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ACTING WITH INHERENTLY UNCERTAIN DATA: PRACTICES OF DATA-CENTRIC KNOWING

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Abstract: Data-driven data science challenges our conceptualization of "data." Significantly beyond capturing a given phenomenon, data, increasingly, *are* the phenomenon. Data may be iteratively manipulated algorithmically, undermining the "faithfulness" of data to any originating phenomenon. Crucially, data that are not "faithful" are inherently uncertain as data risk becoming meaningless symbols. We empirically study how a community of commercially based geoscientists grapple with the phenomenon of offshore oil and gas reservoirs residing kilometers below the seabed. The data available about these reservoirs are algorithmically manipulated sensor-based Internet of Things data. Our main contribution is the articulation of three patterns of work practices detailing *how* inherently uncertain data are woven into consequential work practices: (i) *accumulating*, the cumulative process of supporting and triangulating one set of data with supplementary ones; accumulating captures the conservative approach of backing up existing interpretations of the data, (ii) *reframing*, the process where existing interpretations are contested by new data or models; reframing captures how there are limits to how far data may be pulled by their hair and (iii) *prospecting*, the cultivation of competing, incompatible data interpretations; with the former two patterns essentially attempting to regulate uncertainty, prospecting is about embracing it. Our concept of *data-centric knowing* is constituted by these three interleaved, ongoing practices.

Keywords: data; work practices; uncertainty; empirical; case study; knowing; big data; data-driven; data-science; Internet of Things; commercial;

1 Introduction

Easily mistaken for a purely philosophical concern, data's representational capacity, i.e., data's capacity to represent a phenomenon (Zuboff 1988; Burton-Jones 2014; Kallinikos 2007; Borgmann 1999), increasingly is recognized as being at the core of discourses over big data, data science, and data-driven machine learning (Alaimo et al., 2020; Alaimo & Kallinikos 2020; Markus 2017, Zuboff 2019). Initially referring to a physical object, process, or quality, data iteratively are sliced, recombined, and algorithmically manipulated, taking them increasingly away from their originating physical referents (Kallinikos et al., 2013; Orlikowski & Scott 2016; Lusch & Nambisan 2015). Increasingly, data *are* the phenomena, i.e., "signs" (Knorr Cetina, 1999) or "symbols" (Bailey et al., 2012) of events that otherwise are inaccessible.

However, data's representational capacity is exactly that – a capacity. It may, but most certainly need not, be *actualized* in the sense that data are woven into everyday, data-driven, consequential work practices (Günther et al., 2017). With data's representational capacity but modestly exercised, the conditions for actualization are reasonably well-understood: data need to be a "faithful" (Burton-Jones & Grange, 2013) representation with a "tight coupling" with the phenomenon (Bailey et al., 2012, p. 1500), as "seeing is believing" (Leonardi, 2012, p. 14). What remains unaccounted for, is how data that no longer faithfully represent a phenomenon are actualized (Kallinikos, 1999; cf. also Kitchin, 2014). This paucity in the literature, of increasing empirical relevance and significance with expanding datafication (Newell & Marabelli, 2015), is the focus of our paper. Rather than delegating this to a new role of "data translators" (Henke et al., 2018), we analyze the work practices involved.

Crucially, data no longer faithfully representing phenomena are inherently *uncertain* as their meaning is not (yet) fixed (Alaimo et al., 2020). Actualizing data thus involves practices of sense-making (Weick, 1985) in situations mired in uncertainty. We pose the research question: *how, and under what organizational conditions, are inherently uncertain data actualized in consequential work practices?*

We empirically study how a commercially based community of geoscientists grapple with the phenomenon of offshore oil and gas reservoirs residing kilometers below the seabed. For all practical purposes, the data and algorithmic representations of the reservoirs *are* the reservoirs in everyday work practices. The available data about the oil reservoirs are largely algorithmically manipulated sensor-based Internet of Things (IoT) data with inherent epistemic uncertainty. We analyze the work practices of the geoscientists grappling with incomplete, inconsistent and inherently uncertain data. Their work practices emerge from conflicting tensions where professionally acquired quasi-scientific approaches run up against the commercial push for operational decision-making.

We contribute with the articulation of three patterns of work practices detailing how inherently uncertain data are actualized. First, *accumulating*, which is the cumulative process of supporting and triangulating one set of data with supplementary ones. Accumulating captures the conservative approach of backing up existing interpretations of the data. Second, *reframing*, which is the process where existing interpretations are contested by new data or models. Reframing captures how there are limits to how far data may be pulled by their hair. Third, *prospecting*[1], which is the process of cultivating competing, incompatible data interpretations. With the former two patterns essentially attempting to regulate uncertainty, prospecting is about embracing it. The concept of *data-driven knowing*, then, is a short-hand for the interleaving of these three ongoing patterns of work practices.

The remainder of our paper is organized as follows. Section 2 develops our theoretical framework on understanding the concept of *data*. We review and discuss relevant perspectives on pressing data's representational capacity beyond that of *faithful* representation. Section 3 provides context to our case together with an account of research methods. Our empirical findings are presented in Section 4, organized around the three patterns of practices developed in the data analysis from the preceding section. The discussion in Section 5 pursues two threads. First and foremost, drawing on existing literature, we discuss the theoretical implications of the three interleaved patterns work practices constituting data-centric knowing by critically discussing their enabling conditions. Second, in further pursuing the conditions for data-centric knowing, we analyze the institutional fabric necessary to actualize data. By way of concluding, Section 6 reflects on the relevance of and boundary conditions for data-centric knowing beyond our case, in addition to offering comments on future research.

2 Conceptualizing Data

2.1 Data are "Cooked"

Traditionally, a representational view has data corresponding directly with some given, pre-existing physical object, process, or quality. Such a view, Jones (2019) reminds us, is still evident, albeit in an implicit and diluted

[1] Our use of the term prospecting comes from its analogy with geological prospecting, which is an open-ended, conflictual search for competing, very often mutually inconsistent geological interpretations. In contrast, Slota et al. (2020) use the term to denote the rendering of data amendable to data science methods.

form. For instance, a textbook defines *data* as "raw facts that describe a particular phenomenon" (Haag & Cummings, 2009, p. 508), while the Royal Society (2012, p. 12) defines *data* as "numbers, characters, or images that designate an attribute of a phenomenon" (both definitions are cited in Jones (2019)). However, such a naïve, referential view of data has several problems, as we will discuss.

Contrary to big data hype, in which "the numbers [data] speak for themselves" (Andersen, 2008), considerable, ongoing work is needed to craft data *into* data. The notions of "gathering" or "collecting" data are misleading in that they promote the misconception that data speak for themselves. This downplays to the level of non-existence the way that data provenance – i.e., the methods, procedures, and technologies employed to generate the data – shapes data use and interpretation (Porter, 1996). As Gitelman (2013, p. 3) succinctly puts it, data "are always already 'cooked' and never entirely 'raw'.'"

Thus, both collecting and curating data involve work. Data involve developing and maintaining procedures for cleaning, filtering, and "massaging" them (Leonelli, 2014). Edwards (1999) examined the comprehensive data-gathering process informing climate-change research and reports that measurement devices, such as thermometers, must be calibrated constantly to ensure their readings' validity. In this context, maintaining calibration involves adhering to protocols that compare a given thermometer with a master device and systematically adjusting historic measurement values after discovering that a thermometer is uncalibrated.

A significant source of "big" data, not the least of which is in industrial settings, is sensor based IoT data (Singh et al., 2014). Contrary to appearances, sensors' measurements do not "capture" physical reality straightforwardly. IoT measurements are highly constructed renderings of selected aspects of a physical situation, fitted for designated purposes. Anything but "natural," what you know from sensors is highly mediated – materially as well as epistemologically (Monteiro and Parmiggiani, 2019; Helmrich, 2019).

2.2 The Representational Capacity of Data

Data are inherently editable, re-combinable, and subject to re-purposing (Kallinikos et al., 2013; Alaimo et al., 2020). This underpins discussions about datafication (Newell & Marabelli, 2015; Markus, 2017; Sugimoto et al., 2016). Numerous observations and concepts tap into the same idea, including, but not limited to, Kallinikos' (2007) "increasingly self-referential rendition of reality," Orlikowski and Scott's (2016) "algorithmic phenomenon," "digital objects" (Baskerville et al., 2020), and Nambisan and Lusch's (2015; see also Monteiro & Parmiggiani, 2019) "liquefaction," which denotes data's capacity to decouple from their originating physical objects, processes, or qualities.

Taking a step back, the idea here is to conceptualize data's representational capacity beyond the realm of naïve realism outlined above. Zuboff (1988) early and influentially analyzed data's representational capacity (cf. also Weick, 1985). Her work generated a wealth of interest, but focusing mainly on her analysis of the conditions for engaged, learning-oriented relationship with technology ("informate", as opposed to "automate" in her vocabulary). This is a pity, Burton-Jones (2014, p. 72) notes, as "[Zuboff 1988] may have an even stronger story to tell now than it did when first published" given the proliferation of empirical cases of datafication, i.e., cases exercising data's representational capacity beyond the faithful (Alaimo et al., 2020; Alaimo & Kallinikos, 2020; Burton-Jones, 2014; Burton-Jones & Grange, 2013; Monteiro & Parmiggiani, 2019).

Knorr Cetina (2009) offers a helpful way to approach the issue of data's representational capacity. Her seminal book is based on an ethnography of high-energy physicists' work at the CERN particle collider in Geneva, Switzerland, an example of knowledge work completely immersed in the data of phenomena, but indirectly observable (see also Venters et al., 2014). Knorr Cetina (1999) differentiates (analytically, not necessarily empirically) between three manifestations of data. Physical phenomena, first and traditionally, may be *staged* to produce data that "correspond" with phenomena directly. Second, the physical conditions are manipulated to yield *processed, partial versions* of data that are "equivalent" or similar. Third, and most radically, physical phenomena are mere "signatures" and "footprints" of events, yielding data as *signs*. Bailey et al. (2012) arrive at essentially the same taxonomy of three manifestations of data. Drawing on Peirce's semiotics, they identify data that are *indices* (a direct correspondence, similar to Knorr Cetina's staged data), *icons* (similar or equivalent, as with Knorr Cetina's processed, partial data), and *symbols* (no link to referents, as Knorr Cetina's data as signs).

Data as signs (Knorr Cetina, 1999) or symbols (Bailey et al., 2012) demonstrate the potential – but crucially not necessarily the actualization – of data's representational capacity. Several scholars have grappled with the conditions under which data as signs or symbols actually are woven into work practices, i.e., the conditions under which data become more than mere symbols i.e., what Kallinikos (1999) calls "referential attribution". In her empirical study of digital transformation of pulp factories from experience-based, embodied, tactile handcraft – smelling, tasting, and feeling the temperature of the pulp – into a remotely operated, digitally enabled control room, Zuboff (1988) notes the unease stemming from data "replacing a concrete reality" (p. 63), how data "replace the sense of hands-on" (p. 65) and seek to "invent ways to conquer the felt distance of the referential function [i.e., the decoupling of data from the physical referent]." A lack of sensory feedback undermines the expertise and knowledge from physical, hands-on interaction with the technology. Similarly, Turkle's (2009) work emphasizes the dangers of simulation-based renditions of reality, with their strong, seductive capabilities (cf. Baudrillard, 1994). As users gradually are immersed into simulations, "[f]amiliarity with the behavior of [simulation data] can grow into something akin to trusting them, a new kind of witnessing" (Turkle 2009, p. 63). Also, Burton-Jones and Grange (2013), with their focus on data representations being *faithful*, voice concerns over representational capacity's limits, as data need to "faithfully represent some domain because they provide a more informed basis for action than unfaithful representations do" (2013, p. 636).

2.3 Toward Data-centric Knowing Under Uncertainty

To take stock, data's representational capacity is reasonably well understood as long as this capacity is but modestly exercised, i.e., as long as data is a faithful representation of the "tight coupling" (Bailey et al., 2012) with their physical referent. The problem, however, is that datafication of our lifeworld – the slicing, dicing and algorithmic manipulation of data that undermine the faithfulness of the data – leaves an expanding empirical phenomenon inadequately accounted for. The aim and ambition of our concept of data-centric knowing is to address this paucity in the literature, a theoretical paucity with growing empirical relevance. Our aim is in line with the call made by Lyytinen and Grover (2017, p. 229) "to critically evaluate how we approach and think about data, its provenance, privacy, and related organizational practices.".

Several theoretical problems, resonating with our subsequent empirical analysis, motivate our development of data-centric knowing. Navigating in a situation with, as it were, no stable or fixed ground, data-centric knowing is centered around *fallible* knowing practices hence tenets of pragmatic action (Dewey, 1930). Without faithful representation, inherent uncertainty exists as to what data signify, if anything (Alaimo et al., 2020). A principal task, then, for data-centric knowing is to detail *how* users navigate with inherent epistemic uncertainty.

Ours is a case of data-driven work practices. A defining, somewhat ironic, aspect is that users drown in data at the same time as knowing is always under-determined by the data. So how do users cope? Pragmatism, again, offers a starting point for data-driven knowing.

Abductive reasoning, i.e., neither inductive nor deductive, is particularly relevant in navigating with epistemic uncertainty (Dunne & Dougherty, 2016). Abduction involves short-cutting searches for "innumerable possible hypotheses all accounting for the data at hand" (Brown, 1983 p. 401). The parsimony or satisficing principle (March 1994) regulating abduction sets boundaries (e.g., resources, time) for an otherwise open-ended process. Good-enough solutions ensure arriving at a decision within set limits. However, the satisficing principle assumes that you know what you are looking for. In many situations, you are not looking for "known unknowns," but rather "unknown unknowns[2]" (Loch et al., 2011).

Thus, data-centric knowing addresses what remains under-specified in extant literature viz. detailing the interleaved patterns of work practices that go into grappling with different levels of and forms of uncertainty in the data underpinning operational action- and decision-making. Our case provides a particularly vivid empirical illustration to develop an understanding of data-centric knowing.

3 Method

3.1 Case Context

Our case studies *exploration*, i.e., the practice of searching for commercially viable oil and gas reservoirs through a European-based, internationally oriented, upstream oil operator dubbed OilComp. Distinctly different from its historic, roughneck origins, oil exploration in our case is a decisively knowledge-intensive, data-driven endeavor that represents the most significant investment in OilComp, typically 10-20% of total investments. Oil exploration is fiercely competitive. Exploration is *the* most strategically important activity for an oil operator, strongly influencing long-term viability and global competitiveness.

Empirically, we study the community of "explorationists," a term that they use to refer to themselves collectively (in Norwegian: *tolkere*). Explorationists comprise about 2,000 of OilComp's 20,000 employees worldwide. They are organized into projects of 7-10 people each, and we followed three projects. Explorationists comprise several professional disciplines within the geosciences, including geology, geo-physics, reservoir engineering, petroleum engineering, and petrochemical engineering. We focus empirically on explorationists working in areas already identified by OilComp as commercially interesting[3]. Co-located with the explorationists are several "data managers" that support explorationists' work. The data managers help locate, prepare, and present the geo-data that explorationists require (Mikalsen & Monteiro, 2018). There is approximately one data manager for every 10 explorationists.

The hydrocarbon reservoirs that OilComp explores in our case study lie 3-5 kilometers below the seabed and are knowable largely through sensor-based IoT data, notably *seismic* (acoustic reflection measurements and

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[2] Then-Secretary of Defense Donald Rumsfeld (in)famously used the phrase during his briefing on the Iraq situation.

[3] This corresponds to so-called license exploration. Prior to this, there is screening i.e. deliberations about whether or not OilComp should enter into an area.

processing), *well logs* (electromagnetic and radioactive measurements of rock properties), and *production data* (real-time measurements of flow volume, temperature, pressure, and chemical composition). The work practices of explorationists rely on a portfolio of specialized digital tools for algorithmically manipulating the sensor-based IoT data. Prominent tools include seismic processing (for velocity determination, 2D and 3D seismic imaging in either time or depth), geological modeling (to correlate well logs, build cross-sections and create geological maps), petrophysical tools (to load and manage well logs) and simulation tools (to estimate present and future hydrocarbon reservoirs, but also to interpret, model and validate traps).

For all practical purposes, the physical phenomenon the explorationists struggle to know in their everyday work practices – oil and gas reservoirs kilometers below the seabed hence not directly accessible – is a data-driven algorithmic phenomenon (Bond 2015). *What* the explorationists know is *how* they know it (Monteiro & Parmiggiani, 2019), which is through sensor-based IoT data thoroughly manipulated algorithmically.

The explorationists know only too well that there are inherent epistemic uncertainties from lack of completeness, accuracy, and consistency in sensor-based IoT data, but they have no option but to rely on them. Consider accuracy. With a sigh, one explorationist explained that a down-hole pressure sensor's lifespan "is about two years," before which "calibration will be off." Consistency across data types is challenging for several reasons, including the fact that data granularity varies. Explorationists draw heavily on seismic data. The attraction of seismic data for the explorationists is that they cover wide geographical areas (several square kilometers) thus providing a much-needed overview of the geophysical conditions. The problem, however, is that seismic data is also crude in the sense that the resolution cannot distinguish between entities smaller than a cube with sides 100 meters (i.e., entities smaller than the size of a 15-story building). In contrast, well log data are fine-grained with resolution down to a meter, but necessarily only covering the well's pinpointed location (Figure 1 illustrates these data types).

--- Figure 1 about here ---

Data quality is a chronic concern, not only due to error-prone IoT measurements, but also because data are shaped by the purpose of their collection. For instance, a couple of decades ago, well-logging focused on deep levels, as these corresponded to the geological era of identified interest, Jura[4]. However, more recently, explorationists have become interested in earlier geological eras too, i.e., well logs' shallower stratigraphic

[4] In this area, rivers have transported and sedimented matters in layers. The layers accordingly indicate age.

layers, “but when we go back in time, the shallow levels were not logged properly [i.e., data quality is poor here], [in contrast to] the deep levels.”

Oil exploration entails data-driven predictions about, in their vocabulary, a “prospect[5],” i.e., a candidate for an oil reservoir in a particular geographical location and geological formation. Verifying predictions by actually drilling an oil well can be many years away, if at all, with the cost of drilling at about USD$100 million. Acquiring new seismic data to learn more about prospects is also costly, albeit less so than drilling. Explorationists’ work, then, revolves around identifying, evaluating, and prioritizing these predictions by working with the data at hand in the hope that one day their prospects will indeed by validated by actual drilling.

Oil exploration is a search for particular geological conditions, what they call a *play*. A play fulfills three conditions: a source rock (from organic material, geothermally transformed into hydrocarbons); a migration path (avoiding the fate of most hydrocarbons, to evaporate or dissolve); and a trap (a rock sealing hydrocarbon into a reservoir)[6]. The search takes one of two distinctly different forms. Akin to a search for the proverbial needle in a haystack, you start from “proven plays” in the area, i.e., particular configurations of rocks and formations that, through drilling, have already demonstrated oil discoveries. The other type of search entails working with an “unproven play,” in which you need to develop the concept first, essentially an understanding that contains the three necessary conditions above. It is, as one explorationist explained “about [traveling] into the unknown, toward a new concept.”

Oil exploration in OilComp is regulated by a formally defined, staged funnel model (see Figure 2)

- - - Figure 2 about here - - -

The first stage entails deciding what region (an area the size of about 100 square kilometers) to consider, then zooming in on (several) potential prospects before deciding whether to drill one or more of the prospects. Finally, if a significant discovery is made, the discovery is appraised, which can entail the drilling of delineation wells to determine the size of the oil field more accurately and how best to develop it and produce oil cost-effectively. A plan for development then must be submitted to national petroleum authorities for approval before operations can commence.

[5] The naming of our third pattern of data-centric knowing, prospecting, is inspired by the work with geological prospects. However, we use prospecting (the verb) for the third pattern and prospect (the noun) for concrete, empirical prediction the explorationists are working with.

[6] This is true for traditional or “conventional” oil exploration. Hydrocarbons in “unconventionals”, such as shale gas produced by fracking, is different. There is no trap in unconventionals. The migrating path is a rock with high porosity where very low permeability traps the hydrocarbons. The explorationists we study are searching for conventional oil only.

At each stage ("decision gate") in OilComp's funnel process, there are different, formal requirements for actualizing data from exploration and the character of the decision-making. When proceeding further into the funnel – and, thus, closer to a potential heavy investment – the decision-making process, not unexpectedly, becomes more elaborate, as we illustrate.

3.2 Access to Case

Access to our case was non-trivial and negotiated. The oil and gas sector also in Northern Europe increasingly is globalized, both in its own activities, as well as through international collaborations and ventures. Traditionally open to research collaborations, the companies, especially larger ones such as OilComp, gradually have regulated and tightened collaborations by imposing more formal managerial approval procedures. As a consequence, access to the case on which we report in this paper had to be negotiated. Access was granted by "packaging" it as one element within a larger research center involving several researchers (including the second author) and industrial partners (including OilComp). Piggy-backing onto the technological prototyping that the research center focused on, our access came as a response to the research center's need to understand the demand side of their prototypes supporting oil exploration. Our access to the case accordingly relies on two pillars. The second author's long-standing relationship with the research center's partners was crucial. In addition, we had to make ourselves useful within the research center by facilitating the communication of concerns, demands, and experiences from users (explorationists and data managers included) back to researchers engaged in prototyping. Thus, we prepared presentations of preliminary results and participated in meetings and workshops.

3.3 Data Collection

Our data collection spans more than four years (February 2013 – October 2017) and proceeded in rounds. Starting broadly, we studied the work processes and key concerns of actors implicated in oil exploration and their mode of collaboration. We derived a sense of the cross-pressures in which oil exploration gets caught up, such as defending tall investments, working with deadlines, and grappling with incomplete data of variable quality. Following a suggestion from van Maanen (1988), we took extensive field notes, ensuring that we separated informants´ data from our own comments, reflections, and questions. We gradually focused on the explorationists' work practices, including their use of digital tools and collaboration patterns. During the final round, we focused specifically on *how* the explorationists use their data, growing steadily more aware of the convoluted relationship between data and decision-making in oil exploration.

We rely on three types of data (see Table 1 for an overview). The first author collected most of the data, but the second author also participated, especially during the later rounds. Notably, the second author also draws on background data from more than a decade of sustained research on digitalization in the oil and gas sector.

- - Table 1 about here - -

- - Figure 3 about here - -

First, we rely on participant observations. As the details of explorationists' strategies are core assets, we initially were given office space with the data managers, embedded within the exploration unit. The field researcher spent time getting to know the data managers, asked questions when things happened at the office, had breaks with them, interviewed them, had lunch and dinners with them. Data managers were tasked with finding, preparing, and presenting the required data to explorationists. This provided an effective entry into explorationists' practices. We observed data managers' everyday work, including their close interactions with explorationists. With most offices' walls decorated with maps and geological illustrations of 2D seismic and well logs, a constant buzz from informal conversations can be heard. Explorationists regularly would stroll over to the data managers for a cup of coffee or pop into someone's office to explain what data urgently were needed for a certain purpose.

From our initial home among the data managers, we also gradually got to know the explorationists. Participant observations of data managers accordingly were a resource for identifying and recruiting new informants. Spending time with our informants during their everyday work allowed us to examine nuances, unclarities, and questions that might linger after interviews. In informal conversations over coffee or lunch, we could pick up questions or puzzles that we were unable to pursue within the more fixed boundaries of semi-structured interviews. For instance, we would inquire into why and how searching, in the age of googling, was complicated by different naming conventions across oil fields and professional sub-communities of explorationists. We also conducted participant observations through a variety of meetings, workshops, and seminars. Some formal, but most less so, these events gave us a chance to observe how explorationists backed up their interpretations, how they were challenged and how agreement on how to proceed emerged.

Second, we conducted semi-structured interviews that lasted 45-90 minutes each, with most lasting a little over an hour. Interviews were transcribed. As indicated above, we exploited the interleaving of participant observations and interviews. We conducted the interviews in the informants' workspaces, which allowed informants to draw on examples of problems and concerns as evident in how tools presented geo-data. Typically, they would point to their screens while explaining it all to us.

Third, we relied on electronic and paper-based documents, collecting both internal and external documents. Internal documents included memos, slide presentations, and reports. External documents covered public information on drill results (drill operations, results, and tests conducted), reclassified interpretations (final well reports, core photos, and well logs), and public reports on OilComp discoveries and recoverable reserves. The documents, especially the internal ones, e.g., from presentations, were particularly useful in identifying concerns and discussions. Examples of internal documents include prospects, workflow descriptions, tool screenshots and guides, data types, databases, and procedures and issues concerning database querying and results presentation. We used 150 pages of internal documents in our analysis.

3.4 Data Analysis

Our data analysis process was interpretative (Walsham, 1995) as we sought to capture the perceptions on data actualization from the actors involved in exploration. Data analysis was iterative. Data collection overlapped with data analysis thus granting us the flexibility to continuously consider our partial interpretations towards a gradually growing amount of data, as well as to refine our interpretations together with the actors in the case (Klein & Myers, 1999). Our data analysis may be reconstructed into four main stages.

The first round of coding was open-ended (Wiesche et al., 2017). We sought overview of relevant actors, organizational routines and prominent concerns within the unit of exploration. The first author, who collected most of the data, immersed himself in the data. During this round, we attached initial labels, consisting of sentences and paragraphs capturing salient aspects of the work of explorationists. An example of a label is “well and seismic data turn indications into leads” (with empirical excerpts including; “The process is such that you get many ideas when you are looking at the seismic. 100 ideas, perhaps 200. Beneath them we have different branches, and out of them we have been able to concretize approximately 100 to something that can be a precursor to a prospect, what we call a lead, that means, we set a polygon on a map, you can define an area, you can calculate a volume, and you can calculate probabilities”, and “We use well and seismic data. It is very rarely gravitational data and magnetometric data, here the level of detail is poorer”). We manually coded data using word processing software. We used bold text for descriptive codes and entered the data under the codes. We collected descriptive codes and illustrative empirical data in tables. We developed 432 descriptive codes.

The second round of analysis involved both authors. In this round, we focused on the work practices of explorationists as a particular category of data (Wiesche et al., 2017), looking closer at their use of digital tools in general and the sense in which they worked with data in particular. Using the tables with the open codes from the previous rounds as a starting point, we selectively coded the data. We created a 10-page data analysis document with selective codes and empirical examples. This document served as a basis for discussion between the authors, but also with our research group to refine our understanding by challenging our preliminary interpretations. Through 16 iterations, where codes and data were compared and challenged, we gradually unpacked the professional community of 'explorationists': they consist of a heterogenous set of more than ten professional disciplines with different roles and tasks. The heterogeneity of professional disciplines under the umbrella term 'explorationist' was mirrored in the extensive list of specialized digital tools used by the explorationists. There were corporate databases for seismic data (including navigation data, faults, horizons and grids), well data (such as drilling data, well logs, geochemical analysis and core sample images) and production data (volume, pressure, temperature). The three principal data types we found were used by explorationists are illustrated in Figure 1. In addition, there are extensive, public repositories for all oil activities (exploration, drilling, production, maintenance) on the Norwegian continental shelf (cf. Table 1), a feature of the political and institutional history of North Europe distinctly different from that in North America. We developed an understanding for the collaborative practices within the units explorationists work in, but also why and when they interact with outside specialists or management. We analyzed how explorationists refined and quality controlled their predictions i.e., prospects.

The third round focused on *how* explorationists implicated data in their work practices, an under-researched theme in IS research on data science (Günther et al., 2017; Sivarajah et al., 2017). Through a form of memoing (Wiesche et al., 2017), we wrote up concepts, categories and the relationship between them, We generated, over the life-cycle of prospects for oil reservoirs, visual illustrations and tables depicting how the chronological development of a prospect occurs, including the different units involved, their main goals, the data used, the digital tools used, the actors involved, their assumptions, their evaluation procedures - i.e., an overview of the data that explorationists consume and produce at certain times in the exploration process, and how they use it.

In the fourth round, we engaged with theoretical imports to conceptualize patterns of work practices detailing how data are actualized in oil exploration. Anything but clean slates (Suddaby, 2006), our prior experience influenced our analysis. Our long-standing interests in work practices, knowledge work and organizational change were resources. This round may be characterized as largely inductive but with formative, deductive injections. We were early puzzled by the sparse and under-determined data underpinning exploration: logging from a few wells are literally like pin needles on a vast map together with coarse-grained seismic images. How were these data actualized (Knorr Cetina, 1999) in the work practices of explorationists, we asked ourselves. Clearly, it was not because they "faithfully" represented (geological) reality (Burton-Jones & Grange, 2012; Zuboff, 1989). A principal reason, we inductively found, was the gradual supporting through supplementing data (cf. Leonelli, 2014).

This conservative, cumulative process is captured by the first of our three identified patterns of work practices, *accumulating*. It empirically represents the dominant pattern of working. Although rarer, the continuous work of accumulating does occasionally get punctuated. Similar to pragmatic action, our second practice, *reframing,* captures how new geo-data regularly contest prevalent models and interpretations.

Our third practice, *prospecting*, emerged to capture the strikingly provisional nature of the geological interpretations underpinning the oil prospects. Agreement never arrived. At every juncture, competing interpretations were voiced and mobilized. OilComp, however, surely is no debating club. For operational reasons, in the absence of anything close to agreement, provisional agreement was forged for the purpose of deciding what to do (Kellog et al., 2006; Mol 2002; Oborn et al., 2011). Multiple interpretations are the norm and 'agreement' is but a provisional arrangement to solve the what-to-do-next imperative of pragmatic action.

Figure 4 summarizes the interpretative template resulting from our process of data analysis. It outlines our three patterns of work practices with concepts aggregated from the coding together with illustrative empirical excerpts. The subsequent Findings section is organized around the three patterns of work practices.

--- Figure 4 about here ---

4 Findings

4.1 Accumulating: Gathering Organizationally Credible Evidence

A team of explorationists works extended periods of time, typically years, with its "prospects," i.e., its candidates for yet-to-be-discovered oil reservoirs. A prospect is essentially a prediction about an oil reservoir's location – including risk, volume, and value estimates – should the prospect be considered for drilling at a later stage. Working in co-located teams organized in the same corridor of an office building that is part of OilComp's headquarters, explorationists' everyday work that we have studied revolves around refining interpretations of data that underpin prospects, interweaving individual work with informal discussions between fellow team members. Few bother to close their office doors, making it easy to drop by for consultations about a matter at hand. Small groups of explorationists regularly engage in informal discussions around the whiteboard in someone's office.

For long stretches of time, explorationists work in areas with *proven plays*. This can be areas where they have producing fields already. Producing fields creates assumptions, they know what they are looking for. In a given area, a *proven play* is a particular geological configuration in which necessary (but not sufficient) conditions for an oil reservoir – i.e., source rock, migration paths, and traps – are known to exist (cf. Section 3.1 Case Context). Working with a proven play, exploration focuses on *gaps*, i.e., areas where discoveries have not been made yet, but where they believe hydrocarbons may have migrated. As an exploration team leader explained, "In this area [pointing to his screen], we knew that in the southern [name of the basin], which in this case is 250 kilometers north-south, a lot of hydrocarbons have been generated. So, how far east can those hydrocarbons migrate?"

However, turning opportunities into more credible prospects involves actualizing data as evidence that a gap may contain commercially interesting amounts of hydrocarbons. Working with a proven play implies that large amounts of well and seismic data are available (namely all historic discoveries with that play). Dealing with the vast amount of available, sensor-based IoT data, the team of explorationists mobilize data and, thus, accumulate evidence that its prospect fits the proven play. One of our informants was struggling in front of his screen using a petrophysical analysis tool filled with well-log data. The old well data he had available did not support his prospect. Was he or the data wrong? The data dated from when the well was drilled back in the 1970s. As he explained to us, the knowledge that injecting mud into the borehole while drilling influences the temperature readings in the well "was learned only in the 1980s." Instead of simply contradicting his prospect, he assigned a mark signifying that the data were of low quality to indicate their lack of relevance. To be able to do this, one explorationist explains, experience from parts of exploration work is necessary, e.g., such as creating well logs: "You need to feel confidence in the data you work with. Or else they are but lines on a sheet. And then you will in turn start to feel insecurity when you drive a concept forward." Thus, the work practice implicated in accumulating evidence include ironing out contradictory data.

An important task in determining a prospect's credibility is to see whether assumptions made fit with several types of data, i.e., what effectively corresponds to a form of triangulation. So-called "well tie-ins" are a particularly important way in which this triangulation operates. Digital interpretation tools are used to determine the relationship between boundaries in the well logs and seismic reflections, consequently producing a relationship between the well logs (measured by depth) and the seismic reflections (measured in time). A well tie-in is an effort to find consistency between the broad, but crude, overview provided by seismic data with the much-more-detailed well data that come from measurements from the specific, pinpointed location of an oil well. Perfect consistency between seismic and well data occurs rarely, if ever. Consistency is crafted through well tie-ins, which are labor-intensive endeavors. We sat down with one of the explorationists tasked with a well tie-in and visually superimposed well data onto seismic data (see Figure 1). “We see it in that the definitions of anticlines, faults and irregularities do not match what you see on the seismic, it does not match,” he noted. He did not despair, however, as this could be understood as “[i]t matters how old the wells are, what types of data were collected, how far away the wells are. If they are close, that is obviously beneficial.” He keeps working. The inconsistency between seismic and well data is compounded by the fact that they are measured with different scales: Seismic data are measured as the time that it takes an echo of a particular sound wave to travel back to the sensors after being refracted by subsurface rocks, while well data are measured relative to the depth (distance in meters) into the well where they were recorded. As the speed of acoustic waves differs with different types of rocks, the time-to-depth conversion is non-linear and is about gaining a sense of subsurface “non-conformities.” Non-conformities result from geological processes such as fault lines stemming from earthquakes. As our informant explained, “[i]f you have very steep non-conformities, [the non-conformities] can jump several hundred meters back and forth from time to depth.”

4.2 Reframing: Contesting Prevalent Predictions

The account above is one of continuity in the sense that explorationists gradually accumulate evidence to support a prospect (prediction) in a given geological formation with a proven play. Thus, the actualizing of data amounts to crafting the fitting of data to your predictions or ironing out inconsistencies. The explorationists painstakingly fill in the gaps to back up their leads and prospects, with data marshalled into (more) organizationally credible evidence. Explorationists “stretch” their data, seeking to strengthen, rather than defeat, their predictions. This essentially conservative approach is at times punctuated by new data that can neither be accommodated nor dismissed, which leads us to our second pattern of work practices.

With a bit of drama, one explorationist exclaims, “[A]ny new well can change the basin evolution; any new well can change our predictions!” He knows that a change in the basin evolution is a radical change. The basin model that the explorationists rely on when searching in an area is effectively the prevailing understanding of that area’s geological history – the result of extensive efforts – and represents significant sunk investment in terms of earlier work. One key activity in substantiating a prospect is modelling (“basin modelling”) the history of the area's geological evolution. Once a basin model is conceptualized, it is tested against existing well data for consistency. However, in practice, consistency is never fully achieved. Working on a basin model, one explorationist explains how the team selects 200 reference wells out of a sample of 1,000 wells to support this consistency check. Well data is inconsistent, so they use heuristics such as the well's age (assuming new wells have better data quality than older ones), then consider how much work went into calibrating the data, noting that often, "we must go in and calibrate the well to the seismic [i.e., well tie-in]. And if it is a bad calibration, if things do not match, then the logs are poorly collected." Poor quality can be tied to a variety of reasons, e.g., "things that happened on the rig that are not documented well enough, that give a sloppy [well] log."

In a similar vein, another explorationist recounted how he had grappled with deeply inconsistent data on a field. The seismic data indicated that there should be sand throughout the field, but the well data told a different story: "I have a well here [pointing to her screen] that hits sand, and I have a well here [pointing] that does not hit sand. And then I have a seismic processing [pointing to another location on the screen] that shows me it should be sand all over. Then I need to decide: No, that [pointing] is not sand; this [pointing] is sand."

To account for different probabilities, data sometimes need to be extrapolated from geographic areas that are less known, into geographic areas that are more well-known geologically. For example, because they have drilled more there, or shot more seismic surveys. Data then is extrapolated, as one explorationist explains, talking about a well: "Ok that one, it can be very far off, ok, the data of the well is put in here. If I were right and we are at the same time and in the same kind of rock etc. I take this well and I put it here and say, I use this porosity, I use this permeability. As an analog".

In the world of explorationists, data are king. You can make the most elaborate models, but, if they do not hold up against the data, they never make it into everyday work practices. One explorationist warns: "I do not fall in love with my models, I mean, they are wrong by definition. Some people get really personal, and if new data goes against it, they try to go all around to try to avoid the data. If the data go in an opposite direction of your concept, it is better to just kill it." Explorationists have an unquenched thirst for new data. Well data, with its fine-grained measurements, are particularly appreciated. With seismic data coarse-grained, well data are the closest that explorationists come to "hard" evidence. Given the considerable financial costs of drilling new wells, OilComp invests in the drilling of a few dozen in a typical year in the area reported on in our case study. The explorationists' thirst for new well data makes them cut corners in formal procedures. Rather than use the formal, time-consuming process of quality-control data from an ongoing well-drilling operation lasting a month or two, they import the data directly from the drilling database. Two purposes motivate explorationists' keen interest in new well data. First, they provide immediate validation: Was there an oil discovery as they had predicted? However, new data also provide a much-appreciated occasion on which to consider unproven plays and alternative geological scenarios: “When we have a new well, it is not like we do not care anymore [whether there was oil or not],” one explorationist told us. “We use it for future exploration … I care about the data. Data from the well is key.”

The operational reality of operating within a highly competitive business environment is internalized among the explorationists. Working with prospects is always resource-bounded; thus, they are neither exhaustive nor perfect. Searching for new opportunities in the form of unproven plays is no exception. The resource-demanding nature of assessing the credibility of new concepts (unproven plays) forces settling for good enough, rather than elaborate, assessments: “We often do not have time to work out all [the concepts]; it takes too much time. We very often have limited time to drive concepts forward. It can be a matter of a few months. During that time, a lot of data must be pieced together, [and] a model needs to be built and to run basin simulations. In sum, it is a bit hard”.

4.3 Prospecting: Cultivating Alternatives

The essentially abductive processes described above depict the practical constraints on resources (economy) that regulate and format explorationists’ work, underscoring that prospects are satisficing, i.e., good enough to comply with the institutionalized decision-making process. The explorationists comply to produce the required input. Explorationists estimate the amounts of oil that a well might produce. In one case, volume was estimated from variables such as rock porosity (estimated with well logs and/or core samples), oil saturation in the rock (estimated using electrical resistivity well logs), and the recovery factor (estimated from reservoir permeability and oil viscosity). As a means of bracketing uncertainty, the team performed Monte Carlo simulations (i.e., a statistical approach to risk analysis in which numbers are selected from likely ranges of input data and through iterative calculations to determine a range of probable outcomes) using risk-assessment software. However, the version fed to management as part of the formal decision gates radically under-communicates the prevalence of multiple, competing possibilities known to the explorationists. For purposes of arriving at a managerial decision, the extent and role of multiple, divergent predictions are bracketed. However, among the explorationists there is a healthy robustness for entertaining multiple possibilities at the same time.

Earlier, we emphasized how highly explorationists regard well data, the closest they have to “hard” data. This should not be misconstrued as suggesting that explorationists trust well data at face value, as they regularly provide deeply ambiguous results that feed divergent possibilities, neither of which can be put to rest by the data themselves. Despite the presence of "big" data, the explorationists' prospects (predictions) are under-determined by the data. One explorationist illustrates the dilemma. One aspect or type of well data is the analysis of hydrocarbons' chemical compositions. Hydrocarbons from different oil reservoirs have varying compositions. Each has a unique chemical profile that allows you to discern hydrocarbons from two different oil reservoirs. Normally, you would assume that two wells in close proximity to each other would draw from the same oil reserve. The explorationist is puzzled: "In one of the fields in our area, each well is different when it comes to the [origins of the] hydrocarbons. They have different chemical compositions, which is really strange. They are so close by, you would think they are all the same, but they are not. [The geology] is very complex in some areas". What he refers to with 'complex' geology, is that there are multiple irreconcilable – given available data – interpretations depending on what assumptions about the geological history (erosion, faults). This ambiguity or multiplicity is not so much resolved as relegated to a nagging uncertainty that, in later situations, may turn into a salient, rather than a latent, possibility.

Digital tools for managing and interpreting well logs, processing and interpreting seismic data, doing seismic well tie-ins, plus basin modelling and simulation are crucial to explorationists' ability to juggle multiple possibilities. Increased computing capacity and new digital seismic processing and interpretation tools make the creation of 3D seismic cubes (3D seismic data sets made from other multiple seismic data), previously prohibitively time-consuming, more practical. One explorationist told us over lunch how he was working in a field with 200 variants of the same 3D seismic cube. From the outside, there was no way of knowing the purpose of all 200 variants. The one officially quality-controlled variant shed little light on the other 200. As he was interested in a particular subsurface level in the project, he looked into it. Perhaps there was an underlying implicitly assumed idea that he had missed, as he asked himself: "What was this idea? Why? It is not apparent in that 'pick' ′ [their term, implying interpretation of a subsurface of the seismic level in light of subsurfaces picked from well data]. You have some new data that do not fit. How is it connected?"

Coping with multiple possibilities is fundamentally collective. In formal, but more often and importantly, informal, peer-based discussions, explorationists collectively deliberate multiple possibilities: "When you talk to experts and advisors, they stress the nuances, and the details in it, and not at least the dimensions in it." Peer-based discussions are vital to avoid tunnel vision that working strenuously with a prospect easily might create. As one explorationist confessed, after a while, "you begin to think [your work] is great, [so] we have to drill it."

The prevalence of multiple, as well as radically different, interpretations is internalized by explorationists as part of their professional identity. However, institutional constraints make it organizationally and politically necessary at times to bracket this inherent multiplicity. Multiplicity is not resolved or eliminated as much as put temporarily on hold for purposes of passing one of OilComp's decision gates. The task of "risking" (their term) a prospect is illustrative. *Risking* is the quantification of qualitatively manipulating the prospect. One explorationist comments: "Concerning that part that is named risking, we put a probability that you have a trap, that it is sealed that you have a reservoir, that you have migration." Crucially, you assign quantified measures for variables such as rock porosity and permeability, oil saturation, viscosity, and volumes with your prospect. Despite estimates, risking contains "a lot of speculation and (subjective) opinions," but still necessarily legitimizes OilComp's gated decision processes. The problems with quantifying the probabilities of an oil discovery for different prospects under consideration are particularly pronounced for those with medium-range probabilities, i.e., 10-25%: "Here we are struggling. They diverge in all directions."

5 Discussion

Actualizing data's representational capacity into everyday work processes mired in data uncertainty and ambiguity tests "the limits of meaning" (Weick, 1985, p. 64). Sensor-based IoT data, thoroughly manipulated algorithmically, do not "faithfully" mirror the physical conditions of the geology, i.e., data might easily become mere signs or symbols with little or no relevance to explorationists' work practices. So, how do data acquire meaning in the sense of being woven into work practices (i.e., by being actualized)? We discuss the three patterns constituting data-centric knowing relative to existing literature. We emphasize social and material conditions of data-centric knowing. In addition, we recognize the broader institutional fabric in OilComp embedding the three patterns of practices of data-centric knowing.

The data that inform explorationists' work practices is what Knorr Cetina (1999) identifies as signs and Bailey et al. (2012) as symbols. This makes the problem of "referential attribution" immediate (Kallinikos, 1999). Data are " 'footprints' of [physical] events, rather than ... the events themselves" (Knorr Cetina 1999, p. 41). They are, in our case, "footprints" of physical geology that are mediated (hence distorted) by sensors and algorithmically manipulated to make their correspondence with the originating geology anything but "faithful" (cf. Monteiro & Parmiggiani, 2019). Consider the two types of sensor-based IoT data that are by far the most important to explorationists' work practices: seismic and well-log data. From a campaign of seismic shooting, less than 1% of the data is kept. The remainder is removed through a variety of non-linear mathematical filtering techniques. The seismic data actually used in explorationists' work practices are accordingly a fraction of available data, and mathematically filtered (i.e., algorithmically manipulated). Similarly, well-log data are generated from sensors that capture radioactive radiation, electromagnetic conductivity and electrical resistivity by lowering measuring equipment down into the drilled well. Particular patterns of values in the sensor-based IoT readings are "footprints" of geophysical properties as, for instance, gamma radiation is higher in shale than in sandstone, and electrical resistivity is higher in oil than in water (cf. Bowker, 1994).

With data never being stable – they are transient, dynamic, contingent, and subject to aggregation, slicing, and other manipulation (Kallinikos et al., 2013) – there is, by implication, an "inherent epistemic uncertainty" (Alaimo et al., 2020) that makes the question of *how* the weaving of data into work practices unfolds crucial. The chronic dilemma that explorationists grapple with is how do the data become more than mere symbols, and how are data drawn into consequential action and decision making? Our three patterns of work practices – accumulating, reframing, and prospecting – as demonstrated in the previous section, are key. We discuss how our three patterns resonate with existing literature.

Our accumulating pattern captures the constant hum of mundane work that goes into making the data amendable and accessible *as* data. Scholars have pointed out what Edwards (2011) calls "data friction," which includes washing, calibrating, and slicing up data (cf. Leonelli, 2014). There is ample evidence of data friction also in our case (e.g., the efforts involved in "well tie-ins" or quality-assuring data). However, due to the particular epistemic uncertainty of data, there is a considerable amount of work involved in *supporting and triangulating one* kind of data by connecting and, hence, grounding it relative to other supporting data. In isolation, data literally are a symbol. As Morgan (2010, p. 4) points out that "[W]e depend upon systems, conventions, authorities and all sorts of good companions to get [data] to travel well." By supporting and confirming them, data are grounded in additional data similar to the way triangulation works (cf. Weick (1985) underscoring the importance of triangulation in all human sense-making). How, then, does this form of accumulating confirming otherwise fragile data work? A principal manner is that data are assigned *different* levels of epistemic uncertainty. All data suffer from epistemic uncertainty, but some do more acutely than others (cf. Chang 2004; Østerlie & Monteiro 2020). In our case, well-log data are viewed as more reliable than seismic data because of better resolution. An important way to back up otherwise inconsistent (thereby potentially dismissed) data is by connecting them to other types of data as pointed out by Kallinikos (1999). In our case, this is illustrated when each of the relevant seismic sections are carefully connected to neighboring wells' fine-granular well-log data, a manual process known as well tie-in (see details in the previous Findings section).

The accumulating pattern's modus operandi is that of confirmation, i.e., the conditions and processes for supporting data that otherwise risk being mere symbols. The efforts that go into supporting and triangulating data are investments that risk creating path dependencies. Our second pattern, reframing, addresses the purposeful contesting of accumulated (i.e., supported and triangulated) data. The pattern of reframing accordingly addresses situations at the boundaries of the accumulating work pattern's reach. Efforts covered by the accumulating pattern to iron out wrinkles, inconsistencies, and outliers in the data are attainable only to a certain level. It is contested by the arrival of a new type or new data set triggering and abductively searching for new ways to make sense of all the data, new and old. In our case, this amounts to coming up with a new geological narrative in the form of a sequential process of shifting tectonic plates, up- and down-lifting, erosion and faults that make conditions for hydrocarbons plausible (cf. Wylie (2002), arguing for the importance of a narrative understanding in archaeology). The drilling of a new exploration well – with new, highly appreciated well data – as illustrated in the previous section ("[a]ny new well can change the basin evolution"), provides a possibility to challenge the entrenched, path-dependent understanding that results from the accumulating work pattern.

Challenging abductively the accumulating pattern's everyday hum, the search for new interpretations and geological models is, as already emphasized by Peirce (1931, p. 5.600), regulated and bounded. The work pattern is not an open-ended search, but rather is bounded by time and resource constraints aimed at a plausible, imperfect solution, as pointed out by Lyytinen and Grover (2017). In our case, new data come with a hefty price tag. Well data from drilling in particular, but also new seismic surveys, represent significant economic investments. The abductive nature of the work pattern of reframing is, accordingly, directional and goal-seeking. An example is provided by Dunne and Dougherty (2016, p. 132), who demonstrate how scientists in the biopharmaceutical industry apply abductive reasoning as a "deliberate and methodological" social process to "navigate in the labyrinth" of drug innovation. Adding to such studies that point out how clues enable practitioners working abductively to "conceive of a whole design almost at once" (ibid., p. 151), we find explorationists challenge clues by rubbing them up against historical data. Leads or clues, in the commercial environment of OilComp's explorationists, come with economic returns and risk, because, as one regional explorationist noted "we are in competition with thousands of others, and there are many other very skilled geologists and geophysicists around who have seen and are aware of all the well-known stuff". Reframing is thus generative in the sense that it involves being able to justify the unknown – potentially with bigger economic returns – and simultaneously limited by requiring necessary backing in historical data, i.e., the more well-known.

As a direct consequence of their disconnect with their originating, physical referents (Alaimo et al., 2020; Borgmann, 1999; Kallinikos, 1999; Kallinikos et al., 2013; Knorr Cetina 1999), data as signs or symbols come with inherent epistemic uncertainties. Both of the preceding patterns of work practices were aimed at eliminating or regulating this uncertainty: The accumulating pattern covers practices of conservatively supporting and triangulating otherwise vulnerable interpretations of data, while the reframing pattern covers the abductive refactoring of an earlier interpretation triggered by the arrival of new data that are incompatible with the old. However, our third pattern of work practices is different. It addresses how explorationists, rather than trying to eliminate epistemic uncertainty, cultivate and encourage a multiplicity of interpretations of data, thereby embracing rather than resolving epistemological uncertainty while simultaneously avoiding halting operational decisions. In contrast to both of the preceding patterns of work practicing, prospecting has not been addressed in the context of data and datafication.

To develop the prospecting work pattern, it is helpful to compare it to the notion of *search* (Stark, 2009). Explorationists search for something not yet recognized as a category. In our case, the well-defined search for proven plays (i.e., geological configurations demonstratively yielding hydrocarbons in the areas under scrutiny) could, and regularly does, spill over into the ill-defined search for unproven plays (i.e., potential, but not yet demonstrated, geological configurations for yielding hydrocarbons). The data radically under-determine this search (cf. (Loch et al., 2011). The efforts covered by the former two patterns of work practices bracket the uncertainty, but it may resurface.
Second, the prospecting work pattern fills productive, organizational roles, as it is "through divergent or misaligned understandings that problematic situations can give way to positive reconstructions" (Stark, 2009, p. 192). Keeping an eye open for new, unproven plays is crucial for OilComp. Ambiguity exists over whether the data at hand support proven plays or might, in fact, indicate something radically different. The multiplicity of interpretations is regulated in what fundamentally is a *collective:* They are played out, deliberated, and regulated in collective arenas that result in partial agreements (cf. Oborn et al., 2011). In our case, the formal and informal peer-based feedback sessions exercise this collective, in ways similar to how medical physicians are trained to always be open to secondary, alternative diagnosis in their treatment of patients (Timmermans & Berg, 2000). Third, the prospecting pattern underscores how consensus is never arrived at, but rather is worked around in temporal and local arrangements. Resonating with Mol's (2002) study of how medical specializations such as surgery and pathology – despite radical differences in routines, theories, vocabulary and instruments – forge temporary agreements about how to treat atherosclerosis in patients. Underscoring, as we have done, the

productive role of the prospecting pattern begs the question of how the practical problem *par excellence*, i.e., what to do next, is decided. As Kellogg et al. (2006, p. 38) point out: "Instead of (…) shared meanings and common knowledge, organizational actors juxtapose their diverse efforts into a provisional and emerging collage of loosely coupled contributions." In short, the pattern of prospecting does not undercut decision-making and action-taking; but temporal, partial arrangements, not full-fledged consensus, is required.

The three patterns discussed above that go into data-centric knowing flesh out the work practices of explorationists. As scholars have pointed out (Kallinikos, 2004), practice-oriented perspectives risk becoming near-sighted in the sense of downplaying broader historic and institutional context that go beyond the "here and now" (cf. also Monteiro et al. (2014)). We thus discuss tenets of the institutional fabric that underwrite data-centric knowing. This is in line with Porter (1995, p. 44; cf. also Poovey (1998)) who argues that meshing data with institutional routines is central to their actualization: "Given the ways that [data] measures can be undermined … we may doubt that they correspond to anything in the world. But a plausible measure backed by sufficient institutional support can nevertheless become real."

A key element of the institutional fabric embedding of data-centric knowing in OilComp is the compliance with a formally defined, sequential process known as a "funnel" (see Figure 2). The increased level of formal requirements for data as decisions move through OilComp's decision gates come with markedly ritual connotations. As one explorationist laughingly put it, "all our models are wrong," an insight that explorationists often believe has been lost on "the guys upstairs [management]." In the funnel, when zooming in on candidates for commercially viable oil reservoirs ("prospects"), a need exists to manage the *portfolio* of prospects. There are typically tens, if not hundreds, of prospects, so the operational concern at this decision gate is how to prioritize efforts when pursuing prospects. Briefly, prioritization relies heavily on quantification of prospects' estimated risks, costs, and revenues. However, as Porter (1995) convincingly documents, trust in numbers comes at your own peril as numbers hide as much as they reveal. Nevertheless, the conflation of rich geological interpretations with quantified estimates feeds business operational needs for making decisions (Scott, 1998), as illustrated by the use of Monte Carlo simulations and so-called "risking" (see preceding Findings section).

To summarize, the crafting of institutional facts at OilComp is not a steady march from uncertain, error-prone data to solid facts. What we see is a formalized and sequential process in which, for operational needs to move forward, the epistemological uncertainty of data is *provisionally bracketed* to reach a decision. However, uncertainty is never eliminated. Away from the formal decision gates at the managerial level, the professional deliberations persist and thrive among explorationists. Data engage, as it were, in two different language games: the explorationist community vs. the managerially governed decision gates (Mol, 2002; Oborn et al., 2011).

6 Conclusion

A program launched decades ago (Knorr Cetina, 1999; Zuboff, 1988), the problem of "referential attribution" (Kallinikos, 1999) - how data that lack any immediate correspondence or similarity with physical objects, processes or qualities acquire meaning by being woven into everyday work practices – is gaining empirical relevance and significance with ongoing datafication of our lifeworld. Key to this project is empirical grounding (Günther et al., 2017; Lyytinen & Grover, 2017). Clearly, our articulation of the three patterns of interleaved work practices constituting data-centric knowing emerges from a particular case study. What, then, is the relevance of our analysis to other empirical domains? As Kallinikos (1999, p. 289) points out, "[t]he project [...] needs, therefore, to pass through both the investigation of other empirical contexts and even involve the more successful integration of the relevant available literature".

In translating the analysis underpinning data-centric knowing to other domains, the concept will inevitably be appropriated hence modified. Theoretical concepts travel via, not despite of, appropriation (Walsham, 1995). Our case is characterized by three salient aspects which significantly shaped our analysis: inherently uncertain data and interpretations, quasi-scientific approaches and a corporate, operational logic. We expect generalization qua translation to other domains with similar characteristics. *Inherent uncertainty*: other domains too evolve around uncertain data as e.g., security analysts tasked with predicting the value of stocks to investors grapple with inherent uncertain data-driven interpretation (Beunza & Garud, 2007) or Gartner group's industry analysts (Pollock & Williams 2016). *Quasi-scientific communities*: the search for and openness towards the unknown, captured in our prospecting pattern, is likely to be found in communities with strong scientific identities such as medicine (Timmermans & Berg, 2010), biology (Leonelli, 2014) or high-energy physics (Knorr Cetina, 1999) as scientific models regularly will be under-determined by data. *Corporate logic*: the time- and resource-bounded nature of satisficing search, key to our reframing pattern, is likely to show up across a variety of corporate settings (see e.g., Passi and Jackson's (2018) study of data analytics at a telecom vendor). In addition, the cross-pressure surrounding operational decision-making stemming from competing agendas of professional norms, formal rules and operational demands has been identified in safety-critical, operational settings (Perin 2006; cf. also Fine, 2009).

In closing, our intention is that the analysis articulated in the three patterns of work practices may provide a fertile and generative breeding ground for pursing a research program for "getting under the hood" of data science in IS through practice-oriented studies.

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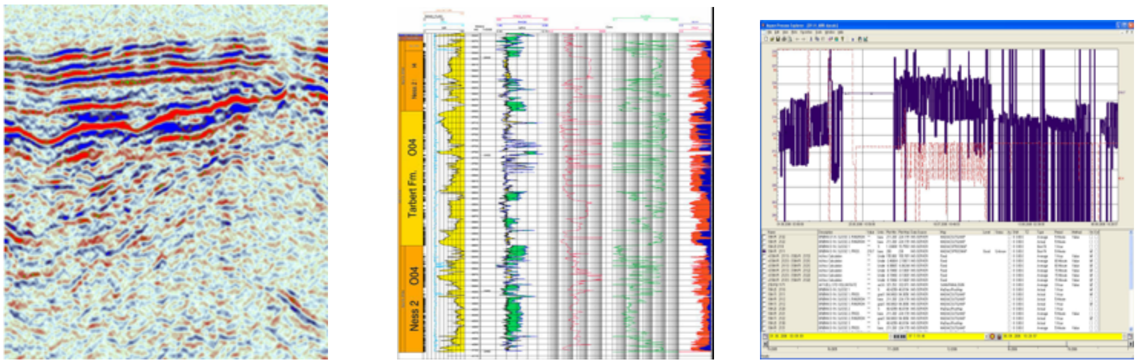


Figure 1. Typical visual representations of the three principal types of data: seismic data (left); well logs (middle); and production data (right).

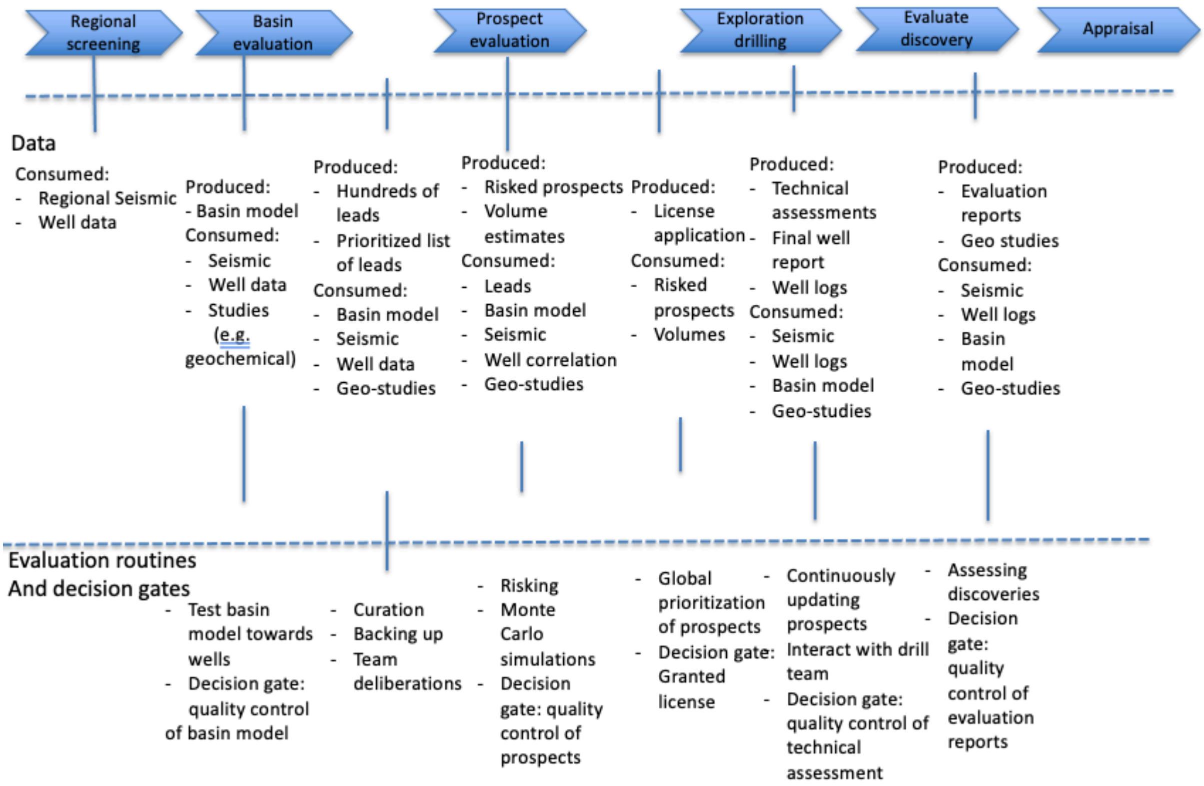
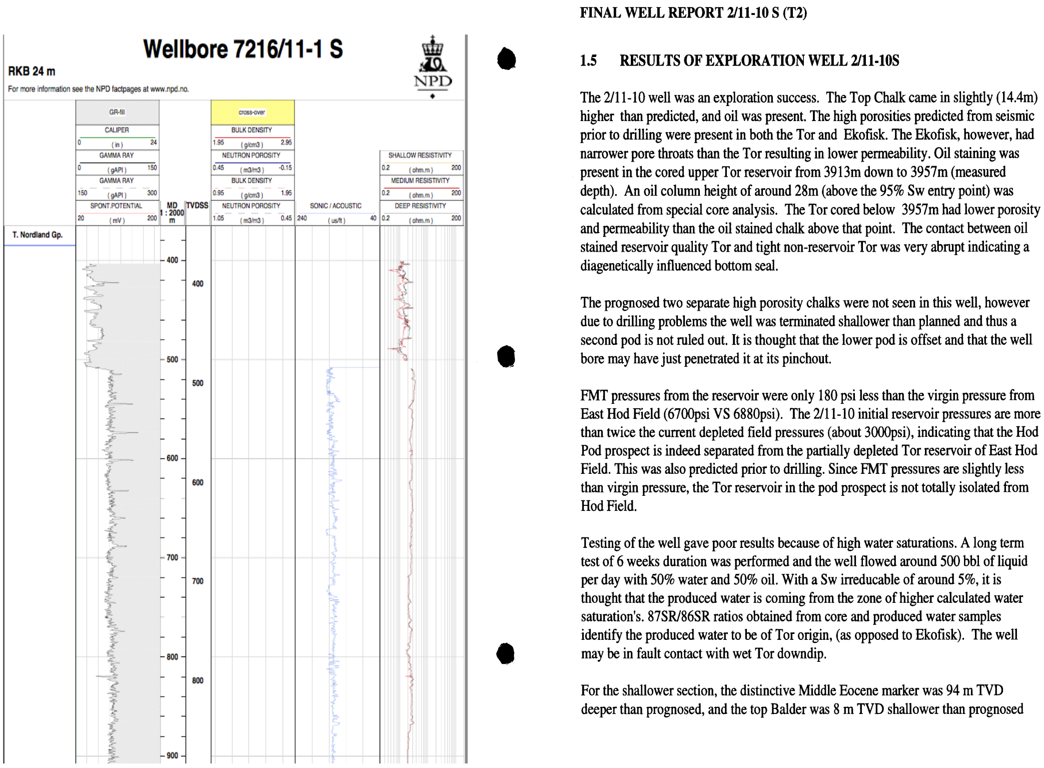


Figure 2: An overview of the funnel model for the life-cycle of prospects with underpinning data.



FINAL WELL REPORT 2/11-10 S (T2)

1.5 RESULTS OF EXPLORATION WELL 2/11-10S

The 2/11-10 well was an exploration success. The Top Chalk came in slightly (14.4m) higher than predicted, and oil was present. The high porosities predicted from seismic prior to drilling were present in both the Tor and Ekofisk. The Ekofisk, however, had narrower pore throats than the Tor resulting in lower permeability. Oil staining was present in the cored upper Tor reservoir from 3913m down to 3957m (measured depth). An oil column height of around 28m (above the 95% Sw entry point) was calculated from special core analysis. The Tor cored below 3957m had lower porosity and permeability than the oil stained chalk above that point. The contact between oil stained reservoir quality Tor and tight non-reservoir Tor was very abrupt indicating a diagenetically influenced bottom seal.

The prognosed two separate high porosity chalks were not seen in this well, however due to drilling problems the well was terminated shallower than planned and thus a second pod is not ruled out. It is thought that the lower pod is offset and that the well bore may have just penetrated it at its pinchout.

FMT pressures from the reservoir were only 180 psi less than the virgin pressure from East Hod Field (6700psi VS 6880psi). The 2/11-10 initial reservoir pressures are more than twice the current depleted field pressures (about 3000psi), indicating that the Hod Pod prospect is indeed separated from the partially depleted Tor reservoir of East Hod Field. This was also predicted prior to drilling. Since FMT pressures are slightly less than virgin pressure, the Tor reservoir in the pod prospect is not totally isolated from Hod Field.

Testing of the well gave poor results because of high water saturations. A long term test of 6 weeks duration was performed and the well flowed around 500 bbl of liquid per day with 50% water and 50% oil. With a Sw irreducable of around 5%, it is thought that the produced water is coming from the zone of higher calculated water saturation's. 87SR/86SR ratios obtained from core and produced water samples identify the produced water to be of Tor origin, (as opposed to Ekofisk). The well may be in fault contact with wet Tor downdip.

For the shallower section, the distinctive Middle Eocene marker was 94 m TVD deeper than prognosed, and the top Balder was 8 m TVD shallower than prognosed

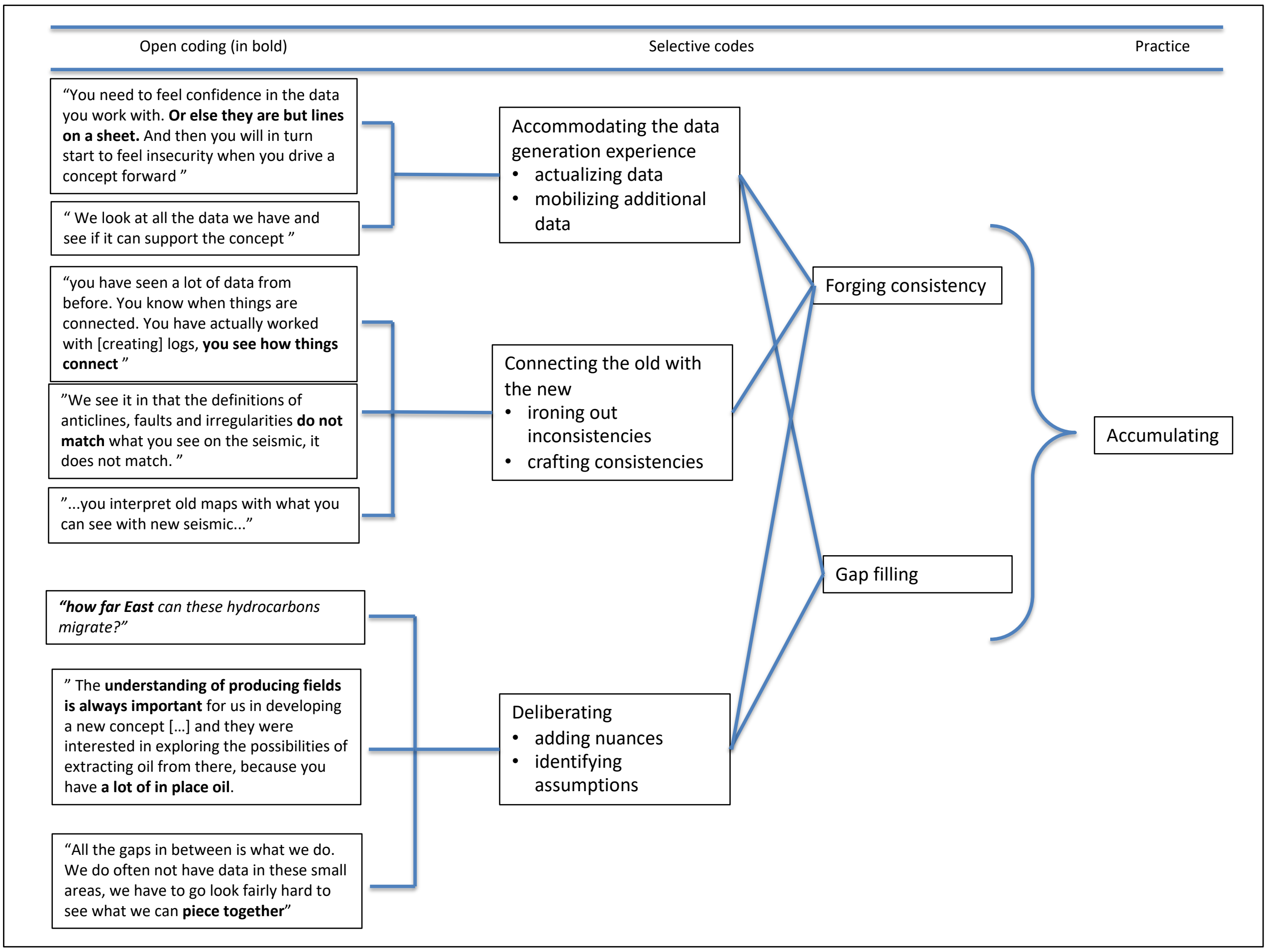
Figure 3. Example of a wellbore log and final well report from NPD FactPages.

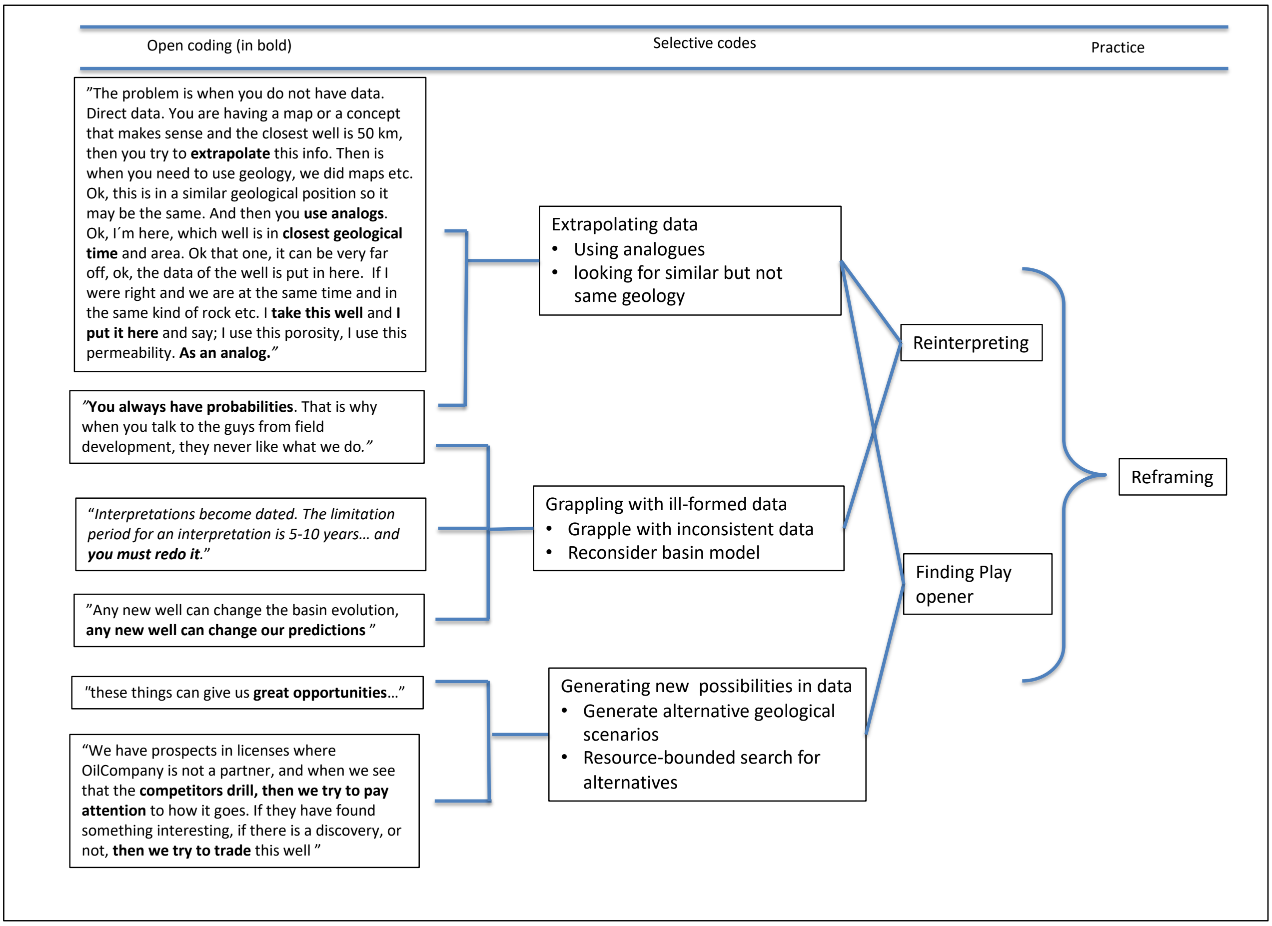
<table>
<tr><td colspan="3">Participant observation: 25 full days, 60 machine-written pages of field notes</td></tr>
<tr><td colspan="2">Everyday work practices of explorationists and data managers</td><td>25 full days of observations and informal conversations with explorationists and data managers in their offices, around coffee tables, and during their lunch breaks</td></tr>
<tr><td colspan="2">Participation in workshops, meetings, and seminars</td><td>Six one-day events with 19 participants altogether (explorationists, data managers, process owners, and IT management)</td></tr>
<tr><td colspan="3">Semi-structured interviews: 27 interviews, 45-90 minutes each, transcribed</td></tr>
<tr><td colspan="2">15 explorationists</td><td>Geologists, geochemists, and geophysicists</td></tr>
<tr><td colspan="2">12 data managers in exploration</td><td>Project and central data managers</td></tr>
<tr><td colspan="3">Documents: electronic and paper-based</td></tr>
<tr><td rowspan="2">Internal</td><td>Documents</td><td>Descriptions of routines and work practices, manuals for tools, example prospects, internal reports and memos, meeting minutes, overviews of challenges with querying databases, and presented results</td></tr>
<tr><td>MS SharePoint team sites</td><td>Project reports, discussions, and slide presentations</td></tr>
<tr><td>Public</td><td>OilComp information</td><td>Drilling operations, tests and results, reclassified interpretations, and reports on discoveries and recoverable volumes</td></tr>
</table>

	Norwegian Petroleum Directorate FactPages	NPD FactPages[7] contain information regarding petroleum activities on the Norwegian continental shelf (see example in Figure 3). The information is synchronized with the NPD's databases on a daily basis.
	Diskos Database	The Diskos National Data Repository (NDR) is Norway's national data repository for petroleum data. Its index is open to the public and contains, in principle, all geo-data (seismic, well, and production). Figure 1 provides examples.

Table 1. Summary of data collection

[7] It is publicly available at http://factpages.npd.no/factpages/


Open coding (in bold)
Selective codes
Practice
"You need to feel confidence in the data you work with. **Or else they are but lines on a sheet.** And then you will in turn start to feel insecurity when you drive a concept forward "
" We look at all the data we have and see if it can support the concept "
"you have seen a lot of data from before. You know when things are connected. You have actually worked with [creating] logs, **you see how things connect** "
"We see it in that the definitions of anticlines, faults and irregularities **do not match** what you see on the seismic, it does not match. "
"...you interpret old maps with what you can see with new seismic..."
*"**how far East** can these hydrocarbons migrate?"*
" The **understanding of producing fields is always important** for us in developing a new concept [...] and they were interested in exploring the possibilities of extracting oil from there, because you have **a lot of in place oil**.
"All the gaps in between is what we do. We do often not have data in these small areas, we have to go look fairly hard to see what we can **piece together**"
Accommodating the data generation experience
• actualizing data
• mobilizing additional data
Connecting the old with the new
• ironing out inconsistencies
• crafting consistencies
Deliberating
• adding nuances
• identifying assumptions
Forging consistency
Gap filling
Accumulating


Open coding (in bold)
Selective codes
Practice
"The problem is when you do not have data. Direct data. You are having a map or a concept that makes sense and the closest well is 50 km, then you try to **extrapolate** this info. Then is when you need to use geology, we did maps etc. Ok, this is in a similar geological position so it may be the same. And then you **use analogs**. Ok, I´m here, which well is in **closest geological time** and area. Ok that one, it can be very far off, ok, the data of the well is put in here. If I were right and we are at the same time and in the same kind of rock etc. I **take this well** and **I put it here** and say; I use this porosity, I use this permeability. **As an analog.**"
"**You always have probabilities**. That is why when you talk to the guys from field development, they never like what we do."
*"Interpretations become dated. The limitation period for an interpretation is 5-10 years... and **you must redo it**."*
"Any new well can change the basin evolution, **any new well can change our predictions** "
"these things can give us **great opportunities**..."
"We have prospects in licenses where OilCompany is not a partner, and when we see that the **competitors drill, then we try to pay attention** to how it goes. If they have found something interesting, if there is a discovery, or not, **then we try to trade** this well "
Extrapolating data
• Using analogues
• looking for similar but not same geology
Grappling with ill-formed data
• Grapple with inconsistent data
• Reconsider basin model
Generating new possibilities in data
• Generate alternative geological scenarios
• Resource-bounded search for alternatives
Reinterpreting
Finding Play opener
Reframing

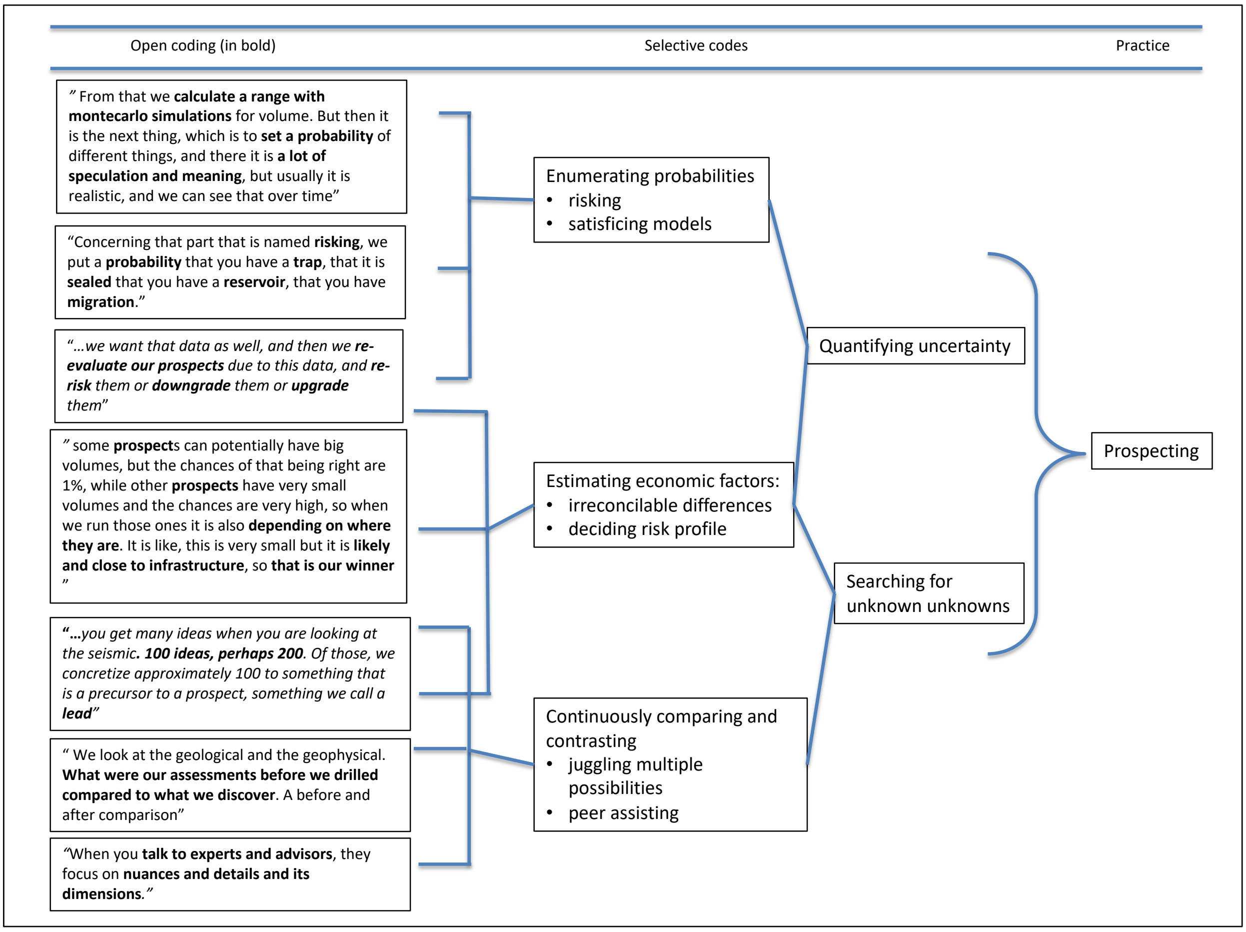


Figure 4: A summary of our interpretative template with three patterns of work practices (main constructs) supplemented with underlying codes and empirical excerpts.

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