022; Vaast and Pinsonneault 2021). As there exists no established or uncontested definition of the occupation, and there are vast overlaps between the skills and tasks done by data scientists and other more traditional professionals, data scientists, through identity work, explain what makes them different and elite. It appears then that data science may be, in many cases, an occupational identity label that professionals choose to adopt for its desirable status (Davenport 2018; Davenport et al. 2010; Davenport and Patil 2012).

In light of this evidence from research and practice, we were surprised to encounter a case of TestU, an organization where, despite being given an opportunity to adopt the seemingly prestigious data science label, a group of data professionals resisted the steer towards labeling them as data scientists. Although data professionals' skills and job tasks were vastly similar to what data scientists do, these professionals often became more entrenched in their incumbent occupational identities, which seems to contradict findings on data science identity work so far. Thus, we became interested in finding out *why professionals reject the opportunity to enhance the perceived attractiveness of their occupational identity*.

To explore this research question, we use insights from existing research on identity conflict that unpacks changes in occupational identities. Identity conflict occurs when individuals feel they are perceived as acting not in line with a desired group identity, or when they feel unable to sustain multiple identities (Croft et al. 2015; Zanette and Scaraboto 2019). For instance, an identity conflict can occur when an individual's personal identity such as their values, beliefs, and personality traits, conflicts with the organizational identity (Song 2022). Moreover, an identity conflict occurs when the occupational identity conflicts with the associated prestige of the profession (Ashforth and Kreiner 1999). This focus of identity conflict is dominant in our study where we find a conflict between how data professionals perceive themselves, and how they perceive the occupational identity of data scientists.

To understand this identity conflict and potential implications, we conducted an in-depth interview-based qualitative study at TestU, a large U.S. company in the educational measurement sector, focusing on occupational identity work of its data professionals. We selected this case as it is a revelatory case (Yin 2021) providing access to a previously unobserved phenomenon. One of its departments is a research department responsible for collecting and analyzing data intended for the development of new tests and products. Shortly before and during our study, TestU was undertaking efforts to steer this department through reorganization and reinvention into a data science department, spearheaded by the Director of Research with a clear mandate from the CEO. Our preliminary findings indicate that three types of identity conflicts may explain this reluctance: 1) task conflict (what data scientists do is different from what I do), 2) role conflict (who data scientists are is different from who I am), and tool conflict (what data scientists work with is different from what I work with).

Our findings, while preliminary, offer a potential contribution to a more nuanced understanding of identity work in emerging occupations that face skill, task, and tool uncertainty, as well as toward a better understanding of the interplay between identity and technology in the workplace (Stein et al. 2013; Vaast and Pinsonneault 2021). We also plan to contribute to literature on identity conflict by showing how such conflicts may emerge or coalesce around technological tools used at work (Stein et al. 2013). Finally, we contribute to a better practical understanding of data science as an emerging occupation, and data scientists' identity.

Research Design

We conducted the study at TestU's Research Department responsible for collecting and analyzing data that go into the assessment of the validity of tests, and the development of new tests and products, rather than the administration of the assessments or communicating the results. The Department employs around 50 data professionals specializing in different areas, from psychometric testing and statistics (involved for example in equating, a procedure to ensure that results of different assessments are comparable across time), through social and emotional learning (measuring and assessing skills such as teamwork or conscientiousness), to machine learning and artificial intelligence (involved in the automated scoring of essay responses, for example). Shortly before and during the study, conducted in summer and fall of 2021, TestU was undertaking efforts to steer this department through reorganization and reinvention into a data science department, which proved to be an opportune moment for us to study how the professionals responded to the opportunity to change their occupational identity to data scientists. In this sense, this is a revelatory case (Yin 2021) which provided an opportunity to observe and analyze a previously inaccessible phenomenon.

Type of data	**Quantity of data**		**Period of data collection**
Semi-structured interviews	43 interviews with 38 employees, 33 from Research Department, 5 outside but working with Research Department (outside department), 5 follow up interviews. In total, approximately 39 hours of audio data, 645 pages of transcripts, Interview 001 – Interview 043		June – November 2021
Interviewee role	No. of interviewees	Interviewee role	No. of interviewees
Scientist (Research Department)	8	Principal Product Owner (outside department)	1
Senior Scientist (Research Department)	8	Lead Data Analyst (outside department)	1
Lead Scientist (Research Department)	6	Content Systems Analyst (outside department)	1
Principal Scientist (Research Department)	3	Senior Business Analyst (outside department)	1
Program Manager (Research Department)	1	Lead Software Engineer (outside department)	1
Support Specialist (Research Department)	2		
Solutions Designer (Research Department)	2		
Director (Research Department)	3		

Table 1. Overview of Data Collection

We engaged in data collection between June and November 2021. We conducted 43 interviews with 38 employees following a semi-structured interview guide (Schultze and Avital 2011). The employees were involved with qualitative (e.g., taxonomies of skills in jobs), quantitative structured (e.g., teamwork skills assessment), and quantitative unstructured (e.g., automated written response scoring) data. Out of 38 interviewees, 33 rejected and opposed the attempts to label their work as data science and themselves as data scientists. We interviewed employees at various levels of seniority, from interns to the director, and with various levels of tenure at TestU, as well as with a variety of data roles, from those working most closely with data, to those helping to set up meetings where data were discussed to ensure multiple perspectives (Schultze and Avital 2011). For simplicity, we refer to all interviewees collectively as data professionals, but similarly to other studies (e.g., Parmiggiani et al. 2022), we found that their roles differ in naming and location in the organization. The interview guide was prepared ahead of the study and was based on our theoretical interest in occupational identity. All interviewees were asked broadly the same questions, first about their role, then about their work with data, and then about what they thought about the term data science and how it related to their work. Finally, we asked for interviewees' impressions of the ongoing reorganization efforts. We grounded the interviews in participants' own experiences and asked for descriptions of their experiences (Schultze and Avital 2011), and as such interviewing was a suitable data collection method as it allowed us to ask questions related to occupational identity. All interviews were conducted remotely, and following participants' consent, recorded and transcribed. A summary of data collected is presented in Table 1.

We analyzed our data using grounded theory methods (Charmaz 2006; Urquhart and Fernandez 2006; Wiesche et al. 2017). We started by conducting open coding (Wiesche et al. 2017) and attached initial labels to all empirical evidence related to identity conflict (relying on prior theory constructs, Weische et al. 2017). We then grouped open codes related to similar, core categories based on Glaserian selective coding (Glaser 1978), and from these we synthesized the three types of identity conflict. To clarify, we did not engage in a grounded theory research strategy (Urquhart 2022), but only deployed grounded theory methods in data analysis. In this process, we oscillated between data and literature analysis (Strauss and Corbin 1990). We proceeded through multiple readings of the data collected as we analyzed and synthesized the findings (Beane and Orlikowski 2015; Eisenhardt 1989). As we did so, we relied on constant comparison, that is the process of constantly comparing units of data in constructs we identified with each other, and we engaged in memoing to capture our ideas of concepts, categories, and the relationships among them (Wiesche et al. 2017).

Findings

Among the 38 employees of TestU that we interviewed, only 5 reported seeing themselves as data scientists. The overwhelming majority of those we spoke with were clear that they did not identify with the label, which often conflicted with how they perceived their own occupational identity. Below we report on three types of conflicts that we identified in preliminary data analysis.

Task Conflict: What Data Scientists Do Is Different from What I Do

First, data professionals who rejected the data scientist label tended to have a relatively clear opinion about what tasks data scientists were responsible for, and how this differed from what they were tasked with at TestU. Interviewees often mentioned that data scientists have far more emphasis on understanding the data and less on domain knowledge. Data scientists were seen as focusing on data, while existing data professionals took the wider context into account: *"I would consider data science more of like, looking at data in different ways and finding patterns in it"* (Interview 006). Referring to data scientists supposedly already in the organization, one interviewee said "*I assume they can come in and manipulate my data sets and break things out and give me summary level results quickly*" (Interview 010). In fact, data professionals were relatively quick to point out what they thought data scientists did: "*I don't think they run a lot of analysis so much as they organize and maintain the data and could run analyses*" (Interview 010).

Data professionals perceived data scientists as mostly pulling data from databases, manipulating and wrangling with the data, crunching numbers, and writing code that is needed for this work: "*Data scientists for sure need programming skills, because, because they, they work with the data directly without solid hypotheses most of the times, so they focus on manipulating the data to see what happens, which is another of the differences*" (Interview 002). In sum, their work with data was largely seen as related to more straightforward data manipulation and organization, and preparing data for analysis and consumption.

This task perception contradicted with task areas that data professionals at TestU considered as central to their work. Many of them work on data analysis that they see as a different task from the way data scientists would approach it, as well as quality assurance and quality control on the reported data, supporting data quality. In fact, they perceived data science as one step before their own tasks: "*their main job to me was actually making the data available and useful for someone like me*" (Interview 010). For many data professionals, the main difference was that their tasks required accounting for the larger context and drawing from their domain expertise to answer business questions: *"what we're doing is we're doing some of that [finding patterns in data], but we're also pulling in a much larger context, in order to not just explain what we're seeing, but also to inform what we're even looking for in the first place"* (Interview 006). This meant that their tasks were more research-related, as they often designed studies, prepared written reports, and even went to conferences to present their findings.

These differences in what data professionals perceive to be the tasks of data scientists *vis-a-vis* their own tasks can be characterized as a task conflict. Data professionals considered their own tasks to be significantly different from what they thought data scientists were doing, and this contributed to them rejecting the new, attractive label. Interestingly, some data professionals admitted they were not sure what data scientists were doing and this lack of certainty led them to reject the label as well. However, among the very few data professionals who accepted and even looked out for opportunities to adopt the new label, we did not observe task conflict. In other words, those data professionals who were eager to call themselves data scientists claimed that their tasks were similar or complementary: "*I would say that's more of a theoretical distinction in my mind, because I think that in my position, I think there's overlap. I would say, I'm a research scientist. But I'm sometimes asked to do things that I would think of as more of a data scientist*" (Interview 001). Some claimed that "*it doesn't necessarily mean that the work that you do as a data scientist is entirely different compared to your [data professional]*" (Interview 039).

Role Conflict: Who Data Scientists Are Is Different from Who I Am

Another identity conflict occurred in how data professionals perceived who they are in contrast to the role of data scientists. Data professionals at TestU perceive data scientists as data-focused professionals who are proficient in statistics and database management: "*to me, a data scientist is someone who has a very strong statistical background, and also has knowledge of database management and strong coding skills*" (Interview 001). This emphasis on technical skills and abilities was present throughout the interviews: "*I meet someone, and they're extremely capable, they have a lot of SAS certifications, or they can write Python, they can write R, they can write SQL. And they're a data scientist*" (Interview 010). At the same time, data professionals suggested that data scientists did not have a lot of formal education, but rather developed their skills informally through online courses or on the job "*like entry level courses in a few different areas*" (Interview 009). Some data professionals perceived the data scientist role as less involved: "*Like, I took a bunch of numbers and created a graph, I'm a data scientist, I did a little math"* (Interview 006).

Data scientists' perceived role lacked clarity in the eyes of data professionals, sometimes described as a "*a kind of a mishmash*" (Interview 009) or an "*almost bizarre*" term (Interview 008) that is "*very trendy… has been bloated, it's almost like a marketing term… it's such a buzzword*" (Interview 006). Taken together, these comments suggest that data professionals consider the role of a data scientist to be unclear but at the same time easy to adopt as it did not require specific training.

By contrast, data professionals perceive themselves as researchers, scholars, scientists, whose role is to create scientifically-backed educational products, as well as develop knowledge. They emphasize this as a difference between their role and this of data scientists: "*my strength is in looking and doing research, design based research and interpreting the findings rather than tinkering with the data or figuring out what is the best analysis to apply to those data"* (Interview 016), adding that "*that's [looking at the data] not necessarily the kind of thing that we do, we're more heavily theory driven before we do our data analysis* (Interview 019). Data professionals are study designers, academics, researchers, conference presenters. In their view, this was outside of the data scientist's role. One interviewee when asked to describe their role stated: "*I always struggle with that, but I think it will be like we measure things that are intangible. And we do that in a way that it's scientifically valid and can be defensible in court*" (Interview 002), which further delineates the differences between the role of a data scientist and what data professionals at TestU saw themselves to be at work.

The difference between who data scientists were perceived to be and who data professionals saw themselves as led to a role conflict. Data professionals had a clear and strong opinion of who they were as researchers and scholars, and that their role involved many years of specialized training and experience. This contrasted heavily with the ambiguity of the data scientist role, as well as the lack of professional standards around it. Few data professionals at TestU expressed the possibility that the label could apply to them in very cautious terms: "*I wonder about that a lot, a lot. I wonder if I really am a data scientist*" (Interview 012). Another interviewee confessed that "*Sometimes I think I'm a data scientist. Because I look at the data, I can try to investigate what the data means, right?*" (Interview 027), interestingly linking their perception of the role to the tasks that were done.

Tool Conflict: What Data Scientists Work with Is Different from What I Work With

Finally, we found a conflict that relates to how data professionals at TestU perceived differences in which tools and how they use tools in contrast to data scientists. In general, data scientists were seen as using data management and engineering tools and thus, a wider range of tools such as SAS, Python, R, SQL, Tableau, and other programming languages: "*To me, a data scientist (...) is really comfortable with SQL who's comfortable with like Postgres, database, databases, all sorts of different types of databases, that you would have to be managing relational databases and other types*" (Interview 001). They were also using tools related to cloud-based computing, coding, and machine learning: "*there are certain jobs … where … this person is using, like Amazon Web Services in coding languages that I don't know, to set up … an automatically updating … Machine Learning model*" (Interview 014). Data scientists were perceived as using these tools to a full extent and a range of possibilities, derived creatively from close knowledge and experience in using them.

In the perception of data professionals, this contrasted with the tools they used. Although interviewees between themselves also used all the tools named as those belonging to data scientists, individually they perceived they did not use as wide a range of tools as an individual data scientist would. Moreover, data professionals emphasized that they use the tools in a different way than data scientists. Data scientists were perceived as having a higher fluency in using the tools more creatively and for a wider range of tasks, while data professionals claimed they only used them as a means to an end in more routine tasks: "*it's more just tables of summary, descriptive stats*" (Interview 007), or "*I can't use Python very well, same thing with basic coding, but it's helpful to at least be able to follow what the data scientists are saying*" (Interview 004). Data professionals also used to stick to the tools they were introduced to in their professional training and showed little appetite for exploring and experimenting with learning new tools.

In sum, data professionals considered their work tools to be different from those of data scientists. Nonspecific tools consistent with broad-based data exploration such as Machine Learning and Python are attributed to the data scientists whereas the research scientists use purpose-built tools like Qualtrics and proprietary software to complement their subject matter expertise. Those in the organization who were open to the data scientist label, however, also exhibited more openness towards learning and using new tools: "*I can use like a lot more Machine Learning models or Machine Learning techniques that your [data professional] may not use to*" (Interview 039).

Conclusion

Building on our preliminary findings, we identify three types of identity conflict that begin to explain why professionals may reject the opportunity to adopt a more attractive occupational identity with higher prestige. Task, role, and tool conflict sometimes led data professionals to speak about the data scientist label in dismissive terms, for example that data scientists "*work with data and do some science*" (Interview 007) to further distance themselves from the label they considered undesirable. Interestingly, the identity conflict we observed was largely based on individual perceptions that often were not rooted in facts, and sometimes contradictory between interviewees. However, many perceptions of how data professionals consider data scientists are related to the image of data scientists portrayed in the media and society (for example "sexiest job of the 21st century"). Thus, it seems that data professionals want to emphasize that their work is more sophisticated than the superficial image of data scientists portrayed in societal discussions by clearly distinguishing themselves. In our next steps, we aim to untangle this mismatch between perceptions further by involving the role of public perceptions and societal images in developing and shifting occupational identity.

Moreover, our first insights offer a potential contribution to a better understanding of the interplay of identity and technology in the workplace, identity conflict, and data science as an emerging occupation. In line with the concept of IT identity which describes how professionals establish their identity through active engagement with a technology (Carter et al. 2020), our findings indicate that the way how technology tools are used and perceived by data professionals play a crucial role in why they reject the opportunity to enhance their occupational identity. We will continue analyzing our data and thereby, dive deeper into the role of technology and disentangle the interplay between identity conflict and technology (drawing from Stein et al. 2013; Vaast and Pinsonneault 2021). We also note that identity conflict literature suggests that negative perceptions of occupational identities threaten the ability of occupational members to construct social identities that enhance their own esteem. In our case, we observe the opposite. Although data science is perceived as a lucrative, exclusive, and elite occupation, professionals still struggle to construct an esteem-enhancing occupational identity around this label.

Overall, our work is relevant to the Digital Technologies and the Future of Work track as the emergence of the data science occupation poses a threat to other, more traditional data-related occupations being replaced, with a potential need for data professionals to, at the very least, adopt a new occupational identity, or even adapt their skills. While we contribute to a better understanding of data science as a new emerging career, we show how this is at the expense of making other occupations obsolete.

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