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Envisioning Higher Education: How Imagining the Future Shapes the Implementation of a New Field in Higher Education

Philippe Saner*

Abstract: Higher education is a site of contesting visions by actors in politics, science and the economy. This article investigates imaginations of the future articulated around the introduction of data science in Swiss higher education through a qualitative analysis of study programmes, policy documents, and business reports. Universities envision data sciences mainly in reference to economic and technological concepts, which contribute to the coordination of the various actors and thus unfolds specific performative effects in the present.

Keywords: higher education, digitisation, data science, curricula, future imaginaries

L'enseignement supérieur du futur. Comment des visions d'avenir façonnent l'introduction d'un nouveau domaine d'études

Résumé : L'enseignement supérieur est un champ de projections pour différentes visions d'avenir par des acteurs politiques, scientifiques et économiques. Cet article examine ces visions autour de l'introduction des sciences des données dans l'enseignement supérieur suisse par une analyse qualitative des programmes d'études, des documents politiques et des rapports économiques. Les hautes écoles envisagent les sciences des données principalement par des concepts économiques et technologiques, ce qui contribuent à la coordination entre les différents acteurs.

Mots-clés : éducation supérieure, numérisation, science des données, programmes d'études, visions d'avenir

Die Hochschulbildung der Zukunft. Wie Zukunftsvorstellungen die Einführung eines neuen Studienfeldes prägen

Zusammenfassung: Hochschulbildung ist eine Projektionsfläche divergierender Zukunftsvisionen von politischen, wissenschaftlichen und wirtschaftlichen Akteuren. Der Artikel untersucht solche rund um die Einführung der Datenwissenschaften in der Schweizer Hochschulbildung durch die qualitative Analyse von Curricula, politischen Dokumenten und ökonomischen Berichten. Die Hochschulen rahmen die Datenwissenschaften vor allem durch ökonomische und technologische Konzepte, die zur Koordination der Akteure beitragen und so performative Effekte entfalten.

Schlüsselwörter: Hochschulbildung, Digitalisierung, Datenwissenschaften, Curricula, Zukunftsvorstellungen

* University of Lucerne, Department of Sociology, CH-6002 Lucerne, philippe.saner@unilu.ch

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1 Introduction[1]

In recent years, universities, corporations and states have formulated digital strategies and agendas to cope with the ongoing sociotechnical transformation and to shape their future development. In Switzerland, the federal government inaugurated "Digital Switzerland." One of its main aims is to preserve the global competitiveness of the Swiss economy, as well as the country's "leading position in innovation and research" (Swiss Confederation 2016, 17; my translation). As part of this strategy, investments of several hundred million Swiss Francs (CHF) into the research and higher education sector have been announced. For example, in 2017 the federal government launched an "action plan on digitisation" to deal with challenges in education, science and research (SBFI 2017), while the Swiss National Science Foundation (SNSF) is funding large-scale research programmes in fields such as robotics, artificial intelligence and data science. At the same time, state agencies (SBFI 2017; Swiss Confederation 2017) and business associations (Herzog et al. 2017) continuously articulate the need for more graduates and an enhanced training in science, technology, engineering and mathematics (STEM) at Swiss universities to address growing "skills gaps" and "talent shortages" in these fields.

What these discussions have in common is that they seldom specify the concept of digitisation: for example, instead of offering a single overarching definition of *the digital,* the strategy "Digital Switzerland" proposes several concepts of *a digital future.* Although these strategies assert that future developments cannot be predicted with certainty, they constantly demand adaptations to the education system and programmes in order to meet the future needs of digitized labour markets. This paper deals with such future needs, and the concomitant constraints, in the field of higher education. I argue that the discussion on digitisation is part of a "sociotechnical imaginary" (Jasanoff 2015) where strategies, visions and other "imaginations" of the future contain scenarios of how *the world could look* while also commenting on *how it should look.* Actors in different societal fields then adopt these "imaginaries," or visions, and coordinate their actions. When the value of a new field is still unclear, this collective imagination can help stabilise societal expectations and contributes to the achievement of the objectives articulated therein. In this sense, sociotechnical visions of the future of a particular field produce specific performative effects in the present and shape its future development. In this context, this paper investigates the emergence of data science, which is considered a key field in an ongoing sociotechnical transformation and for the future of STEM education overall. I specifically ask how political, economic and educational actors imagine data science as a study programme in higher education. To address this question, I

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examine the introduction of data science at Swiss universities, as a case study, using study programme descriptions, policy documents and reports by economic actors to serve as empirical material.

The introduction of data science in Swiss higher education is an interesting case, since it shows the widespread adoption of business concepts and ideas in science policies and educational curricula. Sociotechnical processes of datafication have been identified as important drivers transforming every of corner of society including: industry (Beer 2019), labour markets, education (Williamson 2017), culture and social life (Schäfer and van Es 2017; Prietl and Houben 2018). In this context, further research on how economic imperatives such as "talent shortages" in higher education (Herberg 2018) intermingle with this sociotechnical transformation is necessary. The paper contributes to the sociological discussion on the changing relations between higher education, politics, and the economy in the digital age (Jessop et al. 2008; Grande et al. 2013; Herberg 2018) by looking at educational programmes and curricula, as well as the economic, political, and scientific discussions that shape them.

My empirical analysis starts from an observation of a rapid diffusion of data science within Swiss academia: between 2014 and 2018, almost every university established their own degree programme or specialisation. This introduction of data science in higher education was framed according to different imaginations of the field in the business world, science and higher education. Business actors proclaimed "skills gaps" and "talent shortages" in STEM fields in general and in data science in particular. They also declared data science to be the "sexiest job of the 21st century" (Davenport and Patil 2012). The demand-driven orientation was readily taken up in research and higher education policy. And, in the context of innovation policies and strengthening Switzerland's "competitiveness," it was translated into demands for a guaranteed supply of data science skills for industry. These different imaginations shaped the introduction of data science into contemporary degree programmes at Swiss universities, which helped to align the differing visions of the emerging field and contribute to the coordination of activities by actors in the business world, science policy and higher education.

2 Future Imaginaries of an Emerging Field of Knowledge

To investigate the research question outlined, I will apply the theoretical concept of "future imaginaries" to alternative visions of data science in higher education. In this section, I will introduce the concept of future imaginaries from science and technology studies and show its potential for coordinating actions between actors in different social fields.

2.1 The Coordinating Function of Future Imaginations from a Field Perspective

Discussions surrounding policy and governance reforms in higher education often contain narratives and visions of future development that are part of wider societal discourse. Research has shown that differing concepts and visions by actors from different fields shape the reform of educational and research policies (Jessop et al. 2008; Maesse 2010; Wodak 2015), as well as the development of new programmes and curricula (Young 1998). By providing common goals and possible pathways for the future development of a certain field, future imaginations help coordinate the activities of a variety of actors that partake in these discussions. This argument is supported by recent work in economic sociology (Mützel 2010; Beckert 2016) and science and technology studies (Jasanoff 2015) that emphasises the coordinating role of future imaginations in the conception and emergence of new categories, disciplines or markets.

Analytically, visions of the future can be seen as a form of discourse: "'[The] future' is constituted through an unstable field of language, practice and materiality in which various disciplines, capacities and actors compete for the right to represent near and far term developments" (Brown et al. 2000, 5). The future is thus a "contested" site of differing voices and competing imaginations by actors from different fields. As Jasanoff (2015) elaborates in her work, imaginations of sociotechnical arrangements – especially those by higher institutions of education and research – are an essential part of a modern society's self-understanding. In Switzerland, the Swiss Federal Institute of Technology in Zürich is often referred to as the "flagship of the nation" (Honegger et al. 2007, 11; my translation) to describe its important role in nation-building (Gugerli et al. 2005). Jasanoff defines sociotechnical imaginaries as "collectively held, institutionally stabilized [sic], and publicly performed visions of desirable futures, animated by shared understandings of forms of social life and social order attainable through, and supportive of, advances in science and technology" (2015, 4). In other words, envisioning the future is not exclusively tied to individuals and their capacities of imagination or creativity; rather, it can be understood as a collaborative social practice.

Economic sociology has acknowledged narratives about future actions as central drivers in the construction and stabilisation of markets (Mützel 2010). Drawing on work emphasising the performativity of economic knowledge (MacKenzie et al. 2007), Beckert has recently taken up this line. He posits that economic theories and instruments only appear to predict the future; they are much more influential in coordinating (future) activities between different economic and other actors (Beckert 2016). Predictions and forecasts do not only produce new futures but they also frame, enhance and continuously re-inscribe these futures into current organisational practices and socio-economic policies. And in doing so, they exert a specific discursive power: they envision possible futures and thereby also "creat[e] the present" (Beckert 2016, 217).

Unlike economic forecasting, strategies such as "Digital Switzerland" are not based on complex calculation schemes and formulas; instead they take into account other actors' intentions. For instance, Swiss higher education and research bodies legitimise their funding initiatives by pointing to similar policies in other countries (e. g. SNSF 2015; SBFI 2017). In this way, by deploying similar strategies through mutual observation, actors in different fields contribute to the coordination of their activities. In times of uncertainty, when the value of the contributions of an emerging field – such as data science – is not yet clear, this can help stabilise expectations and development of the field.

The coordinating function of these future visions is situated within specific relations between different social fields according to field theory (Fligstein and McAdam 2012). As Fligstein and McAdam (2012, 59) remind us: "Fields do not exist in a vacuum. They have relations with other strategic action fields and these relations powerfully shape the developmental history of the field." In addition to the internal dynamics of field autonomisation – such as the development of new methods, theories, tools, bodies of knowledge etc. – the emergence of a particular field of knowledge is itself subject to external conditions such as departmental conditions (Small 1999), political regulation, the allocation of resources, economic constraints and opportunities, as well as demands by a variety of stakeholders in other fields (Grande et al. 2013). In other words, fields are always "embedded in complex webs of other fields" (Fligstein and McAdam 2012, 18). For this paper, several macro-fields (Fligstein and McAdam 2012, 57 ff.) beyond science, are of special interest: the business world, science and research policy and higher education. They all contribute in their own way to the making and framing of data science. In the following, I will shortly introduce the recent history of the field under scrutiny by characterising its relations with these surrounding fields.

2.2 An Emerging Field of Knowledge between Science and Industry

Data science is often described as an interdisciplinary field of knowledge that includes people with strong programming skills who are also trained in statistics, mathematics, computer sciences and engineering. In contrast to other academic fields, such as biotechnology or nanotechnology (Jasanoff and Kim 2015), data science methods and techniques are perceived to be applicable to any societal domain. Historically, its roots begin in the mid-20th century, at the intersection of computer science and industrial statistics. However, the field has remained largely at the margins of academic science (Donoho 2017).

The recent history of data science (Gehl 2015) suggest that an epistemological transition is taking place: in the first decade of the 21st century, the availability and abundance of data (often referred as "big data", see Manyika et al. 2011) has created a new interest in this specific set of knowledge practices, methods and tools. The rise of big tech and internet companies has shifted the main locus of innovation from a heterogeneous field at the margins into the rapidly growing data economy: tech companies have taken up methods and tools developed in scientific fields and implemented them into sociotechnical systems, platforms and devices. At the same time, the tech industries have created new occupational roles and titles with specific skill sets (Hammerbacher 2009) and have attracted large numbers of academic researchers (Safavi et al. 2018). These changes are accompanied by repeated calls for more educated data scientists and other data-savvy professionals (Varian 2009; Davenport and Patil 2012).

In addition to science and industry, research policy is funding large-scale programmes and projects to advance scientific knowledge production in big data, artificial intelligence, data science and other adjacent specialties. In times of limited public funds and growing demands on the accountability of science, such decisions must be legitimized to a critical public. The universities themselves are integrated through different kinds of relations: they are subject to federal and cantonal regulation, they collaborate in different bodies of science and higher education policy, while at the same time competing for resources, professors, students and reputation. This institutional arrangement of synchronous collaboration and competition involves continuous mutual observation of each other's strategies and actions. Accordingly, they introduce new degree programmes and adapt existing curricula to remain competitive. At the same time, they need to prove the applicability of the knowledge taught as well as the "employability" of their graduates (Jessop 2008).

Actors in all these fields formulate their own imaginations of data science through reports, policy documents, funding proposals, curricula and course descriptions. By doing so, they take into account each other's visions and contribute to the coordination of these different conceptions of a field for its further development. In the next section, I describe the data and method that allow analysing this coordinating function of future imaginaries.

3 Data and Method

The question of how to analyse projections and imaginations of the future is an ongoing methodological challenge in the social sciences (Mische 2014). According to Jasanoff, discourses are an important element in the study of future imaginations, but – due to their focus on language – they are "less directly associated with action and performance or with materialization [sic] through technology" (Jasanoff 2015, 20). The sociology of knowledge approach to discourse analysis (SKDA)[2]

2 SKDA combines the perspective of the communicative construction of social reality (Berger and Luckmann 1966) with the discourse analysis work by Foucault. Foucault argued that discourses were "performative statement practices which constitute reality orders and also produce power effects in a conflict-ridden network of social actors, institutional dispositifs, and knowledge systems" (Keller 2011, 48; italics in original).

(Keller 2011; 2013) has the potential to function as a bridge in this regard: SKDA not only distinguishes between the structural, institutional and situational contexts of knowledge production, it also considers the material and immaterial implementations of discursive formations (Keller 2011, 49). It thereby emphasises the relatedness of different data types and steps of interpretation, and does not assume that "'consistency of meaning' [is] inherent to one particular document of discourse" (ibid., 62). The researcher needs to reconstruct the different elements of discourse that are articulated in the data. This multiperspectivity enables investigating not only the framing of data science in different types of documents (course descriptions, policy papers, and business reports), but also its materialisation in study programmes' curricula. Following my research question, I concentrated on the structural and institutional contexts to reconstruct the vision presented in ongoing discussions of data science since its introduction in Swiss universities.

The data set for this case study was collected in three phases. First, I gathered publicly available materials (study descriptions, course syllabi and promotional material) from all existing study programmes and specialisations in data science and analytics at universities and universities of applied sciences in Switzerland ($N = 24$; see Table 1 in the Appendix).[3] Then I included policy documents by actors in Swiss science policies ($N = 7$) that address processes and challenges of digitisation in research and higher education.[4] Authors include the Swiss federal government (Swiss Confederation 2016; 2017); the SNSF (2015); the State Secretariat for Education, Research and Innovation (SERI; see SBFI 2017); the Board of the Swiss Federal Institutes of Technology (ETH-Rat 2014; 2016); and the Swiss Data Science Center (SDSC 2017). When I analysed the programme descriptions and promotional material, the relevance of business terms and concepts became clear. Therefore, in a third step, I extended the analysis and included business reports that were referenced in the documents by actors from higher education and science policy ($N = 7$). Authors include business and higher education think tanks such as the McKinsey Global Institute (Manyika et al. 2011; Henke et al. 2016); PricewaterhouseCoopers and the Business and Higher Education Forum (PwC and BHEF 2017); Burning Glass Technologies (Markow et al. 2017); the World Economic Forum (Schwab et al. 2011; Schwab 2016); and protagonists from large tech companies (Davenport and Patil 2012). As public documents directed to the broader public, policy papers and business reports proved especially suited for the analysis as they often contain commentary, predictions and metaphors about possible technological and economic futures.

I imported all documents into the qualitative analysis software ATLAS.ti and selected the passages where definitions of data science, relevant skills and visions of

3 Programmes were considered if they either offered a degree in data science, a related field such as business analytics, or an analytics-oriented specialisation within another programme (such as computer science).

4 Policy documents were included if they explicitly addressed the field of data science.

its future were outlined. Using an open, inductive coding procedure (Flick 2016, 388–392), I first coded recurrent topics in the curricula and programme descriptions. Then I identified the references to notions and concepts in business and science policy documents and analysed their main arguments, goals, and addressees. The inclusion of these documents in the analysis allowed me to contextualise the themes discovered in the curricula in broader economic and political discussions. Finally, I reconstructed the different elements articulated beyond the single documents and sources into more consistent imaginations.

The empirical part of this paper is organized as follows: first, I analysed the representation of data science in business reports. I then turned to the visions in Swiss science and research policies. And finally, I looked at how Swiss universities implemented these differing conceptions of the field into educational curricula and study programmes.

4 The Role of Business Concepts in Producing Demand for Data Science Skills

The business world outlines different visions for the ongoing sociotechnical transformation of society (Dickel and Schrape 2015). Referring to datafication, consulting agencies and think tanks frames the growing importance of "big data" as a "new asset class" (Schwab et al. 2011), even going so far as to call it the "new oil" of the 21st century (ibid., 5). The sociotechnical systems, devices and methods necessary for the analysis of "big data" are imagined to lead the "revolution" (Mayer-Schönberger and Cukier 2013; Schwab 2016). The business world combines these developments with urgent calls to act: first and foremost, these reports created pressure on firms to rapidly adjust their business strategies. At the same time, consulting agencies and researchers called upon politics to recalibrate research funding and higher education to guarantee a supply of a skilled labour force for the digital age (Manyika et al. 2011; Davenport and Patil 2012). In the following two subsections, I will explore how business actors articulate their demands to political bodies and higher education through specific visions of the emerging field of data science.

4.1 The Role of "Skills Gaps" and "Talent Shortages" in Business Reports

"Skills gaps" and "talent shortages" in STEM fields have a long history in science and technology policies: They are a recurrent theme in education and labour market research, and have been articulated in other periods of technological innovations since the mid-20th century (Cappelli 2015; Herberg 2018).[5] In data science, the McKinsey Global Institute first popularised a diagnosis of a "talent shortage" through

5 The historical roots of the concept can be traced back to political efforts during the Cold War when Western countries and the Soviet Union competed in the development of military technology (Cappelli 2015, 254).

their study *Big Data: The Next Frontier for Innovation, Competition, and Productivity* (Manyika et al. 2011), which is of special relevance because seven out of the twenty-four programmes or specialisations examined for this study directly reference it. The main objective of *Big Data* was to show the "transformative potential of big data" in different domains of the private and public sector (ibid., 37 ff.), as well as the economic opportunities that resulted thereof. Furthermore, the report predicted a sharp rise in the demand of analytical talent:

> *However, in a big data world, we expect demand for deep analytical talent could reach 440 000 to 490 000 positions in 2018 – that's a talent gap in this category alone of 140 000 to 190 000 positions. In short, the United States will need an additional supply of this class of talent of 50 to 60 percent.* (Manyika et al. 2011, 104)

The report concludes that "it is imperative that organizational [sic] leaders begin to incorporate big data into their business plans" (Manyika et al. 2011, 111). Referring to unexploited potentials and imminent losses of competitiveness, the authors then suggest "policy makers" to heavily invest in STEM-related subjects to "build human capital for big data" and to reduce barriers of access to analytical talents through "the immigration of skilled workers" (Manyika et al. 2011, 117). Both of these claims are made regularly by employers and business lobbyists to lower labour costs (Cappelli 2015, 275; Gehl 2015).

The McKinsey report played a decisive role in framing the emerging field of data science because it linked the idea of big data as a business model with that of a "deep analytical talent" before the category of data science was established and known to the broader public (see section 4.2). In this way, it put normative pressure on business organisations and the political system for demand-driven higher education policies. Through its widespread acknowledgment,[6] the report became a central benchmark for actors in the business world, science policy and higher education.

Other reports by business actors followed similar strategies but have since become more cautious in their predictions (Markow et al. 2017, 5; see Fitzgerald et al. 2018 for an overview of these reports). Nevertheless, their predictions were incorporated into higher education policies: within a couple of years, Swiss universities created more than 20 programmes or specialisations, and worldwide, thousands of new degree programmes, massive open online courses (MOOCS) and training certificates in data science and analytics have been established (Parry 2018). The number of students in STEM fields in general – and in computer science in particular – has increased considerably since 2011 and these numbers are expected to grow steadily in the coming years (BFS 2017; SBFI 2017, 25f.).

6 According to Google scholar, the report received around 4900 citations in scientific publications, more than any other work on "big data" in the fields of business and social sciences. (Accessed on 04.09.2019)

The McKinsey report, and those that followed, not only envisioned future scenarios of a data-driven economy, but they also contributed to the coordination of companies' organisational practices with science policies and efforts in higher education.

4.2 Promising Futures: the "Sexiness" of Data Scientists as Future Leaders

Technological innovations always capture collective imagination and become part of the popular narrative (Jasanoff 2015). In the case of data science, it was a small group of people at the intersection of big tech companies and academia who formulated their own visions of the field in the last decade (Hammerbacher 2009; Varian 2009; Davenport and Patil 2012). And by doing so, they installed a new and specific understanding of a still inchoate subject.

> *I keep saying the sexy job in the next ten years will be statisticians. People think I'm joking, but who would've guessed that computer engineers would've been the sexy job of the 1990s? The ability to take data – to be able to understand it, to process it, to extract value from it, to visualize [sic] it, to communicate it – that's going to be a hugely important skill in the next decades …* (Varian 2009)

The article, "Data Scientist: The Sexiest Job of the 21st Century," by Thomas H. Davenport and DJ Patil (2012) is paradigmatic for reconceptualising data science and its new symbolic significance. The article combined the notion of the "talent shortage" with a cultural imagination of the "sexiness" of highly qualified professionals and university graduates in STEM fields. This framing of data science as "the sexiest job" became ubiquitous in media representations of data science, study programmes (see section 6.1) and the mission statements of research institutions.[7]

The "sexiness" of data science goes beyond imagining attractiveness of the prospect of a high salaried and "in-demand job." The framing further points to a gendered dimension of the emerging field: as other technology-driven fields, data science currently consists of almost exclusively male professors that teach a predominantly male student body. Programmes that make use of this imagination of data science also emphasise the entrepreneurial side of the field through modules focusing on management, communication, and visualisation (Stockinger et al. 2016). This framing of the data scientist, as someone that is able to "extract value from data" and "communicate" it, is compatible with the recent diagnosis of a "techno-scientific business masculinity" (Paulitz and Prietl 2017). In current knowledge economies, this version of masculinity is a fusion of engineering with business and

7 For example, the Data Lab of the Zürich University of Applied Sciences begins its "Vision & Mission" statement as follows: "We are convinced that doing data science in all its facets is the sexiest profession one can pursue." See https://www.zhaw.ch/en/research/inter-school-cooperation/datalab-the-zhaw-data-science-laboratory/ (12.11.2018).

management skills: "What kind of person does all this? What abilities make a data scientist successful? Think of him or her as a hybrid of data hacker, analyst, communicator, and trusted adviser. The combination is extremely powerful – and rare" (Davenport and Patil 2012, 73).

The broader success story of the reframing of data science can thus be seen in the orientation of the tech field away from engineering aspects towards values such as entrepreneurship, communication, and creativity. Although these concepts were already associated with sociotechnical innovation (Dickel and Schrape 2015), and present in engineering education (Malazita 2019), they became the dominant imagination of the whole field of data science. This is particularly true for internet and tech companies (Morozov 2013). For these companies, the data scientist represents the emblematic figure of the ongoing sociotechnical transformation towards a data-driven society. Addressing data scientists this way enables potential students to imagine themselves not only as engineers working on data-intensive challenges in industry but as future societal leaders.

5 The Field of Data Science in Swiss Academia

As outlined in the previous section, influential actors in the business world and tech industry reimagined the emerging field of data science as the application of data-intensive methods to business problems. They also articulated "skills gaps" and "talent shortages," and framed the data scientist as the "sexiest job of the 21st century."

These sociotechnical transformations have broad implications as other scientific disciplines were also faced with processing a great quantity of data. Observers referred to these transformations as the "fourth paradigm" – a fundamental change to scientific knowledge production (Hey et al. 2009). The epistemological, methodological and societal challenges associated therewith were addressed as well (boyd and Crawford 2012). In the following subsections, I will illustrate how science policies in Switzerland responded to these developments by funding several large-scale research programmes. Then I will show how science policies connected the imaginations by actors in the business world with the vision of Switzerland as an "innovative, future-oriented business and research site" (Swiss Confederation 2016, 3; my translation).

5.1 Funding Strategies and Research Programmes in Science Policy

In Switzerland, it took several years before science and higher education policy began to incorporate topics such as "big data", data science and artificial intelligence into their funding priorities. In 2014, the ETH Domain[8] prioritised "[b]ig data and

8 The ETH Domain includes the two federal institutes of technology, ETH Zürich and EPF Lausanne, as well as four specialised research institutes.

digital sciences" (later renamed as data science) as a "strategic area of focus" in its 2017–2020 strategy (ETH-Rat 2014, 50f.). Addressing political decision-makers at the federal level, the ETH Domain also justified increasing financial requirements for this period. The strategy stipulated an additional 50 million CHF in funding (ETH-Rat 2014, 63) for basic research and developing new technologies and methods, including the education of "data scientists," a "new type of specialist" whose competences rest at the "intersection of informatics, mathematics, statistics, and semantics." Data scientists, as imagined here, were supposed to "bridge the gap between these core disciplines and different fields of expertise" (ibid., 51; my translation).

In accord with this strategy, the ETH Domain launched the "Initiative for Data Science in Switzerland" as an action plan in 2016. The initiative included the establishment of the Swiss Data Science Center, several additional professorships in the above-cited "core disciplines," and two new Master of Science programmes in data science at the Swiss Federal Institute of Technology in Zürich (ETHZ) and Swiss Federal Institute of Technology in Lausanne (EPFL) (ETH-Rat 2016). Meanwhile, the SNSF launched the "National Research Programme 75 Big Data" to promote scientific "[advances] in computing and information technology" and enable applications in different fields, while also addressing related "societal, economical, regulatory … and educational challenges" (SNSF 2015, 9f.). Other research initiatives in adjacent themes are currently in planning (SBFI 2017).

These policy documents share a common line of argumentation: they (1) refer to concepts and visions outlined by actors in the business world (see section 4); (2) identify fundamental transformations ("revolution") through the datafication of business, science and society; and (3), in a synthesizing manner, they present data science as a "new research paradigm" that responds to the technological and methodical challenges associated with the ongoing sociotechnical transformation. For example, the ETH Domain formulates this as follows:

> *The 4th industrial revolution is driven by the convergence of smart, connected systems with breakthroughs in areas ranging from gene sequencing to nanotechnologies. In this new era where 'data is the new oil,' there is little value in 'crude' data. But if crude data can be extracted, refined, and piped to where it can impact decisions, its value will soar. Data science is the new research paradigm concerned with executing this vision.* (ETH-Rat 2016, 2)

At the same time, data science is presented as offering "a new tool" to other scientific fields in order "to understand and influence complex, real-world systems to make progress on some of the most challenging problems of our time" (ETH-Rat 2016, 2). The framing of data science as a "tool" responds to business imaginations that envision it as a solution for specific organisational problems. It emphasises the applicable character of data science methods and techniques in solving complex problems irrespective of the domain. In this way, science policy deploys a solutionist and engineering approach to current and future societal challenges (Morozov 2013; Dickel and Schrape 2015) to legitimise the high funding budgets spent on research projects in this field.

5.2 Competitiveness and the "Rapid Adaptation" to the Market

In addition to portraying data science as a new scientific research paradigm and a tool to solve challenges in different social fields, science and research policies also maintain a pronounced focus on a theme of national "competitiveness." The ETH "Initiative for Data Science in Switzerland" frames competition as follows: "data science is a strategic field of research of the ETH Domain for the period 2017–2020 and the Initiative will ensure that the ETH Domain and Switzerland possess the necessary expertise and remain globally competitive" (ETH-Rat 2016, 1). Similarly, a report by the SERI states that the competitiveness of the Swiss higher education system is threatened by a number of countries from around the globe, specifically referencing East Asian nations (SBFI 2017, 41 ff.). "Falling behind" other countries is perceived as a "central risk" to Switzerland's innovation and research sector (ibid., 53; my translation). To secure "a leading position in innovation and research" (Swiss Confederation 2016, 17; my translation), the SERI report outlines how several hundred million CHF will be invested on basic research and education in fields like artificial intelligence, robotics and data science. These fields are imagined by the federal strategy "Digital Switzerland" as fundamental pillars to the nation's identity as an "innovative, future-oriented business and research site" (Swiss Confederation 2016, 3; my translation).

Another common theme within federal innovation policies is the representation of higher education as a field reacting to developments in other fields, in particular to ongoing sociotechnical transformations in economy. Since the main function of the education system is conceived to be training of skilled personnel for the labour market, universities need to "adapt" to changing skill requirements. Accordingly, the SERI describes "Action Field 3" in its report as the "rapid adaptation of the education system to the demands of the market" (SBFI 2017, 55 ff.). The SERI presents the two new ETH master's programmes in data science as a way to educate the "specialists in this domain that the Swiss economy is desperately looking for" (ibid., 97). Articulated this way, the implementation of data science into new study programmes responds to the high demand for data science skills from industry (see section 4.1). This demand-driven view reduces higher education and universities to mere suppliers of skilled graduates in STEM fields to support the "digital economy" (Swiss Confederation 2017, 46 ff.). In the context of innovation policies, the previously outlined epistemological shift ("new research paradigm") taking place is presented within "an 'economising' logic oriented to profit-and-loss calculation" (Jessop 2008, 14).

6 Data Science in Higher Education Curricula

In the previous section, I showed how science policy developed its own vision of data science by including the field into existing policies to enhance innovation and competitiveness. At the same time, science bodies transformed repeated warnings of "talent shortages" into calls of action to educate more graduates in data science in particular and in the STEM fields overall (SBFI 2017). In this section, I will analyse how Swiss universities responded to these visions. First, I will investigate how the imaginations of data science by actors in the business world and science policy are taken up within the study programmes. Then I will address how the different conceptions of the field materialise in data science curricula at Swiss universities.

6.1 Business and Science Policy Concepts in Data Science Study Programmes

The degree programmes frequently refer to the imaginations articulated in the business world and diagnoses of "talent shortages" are a defining feature of study programmes in data science. A majority of the programmes in my data set deploy this framing of data science. For instance, the master's programme at EPFL introduces data science as "one of the most active fields in industry with a continuing shortage of talent" (EPFL 2017, 3), while ETHZ points more generally to the "[high] demand" for data scientists in industry.[9] Other universities use similar justifications.

Study programmes also emphasise the symbolic value of data science: the "sexiness" of data science is often used by professional education programmes. Emphasising attractiveness functions as marketing for data science to recruit practitioners who may be open to pursuing further education and changing occupations. Most bachelor's and master's degrees also emphasise the future employability of their graduates, but these programmes combine the economic potential of graduates with the symbolic dimension of the field as well.

EPFL advertises that "[i]t only takes an average of [ten] weeks to find one's first job in the field of Information and Communication Technologies (ICT). Moreover, many graduates in the ICT field receive a job offer during the last semester of their training. Companies like Facebook, Google and Microsoft have even begun recruiting directly on campus" (2017, 4). Invoking this image of a promising career in some of the worlds' largest internet and tech companies has actively reshaped the field (see section 4.2) and serves as a specific future "imagination" to potential students. In this manner, the competitiveness argument from science policy is transformed into a more individualised form.

The symbolic dimension of data science is particularly endorsed by programmes that combine data science with business management. For instance, one objective of the University of Geneva's business analytics programme is to "[prepare] students for leadership positions in organizations' [sic] digital transformation aimed at creating

9 See https://www.inf.ethz.ch/studies/master/master-ds.html (27.02.2019).

value for businesses and society."[10] This leadership role of the data scientist in the ongoing "digital transformation" refers to its societal relevance: study programmes repeatedly accentuate the "tool" dimension (see section 5.2), or techniques and methods needed to solve complex societal problems or to "[create] value for businesses and society." As we will see in the next subsection, this is often translated in curricula as applicability and "real-world" orientation.

6.2 Imaginations of Data Science in Educational Curricula as Interdisciplinarity, Applicability, and "Real Worldness"

Data science diffused rapidly among Swiss universities. Between 2014 and 2018, almost every institution established their own degree programme or specialisation. According to their traditions and profiles, universities have opted for different strategies when implementing new degree programmes (see Table 1 in the Appendix). For example, they are offered by technical departments, business departments, as well as combinations thereof. In Swiss universities, new degree programme implementation takes place at the master's level and at an academic professional education level including certificate, diploma and Master's of Advanced Studies programmes. They have also recently been offered at bachelor's level. These institutional choices reflect the local conditions of universities (Small 1999), as well as the disciplinary and departmental affiliations of its initiators.

Despite this organisational variation, several common aspects characterise the structure and content of the curricula investigated. First, there is compositional similarity in the curricula. The interdisciplinary character of data science is seen in the combination of so-called "core courses" of data science (i. e. the methodological and theoretical foundations in computer science, statistics, mathematics and engineering) with applications from different scientific fields (at technical departments) or business as potential minors, specialisations or modules. At ETHZ and EPFL, the core courses are almost identical, which points to the high degree of coordination in the framework of the ETH data science initiative (ETH-Rat 2016). In technical departments, the algorithmic, mathematical and data engineering aspects dominate coursework. Courses on the ethical, legal or social aspects of data science (boyd and Crawford 2012) are rare – except for optional ethics classes for engineers. Programmes in business departments and in academic professional education integrate other skills associated with data science such as entrepreneurship, communication and visualisation (Stockinger et al. 2016). In this sense, they deploy a broader understanding of the field and one that also aligns with recent business perspectives (see section 4.2.1).

Another common point that most programmes share is a component of collaboration with partners from outside academia to guarantee the applicability of the knowledge taught. Although internship is optional at some universities, data science

10 See https://www.unige.ch/gsem/en/programs/masters/business-analytics/ (27.02.2019).

students at EPFL have to take a mandatory and external “engineering internship” that can last between eight weeks to six months: “As a Master [sic] student, it is mandatory to undertake an engineering internship in a company during your studies. This internship aims to facilitate your immersion in the professional world, aware you [sic] of the teamwork and familiarize [sic] yourself with the industry procedures.”[11]

The degree programmes also implement the practical component in different teaching formats such as lab sessions, boot camps or master theses in cooperation with partners in industry. Course descriptions enumerate different methods and modelling techniques to address “real problems” and to build applications with “impact in the real-world.” The curricula suggest that solving complex and “real problems” will become primarily possible through industrial applications. Accordingly, study programmes address students as engineers working in industry. This “imagination” of future students responds to business demands as well as the political strategy to secure Switzerland’s economic competitiveness. Through their orientation on technical “core courses,” applicability and “real worldness,” the programmes actively create the supply of skilled personnel in data science that industry “is desperately looking for.”

7 Conclusion

Higher education and research are experiencing ongoing processes of sociotechnical transformation. At the same time, in economic, political, and societal discourse, they are regularly considered to be important drivers of technological innovation and economic growth. In this environment, new bodies of knowledge emerge while others are being transformed and the emergence of a new scientific field can lead to uncertainties and confusion about its position and value for actors in more established fields. The discussions surrounding the introduction of data-intensive research and study programmes in Swiss institutions of higher education make it clear that all universities are facing similar challenges.

My analysis shows that the introduction of data science in higher education in Switzerland is a site of multiple future visions by industrial, scientific and political actors wherein consulting agencies (and other business actors) frame the emerging field through alarming calls of “skills gaps” or “talent shortages” and repeatedly demand to increase the number of educated professionals in data science. At the same time, protagonists in tech companies reimagine the data scientist as having the “sexiest job of the 21st century.” This finds an equivalent in the tech field which adopted new values beyond engineering such as entrepreneurship, communication, and creativity. The combination of “talent shortages” and sexy future job prospects helped entice people to the field of data science. Actors in science policy envision the emerging

11 See https://ic.epfl.ch/data-science-internships-1 (27.02.2019).

field of data science as a new "scientific paradigm" with the potential to transform every corner of society. They also mobilise its societal relevance in the context of innovation policies as key to the nation's "competitiveness" in science and research. This has translated into generous funding schemes in science and research, and calls of action to increase education opportunities for skilled personnel in industry. Swiss universities have responded to the different conceptions by actors in the business world and science policy. Despite organisational variation in the introduction of data science in Swiss universities according to their different profiles and traditions, several common points characterise current curricula including a strong focus on interdisciplinarity and "real-world" applicability. Relying on a technical and mathematical core with different areas of scientific or business application, they imagine potential students as engineers working in industry.

It is indisputable that an important function of any higher education system is to provide education in the production of skilled personnel for the labour market. The introduction of data science in higher education is marked by the widespread adoption of economic concepts and business terms in science policies on one hand and educational curricula on the other. This finding is consistent with earlier work on the intrusion of economistic practices and concepts into research and higher education (Jessop 2008; Maesse 2010; Wodak 2015). However, sociotechnical imaginations such as "talent shortages," the "sexiness" of data science and its inclusion into innovation policies help to coordinate the practices of a wide array of actors in different fields – from the tech and business world to that of science policy and higher education. This combination of influence not only reshapes earlier conceptions of data science, it also contributes to the achievement of objectives formulated in these visions, which included the rapid expansion of data science programmes in higher education and a supply of data science skills outside academia. The introduction of data science in Swiss universities can thus be seen as an example of close and interconnected relations between industry, science policy and universities in the digital age.

The imagination of data science as an engineering discipline within Swiss higher education refers to juxtaposition of science and the "real-world" that is prevalent both in science policy documents as well as curricula. The "engineering perspective" itself is nothing new for higher education in Switzerland, which is characterised by a strong application-based orientation and a long tradition of close academy-industry relationships. This is especially true in the case of the ETH Domain (Gugerli et al. 2005) and, more recently, in universities of applied sciences (Weber et al. 2010). This instrumentalist distinction reproduces a boundary between scientific and non-scientific aspects of data science that locates "real problems" outside academia (Malazita 2019). This is consistent with cultural "imaginations" that envision data analysis and technology-driven solutions as a powerful force to solve complex challenges for humanity in the 21st century (Morozov 2013). Although the source of this representation is in industry, its broad acceptance in multiple fields point to major cultural changes that accompany the sociotechnical transformation of digitisation.

This paper focused on publicly available materials from different sources, and the material does not necessarily reflect tensions or contradictions articulated during the introduction of a new programme within an institution. Future work will therefore include in-depth interviews with professors and managers of these programmes to consider the reflexive and alternative considerations made in these processes.

Combining the empirical framework of discourse analysis with the theoretical framework of sociotechnical imaginations of the future has proven productive in investigating the coordinating role of such concepts and the specific effects that they produce in the present. The rate and breadth in which data science gained a position within different levels of higher education within the past few years in Switzerland has been striking. The higher education system in this sense proved responsive, flexible and rapidly adaptive "to the demands of the market" in order to fulfil a key requirement on current higher education policies. Future research is needed to investigate whether this is compatible or rather contrasts with the ongoing sociotechnical transformation of digitisation and how it affects the institutional arrangement of Swiss universities.

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8 Appendix 1

Table 1 List of Degree Programmes and Specialisations in Data Science at Swiss Universities (as of December 6, 2018)

University	Department/School	Level of education	Programme name
ETH Zürich	Computer Science, Mathematics & Electrical Engineering	Master of Science (MSc)	Data Science
EPF Lausanne	Computer and Communication Sciences	Master of Science (MSc)	Data Science
University of Zürich	Faculty of Business, Economics and Informatics	Master of Science (MSc)	Computer Science, Major/Minor in Data Science
University of Bern, University of Fribourg, University of Neuchâtel (BENEFRI)	Computer Science	Master of Science (MSc)	Computer Science, with specialisation in Data Science
Università della Svizzera Italiana	Faculty of Informatics	Master of Science (MSc)	Computational Science
Università della Svizzera italiana	Faculty of Informatics	Master of Science (MSc)	Artificial Intelligence
University of Lausanne / University of Neuchâtel	Faculty of Business and Economics (Lausanne), Faculty of Economics and Business (Neuchâtel)	Master of Science (MSc)	Information Systems
University of Lausanne	Faculty of Business and Economics (HEC UniL)	Master of Science (MSc)	Finance, orientation in Financial entrepreneurship and Data Science
University of Geneva	School of Economics and Management	Master of Science (MSc)	Business Analytics
University of St. Gallen	School of Management	Certificate (BA)	Data Science Fundamentals
University of Lausanne & EPFL	Faculty of Business and Economics (HEC UniL), Swiss Data Science Center (EPFL)	Certificate of Advanced Studies (CAS)	Data Science & Management
ETH Zürich	Departments of Computer Science, Mathematics & Electrical Engineering	Diploma of Advanced Studies (DAS)	Data Science
University of Applied Sciences Luzern	School of Business	Master of Science (MSc)	Applied Information and Data Science
University of Applied Sciences Chur	School of Engineering and Business	Master of Science (MSc)	Business Administration, Major in Information and Data Management

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University	Department/School	Level of education	Programme name
University of Applied Sciences Northwestern Switzerland	School of Engineering	Bachelor of Science (BSc)	Data Science
University of Applied Sciences Rapperswil	School of Engineering	Bachelor of Science (BSc)	Informatics, specialisation in Data Engineering & Machine Intelligence
University of Applied Sciences Northwestern Switzerland	School of Engineering	Bachelor of Science (BSc)	Informatics, specialisation in Data Science
Zürich University of Applied Sciences	School of Engineering	Master of Advanced Studies (MAS)	Data Science
Bern University of Applied Sciences	School of Engineering and Informatics	Master of Advanced Studies (MAS)	Data Science
University of Applied Sciences Lucerne	School of Informatics	Certificate of Advanced Studies (CAS)	Big Data Analytics
University of Applied Sciences Northwestern Switzerland	School of Engineering	Certificate of Advanced Studies (CAS)	Data Science
Scuola Universitaria Professionale della Svizzera Italiana (SUPSI)	Department of Innovative Technologies	Certificate of Advanced Studies (CAS)	Big Data Analytics and Machine Learning
Swiss Distance University of Applied Sciences (FFHS)	Department of Informatics	Diploma of Advanced Studies (DAS)	Data Science